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Editorial

Landslide Displacement Prediction Based on Time Series and PSO-BP Model in Three Georges Reservoir, China

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0 INTRODUCTION

Landslides are one of the most frequent geological disasters in the world (Wen et al., 2020; Froude and Petley, 2018), which have occurred frequently and widely distributed in China for a long time. The landslides are essentially a complex multi-dimensional nonlinear dynamic system affected by its own geological conditions and external factors (Ma et al., 2021; Wang et al., 2019), including geotechnical characteristics, hydrogeology, geomorphologic conditions, climate, and weathering (Ma et al., 2020). The interaction of these factors makes the change of landslide displacement random, fuzzy and variable (Park and Michalowski, 2017), and also brings great difficulties to the landslide displacement prediction (Ma et al., 2018).

With the development and maturity of intelligent algorithms, nonlinear intelligent algorithms such as support vector regression machine model (SVR) (Miao et al., 2018; Kavzoglu et al., 2014), artificial neural network model (ANN) (Huang et al., 2020; Afan et al., 2016) are widely used in the landslide displacement prediction. At present, domestic scholars put forward a variety of algorithm combinations in the landslide displacement prediction, which has made many achievements. For example, the PSO-SVR model is used in the landslide displacement prediction (Zhou et al., 2016; Zhang et al., 2015). The grey wolf optimizer (GWO) and genetic algorithm (GA) combined with other models are used to predict the landslide displacement (Liao et al., 2019; Miao et al., 2018). However, there are still many limitations in the landslide displacement prediction.

In this study, we use the time series analysis method to decompose the landslide cumulative displacement into trend displacement and periodic displacement, and we propose a novel model which uses the combination of three order polynomial and the PSO-BP model (Rumelhart et al., 1986) to predict the trend displacement and the periodic displacement on the basis of analyzing the variation characteristics of the landslide displacement and the response relationships of external precipitating factors (Liao et al., 2019). Finally, the predicted values of the two different methods are superimposed to obtain the prediction results of the cumulative displacement of the landslide.

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1 DATA COLLECTION AND PREPROCESSING

In this study, the monitoring points ZG85 and ZG87 with complete data in the main landslide area are selected to analyze the influence factors of the landslide displacement. Compared with ZG87, ZG85 is located at the head scarp of the landslide and its displacement has obvious step-type characteristics. Therefore, the displacement time curve of ZG85 was conducted for it is more deformed and can better represent the dangerous state of the landslide for the displacement prediction and analysis. The monitoring data of monitoring point ZG85 from July 2003 to October 2013 were selected to predict the landslide displacement, in which the data from June 2004 to October 2012 were used as the training set, and the data from November 2012 to October 2013 were used as the verification set.

2 DATA ANALYSIS

The time series data of the cumulative displacement of ZG85 and ZG87 monitoring points of the Shuping Landslide from 2004 to 2014 are shown in Figure 1a. According to the long-term monitoring data, the deformation of the Shuping Landslide is mainly local deformation, which mainly occurs in the head scarp of the landslide. According to the reservoir water level dispatching curve, the monitoring curve is divided into three stages.

Stage 1: the fluctuation range of the reservoir water level was small, indicating that the main factor affecting landslide at this stage was the rainfall. The landslide displacement continued to increase slightly in the flood season, reflecting a certain correlation between the landslide displacement and the rainfall. Stage 2: there are two periodic schedulings of the reservoir water level. The decline of the reservoir water level occurred during seasonal heavy rainfall. When the second reservoir water level dropped sharply, the landslide also produced a step-type deformation. Stage 3: the reservoir water level fluctuated periodically from 144.18 to 174.72 m, and the cumulative displacement of the monitoring points continued to increase in a step-type. This variation laws were more obvious when the reservoir water level increased rapidly from 145.86 to 172.60 m. The corresponding landslide displacement remained stable for a long time.

It is well reflected that the rainfall has a strong correlation

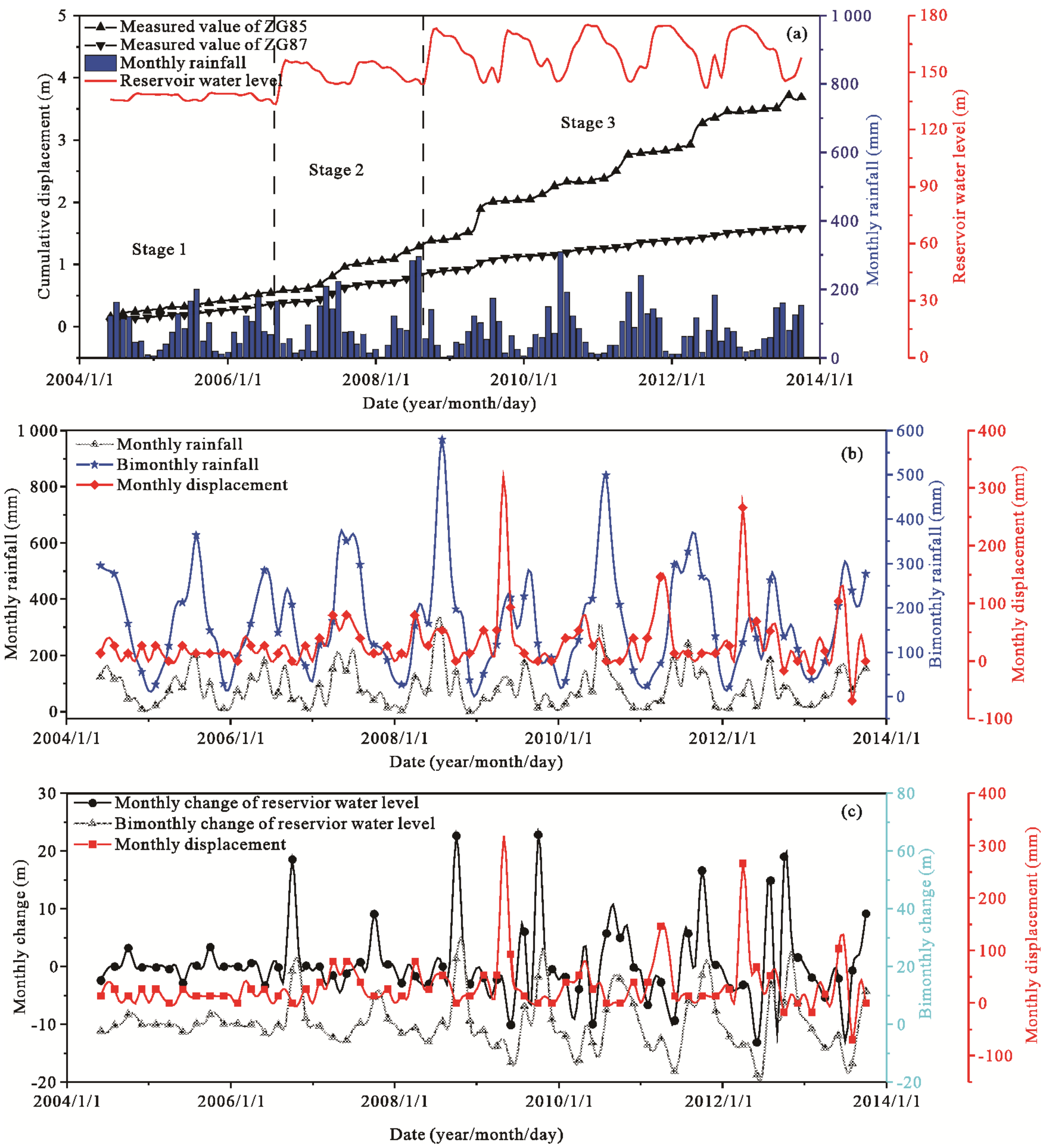

Figure 1. Analysis of data from landslide monitoring sites. (a) The relationship diagram between the measured value of point ZG85 and ZG87 and monthly rainfall and reservoir water level; (b) ZG85 Monthly displacement of landslide, monthly rainfall and bimonthly rainfall monitoring curves of ZG85 monitoring point; (c) Monitoring curve of ZG85 monthly displacement, monthly change of reservoir water level and bimonthly change of reservoir water level.

with the landslide. In the month of concentrated rainfall of each year, the landslide displacement increases significantly during this period (Figure 1b). Figure 1c well illustrates the correlations between the change of the landslide displacement and the change of monthly reservoir water level and the change of bimonthly reservoir water level. At the same time, it is consistent with the variation laws of the displacement. That is, the decline of the reservoir water level leads to a sharp increase in the landslide displacement.

3 LANDSLIDE DISPLACEMENT PREDICTION MODEL

Advance landslide displacement trend terms are used in the moving average method (Window is equal to 6). Subtract the trend term from the observed data to obtain the landslide displacement period term (Figure 2a). The trend displacement extracted from original data presents linear characteristics, and the cubic polynomial fitting of least square method is used in this study. Both the PSO and the BP neural network models are used to predict the periodic displacement.

In the study, five influencing factors (Gray correlation range of 0.78 – 0.99) are selected to predict the periodic displacement (ESM Text S9). The number of nodes in the input layer R is 5, and the number of nodes in the output layer C is 1. The number of nodes in the hidden layer of the BP neural network is usually $P = \sqrt{R + C} + d$, and d is a constant between 1 and 10, so the value of P is between 3 and 12. Considering the convergence performance of the BP neural network, the topological structure of the BP neural network is 5-10-1 when P is equal to 10. The training number of the BP neural network is

10 000, the learning rate is 0.1, and the target error is $1e^{-6}$. The activation functions of hidden layer and output layer are selected Tansig and Purelin, respectively. However, Traingdm is selected as the training function. According to the topological structure of the BP neural network, the dimension of the PSO is $D = 5 \times 10 + 10 \times 1 + 10 + 1 = 71$. Considering the convergence rate of the algorithm and the optimization performance of the particle swarm, the population size N is 30, the weight w is 0.1, the learning factor is $c_1 = c_2 = 1.49$ and the maximum number of iterations is $T = 30$. The PSO algorithm is used to search the parameters of the BP neural network model, and the optimal weights and thresholds of the hidden layer neurons of the BP neural network are obtained.

4 RESULTS AND DISCUSSION

By using Matlab R2018a, the results of the trend term are shown in Figure 2b, and the fitting effect reaches the expectation with the goodness of fit $R^2 = 0.998\ 3$. The parameter value of cubic polynomial is shown in Table S1. In addition, the PSO-BP neural network prediction model is constructed to predict the landslide displacement in the Three Gorges Reservoir. Both the BP and the ELM models are also constructed to predict the landslide displacement in this study. A comparative analysis of the predicted values and relative errors of the mentioned-above three models are conducted. The specific analysis results are shown in Table S3. The maximum relative error of the BP neural network prediction model is 11.44%, the minimum relative error is 0.46%, and the average relative error is 3.87%. The maximum relative error of the ELM neural network prediction model is 20.59%, the minimum relative error is 0.31%, and the average relative error is 6.87%. The maximum relative error of the PSO-BP neural network prediction model is 3.79%, the minimum relative error is 0.04%, and the average relative error is 1.45%. Therefore, the relative error value of the PSO-BP neural network prediction model is much smaller than that of the BP and the ELM. It can be seen that the PSO-BP model is superior to the other two models in predicting the Shuping landslide. In addition, the fitting goodness of the PSO-BP neural network model is $R^2 = 0.91$, root mean square error (RMSE) is 2.377 cm, and mean absolute percentage error MAPE is 14.52, which achieves good prediction results (Figure 2c). In conclusion, the results reveal that the PSO-BP model has great performance in the prediction of the displacement of the Shuping Landslide. The prediction value of the landslide cumulative displacement can be obtained by superposition of the prediction value of the trend displacement and the prediction value of the periodic displacement (Figure 2d).

Although many scholars utilize different models for the landslide prediction at present, the procedures are basically the same. Firstly, the landslide displacement is decomposed and then the prediction model is established. The prediction accuracy is further improved, but various models also have their own shortcomings. It should be pointed out that in this study, the PSO algorithm is used to optimize the weights and thresholds of the BP neural network. The PSO-BP neural network prediction model solves the problems of slow convergence speed and susceptibility to fall into local minimum of the BP neural network, and achieves good prediction results. However, there are also many parameters that need to be trained in the model, which may lead to unstable model output, long calculation time and the difficulty of the parameter selection. It is believed that with the development of science and technology and the advent of the era of artificial intelligence, the prediction of the landslide in the future will be the combination of intelligent algorithms and remote sensing, GIS and other technologies, which will be more accurate and intelligent.

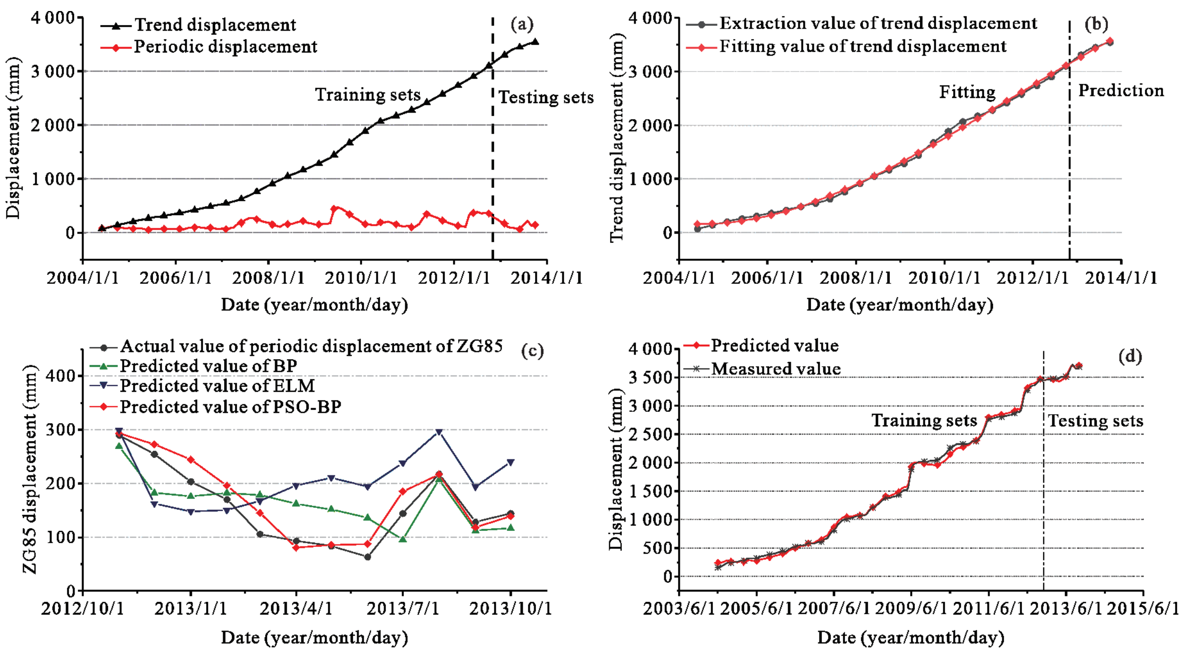

Figure 2. Analysis of the results of landslide displacement prediction. (a) Landslide displacement is decomposed into trend and period terms by time series; (b) the third-degree polynomials predict the trend term; (c) PSO-BP model predicts the period term; (d) comparison of superimposed trend and period terms with the true value.

5 CONCLUSIONS

A novel PSO-BP neural network prediction model of the landslide displacement based on the time series is proposed for the complex non-stationary and nonlinear dynamic system of the landslide. The PSO algorithm is used to optimize the weights and thresholds of the BP neural network. A prediction model based on the PSO-BP neural network is established to solve the problems of slow convergence speed and susceptibility to fall into local minimum of the BP neural network. The combination of the time series and the PSO-BP in predicting the landslide displacement prediction is obviously better than the BP neural network model and the ELM model. Compared with the actual measured value, the predicted value is close to the measured value, and the combination model achieves better prediction results.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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