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IPSO-ELM intelligent prediction of landslide displacement in complex and unstable area of karst landform

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In southern China, the karst landform areas possess a complex geological and topographic environment, a fragile ecosystem, poor surface stability, and frequent occurrences of landslides and other geological disasters. To effectively monitor and predict such events, it is crucial to process landslide monitoring data and establish reliable prediction models. This paper presents an IPSO-ELM displacement prediction model that integrates the improved particle swarm optimization algorithm (IPSO) and extreme learning machine (ELM). The proposed coupling model predicts decomposed displacement subsequences individually, which are then reconstructed to obtain the total displacement prediction value. In this study, displacement monitoring data from a typical landslide in the karst landform area between 2007 and 2012 were selected. Various prediction and verification scenarios were established to validate the accuracy and stability of the prediction model. The MAPE of the IPSO-ELM model is 0.18%, which outperforms the ELM and BPNN models with MAPEs of 0.56% and 0.65%, respectively, in predicting landslide displacement in karst landform areas. This study provides a solid theoretical foundation and practical value for landslide displacement prediction.

KEYWORDS

complex and unstable area of karst, improved particle swarm optimization algorithm, landslide, displacement prediction, extreme learning machine (ELM)

1 Introduction

Karst of China are widely distributed in mountainous areas with complex geological and topographical environments, fragile ecosystems and poor surface stability. The typical landslide disaster in this paper is located in the area with the most active karst landform in China. The karst activities on the underground surface are very frequent, resulting in the very active micro-movement of the underground surface and frequent geological disasters. The prediction of landslide displacement in this area is helpful to predict natural disasters such as landslides (Li et al., 2023; Liu et al., 2023a; Liu et al., 2023b; Liu et al., 2023c; Zhang et al., 2023a; Liu et al., 2022; Zhou et al., 2022; Li et al., 2021).

Landslides seriously damage to the natural environment, and cause social property losses. How to use the landslide monitoring data to predict the deformation of landslide and disaster is an important scientific subject in the research of geological disaster prevention.

The formation of most landslides is a gradual accumulation process, so the long-term deformation monitoring data of landslides is an important basis for landslide deformation prediction at present. There are many prediction methods for landslide deformation based on the monitoring data of landslide cumulative deformation. The mainstream method is to decompose the time series of landslide cumulative displacement into trend, periodic, and random items, and use different methods to carry out targeted prediction. For example, Peng et al. and Zhang et al. decomposed the landslide deformation based on time series and ignored the influence of random items (Peng et al., 2013; Zhang LB. et al., 2023). Qiu et al. used the grey model to solve the trend term, and ignored the random term and then used the AR model to solve the periodic term (Qiu et al., 2020). Guo et al. used the reverse order method to calculate the trend and trigonometric functions to fit the periodic term (Guo et al., 2018). Jiang et al. used the variational mode to decompose the accumulated deformation of the landslide, and then used different methods to solve it respectively (Jiang et al., 2022). Huang et al. used the moving average method to decompose the cumulative displacement into trend term and periodic term displacement, and used the support vector machine model to predict the landslide deformation (Huang et al., 2014). Li et al. and Huang et al. established an autoregressive moving average time series model and used support vector machines, neural networks and other algorithms to predict landslides (Huang et al., 2018; Li et al., 2018).

The research shows that the deformation of landslides is often affected by many factors, and different methods and models are used to decompose the cumulative deformation, and different decomposition results will reduce the accuracy of data fitting. For the prediction of cumulative deformation under the influence of multiple variables, Duan et al. and others used different smoothing parameters to predict the deformation of landslides under different monthly rainfall conditions, but the selection of models and the weight of different factors have a great impact on the results (Duan et al., 2016). Yang et al. used short-term and short-term memory neural networks to predict landslides, proving the feasibility and high accuracy of using neural networks to predict landslides (Yang et al., 2019). Genetic algorithm is used to optimize the structure of BP neural network, and a nonlinear synergetic bifurcation model is established to predict the deformation of single variable (Guo et al., 2011). Cai et al., 2019 and others used FA algorithm to optimize the selection of neural network structure, but the same network structure will also lead to different training effects due to the random selection of initial value (Cai et al., 2019). The above results have been well applied in the study of deformation prediction using long-term monitoring data of landslides, but there are still some areas for improvement in the accuracy of the prediction results. Zhou et al. proposed a new extreme gradient boost (XGBoost) and Hodgrick Prescott (HP) filtering coupling method to predict landslide displacement (Zhou et al., 2022). Tang et al. developed a progressive landslide displacement prediction model driven by Semantic information, which includes the identifier of the displacement stage and the predictor of acceleration stage (Tang et al. . 2022). Miao et al. took the Baishui River landslide as the research object and decomposed the landslide displacement into three parts (trend term, periodic term, and random term) through variational mode decomposition (VMD), introduced a data mining algorithm to select the triggering factors of periodic displacement, and applied the fruit fly optimization algorithm backpropagation neural network to train and predict periodic and random displacement (Miao et al., 2022). Long et al. applied the multi-feature fusion transfer learning method to the Baijiapu landslide scene to obtain sufficient monitoring data and laws, improving landslide prediction ability (Long et al., 2022). Zheng et al. proposed a displacement prediction method based on multi-source domain transfer learning, and used the optimal variational mode decomposition model based on minimum sample entropy to decompose the cumulative displacement into trend component, periodic component and random component (Zheng et al., 2023). The trend component is predicted by the autoregressive model, and the cycle component is predicted by the long-term and short-term memory. For random components, a combination of Wasserstein-generated adversarial networks, and multi-source domain transfer learning is used for prediction to improve prediction accuracy.

Therefore, the difficulty of landslide displacement prediction research lies in the scientific and reasonable analysis of the original data and improving the accuracy of the prediction model as much as possible. On the basis of previous research results, this paper adopts the variational modal decomposition algorithm to decompose the landslide displacement sequence, which can avoid modal aliasing in the process of decomposition and can control the number of sub-sequences. The improved particle swarm optimization algorithm is used to optimize the ELM parameters, and IPSO-ELM is constructed. The model is used to predict the decomposed displacement subsequences respectively, and the prediction results of each subsequence are reconstructed to obtain the predicted value of landslide cumulative displacement. On the basis of the above work, the displacement prediction values obtained by the model used in this paper are compared with those obtained by the traditional ISPO-ELM, extreme learning machine (ELM), and back propagation neural network (BPNN) models. The mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of these models are calculated, respectively. Thus, the prediction accuracies of these three models were quantitatively compared, and the models with the highest prediction accuracy were indicated.

2 Principle and algorithm of variational mode decomposition (VMD)

The landslide displacement sequence is a nonlinear and non-stationary time series. If the prediction is made directly on the basis of the original cumulative displacement monitoring data, it is easy to produce large errors. In relevant research, the method of decomposing the original displacement sequence using a decomposition algorithm (i.e., decomposing first and then predicting) is widely used, and the landslide displacement prediction based on this method has achieved good prediction results. By decomposing the original sequence, on the one hand, the complexity of the data is reduced, on the other hand, the information of the original monitoring data is fully utilized, and the prediction accuracy is improved. Typical sequence decomposition algorithms include wavelet analysis, empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), etc (Shihabudheen, 2017; Miao et al., 2022).

Variational mode decomposition (VMD) can convert the original signal into non-recursive VMD mode. Compared with EMD algorithm and EEMD algorithm, VMD algorithm has an

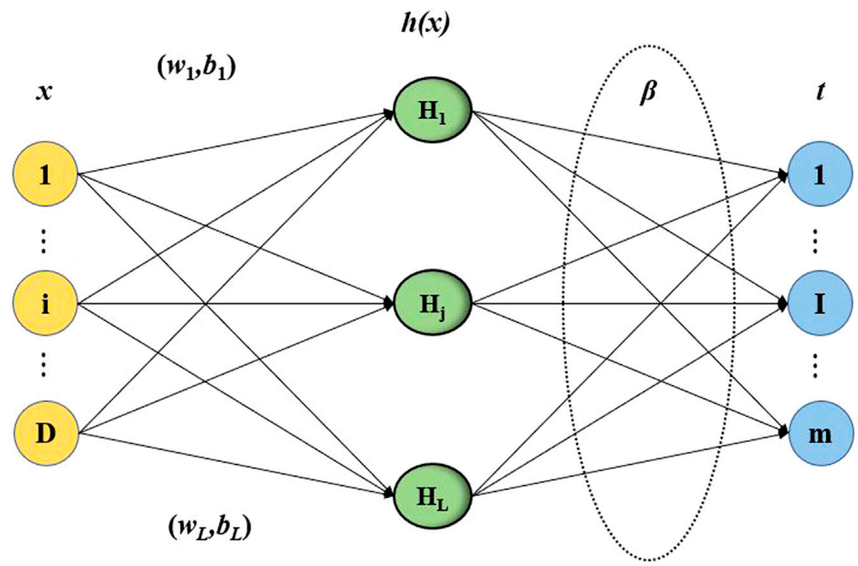

FIGURE 1
The Schematic of extreme machine learning.

excellent performance in anti-noise. In addition, the VMD algorithm controls the convergence conditions and the number of decompositions reasonably, and the number of modes obtained after decomposition is also less than EMD and EEMD. Therefore, VMD has the advantages of solid mathematical foundation and fast calculation speed, which is extremely beneficial to reduce the workload of later prediction.

The overall idea of VMD algorithm is to construct a variational problem first, and then decompose a real value signal S into a discrete number of modes $S_k(t)$, $k = 1, 2, \cdots, K$ by solving the variational problem, and assume that each mode is approximately compact around the center pulse. Wiener filter, Hilbert transform and frequency mixing in signal analysis are the important basis of VMD algorithm.

3 Improved particle swarm optimization extreme learning machine (IPSO-ELM)

3.1 Extreme learning machine (ELM)

The extreme learning machine was proposed in 2004. Because of its simple structure, less parameters and fast learning speed, many scholars have studied and applied the algorithm (Huang et al., 2006; Marti et al., 2011; Xue et al., 2020; Panghal et al., 2021). The principle of extreme machine learning is shown in Figure 1.

In a single hidden layer neural network, it is assumed that there are N samples (x_i, y_i), where $x_i = [x_{i1}, x_{i2}, x_{i3}, \cdots, x_{in}]^T \in R^n$, $y_i = [y_{i1}, y_{i2}, y_{i3}, \cdots, y_{im}]^T \in R_m$, when in a single hidden layer neural network, the output samples can be expressed as:

$$y_i = \sum_{i=1}^{l} \beta_i g(\omega_i g x_i + b_i) \tag{1}$$

Where, β_i is the output weight; $g()$ is the activation function; ω_i is the input weight; b_i is the offset of hidden layer nodes; $\omega_i \cdot x_i$ is the inner product of ω_i and x_i.

The purpose of using ELM model is to minimize the output error value. Assume that when the error value is 0, the output of the existence, and make formula β_i, ω_i and b_i is equal to the actual output, and the following matrix can be established:

$$\begin{cases} \boldsymbol{Y} = \boldsymbol{\beta H} \\ \boldsymbol{Y} = (y_1, y_2, \cdots, y_i) \\ \boldsymbol{\beta} = (\beta_1, \beta_2, \cdots, \beta_i) \\ \boldsymbol{H} = \begin{cases} g(\omega_1 \cdot x_1 + b_1) \ldots g(\omega_1 \cdot x_i + b_1) \\ \qquad \boldsymbol{M} \qquad\qquad\quad \boldsymbol{M} \\ g(\omega_i \cdot x_1 + b_i) \ldots g(\omega_i \cdot x_i + b_i) \end{cases} \end{cases} \tag{2}$$

To sum up, calculate the minimum value $\|\mathbf{H\beta} - \mathbf{Y}\|^2$, where $\mathbf{Y}$ is the actual output; $\mathbf{H}$ is determined according to the value of ω_i and b_i, from which it can be concluded that the prediction model is established.

3.2 Improved particle swarm optimization (IPSO)

Particle swarm optimization algorithm (PSO) is an evolutionary computing technique derived from the study of bird swarm predation behavior. The algorithm was originally inspired by the regularity of bird cluster activity and then a simplified model using swarm intelligence. Each particle represents different possible solutions. The quality of the particle's position is judged according to the fitness function value. Through continuous learning from the global optimization and individual optimization, the particle's position and speed are updated to achieve the optimization purpose.

Assume that in the dimensional space, it represents the position of particles and the speed. Under this condition, $X_i = (X_{i1}, X_{i2}, \cdots, X_{id})$

indicates the position of particles, $V_i = (V_{i1}, V_{i2}, \cdots, V_{id})$ indicates speed, its position and speed are updated according to formulaunder this condition:

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \tag{3}$$

$$V_{id}^{t+1} = \omega \cdot V_{id}^{t} + c_1 r_1 \left(p_{id}^{t} - X_{id}^{t}\right) + c_2 r_2 \left(p_{gd}^{t} - X_{id}^{t}\right) \tag{4}$$

Where, ω is inertia weight; p_{id}^{t} is the best individual under this condition; p_{gd}^{t} is the corresponding global optimum; c_1, c_2 is the sub-factor of students; r_1, r_2 is a random number with a value range of $[0\ \ 1]$.

In particle swarm optimization, inertia weight ω, as one of the important parameters, plays a vital role in the search effect. The value of ω determines the global search ability of PSO. The larger the value of ω, the stronger the global search ability of PSO; otherwise, the stronger the local search ability of PSO. In order to achieve higher search efficiency, the random weight method is introduced to optimize this algorithm in the optimization process. When optimizing based on this method, the PSO algorithm is considered to be random. The advantages of this setting are:

(1) When the initial position is close to the global optimum, the random value obtained is small, which is beneficial to improve the convergence speed.
(2) Overcome the limitation that the algorithm cannot converge to the best point caused by linear decline.

The inertia weight is modified based on the following expression:

$$\begin{cases} \omega = \mu + \sigma \times N(0,1) \\ \mu = \mu_{\min} + \left(\mu_{\max} - \mu_{\min}\right) \times r \text{ and } (0,1) \end{cases} \tag{5}$$

Where, $N(0,1)$ represents the random number of the standard state distribution, and $rand(0,1)$ represents the random number between $[0\ \ 1]$.

The calculation steps of random weight method are as follows.

(1) Initializes the speed of particles.
(2) Calculate and determine the fitness of each particle, save its position and fitness information in p_{best}, and compare and analyze all of p_{best} to get the best individual value and then store it in g_{best}.
(3)The displacement and velocity are updated by the following expression:

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1) \tag{6}$$

$$v_{i,d}(t+1) = \omega \cdot v_{i,d}(t) + c_1 r_1 \left[p_{i,d} - x_{i,d}(t)\right] + c_2 r_2 \left[p_{g,d} - x_{i,d}(t)\right] \tag{7}$$

(4) Update the inertia weight according to the formula.
(5) Compare the current position and the best position of particles, and replace the latter with the current position in the case of proximity. Compare all p_{best} and g_{best} and update g_{best}.
(6) If the algorithm meets the stop condition, the iteration operation is ended and the result is output. On the contrary, return to step (3).

3.3 IPSO-ELM model

The random weight method is applied to the PSO algorithm, which overcomes the shortcomings of the PSO algorithm that the global search ability and local search ability are poor due to the improper value of inertia weight. The improved particle swarm optimization algorithm (IPSO) is used to globally optimize the connection weight and hidden layer threshold of the extreme learning machine (ELM), and thus IPSO-ELM model is constructed for landslide displacement prediction.

4 Landslide displacement prediction process

The steps of landslide displacement prediction based on VMD and IPSO-ELM coupling model are as follows, Figure 2 shows the flow of landslide displacement prediction.

5 Engineering case analysis

5.1 Typical landslide engineering geology and monitoring overview

A typical landslide selected for this project case analysis is located on the south bank of the Yangtze River in the Three Gorges Reservoir area, 56 km away from the dam site of the Three Gorges Dam. The landslide is an old landslide, which has repeatedly occurred bedding sliding in history. The landslide mass is located in the broad valley section of the Yangtze River, a monoclinic bedding slope, high in the south and low in the north, and is distributed in a stepped manner towards the Yangtze River. The rear edge elevation of the landslide is 410 m, bounded by the geotechnical boundary, and the front edge is about 70 m, which has not been below the reservoir water level, the eastern and western sides are bounded by the bedrock ridge, with an overall slope of about 30°.

The deformation of typical landslide mainly occurs in the early warning area of the sliding mass, and the deformation of other parts of the sliding assembly obvious could be clearer. There are currently 6 GPS monitoring points in the early warning area. The monitoring data shows that in 2011, the cumulative horizontal displacement of GPS monitoring points M1, M2, and M3 for the whole year was 182.2, 128.5, and 145.8 mm, respectively, with an average rate of 15.2, 10.7, 12.2 mm/month; The cumulative horizontal displacement of the whole year in 2012 was 239.6, 113.0, and 113.6 mm respectively, with the average rate of 20.0, 9.4, and 9.5 mm/month respectively.

5.2 Prediction of landslide displacement

Reasonable selection of landslide displacement influencing factors is of great significance to the rationality and prediction accuracy of displacement prediction. Based on the previous research experience, the monthly rainfall, reservoir water level value, bimonthly rainfall, inter-monthly reservoir water level variation, bimonthly reservoir water

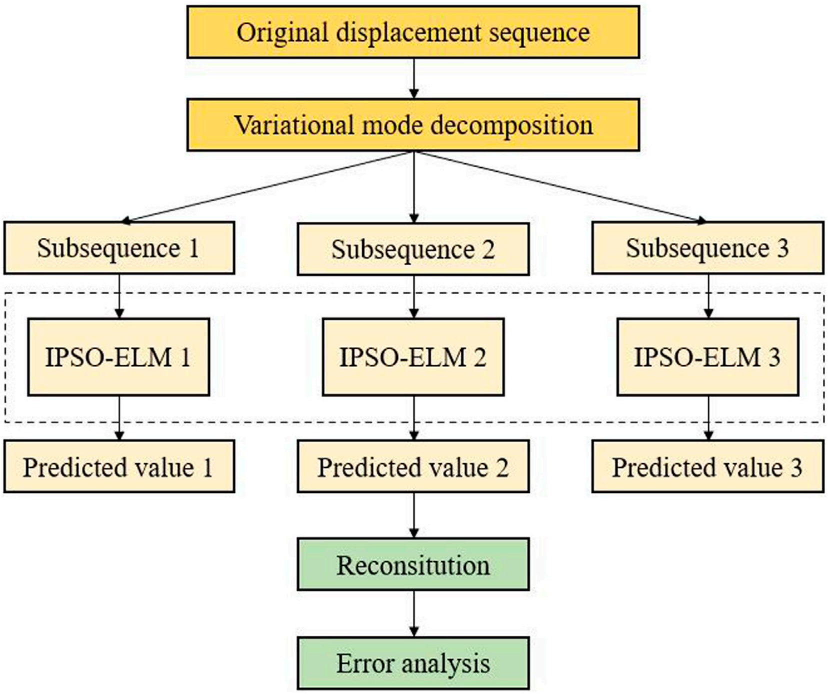

FIGURE 2
Flow chart of landslide displacement prediction.(1) VMD is used to decompose the original cumulative displacement sequence to obtain the subsequence components.(2) IPSO is used to optimize the parameters of ELM, and IPSO-ELM coupling model is established.(3) The IPSO-ELM coupling model is used to predict the subsequences obtained from VMD decomposition.(4) Reconstruct the prediction results of each displacement subsequence to obtain the total displacement prediction value of the monitoring point.(5) Error analysis. In error analysis, the degree of dispersion of prediction results and the degree of deviation between prediction value and actual value are taken as careful consideration, and MSE, MAE and MAPE are selected as accuracy evaluation indicators.

level variation and monthly displacement increment are considered the displacement influencing factors system.

Under the conditions of engineering practice, the prediction model must have strong adaptability to the dynamic monitoring data to accurately and stably output the prediction results. To verify the validity and stability of the proposed model, the monitoring data of this typical landslide monitoring point is divided into two datasets to train and test the model. Select the monitoring data from 2007 to 2010 as the training set, and the monitoring data from 2011 as the corresponding test set.

5.2.1 Selection of mode number

Before the VMD decomposition of the original displacement sequence, the number of decomposition subsequences needs to be set first. In order to facilitate the subsequent prediction, the cumulative displacement sequence of the monitoring point from 2007 to 2011 is decomposed, and the modal number is set as K=2, 3, 4.

According to the previous test, the first sub-sequence (the main component of the cumulative displacement sequence) obtained by decomposition is obviously inconsistent with the original series in the trend when K=4, and it is considered that there is over-decomposition. Therefore, K=3 is more appropriate. To maximize the use of the information of the original data, the original cumulative displacement sequence is decomposed into three sub-sequences, and the three modes are obtained by decomposition.

TABLE 1 Accuracy comparison of three models.

Error index	IPSO-ELM	ELM	BPNN
MSE	115.23	496.21	762.12
MAE	4.95	15.36	20.14
MAPE	0.18%	0.56%	0.65%

5.2.2 Sub-sequence displacement prediction

According to the landslide displacement prediction flow, the three subsequences obtained from the decomposition of the original displacement sequence are modelled and predicted, respectively, and three groups of corresponding displacement prediction values are obtained.

5.2.3 Sub-sequence prediction displacement reconstruction

The final total landslide displacement prediction value is obtained by superposition of three groups of prediction values, and compared with the actual monitoring value. The prediction accuracy results of the prediction model were obtained by the validation of the displacement data in 2011. The comparison of prediction accuracies is shown in Table 1.

The comparison results show that.

(1) Both ELM and BPNN have prediction effects only in a particular range, but the prediction accuracy in a more extensive range is very low, indicating that the robustness and generalization ability of these two models are relatively poor.
(2) The prediction accuracy of BPNN depends on the training of large data samples. For the prediction of small samples similar to this paper, BP neural network's prediction accuracy and generalization ability the are worse than ELM.
(3) The IPSO-ELM model proposed in this paper can adapt to the changing data environment. Displacement data from different scenarios were used for stability testing of the IPSO-ELM model. The displacement data from 2007 to 2011 as training set and the 2012 data as test set. The results show slight differences in prediction accuracy in different scenarios, but high accuracy, indicating the good stability.

6 Conclusion

This paper studies the landslide displacement prediction based on VMD and IPSO-ELM coupling model. In the landslide displacement prediction, the original displacement sequence is decomposed into three sub-sequences, and then predicted separately is an effective method to make full use of the limited data information. On the basis of VMD, IPSO algorithm is used to optimize the parameters of ELM, which can effectively solve the problem of premature particle swarm optimization algorithm. It is easy to fall into the problem of local optimization, and it also retains the advantages of particle swarm optimization algorithm itself, such as fast convergence speed.

The verification results of typical landslide examples show that the coupling model can accurately predict the displacement value of landslides, with good accuracy and stability, and has high application value in landslide displacement prediction. When using IPSO-ELM coupling model based on VMD. When predicting landslide displacement, the K value of VMD can be set manually. When the appropriate K value is selected, the prediction effect of the model is perfect.

Data availability statement

The datasets presented in this article are not readily available because the data used to support the findings of this study are available from the corresponding author upon request. Requests to access the datasets should be directed to qiaojunwei@xust.edu.cn.

Author contributions

JQ wrote and modified this paper; YZ provided algorithm processing for it; WL collected and processed the data in the paper; JT collected on-site data for the paper. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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