Displacement prediction of Liangshuijing landslide based on time series additive model

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Abstract

The evolution of landslide displacement is affected by many factors. This paper studied the displacement monitoring data of Liangshuijing Landslide with Factor Analysis Method and found that the dominant factors influencing landslide displacement were in decreasing sequence: cumulative rainfall of anterior two months> rainfall of current month> the average reservoir level of current month>reservoir level fluctuation of current month. The paper selected three typical GPS monitoring points (ZJC09, ZJC11, ZJC13) of Liangshuijing Landslide to forecast their displacements by adopting the time series additive model on basis of the conclusion of previous factor analysis. The accumulative displacement of Liangshuijing Landslide can be divided into trend term and random term. The polynomial fitting was used for trend term displacement prediction. BP neural network model was used for the random displacement prediction. The final calculation results indicated that combination of factor analysis method and time series additive model could generate a reasonable and accurate prediction of landslide.

Keywords: Displacement prediction, Time series, Liangshuijing Landslide, Factor analysis, BP neural network

1 Introduction

Monitoring data of landslide displacement is a macroscopic dynamic response to external triggering factors (reservoir water level fluctuation and rainfall, etc.), reflecting the whole evolution process of landslide. It also supports important information for landslide inducing mechanism, formation process, prediction and stability evaluation. However, the characteristic of landslide displacement is complex due to the complexity and diversity of landslide formation mechanism and evolution process. Besides, there are many factors affecting the stability of landslide. Usually, it is difficult to find out the dominant factors because the selection of these variables is subjective. Therefore, it is necessary to figure out the dominant influence factors on landslide inducing mechanism and evolution process from these variables [1].

R W Jibson and D K Keefer (1989) [2] took advantage of discriminant analysis and multiple linear regression to study 220 large landslides influenced by 1811-12 New Madrid earthquake, and found that slope steepness had a stronger effect than the other three factors: slope height, slope aspect and stratigraphic variation. S Lee and J A Talib (2005) [3] used GIS and image processing to interpret satellite spatial data of landslide area, then selected topographic slope, topographic aspect, topographic curvature, lithology, land use, vegetation index to analyse factors inducing landslide with probability-frequency ratio method. Deping Guo, Masanori Hamada (2013) [4] analysed landslide influential factors during 2008 Wenchuan Earthquake by using qualitative and quantitative method to find out that slope height, horizontal peak ground acceleration and geological structure had a stronger effect on the sliding area and volume than slope angle and rock type. He Keqiang (2005) [5] found rainfall was the most important dynamic factor among the six factors controlling displacements, using the monitoring data of displacements of Xintan Landslide, China. The above researches mostly focused on landslide stability influence factors including internal factors and external factors. Moreover, more and more attentions have been paid to external factors, (such as rainfall and earthquake). While there is less research focusing on reservoir water level, nevertheless it is an indispensable factor for reservoir bank landslides.

And once the dominant factors are determined, displacement prediction of landslide can be more appropriate and rational as considering multiple exterior influence factors. Since the 1980s, many intelligence theory and methods have been applied in the prediction of landslide displacement, such as the regression analysis, time series, grey system, artificial neural network, wavelet analysis and Kalman filter, obtaining great results [6]-[16]. When bearing a certain load, landslide

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slope will adjust itself into another stable state with small changes in its shape, size, location and time dimension. In addition, it is feasible to use the periodic monitoring data processing and analysis results to reflect physical properties of the landslide mathematically, so as to find out its laws of deformation and failure trend.

In this paper, three typical monitoring points (ZJC09 ZJC11 ZJC13) of Liangshuijing Landslide are selected. On the basis of these monitoring data and geological environment, formation mechanism, deformation and failure characteristics, dominant impact factors of the landslide are obtained from factor analysis method, an improved time series additive model is proposed to forecast its displacement.

2 Methodology

2.1 FACTOR ANALYSIS

Factor Analysis Method was first put forward in 1904 by Charles Spearman when using statistics method to study the scores of intelligence test. In the 1950s, this method began to prevail in Psychology, Medicine, Geology and Economics [17]. Factor analysis which derived from the ideas of dimension reduction can study internal structure of original variable matrix. It is also a multivariate statistical analysis method to transfer some variables with complicated relationship to a few integrated factors. When using factor analysis method, variables are divided into several groups based on correlation value to make high correlation between variables within the same group and low relevance between variables in different groups. Each group of variable represents a basic structure of unobservable variables, and the basic structure is called common factor [18]. Using the sum of linear function of reduced number of unobservable variables (common factor) and specific factor to describe the original observation, factor analysis can deduce the inner link between observed variables. Zhang T T and Yan E C (2012) [19] adopted the factor analysis method to analyse landslide deformation mechanism using monitoring data displacement of one landslide in Three Gorges Reservoir area, and the main factors influencing the landslide deformation is reservoir water level with rainfall followed. Sun X R, Ma F H, etc., (2012) [20] proposed the main influence factors on dam deformation based on Factor Analysis Method and monitoring data. Miao H B, Yin K L, etc., (2010) [21] established the comprehensive evaluation model of landslide displacement to improve the landslide prediction effect by using factor analysis. By using Factor Analysis Method to analyse monitoring data, Bi J L, Liu X, etc., (2010) [22] identified the main factors affecting seepage around the dam. Ma S S, Wang Z W (2002) [1] studied the sliding model and evolution law of one landslide by using factor analysis method which was used to analysis the landslide during different development period from the perspective of quantitative. There is few application of factor analysis method in engineering. Therefore, it is significant and it has bright prospects to study inducing mechanism and evolution process of landslide by using factor analysis.

Suppose we have a set of m samples, each of which has p observable random variables. For the convenience of contrast, the samples were standardized by eliminating the effects of dimension and magnitude. Suppose the new observable random variables are X1, X2, ···, X_p, and after standardization, the common factors are F1, F2, ···, F_m(m<p). The model can be described as follows:

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m \\ \quad \cdots\cdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m \end{cases} . \tag{1}$$

Equation (1) can be called factor model. The matrix term is:

$$X = AF . \tag{2}$$

Here, common factor (also principal factor), F_1, F_2, ···, F_m refer to the factors commonly possessed in the expression of observable random variables, and they are also independent and unobservable.

In the equation (2), the a_{ij} are defined as factor loadings with an absolute value smaller than equation (1). The more its absolute value is, the better X_i and F_i correlate, or the greater loading common factor F_j works on X_i. Therefore, a_{ij} can also be called common factor loadings, and matrix A refers to the factor loadings matrix.

2.2 TIME SERIES ADDITIVE MODEL

As discussed in the previous sections of landslide deformation characteristics, the occurrence of landslide displacement is related to the coupling effect of inherent geological condition and exterior inducing factors (such as rainfall, fluctuation of reservoir water level and so on.). The total displacement can be divided into different parts according to their influences. In a time series model, the total displacement, $y(t)$, contains three response components as expressed in equation (3) [23]:

$$y(t) = f(t) + p(t) + \varepsilon(t) , \tag{3}$$

where, $f(t)$ refers to the trend term described as an increasing function reflecting the tendency of the series; $p(t)$ is the periodic term illustrating the fluctuation of displacement under the influence of periodic exterior factors, such as rainfall, reservoir water level and so on; $\varepsilon(t)$, known as the random term, denotes the random variable caused by the uncertainty. Because of small magnitude of $p(t)$ and unobvious periodic fluctuation of landslide displacement, the trend term in this series model is ignored. As for $\varepsilon(t)$, back propagation(BP) neural network can be used to reflect its complex nonlinear series[24].

Each term in the time series additive model can correspond to each component of landslide displacement, making displacement prediction a significant mathematical and physical meaning. Therefore, based on the factor analysis of displacement characteristics for Liangshuijing Landslide, multivariable neural network was established for extracting the random term of the landslide displacement by using time series additive model. Fig. 1 shows the structure chart of the landslide prediction model.

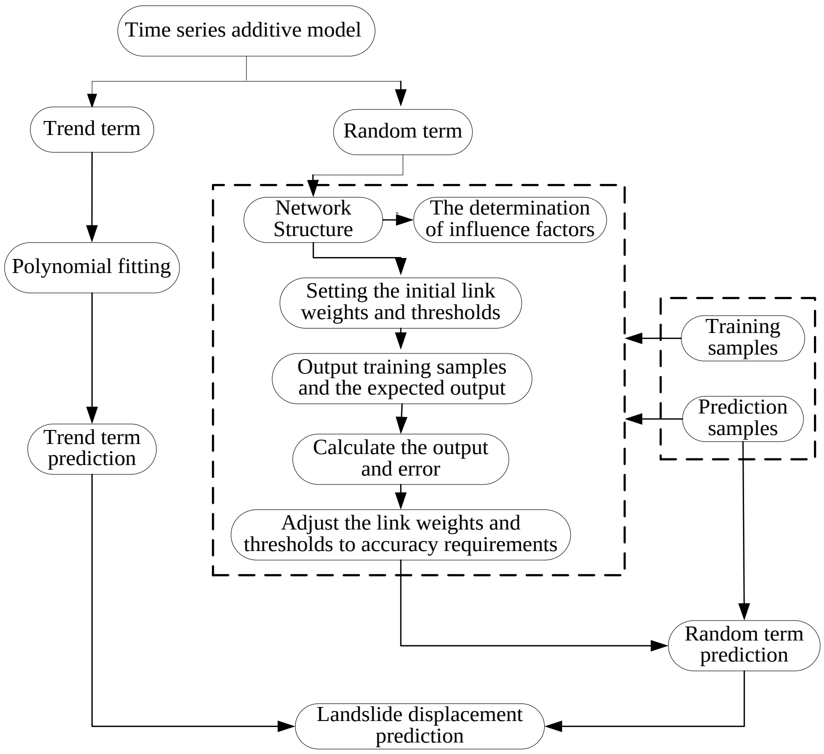

FIGURE 1 Structure chart of landslide prediction model

2.2.1 Polynomial fitting

Trend item of accumulative displacement reflects the long-term development model of landslide deformation and the overall trend. Taking the monitoring information of surface displacement and geological features of Liangshuijing Landslide into consideration, the change cycle of displacement curve can be regarded as one year. Then, Moving Average Method is adopted to smooth the landslide displacement curve, aiming at weakening the mutation effects on the displacement curve caused by influence factors. Moreover, the displacement curve after smoothing can be seen as the trend term of landslide displacement.

As one dimensional time series, landslide displacement can be described by Xi={X1, X2, X3,…, X_t}, and X_t denotes the displacement trend term, as in equation (4):

$$X_t = \frac{x_t + x_{t-1} + ... + x_{t-n+1}}{n}, \ \left(t-n, n+1, n+2, ..., t\right), \quad (4)$$

where, n refers to the periodic value, and in this paper, n=12, accounting for the characteristics of landslide accumulative displacement. Depending on the shapes of displacement curve, different trend term model can be determined [25]. In general, if the trend term displacement has an ideally linear trend or exponential trend, then the least squares method and polynomial fitting method can be used, which have a wide application in landslide displacement forecast. On the contrary, GM (1, 1) and GM (2, 1) can be utilized to describe the case of exponential growth, exponential decay and periodic oscillation, respectively.

Based on the characteristics of trend term displacement of Liangshuijing Landslide, polynomial fitting method with least squares is adopted. Its mathematical model is shown in equation (5):

$$X_t = at^3 + bt^2 + ct + d \, . \quad (5)$$

2.2.2 BP neural network model

With the development of artificial intelligence, neural network has gradually been applied to landslide analysis and forecasting, which has obtained good results. Neural network is composed of large amounts of information processing units (neurons) connected into a wide range of artificial networks to simulate the brain's structure and function of the system, and automatically summarizes laws from the known data to obtain the intrinsic connection between these data. Therefore, it has a strong nonlinear mapping ability. Currently there are many neural network architectures and algorithms. While BP neural networks, one of the widely used neural network, is an error back propagation network and composed by a large number of neurons self-organizing, adaptive dynamic systems, prevailing in a strong learning ability of revealing nonlinear relationship between inherent sample data.

A typical BP neural network has three layers: input layer, hidden layer and output layer. The one layer is fully connected to another; output value of several neurons forming a layer is determined by the input node values, the role of the function and the threshold. Learning process of BP neural network includes information forward propagation and error back propagation. In the process of forward propagation, the training samples spread from the intermediate layer of the input layer to the output layer, and the output values between the function and threshold can be calculated. After comparing with the expected output value, if there is an error, the connection weights should be revised in the direction of reducing errors. And so forth, until the output of the results meets the accuracy requirements. The procedure of the training BP neural network can be described as follows:

The input samples of network are:

$$A_i = \left(x_{i1}, x_{i2}, ..., x_{in}\right),\ \left(i = 1, 2, ..., m\right), \tag{6}$$

where m is the learning model logarithmic; n denotes the number of input layers.

Corresponding output vector is:

$$B_i = \left(y_{i1}, y_{i2}, ..., y_{ik}\right),\ \left(i = 1, 2, ..., m\right), \tag{7}$$

where the m is the number of output model, in relation to input model; the k refers to the number of input layers.

Calculation of the input of hidden layers:

$$S_j = \sum w_{ij} x_n - \theta_{aj}\ , \tag{8}$$

where, the W_{ij} are the collection weighs between input layer and intermediate layer; the θ_{ij} reflect the thresholds of hidden layers; j is the number of neurons of hidden layer.

Calculation of the output of hidden layers:

$$b_j = f\left(S_j\right) = \frac{1}{1+e^{-S_j}}\ \text{(S type function)}, \tag{9}$$

$$\text{Or}\ b_j = f\left(S_j\right) = \frac{1}{1+e^{-2S_j}}\ \text{(tangsig function)}. \tag{10}$$

Calculation of the input, output of output layers:

$$L_i = \sum_{j=1}^{n} v_{ij} b_j - \gamma_i\ , \tag{11}$$

$$Y_i = f\left(L_i\right), \tag{12}$$

where Y_i are outputs; V_{ij} reflects the collection weighs between intermediate layer and output layer; γ_i are the thresholds of output layers; $f(L_i)$ is one kind of S type function.

Repeated training and adjustment of the error:

$$E = \sum_{i=1}^{k} \left(Y_i - B_i\right)^2 / 2\,. \tag{13}$$

If the value of E is less than a certain prediction accuracy request, it can be proved that the network has been trained well enough to predict the displacement of landslide using the new value.

3 Case study

Fig. 2 shows that Liangshuijing Landslide is located on the right bank of Yangtze River, Three Gorge Reservoir, China. The plane form of this landslide shows U-shape, with the terrain of approximate round-backed armchair at the rear part. The front and trailing edge elevation are nearly 100m and 319.5 m respectively, with a total volume of about 407.79×104 m3.After trail storage of Three Gorges Reservoir to 172 m, the landslide began to deform in November 2008, and then obvious deformation appeared in April 2009. With a rate (1cm/day) of landslide fissure development, maximum tension cracks has amounted to 60 cm. Due to the narrow area of the Yangtze River waterway and large volume of sliding materials, the instable landslide will cause a large swell after falling into the river. It is a great threat to the safety of passing ships and passengers, and the economic losses and social influences are incalculable. As a result, the local government paid high attention to the landslide, and began monitoring all-round in May 2009. Fig. 3 shows the monitoring data studied in this paper until April 2012.

4 Displacement prediction of landslide

4.1 DETERMINATION OF DOMINANT INFLUENCE FACTORS

Rainfall and reservoir water level fluctuation are important factors of inducing reservoir bank landslides [26]. Influence of reservoir level fluctuation on the landslide displacement has been introduced in the previous study, and landslide displacement is closely related to submerged body under the reservoir water level. According to the result of Factor Analysis Method, the largest change of current monthly reservoir water level can be regarded as influence factor of landslide deformation. There are a large amount of studies on the relationship between landslide and rainfall, which show that 1-2 month rainfall before the occurrence of landslide has promoting effect on landslide deformation [27, 28].

As a result, rainfall in the current month and rainfall two months before are selected as the influence factors of landslide deformation.

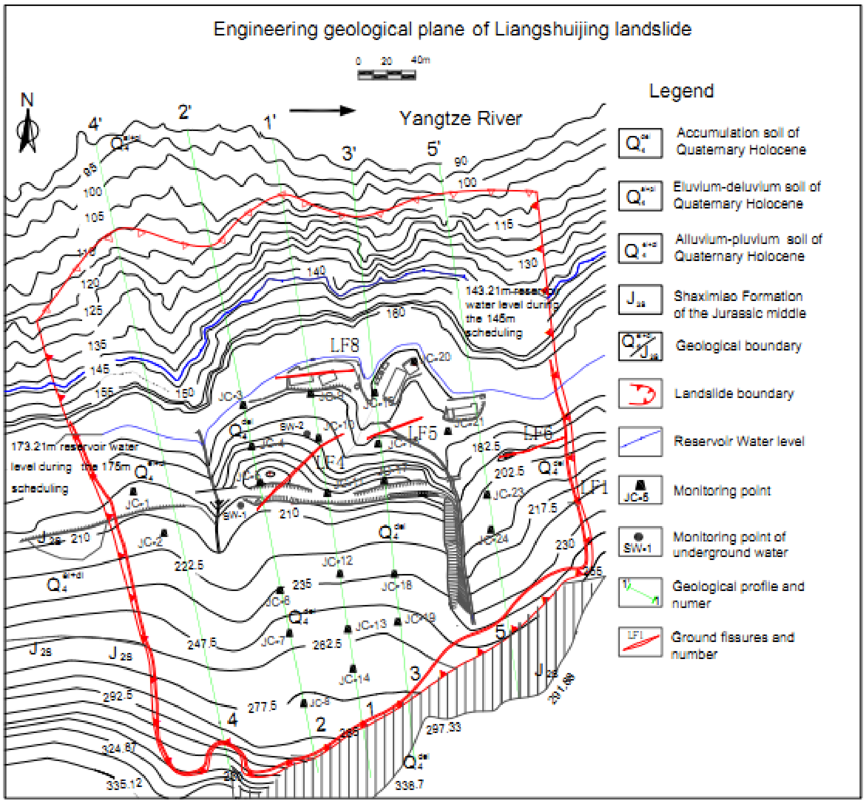

FIGURE 2 Engineering geological plane of Liangshuijing Landslide

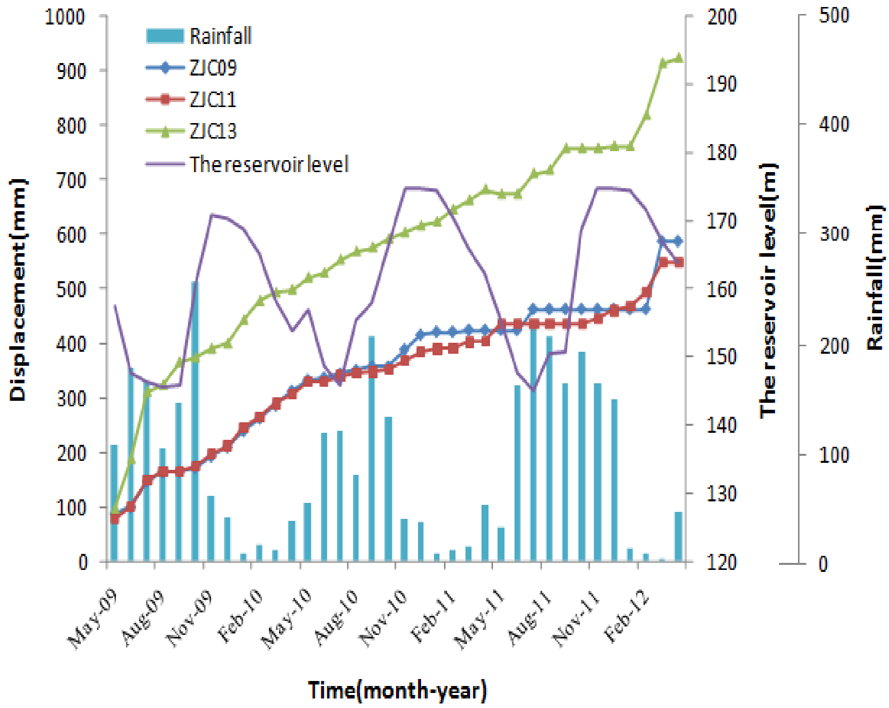

FIGURE 3 Monitoring data of rainfall reservoir water level and displacement

4.2 COMPREHENSIVE ANALYSIS OF PREDITION RESULTS

4.2.1 Displacement prediction of trend term using polynomial fitting

Taking advantages of extraction of trend term and polynomial fitting theory, we can get the parameters of trend term displacement of the monitoring points (ZJC09, ZJC11, ZJC13) after polynomial fitting, which can be seen in Table 1.

The parameters in Table 1 are adopted for landslide displacement prediction. The results are shown in Fig.4. It shows that all these three monitoring points can predict the displacement well, mainly because of large number of monitoring data, relatively gentle development of displacement and great effect of eliminating the influence of the periodic item by moving average method. Increasing the moving cycle n appropriately can eliminate the influence of periodic term more obviously, but at the same time, more early monitoring data are needed.

TABLE 1 Parameters of trend term displacement after polynomial fitting

GPS No	Parameters a	b	c	d	Accuracy /R^2
ZJC09	-0.0126	0.6128	4.5612	87.852	0.9969
ZJC11	-0.0079	0.3438	8.3983	73.754	0.9965
ZJC13	0.0054	-0.5087	29.718	98.359	0.9963

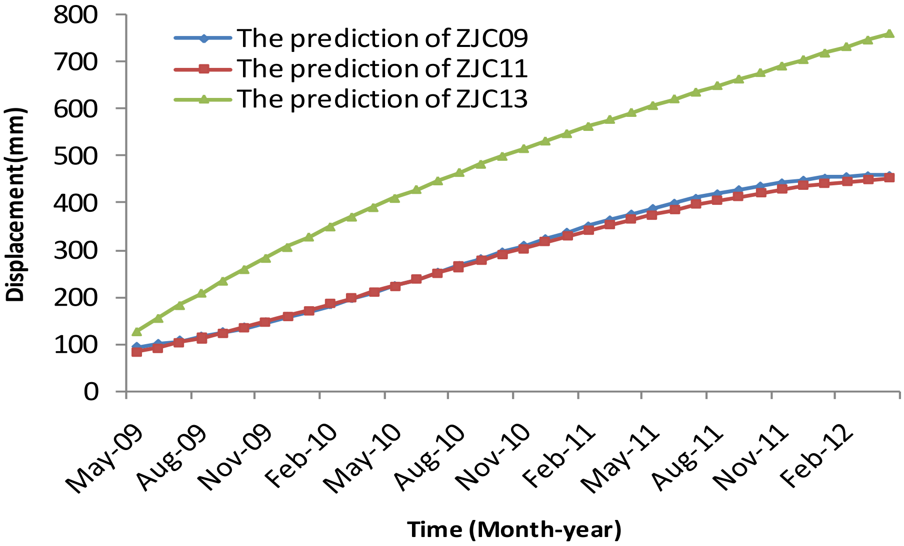

FIGURE 4 The curve of trend term displacement prediction

4.2.2 Displacement prediction of random term

Random term of displacement can be gained after eliminating the trend term from the accumulative displacement, when time series additive model is adopted. However, it is a complex nonlinear time series influenced by multiple factors. Hence, BP neural network mentioned above is used to forecast the displacement of random term by selecting rainfall in the current month, rainfall before two months, monthly average reservoir water level and monthly average reservoir water level variation as the input layer. Prediction results are shown in Table 2.

4.2.3 Accumulative displacement prediction

As mentioned above, trend term and random term of landslide displacement can be obtained by least squares curve fitting and BP neural network respectively. Comprehensive displacement prediction can be obtained after adding these two terms. Finally, the effect of prediction can be tested by comparison with the test sample in advance, which is shown in Fig. 5.Fig.5 shows that the changes of the comprehensive displacement prediction and accumulative monitoring displacement of landslide are consistent, reaching the expected requirements of prediction accuracy. Here, the smoothing in the moving average method is used to extract trend term and the curve fitting method is used for polynomial fitting. The development trend of landslide displacement mainly depends on trend term displacement of landslide. Therefore, the prediction of trend term displacement by using curve fitting method and smoothing in the moving average method can reduce mutation of displacement curve caused by external factors. Predicting displacement random item is a process to revise accumulative displacement trend of landslide according to a variety of stochastic factors in nature. The BP neural network enables the random term displacement to response to the change of external influence factors by sample training and learning, and thus for reaching the self-organizing, adaptive dynamic prediction.

TABLE 2 Calculation of random term displacement of Liangshuijing Landslide

Time	ZJC09			ZJC11			ZJC13		
	Random term	Prediction	relative error	Random term	Prediction	relative error	Random term	Prediction	relative error
May-09	-4.8	-4.5	0.3	-4.5	-4.9	-0.4	-29.0	-28.5	0.5
Jun-09	0.9	0.3	-0.6	7.5	6.3	-1.2	33.6	27.3	-6.3
Jul-09	40.8	36.8	-4.0	46.5	42.6	-3.9	128.1	118.7	-9.4
Aug-09	49.3	48.4	-0.9	52.9	52.2	-0.7	114.8	116.1	1.3
Sep-09	41.0	41.8	0.8	42.0	43.1	1.1	131.6	129.9	-1.7
Oct-09	37.8	38.2	0.4	39.5	39.8	0.3	115.0	116.7	1.7
Nov-09	48.1	47.0	-1.1	50.6	49.4	-1.2	107.3	108.1	0.8
Dec-09	53.0	52.5	-0.5	52.7	52.4	-0.3	93.3	94.7	1.4
Jan-10	70.8	69.0	-1.8	74.4	72.2	-2.2	114.6	112.5	-2.1
Feb-10	81.0	79.9	-1.1	80.0	79.4	-0.6	128.4	127.0	-1.4
Mar-10	90.9	89.9	-1.0	92.4	91.2	-1.2	122.3	123.0	0.7
Apr-10	103.9	102.6	-1.3	97.2	96.7	-0.5	107.5	109.0	1.5
May-10	109.9	109.2	-0.7	106.4	105.4	-1.0	110.4	110.1	-0.3
Jun-10	99.9	100.9	1.0	93.3	95.1	1.8	99.8	100.9	1.1
Jul-10	92.7	93.5	0.8	90.1	90.5	0.4	106.1	105.4	-0.7
Aug-10	85.3	86.1	0.8	81.4	82.3	0.9	103.0	103.4	0.4
Sep-10	77.0	77.8	0.8	70.3	71.4	1.1	93.1	94.1	1.0
Oct-10	62.5	64.0	1.5	62.9	63.7	0.8	91.6	91.8	0.2
Nov-10	79.4	77.7	-1.7	64.3	64.1	-0.2	86.8	87.3	0.5
Dec-10	92.3	91.0	-1.3	68.7	68.3	-0.4	83.5	83.9	0.4
Jan-11	84.0	84.9	0.9	60.8	61.6	0.8	74.6	75.5	0.9
Feb-11	70.6	72.0	1.4	50.5	51.6	1.1	81.8	81.1	-0.7
Mar-11	61.0	62.0	1.0	50.0	50.1	0.1	84.2	83.9	-0.3
Apr-11	48.5	49.8	1.3	39.0	40.2	1.2	89.1	88.5	-0.6
May-11	36.6	37.9	1.3	62.0	59.7	-2.3	65.9	68.3	2.4
Jun-11	25.4	26.6	1.2	51.5	52.5	1.0	51.6	53.1	1.5
Jul-11	53.4	50.6	-2.8	41.5	42.5	1.0	75.4	73.0	-2.4
Aug-11	43.8	44.8	1.0	32.1	33.1	1.0	67.8	68.5	0.7
Sep-11	35.0	35.9	0.9	23.4	24.3	0.9	93.6	91.0	-2.6
Oct-11	27.2	28.0	0.8	15.3	16.2	0.9	79.8	81.2	1.4
Nov-11	20.4	21.1	0.7	16.2	16.1	-0.1	66.0	67.4	1.4
Dec-11	14.7	15.3	0.6	25.3	24.3	-1.0	56.3	57.3	1.0
Jan-12	10.3	10.8	0.5	28.1	27.8	-0.3	42.6	44.0	1.4
Feb-12	7.1	7.4	0.3	48.4	46.3	-2.1	85.5	81.2	-4.3
Mar-12	129.3	117.1	-12.2	98.8	93.7	-5.1	166.7	158.6	-8.1
Apr-12	128.9	128.9	0.0	95.8	96.1	0.3	162.0	162.5	0.5

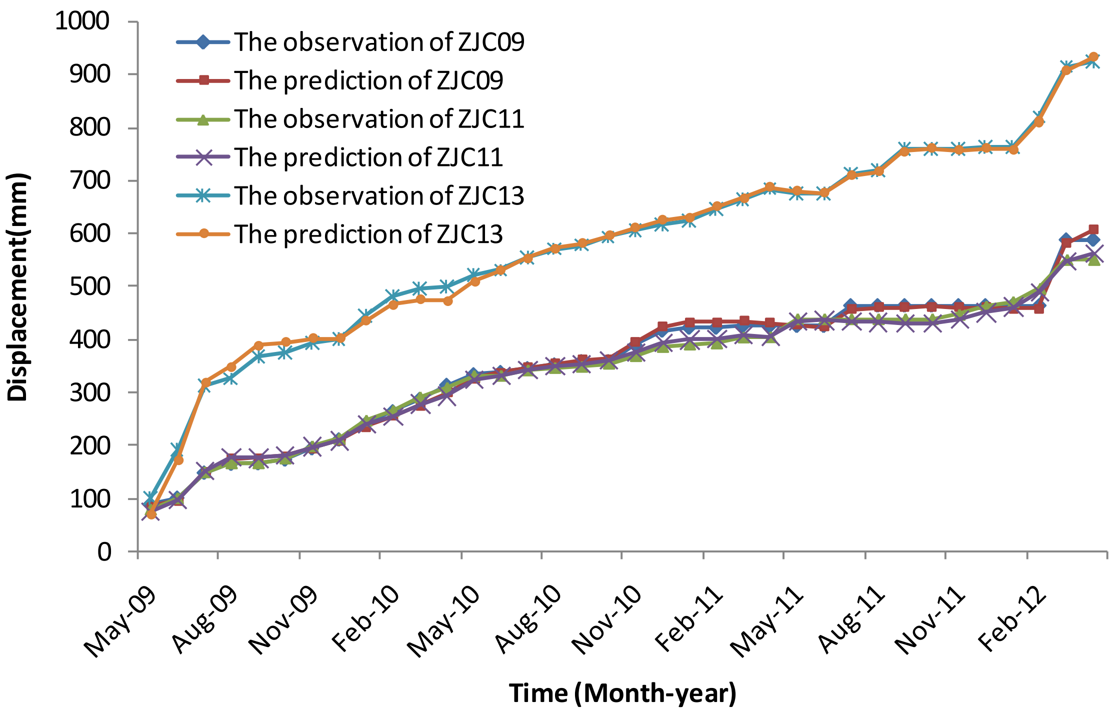

FIGURE 5 The curve of the observation and prediction accumulative displacement

5 Conclusions

This paper takes Liangshuijing landslide as a study case that relates physical movement process of landslide to external influence factors. Accumulative displacement of Liangshuijing Landslide can be divided into trend term and random term. The changes of rainfall and reservoir water level, which both have great effects on landslide, are selected for random term of displacement prediction when using time series additive model. The combination of mathematical function and neural network organically is applied to establish corresponding prediction model, which obtains good prediction effect. The conclusions can be drawn as follows:

(1) The dominant influence factors of Liangshujing landslide displacement are in the decreasing sequence: cumulative rainfall of anterior two months> rainfall of current month> the average reservoir level of current month>reservoir level fluctuation of current month.

(2) Trend term and random term of landslide displacement can be obtained by least squares curve fitting and BP neural network respectively.

(3) The changes of the comprehensive displacement prediction and accumulative monitoring displacement of landslide are consistent by adopting time series additive model, so the displacement prediction of Liangshuijing landslide has reached the expected requirements of prediction accuracy.

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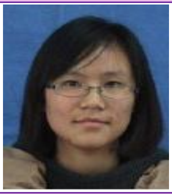

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