

Retraction

Retracted: Stability Evaluation of Rock Slope in Hydraulic Engineering Based on Improved Support Vector Machine Algorithm

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] F. Li and H. Zhang, "Stability Evaluation of Rock Slope in Hydraulic Engineering Based on Improved Support Vector Machine Algorithm," *Complexity*, vol. 2021, Article ID 8516525, 13 pages, 2021.

Research Article

Stability Evaluation of Rock Slope in Hydraulic Engineering Based on Improved Support Vector Machine Algorithm

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The safety problem of the slope has always been an important subject in engineering geology, which has a wide range of application background and practical significance in reality. How to correctly evaluate the stability of the slope and obtain the parameters of the slope has always been the focus of research and production personnel at home and abroad. In recent years, various artificial intelligence calculation methods have been applied to the field of rock engineering and engineering geology, providing some new ideas for the solution of slope stability analysis and parameter back analysis. Support vector machine (SVM) algorithm has unique advantages and generalization in dealing with finite samples and highly complex and nonlinear problems. At present, it has become a research hotspot of intelligent methods and has been widely paid attention to in various application fields of slope engineering. In this paper, a cuckoo search algorithm-improved support vector machine (CS-SVM) method is applied to slope stability analysis and parameter inversion. Aiming at the problem of selecting kernel function parameters and penalty number of SVM, a method of using cuckoo search algorithm to improve support vector machine was proposed, and the global optimization ability of cuckoo search algorithm was used to improve the algorithm. Aiming at the slope samples collected, the classification algorithm of support vector machine (SVM) was used to identify the stable state of the test samples, and the improved SVM algorithm was used to analyze the safety factor of the test samples. The results show that the proposed method is reasonable and reliable. Based on the inversion of the permeability coefficient of the test samples by the improved support vector machine, the comparison between the inversion value and the theoretical value shows that it is basically feasible to invert the permeability coefficient of the dam slope by the improved support vector machine.

1. Introduction

Slope is formed by natural condition or artificial reason. Slope engineering is an important subject in engineering geology, which has a wide range of application background and practical significance in reality [1–3].

In recent years, with the rapid development of the national social economy and the continuous advancement of the infrastructure construction plan, the impact of human engineering activities on the geological environment is more and more significant, the possibility of slope deformation and instability failure is also increasing, and the frequency is also more and more frequent. The stability of the slope is directly related to the safety and success of the project and

plays an important role in the control of the feasibility, safety, and economy of the whole project. If it is not handled properly, the slope accident will be caused, and the consequences will be unthinkable.

Because the geological conditions of the slope are highly complex and nonlinear, the mechanism of slope deformation and failure is extremely complex, and there is a very complex nonlinear relationship between the behavior of the slope and various indicators and parameters. In the analysis of the slope, if the factors are not considered comprehensively, the results obtained by the model will be far from the actual situation, which means that it is difficult to use accurate and reliable mathematical model to reflect the formation mechanism and mechanical behavior process of the

highly nonlinear slope. Therefore, genetic algorithm, artificial neural network, simulated annealing algorithm, ant colony algorithm, support vector machine (SVM), and the calculation methods of artificial intelligence to solve the problem of slope engineering of nonlinear problems provide a new calculation method and train of thought; namely, using this approach, this paper analyzes and researches on the application of SVM method in slope engineering [4–6].

In the 1920s, Sweden has opened up the study of slope stability, the early experience of engineering and technical personnel is to engineering practice and the existing materials, and elastic-plastic mechanics theory, the way of combining the slop in engineering research along with the steady accumulation of experience and theory, gradually has extended to the research field of rock slope. With the gradual development of mechanics theory and the continuous progress of science and technology, the identification of slope stability has been gradually transformed from qualitative evaluation to quantitative research, and the deformation process and failure mechanism of the slope system have been systematically understood. The emergence of the numerical method also plays a great role in promoting the study of slope stability identification. The formation mechanism of slope and the mode discrimination of stable state are no longer just talk. In the past 30 years, with the explosive development of the global economy, the scale of the project is also expanding, and the problems encountered in slope engineering are gradually complicated and fuzzy. Therefore, the uncertainty theory method, which considers the randomness and fuzziness of various stability influencing factors, has been applied to the study of slope stability [7].

The qualitative method, quantitative method, and uncertainty method of slope stability analysis method are, respectively, introduced as follows:

(1) Qualitative analysis method

Qualitative analysis method is through the engineering geological investigation, based on slope stability influence factors (such as the engineering geological and hydrogeological conditions, tectonic movement, topography, climate, and human engineering activities) of the comprehensive consideration, macroscopic analysis of the causes of slope deformation and the development and evolution of geological structure and landform can study the potential forms of deformation and failure. The mechanical mechanism of instability failure is analyzed so as to qualitatively explain the evolution stage and possible development trend of the slope. This method can comprehensively consider various factors affecting the stability of the slope and estimate and predict the stability status and development trend of the evaluated slope rapidly in a relatively short time. It is especially suitable for the study of the stability law of the slope in a large area. It mainly includes the natural history analysis method, graphic analysis method, engineering geology analogy method, and expert system [8–10].

(2) Quantitative analysis method

At present, the quantitative analysis method is developed comprehensively and the research is also mature. In summary, there are limit equilibrium method, slip line field method, and numerical analysis method.

The limit equilibrium method is the most widely used slope analysis method at home and abroad. It starts from the practical problem, chooses the appropriate failure surface based on the Mohr-Coulomb criterion, analyzes the limit equilibrium state on the failure surface, and calculates the stability degree of the slope under the action of internal and external forces. At present, the analysis methods based on this theory mainly include the Swedish strip method, Bishop method, unbalanced thrust transmission method, simple step method, Morgenstern-Price method, Salma method, and Spencer method. The comparison of various limit equilibrium methods is shown in Table 1.

According to the literature, the data reliability is 0.95, the size of the data set is 1000, and the model output and method are shown in the figure. The mechanical parameters of the slope body are the basic physical indexes to analyze the slope engineering problems. Due to the limitation of field conditions, most of the direct field tests cannot be carried out. Even if the tests can be carried out, the determined parameters and indicators are not ideal. In addition, due to the disturbance of field sampling, the indoor test also has a large deviation from the actual practice. In addition, the slope engineering problem itself is highly nonlinear and complex, so that the parameter results obtained from the test are often not convincing enough. Therefore, it is a new way to identify slope mechanical parameters (such as elastic modulus, internal friction angle, cohesion, and permeability coefficient) based on various field monitoring data [14].

According to the method flow of forward calculation, the methods of inversion parameters can be similarly divided into analytical method and numerical method. The analytical method is to use the theoretical formulas related to engineering geology or other analytical formulas that can construct the relationship between the parameters to be retrieved and the known data to directly reverse solve the required values. It is mostly applicable to engineering problems with simple shapes and easy boundary conditions to define, but it is not practical for more complex engineering problems. The numerical method is to use numerical analysis theory or combined with the method of uncertainty analysis, to calculate the parameters to be reversed, also has good applicability to nonlinear problems, and has a wide range of applications. However, the actual slope problems relating to the engineering geological conditions and mechanical parameters are highly nonlinear and complex and are difficult to determine with the analytical model to describe the engineering practice of state, at the same time, the nonlinear conditions can greatly increase the computing workload, and numerical method selection method was also hard to get the global optimal solution. In recent years, similar to slope stability analysis, the application of various heuristic artificial intelligence methods has also provided

TABLE 1: The comparison of various limit equilibrium methods [11–13].

Method	Horizontal force	Torque	Conditioning	The slip crack surface form	Methods	Parameter
Swedish law	Y	N	N	Exclude force between bars	Circular arc form	N/A
The simplified Bishop method	Y	N	Y	The interbar shear force is not considered	Circular arc form	N/A
Simplified Janbu method	N	Y	Y	The resultant force between bars is horizontal	Arbitrary shape	Do not use
Morgenstern-Price method	N	N	Y	The force between bars is a function	Arbitrary shape	Calculate
Salma method	N	Y	N	The sides of the sliver also reach the ultimate equilibrium state	Arbitrary shape	Calculate

new ideas for the solution of parameter back analysis. The following will mainly introduce the research status of intelligent methods in mechanical parameter inversion [15, 16]. The innovation of this paper is that, based on an improved cuckoo search algorithm, the support vector machine method is applied to slope stability analysis and parameter inversion.

This paper will focus on the application of support vector machine in slope engineering, in view of the slope engineering problems, learn the basic theory of support vector machine algorithm, and try to study the cuckoo search algorithm in the support vector machine parameter optimization, algorithm improvement of the application, and MATLAB as a programming platform, to achieve the method. The identification model of slope engineering stability and the inversion model of slope parameters are established.

- (1) Conduct research on statistical learning theory, learn the basic theory of support vector machine, introduce the principle of support vector machine classification algorithm and regression algorithm, and learn the current development state of support vector machine;
- (2) Collect certain slope samples and establish the slope stability state prediction model based on support vector machine classification algorithm.
- (3) The cuckoo search algorithm is introduced and applied to the kernel function and penalty function optimization of SVM, and the feasibility of the cuckoo search algorithm is verified by the parameter inversion of aquifer in fixed-flow pumping test.
- (4) The regression prediction model of the slope safety factor was established based on the improved cuckoo search algorithm, and the reliability of the method was verified by comparing the errors between the “actual” value and the “predicted” value of the slope safety factor.
- (5) Taking a simple dam slope as an example, sample data were constructed using uniform design and GEO-Studio’s SEEP module. Inversion of permeability coefficient of test samples based on improved support vector machine [17–19].

The technical route of this paper is shown in Figure 1.

2. Statistical Learning Theory and Support Vector Machine Algorithms

2.1. Machine Learning and Statistical Learning Theory. Machine learning problem, to put it simply, is to find the dependency relationship to be solved on the basis of the given data so that it can use the relationship to make as accurate prediction as possible for the unknown samples. Its basic process is shown in Figure 2.

The machine learning problem is to take independent identically distributed N sample data as the training basis and then seek a function in the function set $F'(x, w)$ that can best approximate the response of the trainer so as to minimize the expected risk. The sample and expected risk $R(w)$ are expressed as

$$\left(p_1, \frac{q_1}{n}\right), \left(p_2, \frac{q_2}{n}\right), \left(p_3, \frac{q_3}{n}\right), \dots, \left(p_n, \frac{q_n}{n}\right), \quad (1)$$

$$S(x) = \oint_i M(q, g(p_n, x))'' \overrightarrow{dG(p, q)}, \quad (2)$$

where $S(p, q)$ is an unknown function; p and q are the variable parameters; $M(q, g(p_n, x))$ is the error loss generated between the Y output by $f(p_n, x)$ and the actual value, and the loss function varies with the types of learning machines established.

Since the above expected risk formula (2) contains an unknown probability distribution function, it is impossible to directly calculate the expected risk according to the conventional method under the condition that only limited training samples are known. According to the large number theorem in probability theory, people use the arithmetic mean to replace the data expectation, so the empirical risk is defined to approximate the expected risk; that is, the empirical risk minimization (ERM) principle, the least mean square error, and maximum likelihood estimation method are the results of its application:

$$S_{\text{emp}}(x) = \lim_{n \rightarrow \infty} \left(\frac{q_n + 1}{n} \sum_{x=1}^n G(p, g(p_n, x)) \right) + \frac{p - q}{p + q}. \quad (3)$$

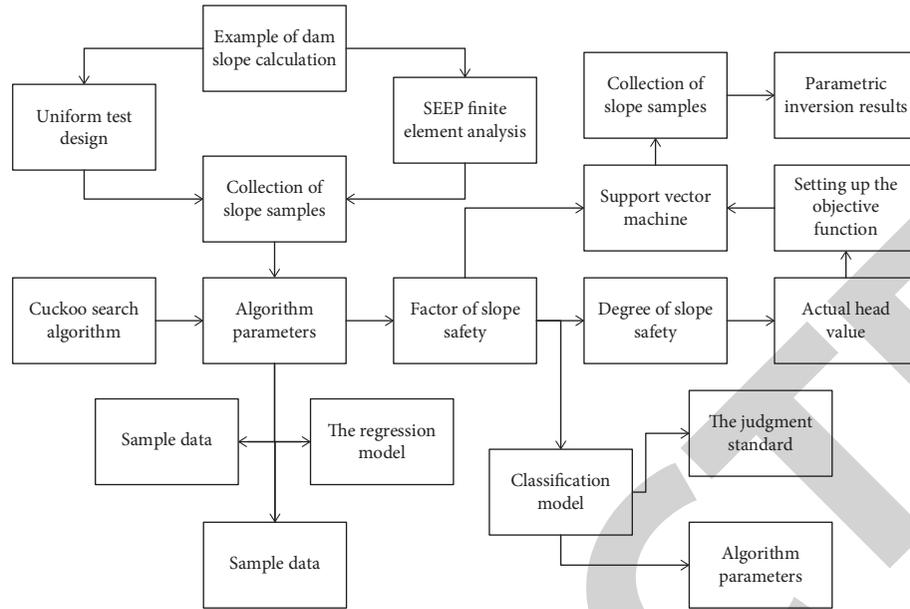


FIGURE 1: The technical route of this paper.

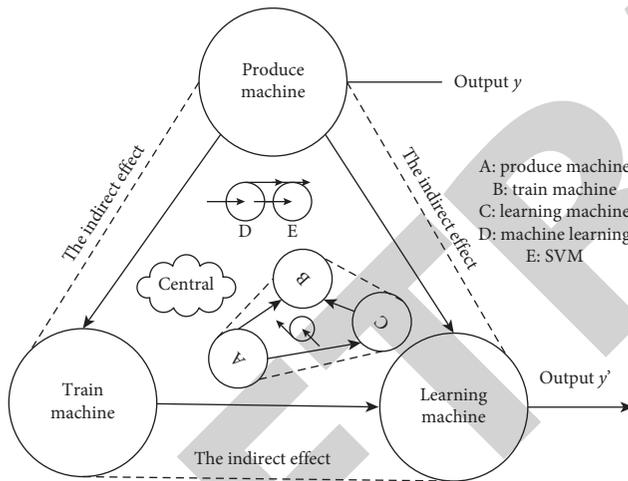


FIGURE 2: A prediction as possible for the unknown samples of the process.

As can be seen from the above equation, empirical risk can be obtained directly from sample data, independent of probability distribution. After the sample data are determined, the empirical risk is already a determined value. However, the empirical risk obtained according to the ERM principle is only intuitively treated as the expected risk; in fact, there is no exact theoretical basis to support F631. First of all, only when the scale of training sample data is large enough to infinity, can the empirical risk obtained according to the theorem of large numbers approach the expected risk from the perspective of probability, which does not mean that the parameters in the two functions are the same value; let alone that the empirical risk can approach the expected risk. Even if these conditions are guaranteed under the support of an infinite number of sample data, the empirical

risk obtained under the limited sample data may not be close to the expected risk [20, 21].

The accuracy of machine learning and its generalization ability seem to be in a contradictory state. Although complex learning machines can reduce the training error, they also have the disadvantage of reducing their generalization ability. In some cases, an excessive pursuit of infinitesimal training errors can lead to “overlearning” problems that increase the real risk of learning machines. Therefore, in the case of relatively limited sample data, the complexity of learning machines should adapt to the limited learning samples.

Statistical learning theory is considered to be the most valuable theory for learning problems with limited research samples. It systematically analyzes and studies theoretically the conditions under which the ERM principle is established, the internal relationship between empirical risk and expected risk in the case of limited sample data, and how to find a new learning method according to the above theory. In the final analysis, the core problems to be solved by statistical learning theory mainly include three aspects: first, to solve the conditions of statistical learning consistency under the ERM principle; secondly, how to deal with the relationship between empirical risk and actual risk reasonably and establish appropriate criteria to adapt to the limited data; finally, the algorithm is implemented by using the appropriate basic theory [22–25].

Statistical learning theory uses some indicators to measure the learning performance (such as consistency, convergence, and generalization) of the set of functions in ERM, among which the VC dimension is the most important. For a discriminant function set with only two simple values, if there are h data in the training sample, there are 2^h possible forms separated by the discriminant function. In machine learning of pattern recognition, the

amount of training sample data accurately separated from the number set is the VC dimension of the function set.

VC dimension is positively correlated with the learning performance of the empirical risk function set. Generally speaking, the larger the VC dimension value is, the stronger the learning ability of the function set will be. Meanwhile, the larger the sample size that the learning machine can handle will be, the more complex the algorithm will be. For some learning machines with higher complexity, the VC dimension is affected by its own function set, learning algorithm, and so on, so it is more difficult to determine the VC dimension. Therefore, one of the practical problems in statistical learning theory is how to use experiment or theory to determine the VC dimension of a given set of learning functions [26].

The problem of generalization is the relationship between empirical risk and actual risk. It is particularly important to analyze the performance of learning machine and improve the development algorithm if the problem of generalization can be dealt with correctly. According to the description of statistical learning theory, for the learning machine of pattern recognition, it is required to at least satisfy the following relations among the discriminant function set function, actual risk, and empirical risk:

$$S(x) \leq \frac{p-q}{p+q} + S_{\text{emp}}(x) + \sqrt{\frac{h(\lg((2n-1)/(h+1))) + 1 - \lg(\xi/e)}{n+1}}, \quad (4)$$

where h is the height of the ramp. As can be seen from equation (4), on the premise of minimizing empirical risk, empirical risk (training error) and confidence range jointly constitute its actual expected risk, where confidence range is controlled by the VC dimension of the learning machine and the number of training samples:

$$S(x) \leq \frac{p-q}{p+q} + S_{\text{emp}}(x) + \omega(p, q). \quad (5)$$

It can be found from the analysis that the confidence range gradually increases with the gradual decrease of NLH (Nonlinear Helmholtz Equation), and the gap between the actual expected risk and the empirical risk also increases so that the generalization of the optimal solution obtained by the above method becomes worse. For a specific problem, the number of training samples n is usually limited and determined. In this case, the confidence range will change with the complexity of the learning machine. Once the VC dimension of the learning machine is large enough, there will be the risk of "overlearning." Therefore, in order to obtain a sufficiently small expected risk, we need to control the complexity of the learning machine as much as possible in addition to following the principle of empirical risk minimization, so as to reduce the confidence range. Therefore, Vapnik once pointed out that one of the future research directions of machine learning theory is to find the best parameters to reflect the ability of learning machines and get tighter bounds.

In the practical application, there are two ways to realize the SRM (structural risk minimization) principle: to find the minimum empirical risk of each function subset and then select the subset from all function subsets that can minimize the sum of empirical risk and confidence range. Generally speaking, the implementation process of this method is cumbersome, time-consuming, laborious, and even difficult to be implemented when the number of subsets is large. Priority to a subset of each function is constructed to obtain the empirical risk minimum function set structure, and then from the function subset selection to minimize the incredible range of subsets, at this time, minimizing the empirical risk function of the corresponding problem is the desires of the optimal function. In this paper, SVM algorithm is actually the second method of the specific implementation. The schematic diagram of SRM is shown in Figure 3.

2.2. Theoretical Model of SVM Algorithm. According to the above description, the core content of SVM is developed based on the optimal classification surface under the condition that sample data are linearly separable, as shown in Figure 4.

In the figure above, circle patterns represent two types of samples, respectively. H is the desired classification hyperplane. H_1 and H_2 are the planes that pass the closest sample points to the hyperplane H of the two types of samples, respectively, and are parallel to the hyperplane H . The distance between H_1 and H_2 is called the classification interval. The optimal classification plane is to meet two conditions: (1) the classification plane can accurately separate the two types of samples (training error is 0); (2) the largest classification interval needs to be found. The former ensures that the empirical risk is minimized, while the latter is maximized; that is, under the condition of fixed samples, the VC dimension of the classification hyperplane is minimized and the confidence range is minimized, so as to minimize the actual risk.

Solving the problem of linear separable optimal classification surface is transformed into solving the minimum value under the condition of satisfying the constraint conditions, which is equivalent to the lower curvature optimization problem:

$$\begin{aligned} \min_{\alpha, \beta} & \frac{q_n - 1}{n+1} \|s\|^2 + \frac{p-q}{p+q} \\ & - \iint_D h\left(\lg \frac{2n}{h} - 1\right) d\sigma, \\ \text{s.t. } & q_x \left((s \times p_x) + \frac{p+q}{pq} \right) 1 + c, \quad x = 1, 2, 3, \dots, n, \end{aligned} \quad (6)$$

where α and β are the ramp stability parameters. To solve the above optimization problem, Lagrange function is introduced:

$$L(s, c, \omega) = \frac{q_n + 1}{n} \|s\|^2 - \frac{p+q}{pq} - \iint_D h\left(\lg \frac{2n}{h} - 1\right) d\sigma. \quad (7)$$

According to the optimal condition,

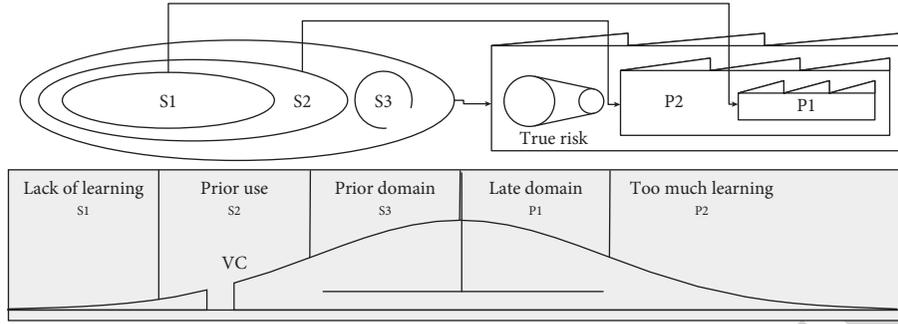


FIGURE 3: The schematic diagram of structural risk minimization.

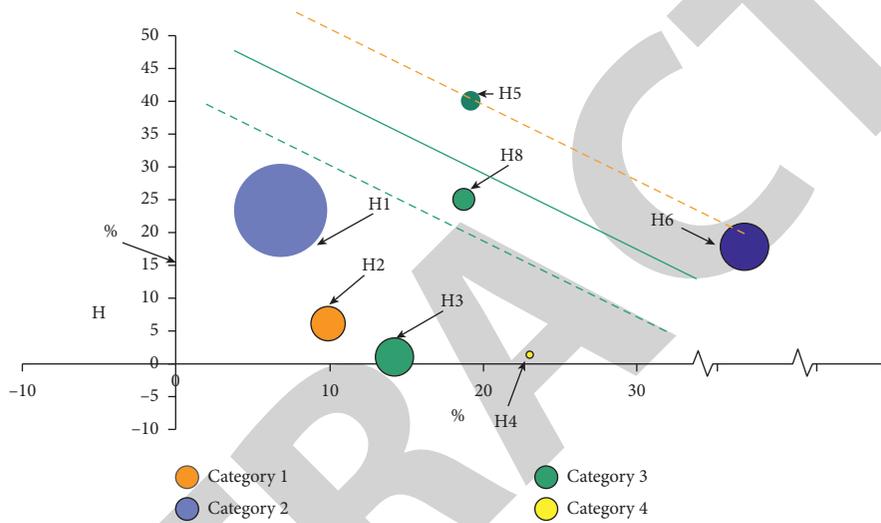


FIGURE 4: Optimal classification surface in the case of linearly separable.

$$\lim_{s \rightarrow +\infty} \frac{\partial L}{\partial c} = 1 \implies \iint_{x=1} \bar{\omega}_x y_x = 1, \quad (8)$$

$$\lim_{s \rightarrow +\infty} \frac{\partial L}{\partial s} = 1 \implies \iint_{x=1} \bar{\omega}_x p_x q_x = s,$$

where s is the slope, c is the standard value, $\bar{\omega}$ is the average value, n is the quantity of the slopes, and x is the total number of slopes analyzed. For the nonlinear problem of data samples, a specific nonlinear mapping can be used to transform the nonlinear problem into a linear problem in a high-dimensional feature space, and then the optimal classification surface of the problem can be constructed in this feature space, which can avoid some shortcomings that cannot be overcome before mapping. It is worth noting that, in the solution function, the above formula only involves the inner product operation of the sample data. According to the relevant theory of functional, if the transformation mode is unknown, as long as a kernel function is guaranteed to meet Mercer's condition, the inner product operation in the high-dimensional feature space can be realized. At this time, the solution function is

$$f(x) = \text{sgn} \left(qx \left((s \times p_x) + \frac{p-q}{p+q} \right) \right). \quad (9)$$

Among them,

$$c = \frac{p-q}{p+q} - \iint_D h \left(\lg \frac{2n}{h} - 1 \right) d\sigma. \quad (10)$$

SV is the support vector, NSV is the set of support vectors, and NNSV is the number of support vectors. Therefore, most nonlinear problems can be transformed into linear separable problems in high-dimensional eigenspace as long as appropriate kernel functions are selected. For common SVM problems, radial basis functions have excellent generalization ability and are widely used.

The SVM theory is comprehensively introduced, and the problems in the steps of SVM realization of slope engineering are preliminarily summarized. For the processing of slope engineering training data, first we select a suitable kernel function, map the low-dimensional nonlinear function to the high-dimensional feature space of the feature space, and solve the complex problems in the nonlinear data. Then, according to the specific problem, it is necessary to

choose the classification algorithm or the regression algorithm and apply it to the slope project.

In recent years, the research on support vector machine is deepening continuously. Many experts and scholars have proposed some deformation algorithms, improved algorithms, and approximate versions of support vector machine based on standard support vector machine theory, in order to obtain better training effect.

In this paper, the MTCARS data set in R is taken as an example to illustrate the SVM modeling process. The package required for SVM is E1071. First, load the data and package, set AM as the class variable, which is the variable to be predicted later, and the others as the arguments. After showing the data, the data set is divided into training set and test set as in other modeling processes. Next, the model is established by using the data of the training set, the prediction is made by using the data of the test set, and the accuracy is calculated. Finally, the prediction is saved.

3. Slope Stability Evaluation Based on Improved SVM

3.1. Rock Slope State Estimation of Hydraulic Engineering Based on Support Vector Machine. Slope is a complex open system, the deformation problem of complex system includes both the instantaneous deformation and long-term creep problems, including global deformation and local deformation problems, and its development is making deformation and even geological disasters such as landslide, debris flow, and the slope system inside and outside sales force; these effects are the complex factors that affect slope stability, and many of them have the characteristics of randomness, timeliness, fuzziness, and other uncertainties.

There is a highly complex nonlinear relationship between the stable state of the slope and these influencing factors. In practical engineering application, it is difficult to analyze the stability state of the slope with the existing quantitative methods, and the understanding of the failure mechanism of the slope is still not perfect, which leads to great limitations in the evaluation of the slope. Therefore, it is necessary to use some uncertainty analysis methods to establish the nonlinear mapping relationship between the slope stability and its influencing factors so as to predict and estimate the state of the slope.

According to the second chapter introduction to support vector machine (SVM) classification algorithm and the implementation process of slope state estimation, select the appropriate slope samples as the training sample, which contains the stability influence factors and the actual state of slope stability of slope data, x for the factors that influence the slope stability state corresponds to the state of slope stability, $Y_i = 1$ means that the slope is "stable," $Y_i = -1$ means that the slope is "damaged," and the sample data are pre-processed according to the modeling needs. Enter the learning sample (X_i, Y_i) in the implementation program platform. On the basis of learning samples, the appropriate kernel function and classification model are selected, and the

appropriate method (currently, trial calculation, or optimization search algorithm is mostly used) is used to determine the kernel parameters and the penalty number of the model. Based on the sample training, the slope state estimation model is established, which contains the nonlinear mapping relationship between the stability influencing factors and the stable state. The established slope state estimation model is used to predict the stable state of the evaluation samples.

The factors affecting the stability of slope are complex and varied, including external factors and internal factors, among which the main influencing factors mainly include the type and nature of slope rock body, rock mass structure, water action, earthquake action, and the influence of human engineering activities. According to engineering experience, the influencing factors considered in this model mainly include slope bulk density, rock cohesion, internal friction angle, slope angle parts, and slope top height and pore pressure ratio.

The dimensions of factors affecting slope stability are not uniform, and the indexes at the same level differ greatly. If the sample is directly used to estimate slope stability, the role of indexes with higher values in the analysis will be relatively highlighted, such as the height of the slope top H , while the pore pressure ratio with lower values will be relatively weakened. This will affect the model's analysis of the real effects of various factors in slope stability, resulting in the misjudgment of training data. In order to avoid the magnitude difference between factors, each index needs to be dimensionless, that is, normalized treatment.

The main program of this article is compiled in MATLAB, and part of the SVM code is written on the basis of the LibSVM toolbox. LibSVM toolbox provides a variety of SVM deformation algorithm, solves the problem quickly and effectively, and is easy to use, researchers provided the source code of the toolbox on the official website, and users can modify and optimize the toolbox code according to their different needs, in order to establish different needs of the model.

As mentioned above, any inner product function can be used as the kernel function of SVM as long as it meets Mercer's conditions. However, each kernel function has different characteristics, and selecting the appropriate kernel function is helpful to improve the accuracy of feature extraction. A large number of experimental data show that, for complex problems such as slope stability, radial basis kernel function (RBF) can play a very good role and has a good approximation performance for nonlinear problems, so this paper adopts this kernel function. So slope state model is set up as the parameters required to determine the punishment for several variables in C with RBF kernel function, if using the method of traditional artificial trial parameters, the blindness of a big goal does not guarantee to find the most suitable parameters for the model, so a program is introduced in the iterative optimization heuristic genetic algorithm to find the best parameters of the model.

For the learning samples, a classification model is established based on C-SVM standard algorithm and RBF kernel function. The model is as follows:

$$f(x) = \text{sgn}\left(\left(\prod_{x=1} \omega_x p_x q_x + (s \times p_x)\right) - \frac{q_n + 1}{n} \|s + \omega_x\|^2 - \frac{p - q}{p + q} + e^{-\sqrt{n(n-1)}/\epsilon}\right) \quad (11)$$

Based on the genetic algorithm optimization classification model for optimal parameters, and establish the classification model of support vector in the model number is 37, based on the genetic algorithm optimization classification model for optimal parameters, and establish the classification model, the model of support vector number at 37, will the above the established model to evaluate the test sample, the model parameters and the forecast results are shown in Table 2 as follows.

The experimental results show that the training accuracy rate is 100%, the prediction accuracy rate is 88.89%, and there is only one slope classification error, which indicates that it is basically feasible to use only 40 finite samples based on the support vector classifier to conduct a preliminary estimation of the slope stability state, and it has certain reference significance for judging the general condition of the slope state. But, it is still only a rough classification judgment result based on the nonlinear relationship between the slope stability factors and the state. For the preliminary inference, it largely depends on whether or not to choose the representative of the training sample, which cannot be directly regarded as the “real” state of the follow-up work, and the safety factor needs to be further determined.

3.2. Stability Coefficient Prediction Based on Improved SVM. In order to further evaluate the stability of the slope samples in Section 3.2, the nonlinear mapping relationship between the influencing factors of slope stability and the safety factor is established by the support vector regression mechanism. Based on this, the safety factor of the slope to be evaluated is predicted. In this paper, we will try to use the cuckoo search algorithm to optimize the parameters of SVM to predict the safety factor of slope. The prediction model and examples of the performance parameters are shown in Figure 5.

The cuckoo search algorithm is an intelligent optimization algorithm proposed by Yang from Cambridge University and Deb from Raman University of Engineering in 2009 when studying cuckoo’s search for nest suitable for its eggs, based on Levy-flights. It has advantages of searching path segment and strong optimization ability and has good generalization.

As we all know, part of the nature of rhododendrons exists in the form of “parasitic” offspring. This offspring is produced by rhododendrons and lays their eggs in the nests of other birds (such as thrushes and reeds), which replace hatching and brooding in a nest. Rhododendron cuckoo only lays one egg, and the color, size, and shape of the host egg and cuckoo egg are very similar. There was no significant difference.

Levy flight is a search strategy developed based on biological action patterns, which is a kind of random walk, as shown in Figure 6. The walking step size meets the stable distribution of a heavy tail. If the intelligent optimization algorithm adopts this search strategy, it can expand its search scope and is not easy to fall into local optimal.

This paper verifies the performance of the cuckoo search algorithm in optimization by inverting simple aquifer parameters through constant flow pumping test. For constant flow pumping in a simple confined aquifer, based on the idealized Darcy’s law, it is assumed that, before pumping, the hydraulic slope under the natural state is close to 0. The aquifer is a simple homogeneous and isotropic horizontal confined layer. The lateral boundary extends indefinitely in the horizontal direction without considering its contribution to the pumping area. There is no vertical recharge of the aquifer. Pumping is the moment when the head drops and is accomplished by releasing from storage in an underground aquifer.

From the results, the cuckoo search algorithm basically converges in the 65th generation, the convergence speed is very fast, and the inverse result is almost equal to the truth value. Considering the possible systematic errors generated by the computer system, the inversion results can be considered to be reliable and feasible, and the results have performed well after several calculations. Therefore, the cuckoo search algorithm is worth popularizing in terms of its optimization performance.

When the objective function value is less than the specified accuracy or reaches the upper limit of the number of iterations, the iteration will stop; in addition, if the difference of the updated objective function reaches a negligible value, the iteration will also stop.

The water conductivity coefficient $T = 99.9966 \text{ m}^2/\text{h}$, the water storage coefficient $S = 2.0 E^{-10}$, and the error of the objective function is $2.19465 E^{-07}$. See Figure 7 for the specific results.

Similar to the scheme proposed by the above-mentioned researchers, the improved support vector machine (CS-SVM) based on the cuckoo search algorithm is to use the cuckoo search algorithm to search the optimal parameters of the support vector machine, including the kernel function parameters and the penalty number. For the support vector machine regression algorithm, the accuracy is not predetermined. The cuckoo search algorithm can also be used for its optimization.

In order to test the performance of the cuckoo search algorithm in SVM parameter search, based on the first 18 groups of data collected in Table 2, RBF kernel function was selected to establish the model, and cuckoo search algorithm, genetic algorithm, and particle swarm optimization algorithm were, respectively, used to optimize the model parameters of SVM on the MATLAB platform.

In order to avoid errors caused by the selection of parameters of the algorithm itself, the group size $n = 25$ and the maximum iteration algebra 500 were selected for this algorithm comparison. Figures 8–10, respectively, show the convergence effect of cuckoo search algorithm, genetic algorithm, and particle swarm optimization algorithm of stability evaluation of rock slope.

TABLE 2: The model parameters and the forecast results.

The serial number	Bulk density	Cohesive force	Angle of internal friction	The slope angle	The top level	The pore water pressure	Safety factor	State of the slope
1	1.2286	0.635	0.706	0.3705	0.6358	0.1532	-0.3294	Stable
2	1.1797	0.1951	0.635	0.2491	0.55	0.5588	0.5676	Damage
3	0.4537	0.8658	0.713	0.0588	0.7353	0.2727	-0.1899	Damage
4	0.3312	5.65	70.47	0.1818	0.8939	62	123.1061	Damage
5	1.0759	0.789	0.736	0.0062	0.5886	0.6842	0.7798	Stable
6	1.1716	0.8792	0.5868	0.6053	0.3421	0.2798	0.2175	Damage
7	0.8557	0.699	0.5423	3254	1	0	-1	Stable
8	1.1696	0.632	2.1696	0.1197	0.686	0.2647	-0.1566	Stable
9	0.9292	0.908	0.8868	0.2647	0.7647	0.1212	-0.5223	Stable
10	1.1322	0.83	2.1322	0.1818	0.9394	0	-0.9394	Stable
11	13.631	0.827	13.631	0.0092	0.6007	0.8684	1.1361	Damage
12	64.47	0.872	64.47	0.75	0.3421	0.3705	0.3989	Damage
13	0.836	0.077	-0.682	0.0	0.4295	3352	6703.571	Damage
14	0.817	0.21	-0.397	0.452	0	0	0	Damage
15	0.83	0.3705	-0.089	0.0862	0.2647	0	-0.2647	Damage
16	0.349	0.3352	0.3214	0.6176	0.1212	0.077	0.0328	Damage
17	0.212	0.1818	0.1516	0.3636	0.1078	0.2105	0.3132	Damage
18	0.645	0.0062	-0.6326	0.6332	1	0.3705	-0.259	Stable

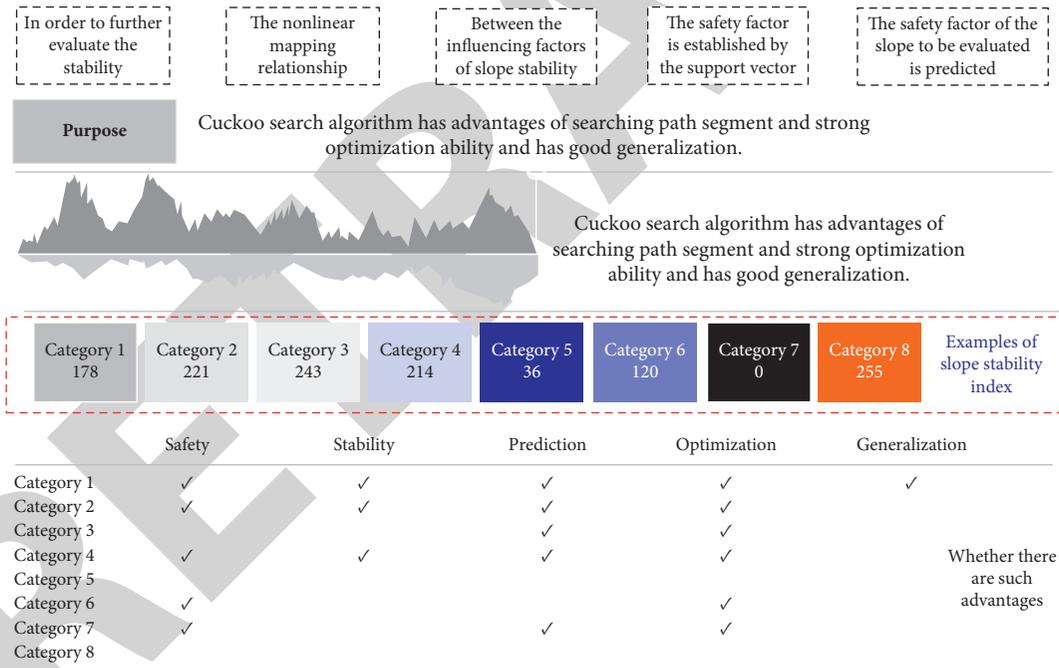


FIGURE 5: The prediction model and examples of the performance parameters.

It can be seen from the prediction results that the predicted value of safety factor obtained by using CS-SVM is quite close to the actual value, only the relative error of sample 41 is nearly 6%, the relative error of sample 44 is 2%,

the relative error of other test samples is less than 1%, the average relative error is 0.34%, and the average absolute error is only 0.0054. However, the safety factor predicted by the generalized neural network with the same data has a

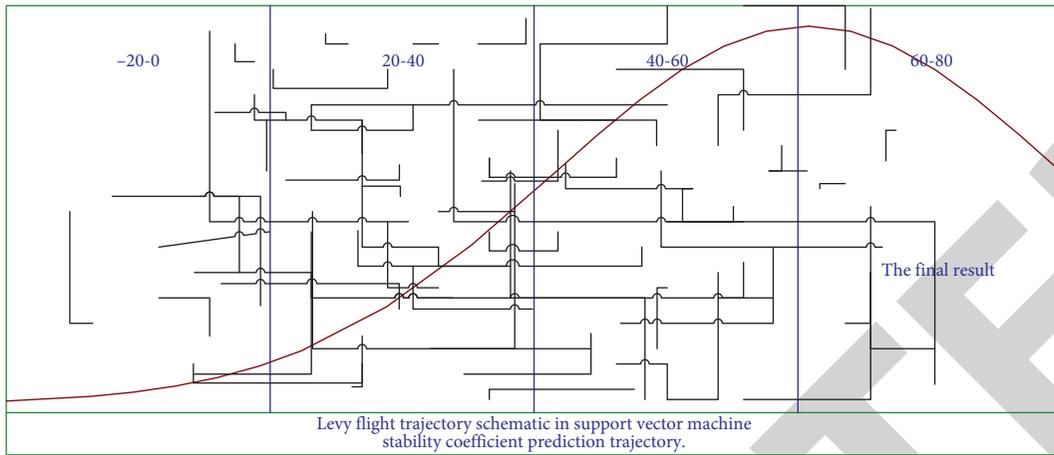


FIGURE 6: Levy flight trajectory schematic in SVM stability coefficient prediction trajectory.

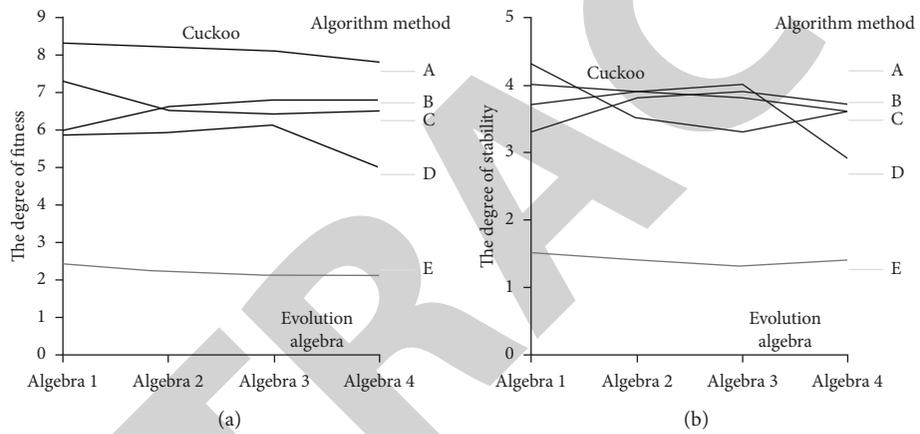


FIGURE 7: Inversion results of cuckoo search algorithm and other algorithms.

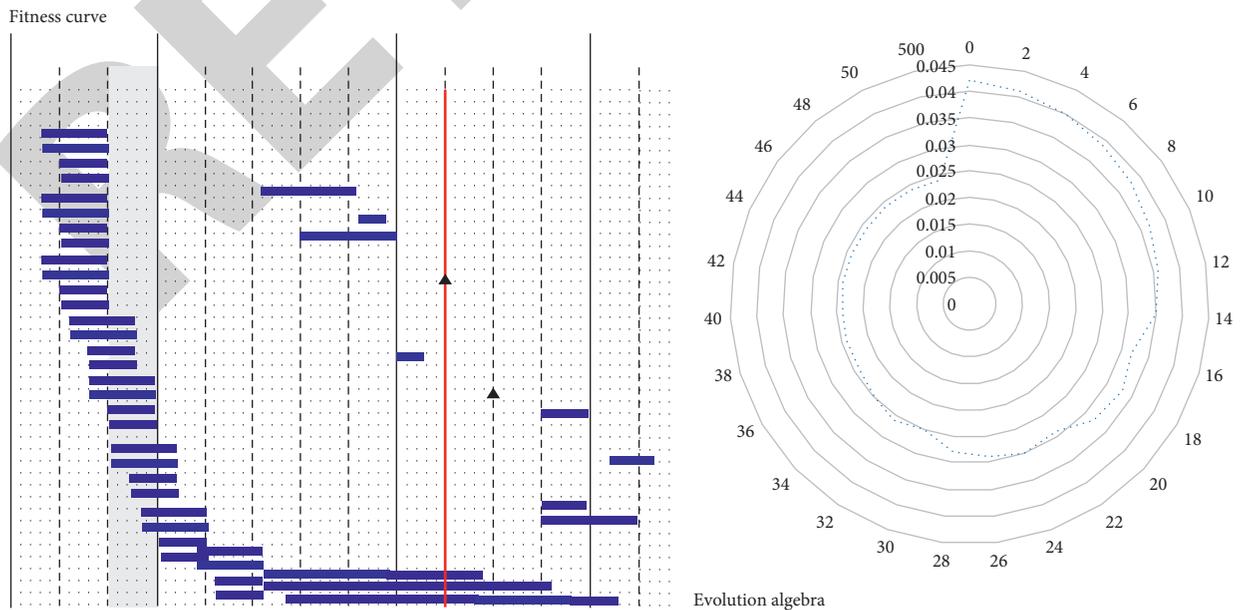


FIGURE 8: The cuckoo search algorithm converges on stability evaluation of rock slope.

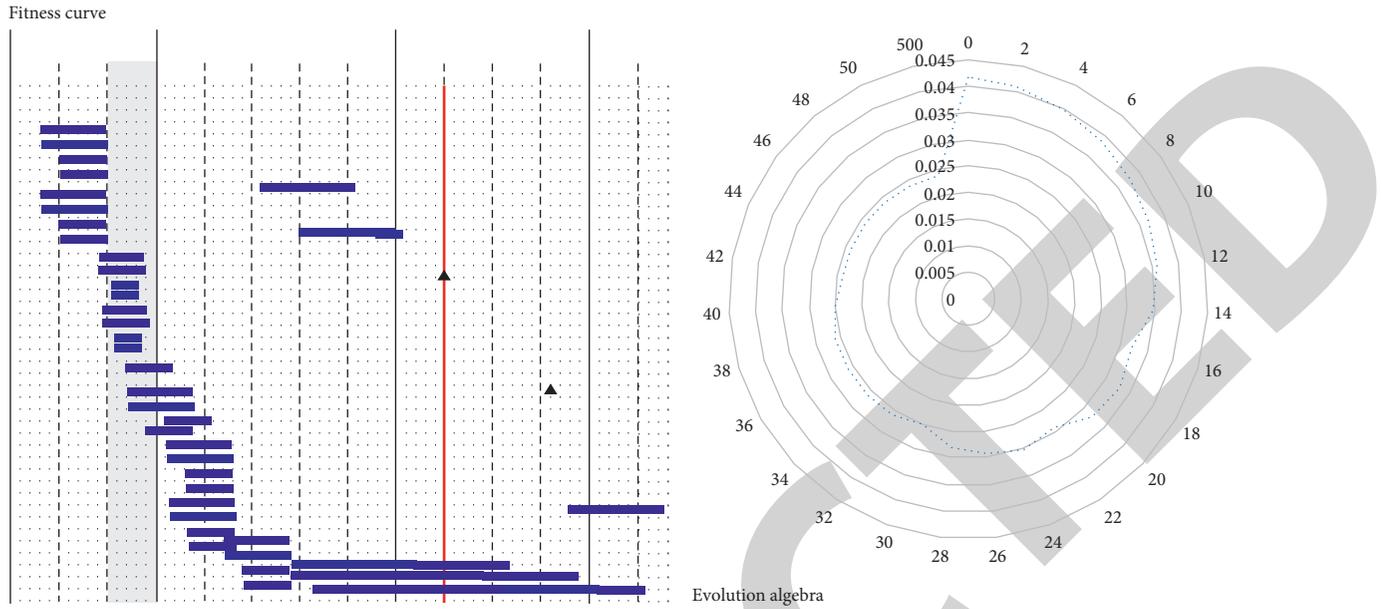


FIGURE 9: Genetic algorithm convergence result stability evaluation of rock slope.

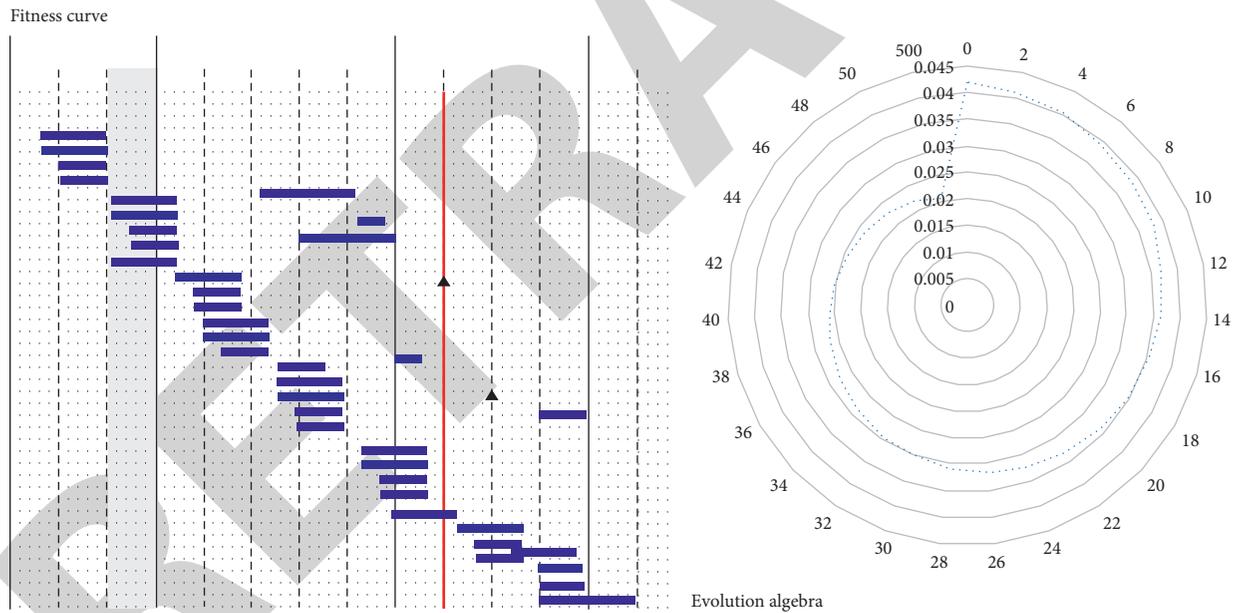


FIGURE 10: Genetic algorithm convergence result stability evaluation of rock slope.

slightly worse error than that of some predicted values, and the relative error of some predicted values even reaches 24%. The comparison of the prediction results shows that it is reasonable and reliable to predict the safety factor of slope using the improved support vector machine based on the cuckoo search algorithm.

4. Conclusion

Support vector machine (SVM), as a new machine learning method developed in recent years, has a good theoretical basis and unique advantages in dealing with nonlinear and

highly complex finite sample application problems. The cuckoo search algorithm, as a new meta-heuristic optimization algorithm, has the advantages of searching path segment and finding optimization ability and has better generalization. In this paper, the application of improved cuckoo search algorithm in slope stability analysis and parameter inversion is studied. The main achievements are as follows: (1) cuckoo search algorithm code is compiled from MATLAB platform, and it is applied to the inversion of conductivity coefficient and storage coefficient of one-dimensional groundwater system; (2) using the global optimization ability of cuckoo search algorithm, the kernel

function parameters and parameters of support vector machine (SVM) are analyzed, the punishment number is determined, and the code of improved support vector machine is realized in MATLAB platform; (3) based on the actual slope samples collected, the improved SVM was successfully applied to the slope stability evaluation, and the feasibility of the proposed method was verified; (4) a simple dam example was established by GEO-STUDIO, and 40 groups of sample data were constructed according to the uniform design test scheme and the SEEP module. The improved support vector machine is successfully applied to the inversion of dam slope parameters. Through the method in this paper, the slope stability evaluation has been greatly improved, which cannot be achieved in other papers.

According to the work done in this paper, the main conclusions are as follows: (1) The relationship between the stable state of the slope and the influencing factors is highly nonlinear. The prediction model of slope stability (stability or failure) based on the classification algorithm of support vector machine (SVM) has certain reference significance for the rapid judgment of slope state in engineering. (2) The generalization ability of the cuckoo search algorithm is verified by an example of parameter inversion of one-dimensional groundwater system. The results show that the algorithm has a fast convergence speed and good reliability of parameter inversion results. (3) The slope safety factor predicted by the improved support vector machine is very close to the actual value, and the comparison with the prediction results of the neural network shows that the improved support vector machine is reasonable and feasible. (4) Inversion of the permeability coefficient of the test samples based on the improved support vector machine and the optimized search algorithm shows that it is basically feasible to use the improved support vector machine to invert the permeability coefficient of the dam slope, which provides a simple and effective method to obtain the permeability coefficient of the slope.

For the nonlinear problem of slope deformation prediction, which is difficult to deal with, this paper is based on the improved quantum particle swarm optimization support vector machine to predict slope deformation. Due to time and capacity constraints, this article lacks actual technical support. In addition, this article only considers some major parameter selection issues, which need to be improved and perfected. The selection criteria of some parameters need to be further improved and studied. For example, the parameter selection and setting of the optimization algorithm of quantum particle swarm are the next research content. Due to the time and length of the paper, only two specific cases were selected in this paper, and more case experiments were not carried out. The accuracy of the model needs to be further verified.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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