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Surface Deformation Prediction Model of High and Steep Open-Pit Slope Based on APSO and TWSVM

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Abstract—**At present, due to the complex and changeable geological conditions, the precise deformation prediction technology of high and steep slope could not achieve an accurate prediction. In particular, the single forecasting model has some problems such as poor stability, low precision, and data fluctuation. In practice, excavating the complex nonlinear relationship between open-pit slope surface deformation monitoring data and various influencing factors and improving the accuracy of the deformation prediction of high and steep slopes is the key to safe open-pit mine production. It proposed to introduce the position factor and the velocity factor into a twin support vector machine (TWSVM). The adaptive subgroup optimisation (APSO) algorithm is selected for parameter optimisation. Through the comparative analysis of TWSVM, genetic algorithm-TWSVM (GA-TWSVM), and the proposed APSO-TWSVM, the experimental data show that the mean absolute error (MAE) values of the three models are 13.29 %，8.17 %, and 1.27 %, the RMSE - 47.83 %，6.52 %, and 3.02 %, respectively; the prediction time for APSO-TWSVM is improved by 62.5 % compared to GA-TWSVM.**

Index Terms—**High and steep slope; Slope surface deformation prediction; Twin support vector machine; Adaptive subgroup optimisation.**

I. INTRODUCTION

The surface deformation of the mine slope is a common phenomenon in the mining process, but when the slope deformation is accumulated to a certain extent, it will cause great damage to the mining area, and even geological disasters such as cracks, collapses, and landslides [1]. Due to the influence of many factors, such as the meteorological environment, the geological structure, and the activities of artificial mining, the slope deformation prediction model is generally a complex and nonlinear model [2]. The open-pit slope surface deformation prediction model of is established to analyse the coupling relationship between the factors that affect slope deformation and the amount of direct deformation, so as to predict and warn the main deformation of the slope in advance, and to take disaster prevention measures in advance to ensure the safety of personnel and properties.

Aiming at the prediction of the surface deformation of the mine slope, many experts and scholars have porposed a variety of different prediction methods. Currently, open-pit slope deformation prediction models mainly include the statistical model, the deterministic model, and the artificial intelligence model [3]. The artificial intelligence model is suitable for the construction of complex nonlinear models, which significantly improves the accuracy of slope prediction [4]. Artificial intelligence models include the random decision forest model [5], the neural network model [6], the support vector machine [7], the extreme learning machine [8], etc. However, when the random decision forest model has a large number of features or contains a large number of decision trees, the system is prone to overfitting [5], and the neural network model is prone to overfitting and local optimal solutions during operation [9]. The SVM model is suitable for processing high-dimensional sparse data with a small number of samples, but the support vector machine (SVM) model is highly dependent on the predictive performance of selected kernel parameters [10]. In addition, the SVM prediction model also has the problem of slow convergence speed. Time is very critical for disaster prevention in short-term deformation prediction, so it is also very critical to improve convergence speed.

The twin support vector machine (TWSVM) is a derivative of the support vector machine. Compared to the support vector machine model, it not only has higher training speed, but also has better generalisation ability [11]. Since the TWSVM model is affected by parameters, the parameters must be optimised by combining the genetic algorithm [12], the particle swarm algorithm [13], the artificial fish swarm algorithm [14], and other search algorithms to improve the

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convergence speed and recognition accuracy of the model algorithm. Therefore, it is necessary to establish the combination prediction model strategy and make full use of the advantages of various models to improve the slope prediction accuracy. At present, the TWSVM model has been widely used in materials, machinery, electric power, and other fields, but it has not been used much in surface deformation prediction of open-pit slope, dam body, bridge, and other structures. In TWSVM, penalty factor and kernel function are the two most important parameters [15], which affect the computing power and the modelling effect of the model. Therefore, parameter optimisation of these two parameters is very critical, and it is necessary to use intelligent algorithms for parameter optimisation to improve the prediction effect [16].

Among commonly used parameter optimisation algorithms, the particle swarm optimisation (PSO) algorithm has a fast running speed, high prediction accuracy, and is easy to implement, but it is easy to fall into local optimal solutions, so it needs to be improved. Based on the particle swarm optimisation algorithm, the adaptive particle swarm optimisation (APSO) algorithm was proposed by introducing the position factor and the velocity factor [17]. Its operating mechanism is to reinitialise the particles before they fall into the local optimal solution, establish the APSO-TWSVM prediction model, and perform prediction verification and comparative analysis with the field measured data.

II. Description of the Proposed Approach

A. Influence Mechanism of Meteorological Factors

The rainfall event in mine area is an important factor that affects slope stability. On the one hand, surface runoff is the main external force of mine slope breakage. The grinding pressure of the surface runoff will corrode the slope surface, erode the slope foot, and form a channel network. On the other hand, rainfall infiltration increases pore water pressure and decreases the cohesion and damping force of the soil. Therefore, rainfall can induce slope slide. The action mechanism of rainfall on slope land surface is shown in Fig. 1. The influence of rainfall events on slope deformation in mining area is so great that we mainly monitor the influence of rainfall events on slope deformation from two aspects, one is the rainfall monitoring data and the other is the rainfall duration monitoring data [18].

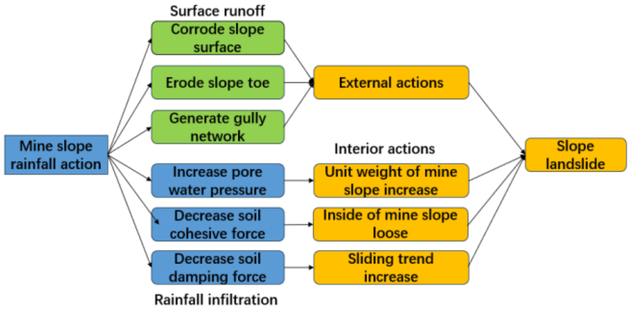


Fig. 1. The mechanism of action of rainfall on the slope landside.

In addition, temperature is also an important factor that causes the deformation of the mine slope. The pore effect of the rock mass increases and the bonding strength of the rock mass decreases with increasing temperature. As a result, the rock strength, elastic modulus, elongation at break, and peel strength all decrease. The effect mechanism of slope regional temperature on slope land surface is shown in Fig. 2.

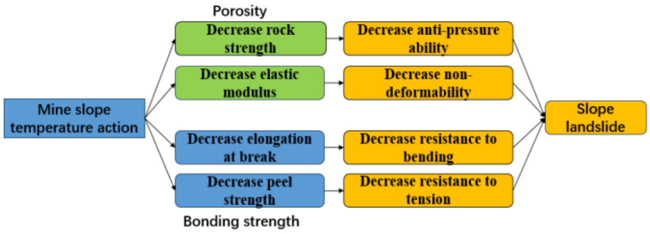


Fig. 2. The mechanism analysis of temperature influencing factor on slope landside.

Rainfall and temperature can be used as important indicators of mine slope deformation and landslide. In addition to these two indexes, some other meteorological factors also have a strong influence on the deformation of the mine slope, such as atmospheric pressure, relative humidity, and artificial mining disturbance. All these will be used to predict the deformation of the mine slope in this work [19].

B. Twin Support Vector Machine

The difference between twin support vector machine (TWSVM) and SVM is that SVM only builds a classification hyperplane for two types of training samples, while TWSVM searches for a pair of unparallel hyperplanes, and requires that one type of sample be relatively close and the other type of sample be relatively far away [20].

As an upgraded version of traditional classifiers, TWSVM has better classification capabilities than SVM, which is intended to find two nonparallel hyperplanes to solve two small-scale quadratic programming problems, and it is very suitable for solving approximate classification problems of samples.

The first step can be taken as the data set of definite meaning training, $T=\{(x_i, y_i) \mid x_i \in R^n, i=1,2,\ldots,m\}$, where x_i is the sample data, $y_i \in \{+1,-1\}$ is the sample category, and m is the total sample size:

$$\min_{w_1,b_1,a_2} \frac{1}{2} \| Aw_1 + e_1 b_1 \|^2 + c_1 e_2^T q_1, \tag{1}$$

$$\min_{w_2,b_2,a_1} \frac{1}{2} \| Bw_2 + e_2 b_2 \|^2 + c_2 e_1^T q_2, \tag{2}$$

wherein c_1 and c_2 are the penalty parameters, w_1 and w_2 are the normal vectors of two hyperplanes, b_1 and b_2 are the offsets of two hyperplanes, $e_1 \in R^{m_1}$, $e_2 \in R^{m_2}$ are all 1 vectors, and q_1 and q_2 are the relaxation variables representing positive and negative class samples, respectively [21].

C. Adaptive Subgroup Optimisation

The particle swarm optimisation (PSO) algorithm is built based on the imitation of the behaviour of birds looking for food. Its basic principle is that random particles constantly update and iterate their position and speed according to their understanding of themselves and their surrounding conditions and find the optimal value of the particles, in order to obtain the optimal solution in space [22].

The information about the particles is represented by the population of particles $X = \left(X_1, X_2, \ldots, X_n\right)^T$ in dimension D [17]. The i[th] particle is represented by $X_i = \left(X_{i1}, X_{i2}, \ldots, X_{iD}\right)^T$, X_i represents the particle's position in the search space, its velocity is $v_i = \left(v_{i1}, v_{i2}, \ldots, v_{iD}\right)^T$. The individual optimal value is expressed as $P_i = \left(P_{i1}, P_{i2}, \ldots, P_{iD}\right)^T$. The global optimal value of the population is $P_g = \left(P_{g1}, P_{g2}, \ldots, P_{gD}\right)^T$.

In each iteration, the particle updates its own position, X_i, and velocity, v_i, taking into account both its own best value and the overall best value for the search space. The formula is as follows:

$$v_{id}^{(k+1)} = wv_{id}^{(k)} + a_1 r_1 \left(P_{id}^{(k)} - X_{id}^{(k)}\right) + \\ + a_2 r_2 \left(P_{gd}^{(k)} - X_{id}^{(k)}\right) \\ \left(d = 1, 2, \ldots, D; i = 1, 2, \ldots, n\right), \tag{3}$$

$$X_{id}^{(k+1)} = X_{id}^{(k)} + v_{id}^{(k+1)} \\ \left(d = 1, 2, \ldots, D; i = 1, 2, \ldots, n\right), \tag{4}$$

where k is the forward algebra, w is the inertia weight, a_1 and a_2 are the acceleration constants, and r_1 and r_2 are the random numbers between [0, 1].

Because PSO algorithms tend to fall into local optimality in their operations, we need to optimise the standard particle swarm. The optimised particle swarm optimisation algorithm is called the APSO algorithm [22].

The inertia weight has an important effect on the search range of the algorithm. A large inertia weight can enhance the global search ability of the algorithm, and a smaller inertia weight can improve the local search ability of the algorithm. To this end, a linear decreasing inertia weight algorithm was proposed; its expression is

$$w = w_{\max} - I\left(w_{\max} - w_{\min}\right) / J, \tag{5}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum weights, respectively; I is the current evolutionary algebra; J is the largest evolutionary algebra.

The linear learning rate strategy can be carried out in the way of first large and then small or first small and then large to control the learning factors. Specifically, the strategy of starting with a large value and then decreasing will use a larger learning rate in the early iterations to accelerate the convergence speed of the algorithm and gradually decrease the learning rate in the later stage to improve the stability of the model.

While the strategy of starting with a small value and then increasing will use a smaller learning rate in the early iterations to ensure the accuracy of the model. Then gradually increase the learning rate to accelerate the convergence speed

$$\begin{bmatrix} c_1 = c_{1s} + I\left(c_{1e} - c_{1s}\right) / J \\ c_2 = c_{2s} + I\left(c_{2e} - c_{2s}\right) / J \end{bmatrix}, \tag{6}$$

where c_{1s} and c_{2s} are the initial values for c_1 and c_2 in the iteration and c_{1e} and c_{2e} are the final values for c_1 and c_2 in the iteration. The ranges of c_1 and c_2 are [2.5, 1] and [1.5, 2.75], respectively.

According to (3), it is known that during the computation process, when particle i approaches the global optimum value P_g, if the last two terms of (3) approach 0, the velocity of the particle basically does not change. From (4), it is known that the position of the particle does not change, if at this point the global optimum is a local optimum, then the local optimum is reached. Therefore, introducing the velocity factor v and the position factor γ $(v, \gamma \geq 0)$, $d_{ij} = \| X_{ij} - P_{gi} \|$ represents the distance between the current position of the i[th] particle in the j[th] dimension and the global optimal position. When the particles are iterating, a judgment is made before executing the position update and velocity update, if $d_{ij} < \gamma$ and $v_{ij} < v$, then the position of the particle needs to be updated again, which can prevent the particle from falling to a local optimum [16].

D. APSO-TWSVM Prediction Model

In this experiment, the proposed adaptive particle swarm optimization-TWSVM (APSO-TWSVM) method uses meteorological data to predict the deformation of the surface of the mine slope. TWSVM inputs are collected meteorological data such as the temperature, atmospheric pressure, cumulative rainfall, relative humidity, and refractive index [23].

The APSO algorithm and the TWSVM model were used to build the prediction model using the following steps.

Step 1: Collect surface deformation data and open-pit slope influencing deformation factors data, select the appropriate impact factor, create training and test sets, and normalise sample data.

Step 2: Use the sample training set to train the TWSVM model and optimise its parameters with APSO: ① Initialise the population, determine the number of cycles of the algorithm, the population size, the optimisation range of the penalty factor C, and the kernel parameter σ, and set the initial position of the particles and the initial velocity by adopting the linearly decreasing method for the inertia weights w and the linearly learning factor c_1 and c_2, respectively; ② Calculate fitness; ③ Update the velocity and calculate the position of the particle according to (3), compare d_{ij} and the position factor γ, the updated velocity v_{ij}, and the velocity factor v. If the position of the particle $d_{ij} < \gamma$ and the flight velocity $v_{ij} < v$, then recalculate the position of the particle, otherwise, update the position of the particle according to (3); ④ Analyse the comparative fitness value f_i with the optimal fitness value P_{best}, if $f_i < P_{best}$, then analyse the comparative fitness value f_i and the optimal fitness value P_{best}. If $f_i < P_{best}$, then $P_{best} = f_i$, otherwise, f_i remains unchanged; ⑤ Analyse the comparison between the optimal adaptation value P_{best} and the global optimal value P_{best}; ⑥ If the end condition is satisfied, then stop the iteration, otherwise, repeat ③～⑥.

Step 3: The optimal parameters are output and substituted into the TWSVM model.

Step 4: Test set samples are used to train the TWSVM model and the accuracy and fitting of the model are compared and analysed.

The flow of the APSO-TWSVM prediction model is shown in Fig. 3.

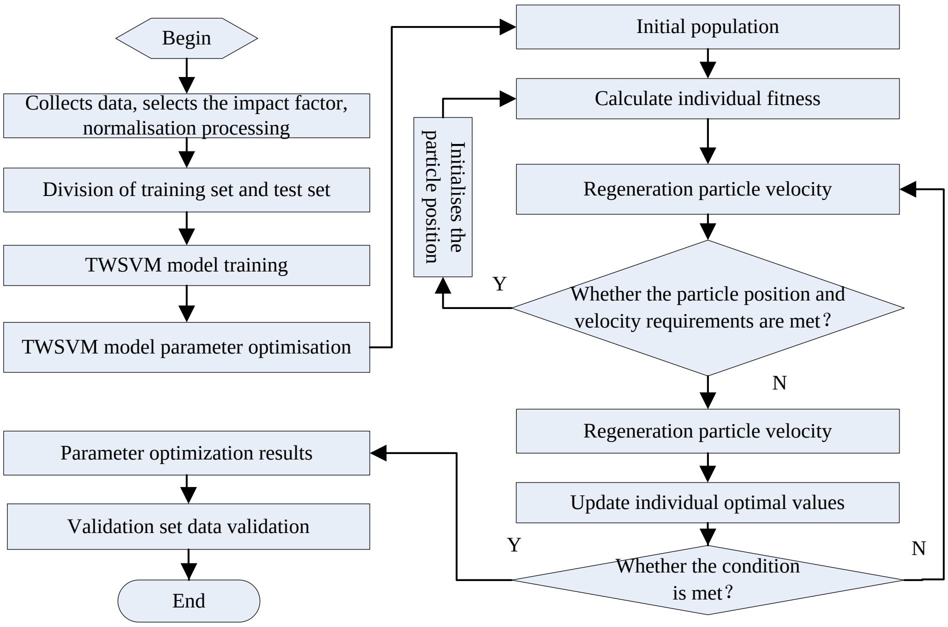


Fig. 3. APSO-TWSVM predictive model flow.

III. APPLICATION OF THE PROPOSED FORECASTING METHOD

A. *Research area*

The research area is the Pingshuo Anjialing open-pit mine, located in Shuozhou City, Shanxi Province, which belongs to the low hills of the Pingshuo platform in the Shanxi loess plateau, and the whole area is mostly covered by loess. The study area belongs to the temperate semiarid continental monsoon climate, with dry, cold, and windy spring and winter and concentrated precipitation in summer and autumn with mild and cool and less wind. Rainfall occurs mainly in summer, which is also the high occurrence period of geological disasters on the mine slopes. The dip angle of the Anjialing open-pit mine is nearly horizontal, no geological fault is found in this mine area, and the influence of the geological structure on the slope is small. According to the geological regulations of the coal mine, the structure of the Anjialing open-pit belongs to a simple type.

Fig. 4. Overview of the monitoring area in the experiments.

The Anjialing reverse fault and collapse column in the study area have little influence on the north slope. Therefore, the north slope of Anjialing is selected as the research object. The factors considered mainly include the physical geography, stratigraphic lithology, geological structure, and geotechnical geological characteristics of the study area. The prediction model mainly selects meteorological induced factors such as rainfall, rainfall duration, temperature and humidity, and human factors of mining disturbance, but does not consider rock lithology, geological structure, and other geotechnical geological characteristics. Figure 4 shows the high and steep slope of the Pingshuo Anjialing open-pit mine at the experimental site in this paper.

B. *Experiment Scheme and Design*

The experiment was carried out during a one-week interval from 3 June to 9 June 2023. During this period, a relatively obvious local collapse accident of surface deformation occurred on the north slope of the mining area due to rainfall. Rainfall data are of great value to verify the reliability of the prediction model and algorithm in this paper. As shown in Fig. 5, the deformation monitoring data are mainly collected by SSR-XT ground-based interference radar, and the data format consists of east coordinates, north coordinates, and elevation of specific points in the monitoring area. The coordinate data obtained by radar monitoring can be used as output data of the deformation prediction model. The SSR-XT ground-based interference radar can achieve the measured deformation accuracy of 0.1 mm within a range of 5 km. It is capable of remote noncontact accurate measurement of the monitored object. In view of the confidentiality of the measurement data, only part of the collected east coordinates are listed. The data on rainfall duration, cumulative rainfall, atmospheric pressure, temperature, and humidity collected by the WXT510 automatic weather station can be used as input data for deformation prediction models. The data of artificial mining activities are quantified according to the actual mining activities at the mining site. One hundred and fifty samples were recorded for the evaluation of the forecasting process. One hundred and forty-five of the samples were used to train the twin support vector machine (TWSVM) and the rest five samples were used to test the well-trained.

The Weather Transmitter (WXT510) is the main actuator in the SSR-XT to collect meteorological data. Figure 6 shows the WXT510. WXT510 consists of 3 wind transducers, a precipitation sensor, a pressure sensor, and a humidity and temperature sensor; hence, it can measure six weather parameters, including wind speed and direction, duration of rainfall, cumulative rainfall, atmospheric pressure, temperature, and humidity. Herein, the precipitation sensor detects the impact of individual raindrops; then the volume of the drops is approximated to be proportional to the impact value to calculate the accumulated rainfall. The randomness of the wind speed and direction affects the stability of the network, so they are not included in the modelling system. The sixth factor in the image is the collection of mining data during that time period.

Fig. 5. Overview of the SSR-XT radar.

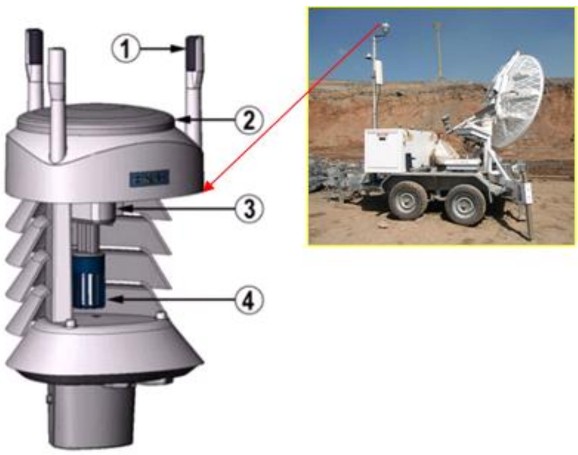


Fig. 6. Cutaway view of the WXT510: ① the wind transducers, ② the precipitation sensor, ③ the pressure sensor; ④ the humidity and temperature sensor.

C. The Proposed Prediction Approach

It mainly considers meteorological data and the disturbance factors of artificial mining and uses the adaptive particle swarm optimization-TWSVM (APSO-TWSVM) neural network to predict the slope deformation. The input of TWSVM is rainfall, duration of rainfall, temperature, atmospheric pressure, relative humidity, and artificial disturbance of the mining slope. Due to the strong randomness of wind speed and wind direction, wind speed and wind direction are not selected as input variables. The meteorological data output by TWSVM are the east coordinates, north coordinates, and elevation coordinates of the monitored location. Figure 7 shows the prediction process of this method.

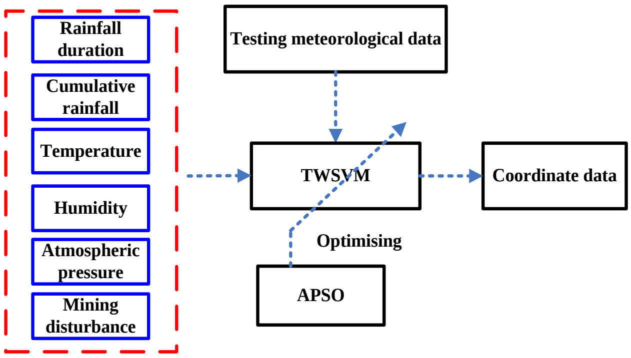


Fig. 7. Diagram of the intelligent prediction method.

IV. THE APPLICATION OF THE PROPOSED PREDICTION METHOD

In this experiment, three kinds of different methods are used to perform deformation data prediction analysis experiment. They are, respectively, twin support vector machine (TWSVM), genetic algorithm-TWSVM (GA-TWSVM), and adaptive particle swarm optimisation-twin support vector machine (APSO-TWSVM). Tables I and II and Fig. 8 show that the APSO-TWSVM model proposed in this paper is significantly superior to other models in terms of deformation prediction accuracy.

TABLE I. THE PREDICTION ERROR USING TWSVM, GA-TWSVM, AND APSO-TWSVM PREDICTION METHOD [M].

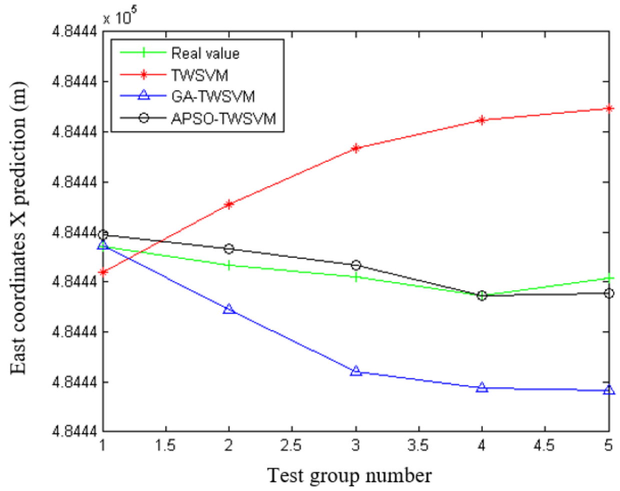
Method	Point 1	Point 2	Point 3	Point 4	Point 5
TWSVM	0.1497	-0.3585	-0.7605	-1.0432	-1.0076
GA-TWSVM	-0.0070	0.2671	0.5595	0.5466	0.6620
APSO-TWSVM	-0.0675	-0.0935	-0.0676	0.0011	0.0888

TABLE II. MAE AND RMSE USING DIVERSE METHODS.

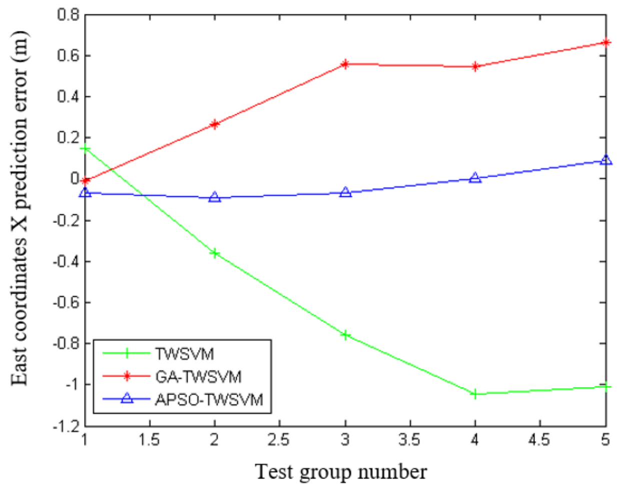
Method	MAE (%)	RMSE (%)
TWSVM	13.29	47.83
GA-TWSVM	8.17	6.52
APSO-TWSVM	1.27	3.02

In addition, it also has the lowest prediction error compared to other prediction models. From the comparative analysis of the prediction data in this experiment, it can be seen that it is necessary to use the algorithm to optimise the TWSVM model, which greatly improves the prediction accuracy of TWSVM. In addition, for the optimisation part of TWSVM, APSO can better optimise the TWSVM model, on the one hand, optimise its prediction accuracy, and on the other hand, optimise its convergence speed.

Figure 9 clearly compares and analyses the entire optimisation process of the TWSVM prediction model by GA and APSO optimisation algorithms.



(a)

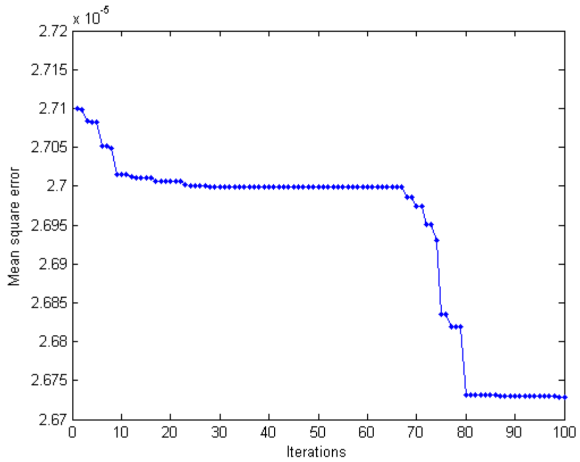


(b)

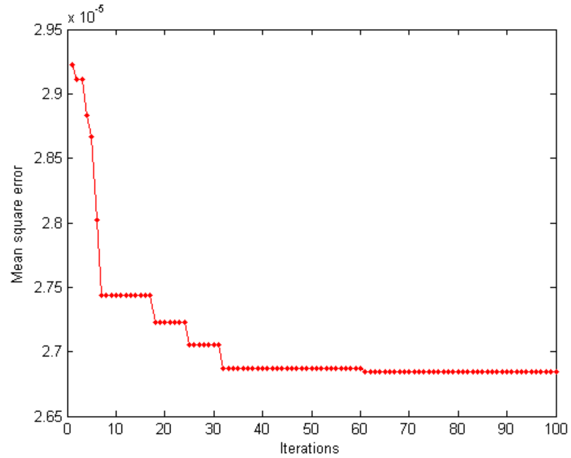
Fig. 8. Comparison of (a) forecast results and (b) forecast errors.

As can be seen in Fig. 9(a), in the prediction process of the TWSVM model by the GA optimisation algorithm, the prediction model reached the convergence state after about 80 iterations. However, as can be seen from Fig. 9(b), in the prediction process of the TWSVM model by the APSO optimisation algorithm, the prediction model reached the convergence state after only about 30 iterations.

When comparing prediction results, it can be seen that APSO has unique and larger advantages in optimising TWSVM. Hence, the presented APSO-TWSVM model is an efficient deformation prediction model of the mine slope.



(a)



(b)

Fig. 9. Optimisation convergence curve of (a) GA-TWSVM model and (b) APSO-TWSVM model.

V. CONCLUSIONS

To improve the prediction accuracy of the surface deformation of the open-pit slope, the APSO-TWSVM model is proposed. The proposed model is faster and more predictive than SVM model. Due to the introduction of position factor and velocity factor, APSO optimisation algorithm has stronger global optimisation ability. In the process of establishing the deformation prediction model, the prediction accuracy and convergence speed of TWSVM, genetic algorithm-TWSVM (GA-TWSVM), and APSO-TWSVM are compared and analysed. The APSO-TWSVM model was formed by introducing the position factor and the velocity factor into the PSO algorithm. Therefore, among the three models compared, this model has the best prediction accuracy and the fastest convergence speed, and can better perform the task of predicting the deformation of the surface of the mine slope. Compared to the TWSVM model (13.29 %) and the GA-TWSVM model (8.17 %), the mean absolute error (MAE) value of the algorithm proposed in this paper is the lowest (1.27 %). In terms of convergence speed, compared to the 80-step iteration of the GA-TWSVM model, the proposed model requires only 30 steps of iteration, and its prediction time is improved by 62.5 %.

Compared to other prediction models, the model has the following three advantages. First, because the model fully considers the factors that affect open-pit slope deformation, including meteorological factors and artificial mining disturbance factors, the model has a higher reliability than the traditional time series prediction model. Second, due to the combination of the APSO optimisation algorithm and the TWSVM model, the model has a higher prediction accuracy than the traditional model. Third, the fundamental difference between the TWSVM and the SVM model is that TWSVM solves binary classification problems by solving two sets of small quadratic programming, while SVM solves all classification problems by solving one large quadratic programming, so the predicted convergence speed of TWSVM is theoretically four times that of the SVM model.

Coincidentally, every method has its shortcomings, and the TWSVM prediction method proposed in this paper also has its limitations and shortcomings, which are mainly reflected in that only five factors that affect the deformation of the open-pit slope are considered in the modelling process of the prediction method, and the premise of its application is that the geological structure of the slope in the applied mining area has been verified. The influence of geological structure factors on slope deformation is excluded, so its application is limited. Often open-pit mine slopes are affected by geological structure factors, and the influence data of geological structure factors are generally difficult to collect and quantify, putting forward higher requirements for the popularisation and application of this method.

From an economic point of view, such a prediction model can bring some associated savings to open-pit mines, considering that a radar used to monitor open-pit slopes costs around 200,000 euros. The traditional monitoring method is that one radar can only monitor one specific open-pit slope, but the application of this prediction method can apply one radar to the monitoring application of two or even three open-pit slopes. Therefore, this method can save 33 %~66 % of the monitoring cost for open-pit mines, and can predict and obtain the deformation of open-pit slopes in advance. It provides a valuable time and data base for mine to take preventive measures in advance.

VI. Future Work

Further work on this research will be carried out in the direction of accelerating the practical application of the proposed deformation prediction method in the mining industry. It's industrial application will be explored in mine accurate deformation monitoring and early warning.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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