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The Deformation Prediction of Mine Slope Surface using PSO-SVM model

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Abstract

Based on the main factors with important influence on the deformation of the mine slope, a new method integrating support vector machine (SVM) and particle swarm optimization (PSO) was proposed to predict the deformation of mine slope surface. The meteorological factors and the deformation data of the research area are acquired using the advanced deformation monitoring equipment Ground Based-Synthetic Aperture Radar (GB-SAR). Then the SVM is used to predict the mine slope deformation. The PSO is employed to optimize the structure parameters of the SVM. The proposed new method was applied to predict the mine slope surface deformation of the Anjialing diggings in China. The obtained experiments results indicated that the proposed method can provide precise prediction of the mining slope surface deformation and its performance is superior to its rivals.

Keywords*: geologic measurements, meteorological factors, forecasting, particle swarm optimization, support vector machine*

1. Introduction

The excavation of open-pit mine and underground openings of other underground mines around Anjialing diggings causes the open-pit mine slope surface deformation. Evaluation of the mine slope surface deformation is an important aspect of the safety assessment for open-pit mine in complex conditions, contributing to detect the mine geological disaster as soon as possible. Large deformation may significantly reduce the stability of the mine slope and lead to the mine geological disaster such as collapse and landslide. Considering the safety production and the safety of the miners, mine slope deformation is required to be estimated real-time. The monitoring of slope deformation is of great importance for mine safety evaluation. Using intelligent methods to forecast deformation of the mine slope could save manpower and material resources to a great extent. Accurate prediction of mine disasters could ensure the safety of mine workers and improve the mine safety level [1].

Currently, there are mainly two kinds of method for the deformation prediction of the mine slope surface. One is the deterministic method, such as the Limit Equilibrium Analysis Method which is using the corresponding mechanics theory to evaluate the stability of the slope. The other is the uncertainty method. It combines the mathematical physics theory and the various influencing factors to give the quantitative analysis of the slope stability. The uncertainty method contains the Fuzzy mathematic theory, Grey system theory, Expert system theory and Artificial neural networks theory. The mine slope is a complex dynamic system influenced by multi-influence factors and time and space variation. If using the deterministic method, there may be exist multiple sliding surfaces and the mechanics mechanism of the slope destruction is not very clear sometimes because of the location and the shape of the sliding surface can't be determined well. Hence, the deterministic method could not evaluate the stability of the slope accurately. Owing to the variability, uncertainty, without a precise prototype, the limited data and complex geological environment features, the research method of the uncertainty method be able to fully consider the various factors affecting the mine slope. In the scope of the uncertainty analysis method, Artificial neural network (ANN) is most widely used. ANN is based on the heuristic mode, and it has not fairly complete theoretical basis.

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ANN has the disadvantages of controlling the network promotion after training not very well and can not reach the global optimum sometimes [2].

However, SVM can effectively make up the shortage of the ANN. Many works about the application of the SVM prediction regression analysis have been investigated in [3, 4]. The quantitative relation between the terrain factor, geological factor, human engineering activity factors and the mining slope surface deformation have been widely studied by the international and domestic academics to establish the prediction model for the mining slope surface deformation [5]. However, it is very regretfully finds that very little work has been done in prediction of mining slope surface deformation using meteorological factors. To address this issue, a new method is proposed using the meteorological factors to forecast the mining slope surface deformation. In this experiment, the meteorological factors include five parameters: the temperature, atmospheric pressure, cumulative rainfall, relative humidity and refractive index of the mining slope surface.

A key problem in the prediction process is to extract the relationship between the meteorological factors of deformation area and the deformation value based on the observed data, which shows great complexity and non-linearity and is difficult to model by traditional mathematical methods [6].

The experiments have been implemented to evaluate the new approach and a comparison between the SVM, GA-SVM and PSO-SVM prediction models has been carried out. The analysis results show that the proposed method can provide precise prediction of the mining slope deformation and its performance is superior to its rivals.

2.The Proposed Algorithm

2.1. Support Vector Machine and Its Optimization

SVM is a supervised machine learning method based on the statistical learning theory. The SVM was proposed by Vapnik [7]. It is used to train nonlinear relationships based on the structural risk minimization principle that seeks to minimize an upper bound of the generalization error rather than to minimize the empirical error implemented in neural networks [8]. Merit of the SVM is that training is a uniquely solvable quadratic optimization problem [7].

Assuming that sample set $S=\{(x_{j,}\ y_j)\,|\,j=1,2,...,n\}\in R^p\times\{-1,1\}$ is linear separable, and exist a hyperplane $\omega^T\mathbf{x}+b=0$ that makes arbitrary sample $(x_{j,}\ y_j)$ satisfy the following condition [7]:

$$\begin{cases}\omega^T x_j+b\geq +1\,(when\ y_j=+1)\\ \omega^T x_j+b\leq -1\,(when\ y_j=-1)\end{cases} \tag{1}$$

Where, ω is the weight vector and b is a constant. Then the goal of SVM is to find the optimal hyperplane $\omega^T\mathbf{x}+b=0$ and make (ω,b) subject to the following convex quadratic optimization problem [7]:

$$\begin{cases}\min(\dfrac{\|\omega\|^2}{2})\\ s.t.\ y_j(<\omega,x_j>+b)\geq 1\end{cases} \tag{2}$$

When the sample set S is not linear separable, a slack variable ξ is needed such that Equation (2) can be rewritten as [8]:

$$\begin{cases}\min(\dfrac{\|\omega\|^2}{2}+C\sum_{j=1}^{n}\xi_j)\\ s.t.\ y_j(<\omega,x_j>+b)\geq 1\end{cases} \tag{3}$$

Where, C is the penalty parameter.

Equation (3) is typical convex quadratic optimization problem. To solve this problem the Lagrange multiplier method as well as kernel trick have been introduced. The RBF kernel is defined as [8]:

$$K(a,b) = \exp(\frac{\|a-b\|^2}{2\sigma^2}) \tag{4}$$

Where, σ is the wideth of the kernel function.

In the present study we describe a SVM model using the radial basis kernel function (RBF). The values of penalty parameter C and the wideth of kernel function σ greatly affect the training and generalization capability of the SVMs [9]. Reasonable values of C and σ can be obtained via the PSO method [11] and genetic algorithm (GA) method [10]. The main research architectures of the PSO-SVM and GA-SVM prediction methods are shown in Figure 1.

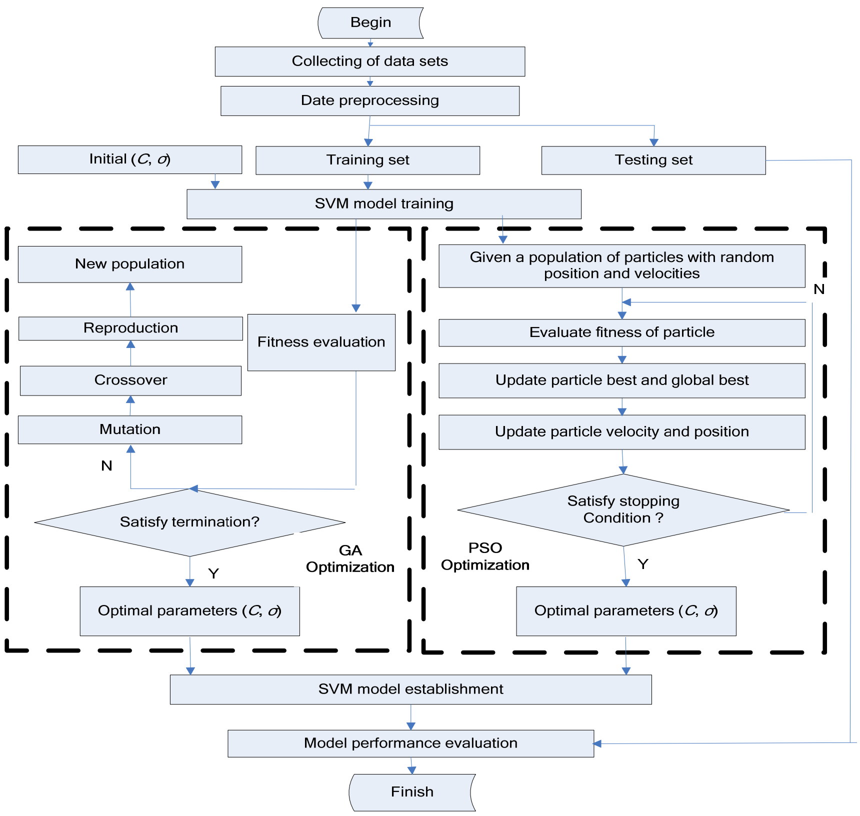

Figure 1. Research Architectures for the SVMs-based Approach with GA and PSO Optimization Method

The free parameters C and σ greatly affect the prediction accuracy of SVMs. However, it is not known beforehand what values of the parameters are appropriate. The genetic algorithm (GA) is inspired by theory of evolution. GA has been considered with increasing interest in a wide variety of applications [10]. Therefore, GA is used to search for better combinations of the parameters in SVMs. Based on the darwinian principle of 'survival of the fittest'. GA can obtain the optimal solution after a series of iterative computations. The process of the GA can be summarized as the left part of the Figure 1. PSO is a populated search method, which derives from the research for the movement of organisms in a bird flocking or fish schooling [9]. Similar to genetic algorithms, PSO performs searches using a swarm of particles that are updated from iteration to iteration. The process of optimizing the SVMs parameters with PSO is presented, which can be summarized as the right part of the Figure 1.

2.2. The Proposed Forecasting Approach

In this work, the proposed PSO-SVM method uses the meteorological data to predict the deformation of the mine slope surface. The inputs of the SVM are collected meteorological data such as the temperature, atmospheric pressure, cumulative rainfall, relative humidity and refractive index of the mining slope surface. The east coordinates, north coordinates and elevation coordinates of the monitored positions are the output variables. Figure 2 illustrates the solution procedure of the PSO optimized SVM method for deformation forecasting of mine slope.

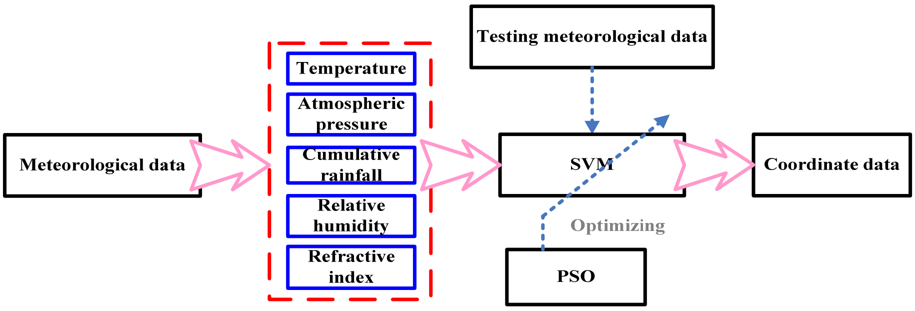

Figure 2. The Diagram of the Intelligent Forecasting Method

3. Research Method

3.1. Influence Mechanism of the Meteorological Factors

The meteorological factors, such as the rainfall and the temperature, etc., can provide significant evident to the deformation condition of the mine slopes. The surface runoff has the main erosion effect on the mine slope surface. The infiltration action along the slop top and surface decreases the soil cohesive force. The infiltration action along the slop fracture supplies the water level of the ground water. The seepage flow into the soil mass and the seepage flow inside the soil mass soften the soil mass. As a result, the rainfall could induce the slope landslide [11]. Table 1 gives the statistic of the occurrence rate of the landslide in rainy seasons in Hubei province. It can be see in the table that the rainfall has significant influence on the landslide.

Table 1. The Time Distribution Table of the Landslides in Hubei

	January	February	March	April	May	June
The monthly average rainfall	20	27	55	97	142	156
The rainfall percentage throughout the whole year（%）	10.2	10.2	10.5	10.9	11.3	11.4
Number of landslides	3	3	6	12	29	44
The landslide percentage throughout the whole year（%）	10.1	10.1	10.3	10.6	11.4	12.1
	July	August	September	October	November	December
The monthly average rainfall	199	153	124	92	50	20
The rainfall percentage throughout the whole year（%）	11.8	11.3	11.1	10.8	10.4	10.2
Number of landslides	53	27	15	13	4	3
The landslide percentage throughout the whole year（%）	12.5	11.3	10.7	10.6	10.2	10.1

The temperature may increase the porosity effect of the rock mass and decrease the bonding strength. As a result, the rock strength, elastic modulus, elongation at break, and peel strength are all decreased. As a result, the rainfall and temperature could be used as important indexes to indicate the deformation condition and landslide of the mine slopes. Besides these two indicators, some other meteorological factors also have strong influence or/and connection to the deformation condition of mine slopes, such as the atmospheric pressure, relative humidity and refractive index. All of them will be adopted to predict the deformation condition of mine slopes in this work.

3.2. Experimental Setup and Tests

The continuous experiment test has been carried out during 23th July to 29th July 2012. The mine slope at the Anjialing diggings of the China Coal Pingshuo group co., Ltd in North China was selected as the experiment test area. In the experiments, the meteorological factors data as well as the deformation data have been collected using a Image By Interferometric Survey-for mines radar (IBIS-M) [12]. The recorded meteorological factors contain the cumulative rainfall, relative humidity, atmospheric pressure, temperature and refractive index of the mining slope surface. The recorded deformation data includes the east coordinates, north coordinates and elevation coordinates of the monitoring probable deformation points. Then the collected data is used to establish a generalized regression neural network to forecast the deformation data of the mine slope surface.

Figure 3 shows the topography of the experimental strip mine. The monitoring mining area has several mining platform. The IBIS-M was installed at the platform of the western part of the strip mine and was responsible for monitoring the eastern part of the strip mine. The distance between the IBIS-M radar to the monitoring area was 2.3km, which was a suitable range for the IBIS-M radar.

Figure 3. The Topography of the Monitoring Area in the Experiments

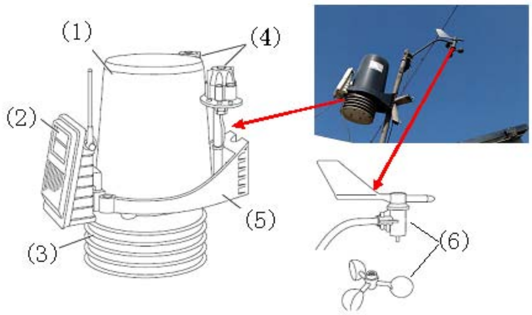

Figure 4. Meteorological Sensor Module (1) Rain Collector (2) Solar Panel (3) Radiation Shield (4) UV and Solar Sensors and Sensor Mounting Shelf (5) ISS Base (6) Anemometer Vane and wind Cups

The Weather Station (Vantage Pro2) is the main actuator in the IBIS-M to collect the meteorological data. Figure 4 shows the Vantage Pro2. The Vantage Pro2 is a kind of Integrated Sensor Suite (ISS). Vantage Pro2 contains a rain collector, temperature sensor, atmospheric pressure sensor, humidity sensor and anemometer. It can measure six weather parameters, including the wind speed and direction, precipitation, atmospheric pressure, temperature and relative humidity.

4. Results and Analysis

Table 2 shows the comparison between the prediction value using the SVM, GA-SVM and the PSO-SVM model and the real value. Within the scope of the five prediction test points, the PSO-SVM method prediction values are presenting a perfect performance. The point 2, 3, 4 and 5 prediction values using the PSO-SVM method are better than using the SVM and GA-SVM methods. The experimental results of the PSO-SVM method reflected great advantages.

Table 3 shows the prediction error comparison between the SVM, GA-SVM and PSO-SVM method and the real value. From the Table 3, it could be informed that the prediction error of the GA-SVM and the PSO-SVM methods is significantly less than SVM method. The prediction error of the PSO-SVM prediction model is the lowest on the whole.

Table 2. The Prediction Value using SVM, GA-SVM and PSO-SVM Prediction Method

Method	Point 1	Point 2	Point 3	Point 4	Point 5
Real Value	484436.67541607	484436.67468012	484436.67420401	484436.67344814	484436.67413648
SVM	484436.67440468	484436.67709907	484436.67933136	484436.68047348	484436.68092876
GA-SVM	484436.67481319	484436.67669500	484436.67806744	484436.67891236	484436.67932376
PSO-SVM	484436.67389035	484436.67576397	484436.67672134	484436.67714885	484436.67758350

Table 3. The Prediction Error using SVM, GA-SVM and PSO-SVM Prediction Method

	Point 1	Point 2	Point 3	Point 4	Point 5
SVM	0.14974356758	-0.35853297606	-0.76050381389	-1.04318995407	-1.00755245587
GA-SVM	0.06780517774	-0.31493002104	-0.58225615796	-0.81704170337	-0.77591418735
PSO-SVM	0.29093387402	-0.14852384595	-0.40143882545	-0.60042074706	-0.56950441930

Figure 5 (left) shows the convergence curve of the GA optimization. It can be seen in the figure that at the beginning of the training process, the initial weight values of the SVM score a low mean square error, the GA can search relative satisfactory weight values to enhance the prediction ability of the SVM. After about 30 steps iterations, the GA algorithm gains the lowest mean square error. Figure 5 (right) shows the changing process of mean square error of SVM comparing with the real value. It can be seen in the figure that the mean square error value of SVM is very smaller than the GA optimization method in the process of the entire 100 iterations.

Figure 6 shows the performance comparisons of the prediction values for the east coordinate among the following methods, SVM, GA-SVM, and PSO-SVM. It can be seen in the figure that the prediction precision of the PSO-SVM is higher than that of others. The prediction error of the PSO-SVM is much smaller than that of using other methods in the whole process. These comparisons indicate that taking the advantages of the PSO optimization, the SVM could be trained well with high genelization ability and hence the forecasting performance is superior to the other methods.

From Figure 5 and 6, it can be seen that the PSO optimization not only increases the convergence speed of the SVM in the training process but also the genelization ability. Thus the PSO-SVM could provide satisfactory performance in the prediction process.

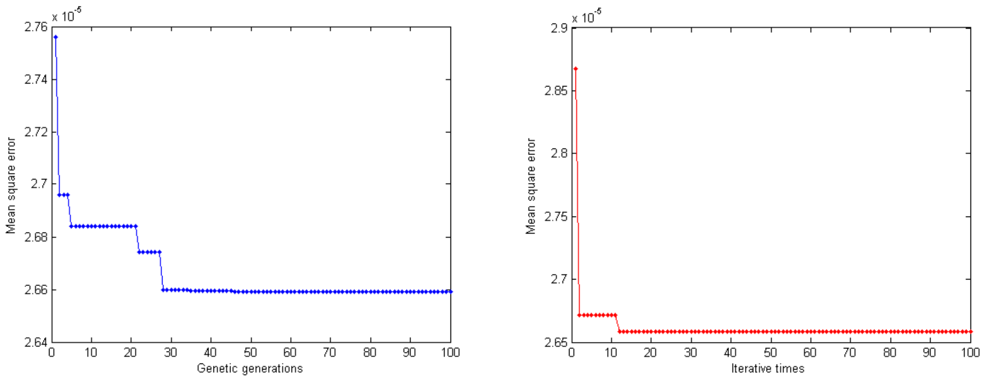

Figure 5. The Convergence Curve of the GA Pptimization (left), The Convergence Curve of the PSO Optimization (right)

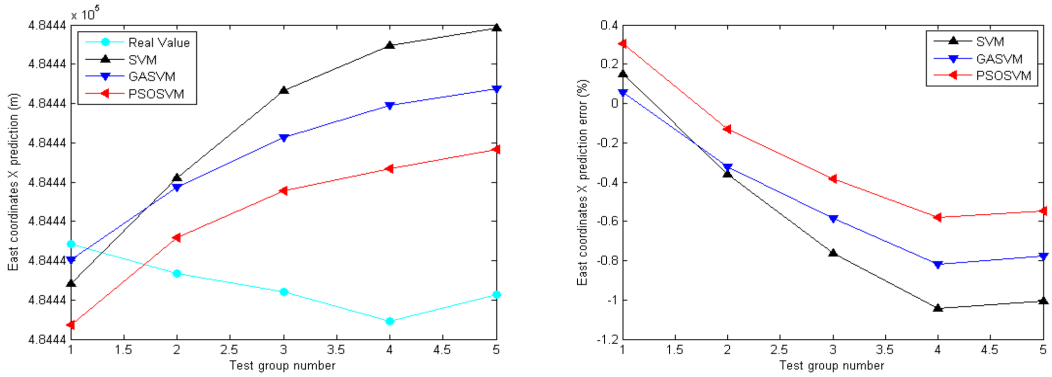

Figure 6. The Forcecasting Performance: (left) the prediction results of the SVM, GA-SVM, and PSO-SVM, (right) the prediction error of the SVM, GA-SVM, and PSO-SVM

Table 4 lists the MAE, MAPE and RMSE prediction errors. In the table we can see that the prediction precision of the PSO-SVM is higher than that of GA-SVM or SVM. The prediction mean absolute errors of SVM and GA-SVM are 0.00447506 and 0.00191506, respectively. Contrast with them, the prediction mean absolute error of PSO-SVM is 0.00162960. As a result, we can see that the PSO-SVM algorithm has better performance than SVM and GA-SVM.

Table 4. The MAE, MAPE and RMSE using SVM, GA-SVM and PSO-SVM Prediction Methods

Method	MAE (%)	MAPE (%)	RMSE (%)
SVM	0.00447506	0.00000084	0.00000084
GA-SVM	0.00191506	0.00000066	0.00000066
PSO-SVM	0.00162960	0.00000038	0.00000038

5. Conclusion

In this study, the proposed method that the particle swarm optimization (PSO) optimized support vector machine (SVM) model was effectively used to predict the mine slope surface deformation of the Anjialing diggings, which is a open-pit mine of the China Coal Pingshuo group co., LTD. in China. Our purpose was to compare the effectiveness of the proposed PSO-SVM forecasting method with those of other well-known intelligent forecasting methods such as SVM and GA-SVM in the experimental investigation. The analysis results on experimental data demonstrate that, PSO-SVM forecasting method has the most accurate predicting outcomes and the least mean square error. PSO-SVM shows a higher coefficient of determination (CoD) and lower mean absolute error (MAE). Based on the study, it is evident that PSO-SVM seems to be a better option than SVM and GA-SVM for the close and appropriate prediction of mine slope surface deformation. Future research is planned to further investigate the practical use of the proposed deformation forecasting approach in mining industry. Their industrial application will be explored in the mine safety production.

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