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An Intelligent Model for Predicting the Damage Depth of Coal Seam Floor Based on LS-SVM Optimized by PSO

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Abstract: Based on the damage depth of coal seam floor prediction method and theory, according to the cases of the coal seam floor damage depth collected on site in mining fields, it is analyzed that the mining depth, coal seam pitch, mining thickness, working face length, the floor damage resistant ability and the existence of fault or fracture are main factors influencing the damage depth of the coal seam floor. To overcome the overfitting problem for the artificial neural network method, a novel method for predicting the damage depth of coal seam floor by Least-Squares Support Vector Machines (LS-SVM) is proposed in this paper whose hyper-parameter selection is presented based on the Particle Swarm Optimization (PSO). As it is difficult to determine the machine parameters of LS-SVM and the prediction accuracy is not high, the PSO is applied for its high convergence speed and global optimization ability, this paper optimizes the penalty factor and kernel function parameters of LS-SVM model to avoid the blindness of the manual parameter choice and to improve the training speed and the generalization ability of the prediction model. Statistical data of the mining-induced coal seam floor damage depth were calculated for the main mining areas in China by applying the LS-SVM prediction model and the results indicate that the value predicted by the model coincides with the actual measured data and is more reliable than the value calculated by the empirical formula. The model has not only a reliable theoretical basis but also good application value.

Key words: SVM, LS-SVM, PSO, damage depth of coal seam floor, parameter optimization

INTRODUCTION

Coal seam floor damage depth is one of the important factors related with the safety issues of the coal mining on confined water. At present, the non-measured acquiring method commonly used in the floor damage depth includes: The theoretical formula calculation method (Shi and Han, 2005), empirical formula method (Peng and Wang, 2001), neural network prediction method (Wang *et al*., 2009; Yu *et al*., 2009) and etc., Certain effects have been received. However, for these methods, the conditions required by the theoretical formula calculation method are hard to satisfy. The application prospect of the empirical formula is not wide. Recent artificial neural network method is based on the traditional statistics theory, the assumption of the infinitely large sample sizes and the principle of the minimum empirical risk, but it fails to realize the expected risk minimization principle which was derived from Bayesian decision theory, hence, it's easy to cause a overfitting problem.

The statistical learning theory established by (Vapnik, 1998 and 1995) points out that the learning machine with good generalization ability can only be obtained by controlling the empirical risk as well as the learning machine capacity under the condition of the small sample. The Support Vector Machine (SVM) algorithm is also suggested. Following the structural risk minimization principle, SVM remedies the defects of the neural network and has good generalization ability under the condition of the small sample. Least squares support vector machine (LS-SVM) method is an improved method (Suykens and Vandewalle, 2000 and Chua, 2003) based on the standard SVM method. The least squares linear system is taken as the loss function in this method, in which the solving process becomes the solution of a set of equations and the calculation speed increases. This method is widely used in the pattern recognition and nonlinear function estimation. For both of the standard SVM method and the improved method, the performance depends on the parameters of the learning machine. Until now, how to determine the optimal parameters has been a research hot spot and a difficult point.

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Based on the existing researches, the LS-SVM method and the PSO algorithm (Kennedy and Eberhart, 1995; Van den Bergh and Engelbrecht, 2004) are combined in this paper to predict the coal seam floor damage depth. The LS-SVM method is used to describe the complex nonlinear relationship between the coal seam floor damage depth and the influential factors and the PSO is used to search the optimal parameters of the LS-SVM. Calculation results indicate that the LS-SVM method based on the PSO with the optimized parameters can simply and effectively predict the coal seam floor damage depth. The method is applied in the coal seam floor damage depth prediction in the mining areas and the results are satisfying by compared with the present methods.

SVM AND PSO ALGORITHM

SVM and LS-SVM: Firstly, the standard SVM is introduced. For the problem of the pattern recognition, a calculable recognition function $y = f(x)$, $x \in R^n$, $y \in \{-1, 1\}$ is found. For the N samples (x_1, y_1), (x_2, y_2), ..., (x_n, y_n) given, a hyper face (decision-making face) is found to separate the sample, i.e., $Wx+b = 0$, $W \in R^n$, $b \in R$, the corresponding recognition function is:

$$f(x) = \text{sign}((Wx)+b) \tag{1}$$

Decision making face should satisfy the constraints:

$$y_i[Wxi+b] \geq 1-\xi,\ i = 1, 2,..., N \tag{2}$$

Optimal decisions should satisfy that the minimal distance between the two kinds of samples and decision surface is the maximal. Thus, the classification problem is how to satisfy $\xi \geq 0$ and the minimization of the Eq. 2, which is:

$$\text{Min}: \tau(W) = \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{N}\xi_i \tag{3}$$

where, the first item makes the minimal distance between the two kinds of samples and the decision-making face the maximal, the second item makes the error minimum and the constant C is the compromise of the two items. The optimization problem with constraints can be converted to the antithesis problem by using the Lagrangian optimal method:

$$\left.\begin{array}{l} \text{Max}: W(\alpha) = -\frac{1}{2}\sum_{i,j=1}^{N}\alpha_i\alpha_j y_i y_j (x_i \bullet x_j) + \sum_{i=1}^{N}\alpha_i \\ \text{s.t.}: 0 \leq \alpha_i \leq C, i = 1, 2, \cdots, N \\ \sum_{i=1}^{N}\alpha_i y_i = 0 \end{array}\right\} \tag{4}$$

The classification of the corresponding function can be deduced to:

$$f(x) = \text{sign}(\sum_{i=1}^{N}\alpha_i y_i (x_i \bullet x) + b) \tag{5}$$

For the nonlinear separable cases, a nonlinear function ϕ can be used to map the data into a high-dimensional feature space and establish an optimal hyper face in the high dimensional feature space, the corresponding hyper face is $W\phi(x)+b = 0$, thus, the classification function is:

$$f(x) = \text{sign}(\sum_{i=1}^{N}\alpha_i y_i (\phi(x) \bullet \phi(x_i)) + b) \tag{6}$$

Usually, function ϕ is difficult to determine. Only the dot product $K(x, y) = \phi(x) \bullet \phi(y)$ of the high dimensional feature space instead of directly using the function ϕ is considered in the SVM theory. $K(x, y)$ is called the kernel function. The classification function is then changed to:

$$f(x) = \text{sign}(\sum_{i=1}^{N}\alpha_i y_i K(x_i, x) + b) \tag{7}$$

Different slack variables are chosen as the LS-SVM suggested by Suykens and the standard SVM suggested by Vapnik utilizes the structural risk minimization principle. The former one is the 2-norm of ξ and the latter one is ξ. For LS-SVM, the optimization problem is as follows:

$$\begin{array}{l} \text{Min}: \tau(W, \xi) = \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{N}\xi_i^2 \\ \text{s.t}: y_i = \varphi(x_i)W^T + b + \xi_i, i = 1, 2, \cdots, N \end{array} \tag{8}$$

Equation 8 is calculated by using the Lagrangian optimization method, then:

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

As the least squares method is used in the solving process, it was named as the least-squares support vector machine. Compared with the standard SVM and the quadratic programming problems solving, the LS-SVM is much faster and requires less computing resources. There are three kinds of kernel Function K commonly used in Eq. 7 and 9. In this study, the kernel Function is the linear kernel function $K(x, y) = (x \bullet y)$ and RBF kernel function, $k(x, y) = \exp(-\|x-y\|^2/2\sigma^2)$.

When LS-SVM is used to establish models, two kinds of parameters are important, i.e., penalty factor C and kernel function parameters (ϕ in this study), which directly affect the model prediction accuracy. Seeking the best C and ϕ is necessary for selecting the best model. Since, PSO algorithm is characterized with the fast and global optimization properties, this paper uses PSO algorithm to search the logarithmic C and ϕ.

Particle swarm optimization algorithm: Kennedy and Eberhart were inspired by the foraging behavior of the birds and found a new kind of random global optimization algorithm in 1995, which was named as the particle swarm optimization algorithm. The basic idea is: Each of the solution of the optimization problems is called a particle. An adaptive value function is defined to measure the superior degree of each particle solution. Each particle swims according to its own and other particle's flying experiences to achieve the goal of searching the optimal solution from the whole space. Specific search process is as follows: each particle in the solution space approaches two points at the same time. The first point, which is called the best global optimal solution (gbest), is the optimal solution in all particles in the particle swarm during the past process of searching. Another point is an optimal solution achieved by itself in the process of past process of searching. The solution is called the best individual optimal solution (pbest). Each particle is represented as a point in the n-dimensional space. The ith particle is expressed as $x_i = [x_{i1}, x_{i2}, ..., x_{in}]$. The individual optimal solution of ith particle is expressed as $pbest_i = p_{i1}, p_{i2}, ..., p_{in}$. The global optimal solution is expressed as $gbest = [g_1, g_2, ..., g_n]$. While the kth iteration correction (particle movement speed) of x_i is expressed as $v^k_{id} = [v^k_{i1}, v^k_{i2}, ..., v^k_{in}]$. The speed and location of each particle are updated according to the following Eq.:

$$v_{id}^{k} = w_i v_{id}^{k-1} + c_1 rand_1 (p_{id}^{k-1} - x_{id}^{k-1}) + c_2 rand_2 (g_d^{k-1} - x_{id}^{k-1}) \tag{10}$$

$$x_{id}^{k} = x_{id}^{k-1} + v_{id}^{k} \tag{11}$$

where, k represents the first kth iteration, i = 1, 2, ..., m, m is the number of particles in the particle swarm; n is the dimension of the solution vector; c_1 and c_2 are the accelerate factors, which are two positive constants; $rand_1$ and $rand_2$ are two independent random numbers between [0, 1]; w_i is the momentum coefficient, the search ability can be changed by adjusting its size.

LS-SVM MODEL FOR PREDICTING COAL SEAM FLOOR DAMAGE DEPTH

Main influence factors: According to the theoretical analysis and the on-site test, the main factors affecting the floor damage depth are:

- Mining depth. As the mining depth increases, the weight of overburden increases, the original rock stress within the coal seam floor increases and the floor destruction is severe
- Coal seam pitch. Laboratory experiments show that the change of the coal seam dip angle causes the change of the stress concentration degree and the concentration area of the floor area, thus the coal seam floor damage depth changes
- Mining thickness. Under a certain condition of the mining depth and established coal bed, mining thickness reflects the mine pressure in the working face. The greater of the mining thickness, the greater of the damage extent of the coal seam roof and floor;
- Working face length. Damage depth of the coal seam floor increases with the working face length. Meanwhile, it also increases the probability of confronting with fracture structure in the working face
- Anti-destructive capacity of coal seam floor. This index is a comprehensive reflection of coal seam floor's rock strength, the rock combination and the original development condition of the crack. When the basic data is unavailable, it can be determined comprehensively according to the type of the rock, the rock combination and the status of the original fracture development
- Whether the cutting fault or the fracture zone exists in the working face. When there is the cutting fault or fracture zone in the coal seam floor, the maximum damage depth occurs near the fault or fracture zone. Due to the weak face, the damage depth will be enlarged near fault or fracture zone
- The coal mining technology and roof management method. The coal mining technology and the roof management method have a certain impact on the floor damage depth. However, the long wall mining method is widely used in the mining process in China and the roof management method is mostly the caving method. Since, the mining method collected in this paper is the same as the roof management method, the influence of the factors is deemed as identical and will not be reflected in this study

Establishment of the prediction model: Quoted from reference[2], the mining-induced floor damage depth of the main mining area in China is shown in Table 1, in which the top 26 examples are selected as the learning samples. The last 5 examples are selected as the testing samples to test the model prediction performance. The flowchart of the PSO-based parameters selection algorithm for the LS-SVM is shown in Fig. 1. PSOLS-SVM modeling steps for predicting the coal seam floor damage depth are as follows:

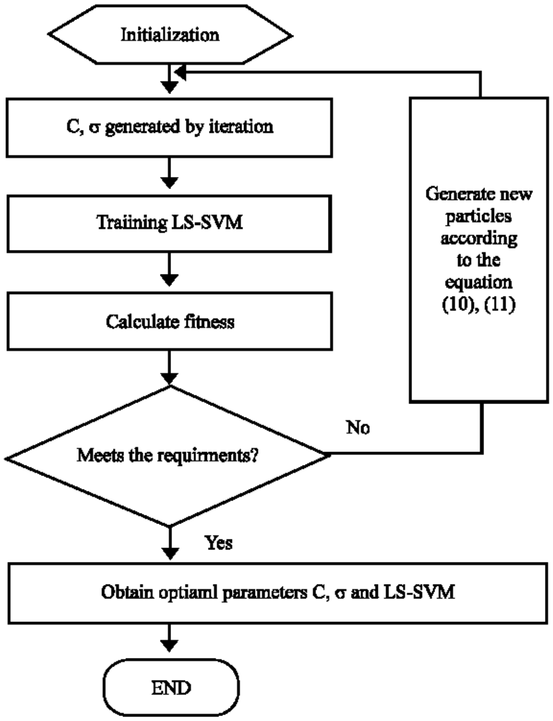

Fig. 1: Modeling flowchart of PSO-based LS-SVM

- Summarize the learning samples and the testing samples to quantify the qualitative description data and conduct the normalization process for all data
- Initialize the settings, including population scale setting, iterations times, random initial particles z_i^0 and particle initial velocity v_i^0, C in SVM and kernel function parameter σ that the individual particle corresponds with
- Use the corresponding value C and kernel function parameter σ of the individual particles to establish the prediction model of LS-SVM. Calculate each individual adaptive value f (z_i) to represent the prediction value of the promotion ability of the LS-SVM model. The adaptive value function is as follows:

$$f(z_i)=\min(\max(\left\{\frac{\left|x_j-x_j^{'}\right|}{x_j^{'}}\right\},j=1,2,\cdots,l)) \tag{12}$$

where, x_j is the predicted value of the corresponding jth observed samples for the z_i particle; x'_j denotes the measured value of the jth test sample

- According to PSO algorithm and compare the adaptive value f (z_i) with the optimal value f $(pbest_i)$ of the particle per se, if f (z_i)<f $(pbest_i)$, replace the previous optimization solution with a new adaptive value and replace previous particles with new ones:
- Compare the best fitness value f $(pbest_i)$of each particle and the best fitness value f $(gbest_i)$ of all particles. If f $(pbest_i)$<f $(gbest_i)$, replace the original best fitness value of all particles with the best fitness of each particle and at the same time save the current state of the particle
- Verify whether the fitness value or iteration time meets the requirement. If not, another round of calculation will be carried out. Move particles to generate new particles (i.e., new solutions) according to Eq. 10 and 11 and return to step 3; if yes, end computing, the individual particle is the most suitable C and kernel function parameters σ
- Use optimized C and σ to establish the LS-SVM model and to make predictions

RESULTS AND DISCUSSIONS

According to the established PSOLS-SVM model for predicting the mining-induced coal seam floor damage depth, the five floor damage depth examples from No.27 to No.31 in Table 1 were calculated. The corresponding floor damage depth value was obtained. The model prediction results are compared with the measured results from the empirical formula calculation using the given rules (Table 2).

According to the calculation results, it can be known from the analysis that the maximum absolute error of coal seam floor damage depth is 1.076 m predicted by the PSOLS-SVM model. The largest relative error is 9.2%. According to the "Three Under" mining regulations, the maximum absolute error in the related formula calculation results is 1.882 m. The largest relative error is 17.40%. The prediction results of most samples are much better than the empirical formula results. It is shown that the model calculation results are closer to the reality than the empirical formula. The error is small and the precision accuracy is high, thereby satisfying the engineering practice need.

In the model test, the linear kernel LS-SVM is also tested and the results predicted by RBF and the linear kernel are found similar. The RBF kernel prediction has better effect. The results comparison between the prediction results with the linear kernel and the RBF kernel are shown in Table 2. It is indicated that the mining coal seam floor damage depth has obvious linear correlation with the main influencing factors. It is consistent with the current theoretical analysis. However, due to the reasons such as the complexity of the coal seam floor per se, the difficulty in describing the mining damage mechanism, the randomness of the damage process, and the interaction

Table 1: Cases of destroyed floor depth in China coal field

Workface	Mining depth (m)	Coal seam pitch (°)	Mining thickness (m)	Working face length (m)	Anti-destructive capacity of coal seam floor	Fault or broken zone	Damage depth of coal seam floor (m)
Handan	123	15.0	1.10	70	0.2	0	7.00
Handan Wangfeng	123	15.0	1.10	100	0.2	0	13.40
Fengfeng II	145	16.0	1.50	120	0.4	0	14.00
Fengfeng III 3707	130	15.0	1.40	135	0.4	0	12.00
Fengfeng IV 4804	110	12.0	1.40	100	0.4	0	10.70
Feicheng	148	18.0	1.80	95	0.8	0	9.00
Feicheng	225	14.0	1.90	130	0.8	0	9.75
Zibo Shuanggou	308	10.0	1.00	160	0.6	0	10.50
Zibo Shuanggou	287	10.0	1.00	130	0.6	0	9.50
Cenghe II 22510	300	8.0	1.80	100	0.4	0	10.00
Hancheng	230	10.0	2.30	120	0.6	0	13.00
Hebi III 128	230	26.0	3.50	180	0.4	0	20.00
Xingzhuang Zi 4303	310	26.0	1.80	128	0.2	0	16.80
Xingzhuang Zi 4303	310	26.0	1.80	128	0.2	1	29.60
Xingtai 7802	259	4.0	3.00	160	0.6	0	16.40
Xingtai 7607	320	4.0	5.40	60	0.6	0	9.70
shallow working face							
Xingwen	520	30.0	0.94	120	0.6	0	13.00
Jinjing I 4707 little1	400	9.0	7.50	34	0.4	0	8.00
Jinjing I 4707 little 2	400	9.0	4.00	34	0.4	0	6.00
Jinjing III 5701 (1)	227	12.0	3.50	30	0.4	0	3.50
Jinjing III 5701 (2)	227	12.0	3.50	30	0.4	1	7.00
Kaibian	900	26.0	2.00	200	0.6	0	27.00
Kaibian	1000	30.0	2.00	200	0.6	0	38.00
Huoxian	200	10.0	1.60	100	0.2	0	8.50
Wucun 32031 (1)	375	14.0	2.40	70	0.6	0	9.70
Wucun 32031 (2)	375	14.0	2.40	100	0.6	0	12.90
Handan	118	18.0	2.50	80	0.2	0	10.00
Fengfeng II	145	15.5	1.50	120	0.4	1	18.0
Xingtai	320	4.0	5.40	100	0.6	0	11.70
Jinjing I	400	9.0	4.00	45	0.4	0	6.50
Wucun 3305	327	12.0	2.40	120	0.6	0	11.70

Table 2: Calculation results comparison about PSOLS-SVM, empirical formula and field measurement

Damage depth of coal seam floor (m)							
PSOLS-SVM				PSOLS-SVM vs. field		Empirical formula vs. field	
RBF kernel ($C = 10.3$, $\sigma = 2.4$)	Linear kernel $C = 20$	Empirical formula	Field measurement	Absolute error (m)	Relative error (%)	Absolute error (m)	Relative error (%)
10.15	09.6603	8.274	10.00	0.150	1.50	-1.726	-17.26
18.614	18.0844	18.605	18.00	0.614	3.41	0.605	3.36
12.608	11.0293	9.818	11.70	0.908	7.76	-1.882	-16.08
6.9193	07.5795	5.396	6.50	0.419	6.45	-1.131	-17.40
12.776	12.0564	13.367	11.70	1.076	9.20	1.667	14.20

among effecting factors, the damage depth value presents a nonlinear, uneven and uncertainty characteristic, thus, it is more suitable to use the artificial intelligence method to build the prediction model. The influential factors of the coal seam floor damage is considered in the PSOLS-SVM model proposed in this paper and the predictive model can be built conveniently through the study of the measured sample per se and the prediction ability. It also has strong adaptability and wider application area, in addition, the predicted results are closer to the reality, which indicates that the machine learning method has good feasibility and application potential in the mining coal seam floor damage depth prediction.

CONCLUSION

- As the LS-SVM is used to predict the parameters C and σ, the parameter selection is very important. If the parameter selection is not reasonable, the prediction precision will be directly affected. This study optimizes LS-SVM's parameters by the PSO algorithm, thereby improves the model's generalization ability
- Based on the comprehensive analysis of the main influential factors of the coal seam floor damage depth, this paper established a mining coal seam floor damage depth prediction model (PSOLS-SVM).

According to the measured data from the model training and the performance test, it has been proved that it is feasible to use the PSO-LSSVM model to calculate the floor damage depth

- By comparing the floor damage depth results predicted by PSOLS-SVM model with the results calculated by the relevant empirical formula and the results measured by the contrastive analysis, the nonlinear mechanism between different influential factors is considered, so it is more correspondent with the engineering practice and has a higher accuracy than the empirical formula. PSOLS-SVM model has not only a reliable theoretical basis but also a good practical application value

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