GPS Monitoring Landslide Displacement Prediction Using Nonlinear Analysis and Back-Propagation Neural Network

Qiang Yue*

China Energy Engineering Group Hunan Electric Power Design Institute Co., Ltd.
Hunan Changsha 410007, China
Yueqiang2016@sina.com

Jie Yuan

Department of Economics and Management, Hunan Chemical Vocational Technology College, Hunan Zhuzhou 412000,China

ABSTRACT

Global Position System (GPS) has been widely applied for landslide displacement monitoring. Displacement prediction is of great significance for landslide stability assessment and early warning. Traditionally, the linear autoregressive model was mainly used for landslide displacement prediction. However, it is difficult to predict the landslide displacement reliably because of the nonlinear feature in landslide displacement. In this study, an effective nonlinear model named Back-Propagation Neural Network (BPNN) was proposed to overcome this shortcoming. First, the GPS stations were built to monitoring the landslide displacement. Second, the landslide deformation characteristics were analyzed and autoregressive method was used to select the input and output variables for nonlinear predictors. Then BPNN model was used to predict landslide displacement. Meanwhile, the forecast accuracy of BPNN model has been compared with linear autoregressive model. Real landslide displacement data from GPS monitoring station ZG86 on Shuping landslide in the Three Gorges Reservoir Area (TGRA) was used as examples. The Results show that BPNN model is an effective predictor to forecast landslide displacement and has better prediction accuracy than linear autoregressive model.

KEYWORDS: Globe Position System; reservoir landslide; displacement prediction; Back-Propagation Neural Network; linear autoregressive model

INTRODUCTION

A large number of reservoir landslides have been reactivated as a result of the fluctuation of reservoir water level and heavy rainfall since the impoundment of the Three

Gorges Reservoir in 2003. The safety of human lives and their property have been threatened by the instability of landslides. Therefore, it is crucial to forecast the development process of landslide displacement for landslide early warning [1]. The aim of this study is to propose an efficient model to predict landslide displacement.

In recent years, GPS technology has been more and more widely used for landslide displacement monitoring than conventional geodetic methods [2]. The GPS technology was also applied in this study. For the problem of displacement prediction, a geological model was difficult to obtain accurate forecast vales because of the complexity of geological environment. However, time-series models became more and more popular because wealth displacement monitoring data can be collected by GPS. A lot of time-series models for landslide quantitative prediction have been developed, such as grey theory model [3], regression model [4], nonlinear model [5]. The forecast results of these time-series models show that it is possible to obtain reasonable displacement prediction results [6].

It is found by many researchers that there are nonlinear features in the process of landslide displacement development, which is caused by the geological structure of slope, seasonal heavy rainfall, water level fluctuation and other affecting factors. Through the analysis of landslide displacement time series, the nonlinear models has been introduced to analyze landslide displacement time series and to predict landslide displacement in recent years [7]. The landslide original displacement and its dynamic evolution can be effectively rebuilt by nonlinear models. Artificial intelligence models [8-10], which belong to nonlinear models, have been successfully applied to analyze the landslide displacement time series. Therefore, in this study, a typical artificial intelligence model, named Back Propagation Neural Network (BPNN) model is proposed. It has significant advantages in the areas of problem learning, generalization ability and estimated performance [11-12]. The BPNN predictor has been also successfully used in many areas [13-17].

To data, this study took the advantages of BPNN model and nonlinear analysis to predict landslide monthly cumulative displacement. Shuping landslide in TGRA was taken as example to verify the validity of the proposed model in this study.

RESEARCH METHOD

The flowchart of predicting landslide displacement based on nonlinear analysis and BPNN model was shown in Figure.1. First, the nonlinear features of monthly cumulative displacement time series were analyzed. Second, BPNN model was used to forecast landslide displacement values. Third, the predictive results of the proposed models were assessed.

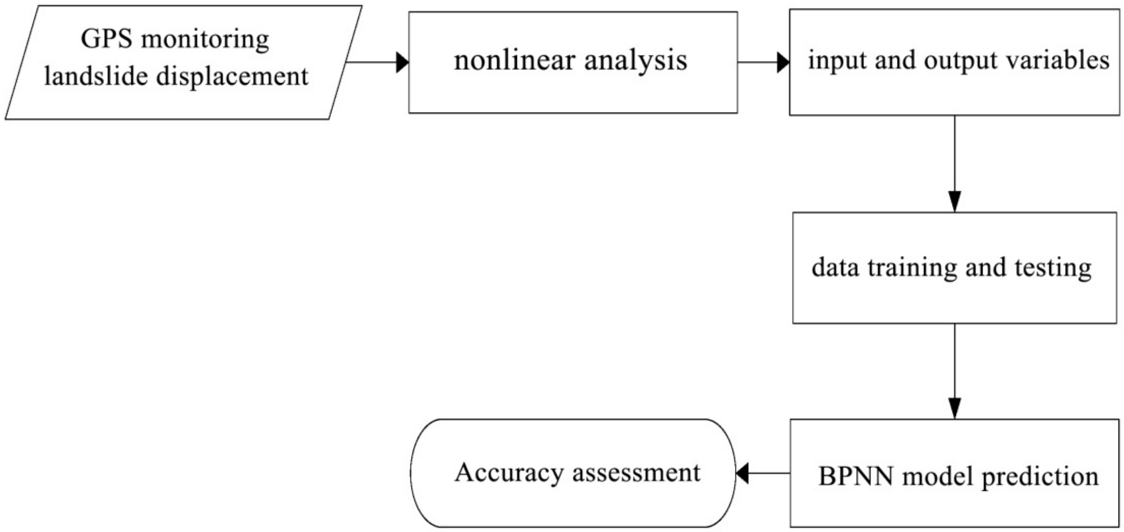

Figure 1: The flowchart of BPNN model

Back-propagation Neural Network model

For the running process of BPNN [18] , firstly the learning samples were put into the input Network, then the back-propagation algorithm was used to respectively train the weight and deviation of the network to match the output vectors with expectation vectors more closely. Finally, the network training will be finished if the sum of squared errors less than designated error.

Back-propagation algorithms is available for adjusting the weight coefficient $w_{ij}^{p-1,p}$ between node i in layer p-1 and node j in layer p. The learning proceeds are from the output layer toward the input layer in back-propagation. It is in the direction opposite to signal propagation. The output y_j^p from node j in layer p can be obtained from Eq.1.

$$y_j^p = \sum_{i=1}^{m} w_{ij}^{p-1,p} y_i^{p-1} \qquad (1)$$

where m is total number of inputs applied to node i in layer p-1. This method defines the change of weight with the progress of learning by Eq.2.

$$\Delta w_{ij}^{p-1,p}(n+1) = \varphi \delta_j^p y_i^{p-1} + \beta \Delta w_{ij}^{p-1,p}(n) \qquad (2)$$

where n = iteration number; y_i^{p-1}= output from node i in layer p-1; δ_j^p =local gradient for node j in layer p; φ =learning-rate parameter; β =momentum constant; and φ and β = positive constants. The δ_j^p term can be calculated by Eq.3.

$$\delta_j^p = \begin{cases} e_j \frac{df(y_j^l)}{dy_j^l} & \text{for node j in output layer l} \\ \frac{df(y_j^p)}{dy_j^p} \sum_{r=1}^{m_{p+1}} \delta_r^{p+1} w_{jr}^{p,p+1} & \text{for node j in hidden layer p} \end{cases} \tag{3}$$

where f is output function for each node, m_{p+1} is total number of inputs applied to node r in layer p+1, and $e_j =$ error at the output of node j. The output function f() is a nonlinear function, it is produced by a transfer function of its summed input. The sigmoid function is most often used as output function for BPNN as Eq.4.

$$f\left(y_j^p\right) = \frac{1}{1+\exp(-y_j^p)} \tag{4}$$

where y_j^p can vary within the range $\pm\propto$, but $f\left(y_j^p\right)$ is bounded between 0 and 1.

Autoregressive model

An autoregressive (AR) [19] model is a type of random process in statistics and signal processing. It is often used to model and predict various types of time series. The AR model is one of a group of linear prediction formulas that attempt to predict an output of a system based on the previous inputs. Definition the notation AR(p) model indicates an autoregressive model of order p. The AR(p) model is defined as Eq.5.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{5}$$

where $\varphi_1, \varphi_2, \cdots\cdots, \varphi_i$ are the parameters of the model, c is a constant (often omitted for simplicity) and εt is white noise. An autoregressive model can thus be viewed as the output of an all-pole infinite impulse response filter whose input is white noise. Some constraints are necessary on the values of the parameters of this model in order that the model remains wide-sense stationary. For example, processes in the *AR(1)* model with $|\varphi_1| \geq 1$ are not stationary. More generally, for an *AR(p)* model to be wide-sense stationary, the roots of the polynomial $z^p - \sum_{i=1}^{p} \varphi_i z^{p-i}$ must lie within the unit circle, i.e., each root z_i must satisfy $| z_i | < 1$.

SHUPING LANDSLIDE

Shuping landslide was reactivated by the fluctuation of reservoir water level and heavy rainfall [20]. The GPS monitoring displacement data of Shuping landslide in TGRA was used to validate the proposed model.

Geological conditions

Shuping landslide [21] is on the south side of Yangtze River. It is located in the Zigui town. And it is a giant active landslide. The slope of this landslide is 9º～38º and both sides of the landslide boundaries are gully. The estimated volume of Shuping landslide is 2.89×10^7 m3 with a maximum longitudinal length of 800m and an average width of 700m. This landslide is a loose structure soil slope. Its bedrock overlie by Silty clay fragment stone. The topographic map of the research site and landside GPS monitoring network are shown in Figure 2.

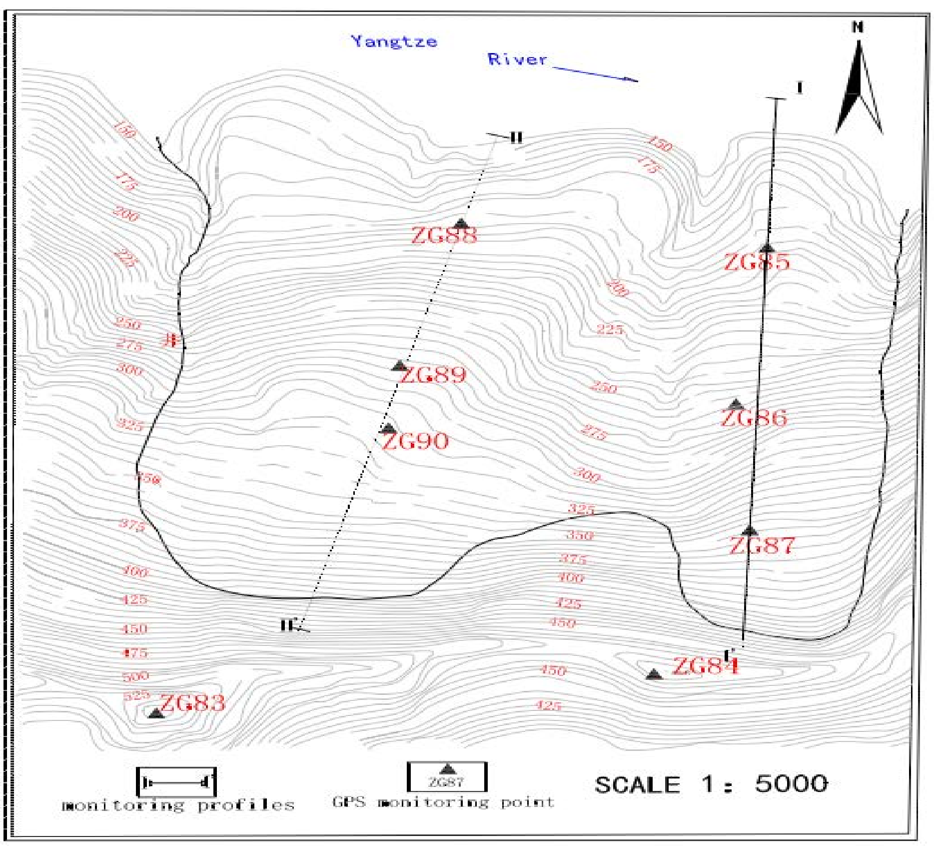

Figure 2: Topographical map of Shuping landslide, with location of GPS monitoring points

GPS monitoring network

In order to monitor the displacement tendency and displacement direction of Shuping landslide, GPS control network [22] has been built on Shuping landslide since June 2003. The landslide surface deformation firstly occurred since 2003. The landslide was divided into two regions, stable region and unstable region based on landslide field investigation. Secondly, two GPS reference stations were built in the stable region and several GPS observation stations were built in the unstable region. Therefore, the GPS reference stations and observation stations formed the landslide GPS control network. The Points ZG85～ZG90 were set as GPS observation points while the points ZG83 and ZG84 were set as reference stations as shown in Figure 3.

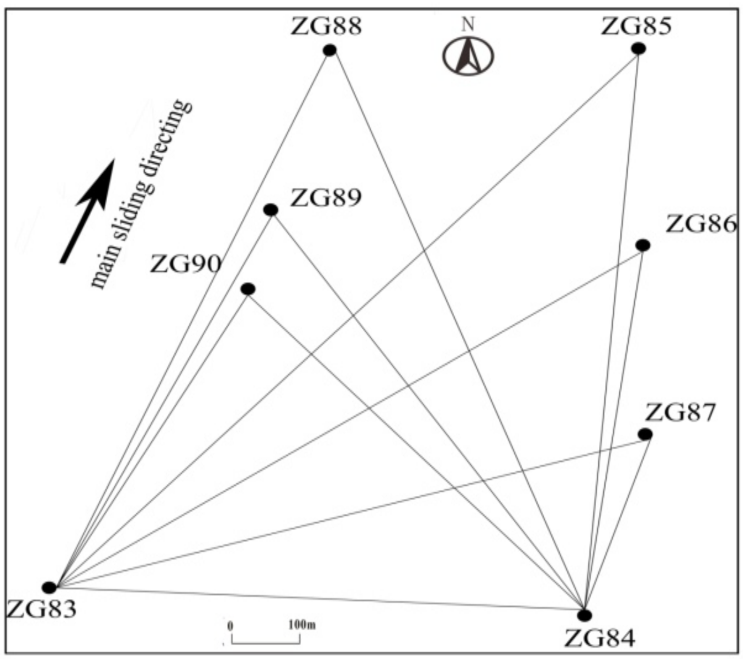

Figure 3: GPS monitoring network

Every month landslide monitoring was carried out, two GPS devices were placed on reference station, and one GPS device was placed on every observation station in turn. The GPS received signal was processed by baseline processing and network adjustment in GAMIT/GLOBK software. Landslide monitoring errors displayed by the coordinate of observation stations were not more than 3. 00 mm.

Nonlinear features analysis

In this study, GPS monitoring landslide displacement time series has been obtained from this GPS monitoring work in the period of June 2003 to November 2012 as shown in Figure 4. It can be found that the cumulative displacement of points ZG85, ZG86 and ZG88 GPS on bottom part of the landslide were more serious than the points on the upper part. It can be also observed that the displacement time series of reservoir landslides have nonlinear and non-stationary characteristics. The nonlinear features make it difficult to forecast the displacement. In this study, GPS monitoring cumulative displacement time series of points ZG86 were set as examples to compare the forecasting performances of the present BPNN model and linear autoregressive respectively.

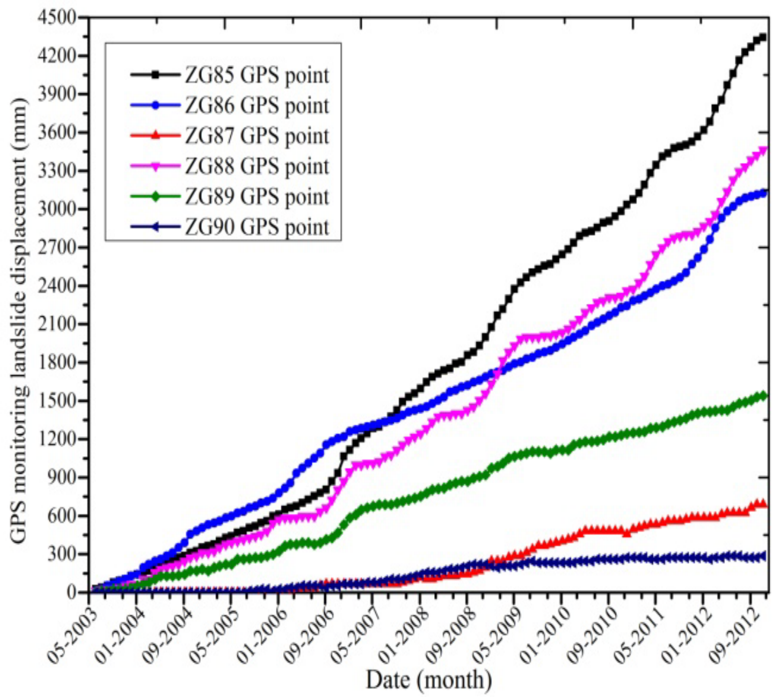

Figure 4: Monthly Cumulative displacement time series monitored by GPS

DISPLACEMENT PREDICTION USING BPNN MODEL

Input and output variables

First, GPS monitoring displacement were normalized into [0,1]. Then the experimental data were divided into the two subsets, one is the training data set and the other is testing data set. A total of 94 months of points ZG86 GPS monitoring data from June 2003 to March 2011 were used for model training and the rest data were used for model testing.

The delay time of ZG86 GPS points cumulative displacement time series was set as 1, Based on autoregressive analysis [23], the one-dimensional ZG86 monitoring cumulative displacement time series were able to be transformed into m-dimensional vectors. The input variable and output variables of BPNN model for ZG86 GPS monitoring displacement prediction can be obtained from the m-dimensional vectors. Suppose the ZG86 displacement was Y_i, where $i=1,2, \ldots N$. as shown in Table 1.

Table 1: input and output variables

GPS	Number of hidden neuron	Output variable	Input variables
ZG86	4	Y_i	$[Y_{i-2}, Y_{i-1}]$

For the BPNN model, the transfer function for hidden layer and output layer neurons were *tansig* function and *purelin* function respectively. Gradient descent algorithm based on iterative solution was used for BP network training. In addition, the minimum prediction error method was adopted to determine neuron number of hidden layer of BP network model. The calculated results of optimal neuron number of hidden layer of BP model were shown in Table 1.

For the linear autoregressive, the input and output variables were the same with the BPNN model, that is to say, the displacement values of the first two months were used to predict the displacement of the next one month. The linear autoregressive was calculated in the Excel as shown in the [24].

Prediction results

The final predict displacement values of BPNN model were present in Figure 6. Forecasting accuracy was measured by absolute percentage error (MAPE) method and root mean square error (RMSE) method [25,26]. Comparison results of two models were shown in Table 2.

The results in Figure 5 showed that the BPNN model has better prediction effect and higher prediction precision than linear autoregressive model. As shown in Table 3, the RMSE accuracy of ZG86 points GPS monitoring landslide displacement values predicted by BPNN model is 34.44mm, and the MAPE is 0.96%. However, the RMSE accuracy of ZG86 GPS monitoring displacement predicted by linear autoregressive is 57.81mm, and the MAPE is 1.79%. Therefore, it can be concluded that the proposed model overcame the shortcoming of nonlinear and non-stationary features existed in displacement time series and increased the prediction accuracy.

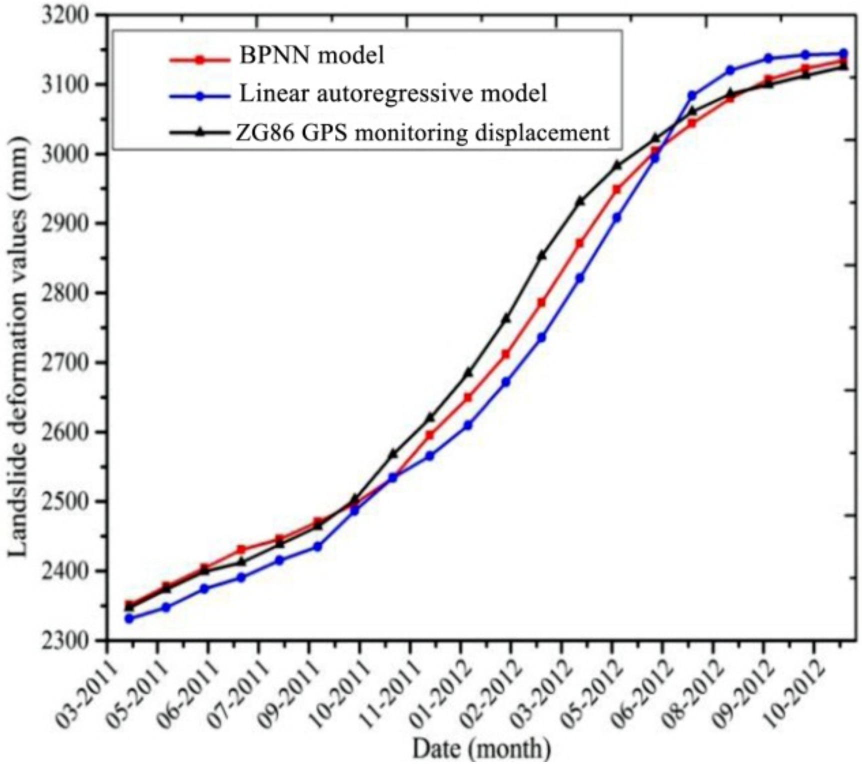

Figure 5: Comparison of predicted and measured monthly cumulative displacement values

Table 2: Prediction results comparison of BPNN model and linear autoregressive in ZG86 GPS stations

Model	RMSE(mm)	MAPE(%)
BPNN	34.44	0.96
Linear autoregressive	57.81	1.79

Discussion

In this study, nonlinear BPNN model was established to forecast the GPS monitoring displacement values of reservoir landslides. The monitoring displacement time series denoted that the deformation of landslide is a nonlinear process. It can be seen that the BPNN model is more accurate and credible than linear autoregressive model. In additional, based on the analysis of Shuping landslide, it can be observed that, the nonlinear model has more physical significance than linear autoregressive model.

However, the both models are of relatively low precision when forecasting the cumulative values. One important reason for the low precision is that the length of displacement time series is not long enough and the nonlinear features was not reflected completely [27].

CONCLUSION

Landslide displacement prediction is important for landslide failure warning. In this study, a nonlinear landslide displacement prediction model which has been integrated nonlinear theory into BPNN model is proposed. The nonlinear model can transform the one-dimensional time series into multi-dimensional input and output variables for prediction model. Based on the input and output variables, the BPNN model can predict the nonlinear displacement time series accurately. It is shown that the deformation of reservoir landslide was monitored by GPS effectively. And it also suggests that the BPNN model not only extract detail information from the primary displacement time series effectively, but also propose an effective way to solve displacement prediction problem. It is expected that the nonlinear BPNN model may provide new insights for GPS monitoring landslide displacement prediction.

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