Landslide Displacement Prediction Based on Extended Escendant Strategy PSO Neural Network

Yuqiu Lin¹, Wenxing Jian¹*, Chang Xu², Yongliang Pan¹ and Linjun Li¹

¹Faculty of Engineering, China University of Geosciences, Wuhan, China
²School of mechanical engineering and electronic information, China University of Geosciences, Wuhan, China

*Corresponding author e-mail:wxjian@cug.edu.cn

Abstract. A new PSO algorithm based on extended escendant strategy was proposed. The dynamic change of the landslide displacement time series is nonlinear and uncertain. Combine extended escendant strategy PSO with the Elman neural network, and establish a landslide displacement prediction model based on EESPSO-ENN to realize the dynamic prediction of landslide displacement. Taking the Baishuihe landslide in the Three Gorges Reservoir area as an example, select the monitoring data of ZG93 from 2013 to 2016 as training samples and test samples for training and prediction. Comparing the prediction results of EESPSO-ENN with the BP neural network and SVM method, the results demonstrate that the EESPSO-ENN model has a small prediction error and its prediction effect applied in the Baishuihe landslide is better than BP neural network and SVM method. The validity of EESPSO-ENN was verified.

Keywords: Particle Swarm Optimization, Elman Neural Network, EESPSO-ENN, Landslide Displacement Prediction

1. Introduction
Landslide hazard threatens the safety of human life and property seriously, research on landslide prediction is of great significance. The main idea of statistical method to predict the landslide is to track and predict various deformation trajectories and complex data sequences based on time series data of landslide displacement, then establish mathematical models for landslide prediction.

Artificial intelligence is widely used in landslide susceptibility prediction. Kumar Deepak et al. used support vector machine the hybrid machine learning method to establish the landslide spatial prediction model [1-3]. In terms of landslide displacement prediction, Huang et al. used the multivariate chaotic extreme learning machine to predict the landslide displacement [4]. Jiang et al. proposed a generalized regression neural network landslide displacement prediction method based on K-fold cross-validation [5]. Marjanović et al. used the Decision Tree Structure to roughly estimate and extrapolate the landslide threshold [6]. Lian et al. used part of the selected neural networks to construct high-quality landslide displacement prediction intervals [7]. Li et al. polynomial model, extremal learning machine and the long short-time memory neural network to dynamically predict the landslide...
[8,9]. In the study of intelligent landslide prediction, researchers try to combine intelligent algorithms with monitoring data.

In this paper, the extended descendent method is used to improve the particle swarm optimization algorithm so that the ENN network has better convergence ability and prediction accuracy. Taking the monitoring data of the Baishuihe landslide as the research object, use the monitoring data of two years as training samples to predict the displacement of the next year.

2. Particle swarm optimization based on extended descendent strategy

2.1. Standard particle swarm optimization

PSO algorithm is inspired by the predatory behavior of birds. For the $i^{th}$ particle, in $d$-dimensional search space, the velocity and position are as follows:

$$ V_{id} = \alpha V_{id} + \eta_1 \text{rand}((P_{id} - X_{id}) + \eta_2 \text{rand}((P_{gdb} - X_{id})) $$

$$ X_{id} = X_{id} + V_{id} $$

Where $V_{id}, V_{id}$ represent the updated and previous velocity of the particle $id$, $X_{id}, X_{id}$ represent the updated and previous position of the particle $id$, $\alpha$ is the inertia weight factor, $\eta_1$ and $\eta_2$ are positive acceleration constants, $\text{rand}()$ represents a random number; $P_{id}$ and $P_{gdb}$ represent respectively the historical best position of the particle $id$ and the particle swarm.

2.2. PSO based on extended descendent strategy

The standard PSO converges fast, and easily leads falling into the local optimum. PSO based on extended descendent strategy can record the best and the worst historical positions. It makes the particles move towards the historical best position of themselves and the particle swarm and away from the historical worst position.

The update formulas of velocity and position are as follows:

$$ V_{id} = \alpha V_{id} + \eta_1 \text{rand}((X_{id} - P_{id}) + \eta_2 \text{rand}((X_{id} - P_{gdb})) $$

$$ X_{id} = X_{id} + V_{id} $$

Where $P_{id}$ and $P_{gdb}$ represent respectively the historical worst position of particle $id$ and the global historical worst position of the particle swarm.

3. Elman neural network based on EESPSO

In order to realize the memory function of the neural network, feedback and modify the weight and threshold of the network, the Elman neural network adds a context layer. Therefore, aiming at the nonlinear growth characteristics of the cumulative displacement curve of the landslide, ENN is more suitable for the dynamic prediction of landslide disaster than the BP neural network. The architecture of the Elman network is shown in Fig. 1.
Where $y(t)$, $x(t)$, $u(t)$ and $x^c(t)$ are the output of the output layer, the hidden layer, the input layer and the context layer; $\omega^{(1)}$, $\omega^{(2)}$ and $\omega^{(3)}$ are the connection weight matrix between two layers; $\theta^{(1)}$ and $\theta^{(2)}$ are the threshold value.

In a complicated and nonlinear system such as landslide prediction, the Elman neural network is easy to fall into the local optimum. EESPSo’s new mechanism of information sharing makes it have strong global search ability. The proposed model is helpful to solve nonlinear time-varying problems such as the dynamic prediction of landslide displacement.

4. Application of EESPSo-ENN in the prediction of the landslide

4.1. Overview of the study area

Because of the seasonal rainfall and periodic fluctuation of reservoir water level, colluvial landslides in the Three Gorges Reservoir area move intermittently. The Baishuihe landslide is located in Zigui County, Hubei province (Fig. 2). The sliding body is quaternary deposit, the sliding bed is Jurassic thick bedded sandstone mixed with thin bedded mudstone. The slide-belt soil is silty clay with gravel (Fig. 3). Rainfall and drawdown of reservoir water level are the main inducing factors for its deformation [10].

Figure 1. Architecture of the Elman Network

Figure 2. Geographical location of the Baishuihe landslide
4.2. Analysis of monitoring data

The distribution of 11 monitoring points in the Baishuihe landslide is shown in figure 4. The ZG93 monitoring point has the longest monitoring history and the most complete monitoring data. Fig. 5 shows the deformation of the Baishuihe landslide from 2003 to 2016. The time series of landslide cumulative displacement is “steped”. Select the displacement monitoring data of ZG93 from May 1, 2013 to June 1, 2016 for analysis. The cumulative deformation of the landslide in this period was 484mm. Landslide deformation accelerated from May to August each year, while it is slow in other months. Collect the data of rainfall and reservoir water level from May 2013 to June 2016. It can be seen from figure 6 that the relationship between the cumulative displacement of the landslide and rainfall and the decline of reservoir water level.

When the reservoir water level remains at about 145m, the landslide displacement increases with the increase of rainfall. From June to September, rainfall increases and the landslide displacement rate reaches its maximum in a year. From 2013 to 2016, the water level dropped from the high water level of 170m and above to 145m for four times, and the landslide displacement curve showed a step-type characteristic. The sharp increase of landslide displacement mainly occurs in the middle and late period of the reservoir water level decline. Therefore, rainfall and reservoir water level decline are the main factors that lead to the deformation of the Baishuihe landslide. It is reliable to predict its displacement according to the relationship between landslide displacement and rainfall and the reservoir water level decline.
Figure 4. Monitoring map of the Baishuihe landslide

Figure 5. Cumulative displacement -time curve of the Baishuihe landslide

Figure 6. Relationship between the landslide cumulative displacement and rainfall and the reservoir water level decline.
4.3. The dynamic prediction of landslide based on GSSPSO-ENN

4.3.1. Sample data processing. Monitoring data of the first two years were used as training samples, and monitoring data of the next year were used as test samples. Use the cumulative displacement data and normalize them, and use the cumulative distribution function (formula 5) to process the displacement monitoring data. Similarly, normalize and standardize the data of rainfall and reservoir water level decline. The normalized formula is the formula (6). Convert the output sample according to the formula (7).

\[
X_k = \sum_{i=0}^{k} \frac{x_i}{X} \tag{5}
\]
\[
y' = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \tag{6}
\]
\[
x = x' \cdot X \tag{7}
\]
Where \( X \) is the cumulative displacement, \( y' \) is the original sample data, \( y' \) is the normalized sample data, \( y_{\max} \), \( y_{\min} \) are respectively the upper and lower bounds of samples, which are determined according to actual engineering problems, \( x' \) is the output value of the system, \( x \) is the output of the inverse transform.

4.3.2. Model prediction and results comparison. Take the data of rainfall and reservoir water level decline as input, and take the landslide cumulative displacement as output to train and predict this model. The training results and errors of the model are shown in Fig. 7. Compare the prediction result of EESPSO-ENN method with the actual value of monitoring data, the prediction value of BP neural network method and SVM method, as shown in Fig. 8. The predicted value of the EESPSO-ENN model is the closest to the actual value, and the predicted result is better than BP neural network and SVM method. Use the average relative error and the mean square error to compare different prediction methods, the formulas are (8) - (10). Training errors and prediction errors are in table 1 and table 2, showing that the prediction value of the EESPSO-ENN model is close to the actual value.

\[
\epsilon_i = \left| \frac{x'(\tau) - x(\tau)}{x(\tau)} \right| (\tau = 0,1,\ldots,N_p) \tag{8}
\]
\[
\sigma_{ave} = \frac{\sum \epsilon_i}{n} \tag{9}
\]
\[
\sigma = \sqrt{\frac{\sum \epsilon_i^2}{n}}, i = 0,1,\ldots,n \tag{10}
\]
Where \( x(\tau) \) and \( x'(\tau) \) are the deformation and its training value at time \( t \), \( \epsilon_i \) and \( \epsilon_{\tau} \) are the error and the relative error of the \( ith \) sample, \( \sigma_{ave} \) and \( \sigma \) are the average relative error and the mean square error.
Figure 7. Model training results and errors

Figure 8. Model prediction results and comparison
Table 1. Comparison result of training errors of EESPSO-ENN, BP and SVM.

|                | EESPSO-ENN | BP neural network | SVM  |
|----------------|------------|-------------------|------|
| Average relative error/% | 1.53       | 5.44              | 6.15 |
| Mean square error         | 0.01       | 0.48              | 0.24 |

Table 2. Comparison result of prediction errors of EESPSO-ENN, BP and SVM.

|                | EESPSO-ENN | BP neural network | SVM  |
|----------------|------------|-------------------|------|
| Average relative error/% | 31.50      | 76.22             | 47.98|
| Mean square error         | 19.10      | 48.81             | 32.34|

5. Conclusion

Extended descendent strategy PSO algorithm remedies the problems of the Elman neural network, such as slow convergence velocity and easy to fall into local optimum. Combine the EESPSO and the Elman network to establish a dynamic landslide displacement prediction model. Taking the Baishuihe landslide as an example, the monitoring data from 2013 to 2015 were used as training data, and the monitoring data from 2015 to 2016 were used as test data. Compare the predicted results with the actual values, the result shows that the EESPSO-ENN model has low error and high precision. Compared with the BP neural network and the support vector machine method, the result shows that the EESPSO-ENN model in the Baishuihe landslide prediction is better than the BP neural network and SVM method.

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