Theoretical research of Stand Error of Mean Coupling Markov chain models for early warning of landslide displacement rates: A case study of human-induced landslide in Inner Mongolia (Northern China)

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Abstract. Slope failures are always frequent and important issues in surface mining, where a single calamity can disarrange mining schemes and endanger workers’ lives. Simultaneously, the design and verification of “landslide early warning systems” in open-pit mines is a pivotal tool for mitigating risks. Notwithstanding, a prevalent model for heralding slope impending failures has not been available yet. The purpose of this article is to present a novel approach based on mean standard deviation (MSD) coupling weighted Markov chain (WMC) model to evaluate and perform the evolution that can detect onset-of-acceleration of landslides analysis procedure based on the indicator of real-time ground-based radar low-frequency measurements (e.g. displacement rate). The proposed method has been applied and tested in a open-pit coal mine situated in Inner Mongolia, China. An explanatory example of back analysis of a 4-month continuous surface monitoring dataset were regarded as a random process, and a binary classifier (i.e. steady-state and unsteady-state) was constructed based on the characteristics of mean standard deviation (MSD). Afterwards, properties of none aftereffect and bouncing allocation on the efficiency of Markov chains are studied. In order to modify and optimize the model, three indexes are integrated to verify the accuracy of the model and proof the predicting results: (1) precaution sensitiveness; (2) proper rate; (3) consensus rate. The consequences show that when the size of training samples was 20 days, the early warning accuracy reached 93%. When the model was performed seven days before the landslide
occurrence, the true positive rate of the model was 84%, thus indicating the early warning for the landslide was timely. The integration of the proposed model and on-site monitoring data provides a useful tool for early warning of landslide displacement rates, and opens new perspectives on predicting slope instabilities.

**Keywords:** Landslide; Early warning; Monitoring data; Stand Error of Mean; Weighted Markov chain; Displacement rate

1. Introduction

In slope prediction and early warning, summarizing and cataloging the past behavior of the slope in the study area is also the key to predict the future behavior of the slope. Many countries in the world are faced with the problem of frequent geological disasters [1-2], which seriously threatens the safety of people's lives and property and social development [3-4]. With the development of measurement technology and the improvement of instrument accuracy, safety monitoring has been applied more and more widely in slope engineering [5-6], making up for the deficiency of limit equilibrium method, numerical simulation and other means in slope dynamic stability analysis. It has become a research hotspot in the field of geotechnical engineering to make full use of the obtained dynamic monitoring data to carry out early warning of unstable slopes [7-8].

To solve this problem, Saito M[9] first proposed the "Saito Model" based on the inspection of the field measured records of slope failure, which provided a theoretical framework for understanding how the strain rate of stable creep and accelerated creep stages affect the location, time and velocity of landslide. Kawamura [10] used the least square method and the hysteresis operator decomposition form of p-order difference equation to solve Saito formula, which greatly improved the accuracy of Saito model. On this basis, more and more landslide warning methods have been proposed in recent years, such as statistical method [11-13], grey theory [14-15], slope displacement prediction model [16-18], etc. Most of these methods need to clarify the potential relationship between the landslide and the geological and geomorphic conditions, hydrological environment and other static characteristic factors to analyze the landslide evolution state. However, these models also have obvious disadvantages, such as limited scope of use and high demand on the quality of raw monitoring data. Due to the constraints of high cost of monitoring equipment, dynamic mining and difficult layout of monitoring equipment, the open-pit mine has limited the observation of the characteristic response of the landslide under various external influence factors through multivariate data. Therefore, the landslide warning model should be established and analyzed according to the GPS displacement monitoring equipment commonly used in the existing open-pit mine and the obtained surface displacement monitoring data. Slope displacement monitoring data are usually binary attribute variables, namely safety and insecurity. Average standard deviation analysis method can extract state patterns from data, further simplify the data, and make the data free from the interference of other noises such as unit magnitude [19-23]. In the open pit mine landslide warning, the system clustering method can express the status of the collected monitoring data, which provides a basis for further data analysis. With the continuous development of
information theory and numerical calculation methods, the emergence of Markov chain provides a possibility for landslide early warning. Under the condition of grasping limited data, it can use its prediction advantage of no after-effect [24-26] to describe the random state of landslide evolution and its movement law. Systematic Clustering Analysis and Markov Prediction Theory are widely used in information science and engineering science respectively, but the application of their coupling models in landslide warning is still less studied.

The selection of early warning indicators is an important step in the early warning process. Most previous studies took relatively conservative landslide deformation criteria with mostly empirical components as the basis for early warning. For example, Li et al. [27] chose deformation rate as the index to explore the evolution rules of different evolutionary stages of landslides. Xu et al. [28] further subdivided the state of slope acceleration deformation stage by using the improved tangential Angle model. However, the warning accuracy and the accuracy of the warning area of these models still need to be improved. In view of this problem, Wang et al.[29] believed that acceleration should be "the basis for predicting landslide failure", and suggested that acceleration greater than 0 should be taken as the landslide early warning criterion[30,31]. This criterion was described from the perspective of statistics, and an evaluation method of early warning model for DYMIS was proposed. It overcomes the shortage that the rate threshold warning is not universal in the past. However, this method can generally make a judgment after the landslide starts, so there is some problem of early warning lag. Therefore, based on the Markov chain prediction theory and the basic idea of average standard deviation, starting with the reasonable selection and description of landslide criteria, and taking into account the timeliness, anti-interference and credibility of early warning, the author explores a new landslide early warning method, so as to provide scientific means for the accurate and timely implementation of landslide early warning.

2. Geological setting

2.1. Study area

The West Coal Mine (Fig. 1), located at Pingzhuang town (119°13′79″E, 42°36′82″N) in the southeast suburb of Chifeng city and on the south end of the Xar Moron River, has a long history and has been active for more than 100 years (Wang and Du, 2020). The coal mine has a length of roughly 3 km in the east-west direction, a width of between 1.31 km and 1.35 km in the north-south direction and a depth of 510 m. The mine covers an area of 3.4458 Km$^2$, making it one of the large scaled state-owned enterprises in Inner Mongolia Autonomous Region, reserving thereabouts 335 million tonnes of mineral ore. Although Pingzhuang West Open-pit Mine has been exploited for nearly half a century, it has made outstanding contributions to the economic development of Inner Mongolia and the coal energy economy of China. Since the construction of the mine, there have been more than 40 large and small landslides (Fig.
2), among which the main ones are plane landslide and wedge slide mechanism. However, no deep movement records have been recorded. The cumulative amount of earth and rock sliding is more than $400 \times 10^4 \text{ m}^3$, among which the landslides have been more frequent since the implementation of open-pit combined mining in 2000, causing huge economic losses and posing a security threat to the open-pit mine.

![Location of Pingzhuang open-pit mine, Inner Mongolia Autonomous Region, China](image)

Fig.1. Location of Pingzhuang open-pit mine, Inner Mongolia Autonomous Region, China

2.2. Description of the landslide

With long-term manual excavation and mining activities in Pingzhuang West open pit Mine, in order to meet greater production demand and economic benefits, pingzhuang West open pit Mine has adopted the mode of horizontal mining and internal drainage for mining since 2008. The mining depth and exposed width directly affect the overall stability of the slope. The high frequency of the top slope landslide becomes a potential risk source for the related workers, the social effects of enterprises and the cost of enterprises.

On April 17, 2013, a landslide occurred on the southern bench of the mine and slid towards the northern (Fig. 2). The heights and widths of the benches are 15 m and 20m, and the total slope angle of the southern slope is between 35° and 50°. Through
geological survey, the total track length of Pingzhuang open pit mine landslide with a maximum width of about 400 m, the estimated area was about $31 \times 10^4 \, \text{m}^2$, the terrain gradient of slope was 26°, the elevation is 530 to 815.6 m, the height difference is 285.6 m, and estimated volume is up to 5.0 million m$^3$. After weathering and denudation effect of shallow topsoil landslide and tertiary stratification and bedding failure, the top slope of Xilu mountain is mainly composed of Jurassic sand and mudstone interbedded.

3. Methods

3.1. Calculation method

With the Markov chain theory, the future state change trend can be predicted by obtaining the transition probability between different states, and the prediction steps are as follows:
Step 1  Find the step size as k (k = 1, 2... M) of Markov chain prediction results. The state with step size k is calculated according to the data state sequence Transfer frequency matrix (Equation (1)); Calculate the state transition probability matrix (Equation (2)) according to (Equation (1))

\[
q^k = \begin{bmatrix}
q_{11} & q_{12} & \cdots & q_{1r} \\
q_{21} & q_{22} & \cdots & q_{2r} \\
\vdots & \vdots & \ddots & \vdots \\
q_{r1} & q_{r2} & \cdots & q_{rr}
\end{bmatrix}
\]  

(1)

\[
p^k = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1r} \\
p_{21} & p_{22} & \cdots & p_{2r} \\
\vdots & \vdots & \ddots & \vdots \\
p_{r1} & p_{r2} & \cdots & p_{rr}
\end{bmatrix}
\]  

(2)

Where \(q_{ij}\) is the frequency of transition from state I interval k-1 states to state j in state sequence. \(p_{ij} = \frac{q_{ij}}{\sum_{j=1}^{r} q_{ij}}\).

The initial state probability vector \(A^T(n)\), when the step size is determined as k, is expressed as:

\[
A^T_k(n) = (p_1, p_2, \ldots, p_l, \ldots p_r)
\]  

(3)

Where, when the state of \(x_{n-k+1}\) is 1, \(p_i = 1\); If \(x_{n-k+1}\) is not L, \(p_i = 0\).

When the step size is determined as k, the expression of the state distribution matrix \(B^{(n+1)}_k\) of \(x_{n+1}\) predicted by Markov is as follows:

\[
B^{(n+1)}_k = A^T_k(n) \cdot P^k
\]  

(4)

When k takes different values, \(B^{(n+1)}_k\) forms a matrix \(B = (B^{(n+1)}_1, B^{(n+1)}_2, \ldots B^{(n+1)}_m)^T\)

Step 2  Based on this, the weight vector of order m was obtained. The autocorrelation coefficient is calculated for the same time series data, and the expression is as follows:

\[
r_k = \frac{\sum_{i=k}^{n-k} (x_i - \bar{x})(x_{i+k} - \bar{x})}{\sqrt{\sum_{i=1}^{n-k} (x_i - \bar{x})^2 \cdot \sum_{i=k}^{n-k} (x_{i+k} - \bar{x})^2}}
\]  

(5)

Where \(\bar{x}\) is the mean value of data series.

The weight of each step size constitutes an m-order weight matrix \(w = (w_1, w_2, \ldots, w_k, \ldots, w_m)\), then the expression of \(w_k\) is:
Step 3 The probability distribution vector \( \mathbf{C} \) of \( m \)-order weighted Markov next day prediction state is calculated. The state corresponding to the column of the largest element in \( \mathbf{C} \) is the most likely state of \( x_n + 1 \) predicted by the weighted Markov chain.

\[
w_k = \frac{|\mathbf{p}_k|}{\sum_{k=1}^{2^m} |\mathbf{p}_k|} \quad (1 \leq k \leq m)
\]

\[ (6) \]

3.2. Pre-warning model based on Markov chain

The prediction state information of future displacement velocity and the real state information of current displacement velocity sum up the evaluation of slope stability by Markov chain prediction theory. Based on these information, we can judge whether to give early warning or not. The construction steps of landslide warning model are as follows: ① The sample displacement velocity data are divided into states. The displacement velocity is small and is normal, which is represented by 1. Otherwise, it is an exception, denoted by 2. ② The early historical data are eliminated, and the future displacement velocity state is predicted continuously with the weighted Markov chain. ③ Only current day, day and next day status Warning signals are given when they are abnormal.

3.3. Assessment of pre-warning model

The essence of landslide early warning is to give an alarm in time when there are signs of landslide, and there is a period of emergency preparation before the landslide occurs. The validity evaluation criteria of the early warning model are determined from the following three perspectives. Early warning intensity (timeliness): If in the early warning judgment of \( R \) times (once a day) before the landslide, the number of early warning signals given by the early warning model based on the monitoring data is \( R^* \), then the early warning consequences within \( R \) days before the landslide is defined as \( I \)

\[
I = \frac{R^*}{R}
\]

In order to facilitate the evaluation of the early warning model, considering the actual needs, the emergency preparation time before the landslide was determined to be 7
days, so the timeliness standard of the early warning was set as the slope failure. The warning intensity within 7 days before the occurrence of the slope (hereinafter referred to as the 7-day warning intensity) was measured. Accurate warning rate (anti-interference): if the warning model makes $M$ early warning judgments (including early warning and no early warning), in which $M^*$ times gave early warning signals,

$$W = 1 - \frac{M^*}{M}$$ (9)

Forecast consistency rate (reliability): before the landslide, the warning model gives a total of $Q$ times of prediction for the velocity of the next day, among which, if $Q^*$ is consistent with reality, the predicted consistency rate is defined as $Y$.

$$Y = \frac{Q^*}{Q}$$ (10)

The timeliness of early warning is the most basic and important evaluation criterion, and the anti-interference criterion of early warning is based on the premise that the model meets the timeliness criterion. Optimization, warning credibility criteria are set for further optimization of the model under the premise that the model meets the first two criteria.

4. Results

4.1 Data state classification is based on mean-standard deviation method

The monitoring interval was selected as 2013/01/01-2013/04/17. Since the displacement of the landslide is mainly in the horizontal direction, only the horizontal displacement data are studied in this paper. According to the environmental conditions, adjacent structures and surrounding facilities, the monitoring network layout, monitoring purposes, monitoring means and monitoring instruments that meet the actual engineering conditions were selected, and a number of vertical and horizontal monitoring lines were placed and controlled in the study area and its surrounding areas to form a network and monitoring profile (Fig. 3). On the other hand, due to the large amount of data, only the data of WY200-512 monitoring points in the landslide area are listed.

The sample size is 20 and the standard deviation multiple is 0.4 to illustrate the prediction process. For the first 20 data of the monitoring point WY2300-512, the mean value $\bar{x} = 1.0215$ and the calibration difference $s = 0.6982$ were obtained according to Equations (11) and (12), and the boundary point $D = 1.3008$ was determined according to Equation (13) when $k$ was 0.4.
The minimum value of 20 displacement velocity data is -0.12, and the maximum value is 2.39. D is taken as the boundary point, and the data states are divided into two categories according to the regions [-0.12, 1.30) and [1.30, 2.39], which fall at [-0.12, 1.30) and [1.30, 2.39], which fall at 

The data between regions is classified as positive and shown in Table 1; the data falling in [1.30, 2.39] is classified as abnormal and represented by Table 2.

| Date | H Vel. (mm/day) | S | Date | H Vel. (mm/day) | S | Date | H Vel. (mm/day) | S |
|------|----------------|----|------|----------------|----|------|----------------|----|
| 01-02 | 0.810          | 1  | 01-07 | 1.630          | 1  | 01-18 | 0.295          | 1  |
| 01-03 | 0.460          | 1  | 01-08 | -0.120         | 1  | 01-19 | 1.630          | 1  |
| 01-04 | 1.560          | 1  | 01-09 | 0.780          | 1  | 01-21 | 0.650          | 1  |
| 01-05 | 1.540          | 1  | 01-10 | 0.730          | 1  | 01-22 | 0.000          | 1  |
|       |                |    |       |                |    |       |                |    |

Tab. 1 Status demarcated of monitoring point WY2300-512
4.2 Calculation based on weighted Markov chain prediction

According to Equations (3) and (4), the state transition frequency matrix and state transition probability matrix with step size of 1, 2, 3, 4, 5 are calculated as follows:

\[
q^1 = \begin{bmatrix} 7 & 6 \\ 5 & 1 \end{bmatrix} \quad p^1 = \begin{bmatrix} 0.5385 & 0.4615 \\ 0.8333 & 0.1667 \end{bmatrix}
\]

\[
q^2 = \begin{bmatrix} 7 & 5 \\ 4 & 2 \end{bmatrix} \quad p^2 = \begin{bmatrix} 0.5833 & 0.4167 \\ 0.6667 & 0.3333 \end{bmatrix}
\]

\[
q^3 = \begin{bmatrix} 6 & 5 \\ 5 & 1 \end{bmatrix} \quad p^3 = \begin{bmatrix} 0.5455 & 0.4545 \\ 0.8333 & 0.1667 \end{bmatrix}
\]

\[
q^4 = \begin{bmatrix} 8 & 2 \\ 3 & 3 \end{bmatrix} \quad p^4 = \begin{bmatrix} 0.8000 & 0.2000 \\ 0.5000 & 0.5000 \end{bmatrix}
\]

\[
q^5 = \begin{bmatrix} 5 & 5 \\ 5 & 0 \end{bmatrix} \quad p^5 = \begin{bmatrix} 0.5000 & 0.5000 \\ 1 & 0 \end{bmatrix}
\]

For the 20 selected data, the state of the 20th data is 2, so the initial state vector \( A^T(n) = (0, 1) \) with step size of 1 is obtained according to Equation (5) = (0, 1). Similarly, the data states of the 19th, 18th, 17th and 16th are 1, 1, 1, 2 respectively. Therefore, the initial state vectors of each step size are \( A^T_2(n) = (1, 0) \), \( A^T_3(n) = (1, 0) \), and \( A^T_5(n) = (0, 1) \).

According to Equations (7) and (8), the autocorrelation coefficient and weight vector of each step size are calculated. The number of self-correlation lines of step size is \( r_1 = -0.5176 \), \( r_2 = 0.2228 \), \( r_3 = -0.5072 \), \( r_4 = 0.2757 \), and \( r_5 = -0.2833 \). According to Equations (6) and (9), the probability distribution vectors of the predicted future displacement velocity in each state are obtained. For each vector, the corresponding state of the column in which the largest element is located is the most likely state of the weighted Markov chain of this order to predict the future displacement velocity. The results are shown in Table 2.

Tab. 2 Status probability distributing condition and weight of each order

| Numbers of orders | Weight | Probability of being in status 1 | Probability of being in status 1 | Prediction of future state |
|-------------------|--------|----------------------------------|----------------------------------|---------------------------|
|                   |        |                                  |                                  |                           |

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4.3 Evaluation of prediction results

After dynamically updating the data, the state prediction sequence can be obtained by executing the above weighted Markov prediction process. According to the real state information and the predicted state information, the warning judgment can be made according to the above warning criteria, as shown in Table 3.

It can be seen from the analysis of Table 3 that the 7-day warning intensity of the warning model for this monitoring point is 57%, the error warning rate is 0, and the prediction consistency rate is 58%. The actual situation is that the landslide happened on April 17, 2013. Among the 83 predictions, the early warning model only gave 4 consecutive early warnings on the 4th, 3rd, 2nd and 1st day before the landslide, indicating that the model meets the standard of early warning timeliness, while the error early warning rate is 0, which meets the standard of early warning anti-interference, and the prediction consistency rate is 58%.

| Date | H Vel. (mm/day) | Real state of T (day) | Real state of T+1 (day) | Pre warnin g days | Date | H Vel. (mm/day) | Real state of T (day) | Real state of T+1 (day) | Pre warnin g days | Date | H Vel. (mm/day) | Real state of T (day) | Real state of T+1 (day) | Pre warnin g days |
|------|-----------------|----------------------|-----------------------|-----------------|------|-----------------|----------------------|-----------------------|-----------------|------|-----------------|----------------------|-----------------------|-----------------|
| 01/0 2 | 0.81 | 1 | 02/0 8 | 1.49 | 2 | 1 | 03/1 6 | 0.91 | 2 | 1 | 01/0 3 | 0.46 | 1 | 02/0 9 | 1.83 | 2 | 1 | 03/1 7 | 4.22 | 2 | 1 |
| 01/0 4 | 1.56 | 2 | 02/1 0 | -1.53 | 2 | 1 | 03/1 8 | -0.33 | 2 | 1 | 01/0 5 | 1.54 | 2 | 02/1 3 | 3.31 | 2 | 1 | 03/1 9 | 1.23 | 2 | 1 |
| 01/0 6 | 0.86 | 1 | 02/1 2 | 0.04 | 1 | 1 | 03/2 0 | 1.1 | 1 | 1 | 01/0 7 | 1.63 | 2 | 02/1 5 | 1.1 | 1 | 1 | 03/2 1 | 3.02 | 2 | 1 |
| 01/0 8 | -0.12 | 1 | 02/1 4 | -0.1 | 1 | 1 | 03/2 2 | 0.01 | 1 | 1 | 01/1 0 | 0.73 | 1 | 02/1 6 | -1.06 | 1 | 1 | 03/2 4 | 1.59 | 1 | 1 |
| 01/1 1 | 2.3 | 2 | 02/1 1 | 0.85 | 1 | 1 | 03/2 5 | 1.42 | 1 | 1 | 01/1 2 | 0.295 | 1 | 02/1 8 | 1.08 | 1 | 1 | 03/2 6 | 2.34 | 2 | 1 |
| 01/1 3 | 1.65 | 2 | 02/1 9 | -0.15 | 1 | 1 | 03/2 7 | 2.54 | 2 | 1 | 01/1 4 | 0.65 | 1 | 02/2 0 | 1.69 | 2 | 1 | 03/2 8 | 0.66 | 1 | 1 |
| 01/1 5 | 0.67 | 1 | 02/2 1 | 1.57 | 2 | 1 | 03/2 9 | 1.23 | 1 | 1 | 01/1 6 | 0.88 | 1 | 02/2 2 | 1.07 | 2 | 1 | 03/3 0 | 2.62 | 2 | 1 |
| 01/1 7 | 1.74 | 2 | 02/3 0 | 1.87 | 2 | 1 | 03/3 1 | 1.2 | 2 | 1 | 01/1 8 | 0.486 | 0.231 7, 0.228 6, 0.033 4, 0.078 3 | 0.915 6 | 0.084 4 | 1 |
| Date | a (m/year) | b (m/year) | c (m/year) | d (m/year) | e (m/year) | f (m/year) | g (m/year) | h (m/year) | i (m/year) | a (m/year) | b (m/year) | c (m/year) | d (m/year) | e (m/year) | f (m/year) | g (m/year) | h (m/year) | i (m/year) |
|------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| 01/1 | 0.38       | 0.52       | 0.88       | 1.57       | 1.57       | 1.57       | 1.57       | 1.57       | 1.57       | 0.38       | 0.52       | 0.88       | 1.57       | 1.57       | 1.57       | 1.57       | 1.57       | 1.57       |
| 01/2 | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       |
| 01/3 | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       | 0.09       |
| 01/4 | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       | 2.39       |
| 01/5 | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      | -0.29      |
| 01/6 | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       | 1.47       |
| 01/7 | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       | 1.21       |
| 01/8 | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       | 1.09       |
| 01/9 | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       | 2.57       |
| 02/0 | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       | 0.26       |
| 02/1 | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       | 1.54       |
| 02/2 | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       | 1.15       |
| 02/3 | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       |
| 02/4 | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       | 1.87       |
| 02/5 | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      | -0.02      |
| 02/6 | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       | 1.99       |
| 02/7 | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      | -0.26      |
| 02/8 | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       | 0.08       |

5. Conclusions

Based on the research, the following conclusions are presented:

(1) Based on the characteristics of displacement evolution in the process of landslide evolution, the displacement velocity data obtained from slope monitoring are defined as “normal” and “abnormal”; Taking the displacement acceleration \( a \geq 0 \) as the landslide criterion, the real state of the displacement velocity data of the previous day and that day as well as the predicted state of the next day's displacement velocity data are abnormal as the criterion of landslide early warning.

(2) From the landslide early warning timeliness, anti-interference and credibility of three requirement, To determine the Early warning consensus rate, we choose three indicators: accurate early warning rate, and forecast consistency rate. The evaluation criteria for the warning effect based on these three indicators are proposed, that is, the warning results given by the ideal landslide warning model should simultaneously meet the requirements of warning consensus rate and accurate early warning rate rate, and on this premise, have a high prediction consistency rate.

(3) The warning model can be used to realize the landslide warning at a single monitoring point. Among the 83 predictions of a single monitoring site, the warning model only gave 4 consecutive warnings on the 4th, 3rd, 2nd and 1st day before the landslide, and the 7-day warning intensity was 57%, the error warning rate was 0, and the prediction consistency rate was 58%. It shows that the model has high timeliness, anti-jamming and reliability.

(4) The stability and parameter sensitivity of waste dump under complex working
conditions were analysed. The sensitivity of the dump stability to the angle of Grade III slope, basement cohesion, the mechanical vibration strength is moderate; the sensitivity of the dump stability to the height of Grade III slope, basement friction angle, basement moisture content and the excavation angle of Grade I slope is high. The dump stability decreases with the increase of the height and angle of Grade III slope, basement moisture content, excavation angle of Grade I slope, and mechanical vibration strength. Dump stability increases with the increase of the basement friction angle, basement cohesion.

(5) The established warning model is suitable for the case that the displacement velocity degree data are sufficient, and the data used are not limited to displacement velocity. It can be extended to displacement acceleration, etc., and the optimal parameters of the model also need to be further determined in the verification to achieve the refinement and classification of the landslide early warning.

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