Short-Term Forecasting Management Research of Deep Horizontal Displacement of Slope Soil Based on ARIMA Model

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Abstract

The forecasting of deep horizontal displacement of slope soil is an important part of slope deformation monitoring, which has important guiding significance for the prevention of slope safety accidents. The historical data of deep horizontal displacement of slope soil are non-stationary time series with both random growth and time-varying fluctuation, and ARIMA model is suitable for forecasting such time series. In this paper, 648 historical data of deep horizontal displacement of soil were selected as the original sequence of empirical analysis, and forecasted the law and trend of displacement change by establishing ARIMA model. The results of empirical analysis showed that the effect of short-term static forecasting was good, which could provide useful reference for managers of slope quality safety govern slope and analyze the slope stability.

Subject Areas

Civil Engineering

Keywords

Engineering Management, ARIMA Model, Short-Term Forecasting, Deep Horizontal Displacement of Slope Soil

1. Introduction

Slope stability has always been an important research content of slope engineering [1]. In recent years, despite the rapid development of China's social economy

and the rapid growth of large-scale rock mass engineering, a large number of slopes have been formed in the construction of railway, highway and other projects in mountainous areas. Landslides have now become one of the three major geological disasters in the world along with earthquakes and volcanoes [2] [3]. For example, in 1963, a landslide occurred on the slope of the way on reservoir in Italy, killing more than 2500 people; in 1970, about 25 km west of the city of Chimbote, Peru, a 7.7-magnitude earthquake occurred, which triggered a large number of landslides and collapses, resulting in a total of 67,000 deaths [4]. In June 2014, a landslide occurred between Lianghekou and Zhenzijie station area of the Chongqing-Guizhou railway, resulting in the detour or suspension of 29 passenger trains; in November 2014, a landslide occurred on the Xunyang to Chongxi upbound line of Xiangyu railway in Shaanxi province, causing the derailment of 1 - 12 carriages of the 75,228 train, resulting in the death of two drivers and the delay of some trains [5].

It can be seen that for natural slope collapse, landslide, etc., or man-made slope instability caused by human engineering activities, these geological disasters have caused huge losses to economic construction and people's property [6]. Therefore, it is of great significance to seek a scientific management method to prevent slope accidents.

However, slope engineering is an uncertain, nonlinear and complex system [7], and there are a variety of slope safety monitoring technologies at home and abroad. For example, in 2010, Pieraccini, Barla, Gischig *et al.* first used GB-In SAR to monitor and study the deformation of slope [8] [9] [10]; in 2012, Ruan Zhixin used the inclinometer to monitor the expressway slope and proved the correctness of the monitoring [11]; in 2013, Wang Zhiyong used In SAR technology to monitor the landslide in Fangshan area of Beijing [12]; in 2015, Xu Maolin used TM30 to carry out a monitoring experiment on the slope displacement of an open pit mine in Anshan city, realizing automatic monitoring [13], etc. Most of these slope engineering monitoring technologies are used to monitor the slope deformation, so it is concluded that the slope deformation is very important to the slope stability analysis. Therefore, this paper attempts to start with the deep horizontal displacement of soil in slope deformation monitoring, builds ARIMA model, and uses EViews to forecast and empirically analyze the deep horizontal displacement of soil.

2. Forecasting Theory and Methods

2.1. Forecasting Theory of Deep Horizontal Displacement of Soil

The forecasting of deep horizontal displacement series of soil mass refers to the estimation of the displacement value of a certain period or periods in the future by using historical data of the evolution of things, comprehensive consideration of various influencing factors and some scientific research methods. The time series of the known horizontal displacement value of deep soil is $\{H_1, H_2, H_3, \cdots, H_T\}$, to forecast the displacement value of

$H_{T+1}, H_{T+2}, H_{T+3}, \cdots, H_{T+m}$, the formula is defined as:

$$\hat{H}_{T+1}, \hat{H}_{T+2}, \cdots, \hat{H}_{T+m} = f\left(H_1, H_2, \cdots, H_T\right) \tag{1}$$

Among them, only doing the one-step forecasting, so the H_{T+1} is estimated, which is called single-step forecasting; When H_{T+m} and $m > 1$ are forecasted, it is called m-step forecasting. It is obvious that m-step forecasting is composed of multiple single-step forecasting, that is, formula (1) can be written as:

$$
\begin{aligned}
\hat{H}_{T+1} &= f\left(H_1, H_2, \cdots, H_T\right) \\
\hat{H}_{T+2} &= f\left(H_1, H_2, \cdots, H_{T+1}\right) \\
&\vdots \\
\hat{H}_{T+m} &= f\left(H_1, H_2, \cdots, H_{T+m-1}\right)
\end{aligned} \tag{2}
$$

The purpose of forecasting research is to understand the future development state or trend of things. It is widely concerned because the current state of things may affect the future results. The appropriate forecasting method is applied to the forecasting of deep horizontal displacement of slope soil, and the Suggestions are provided for the slope quality and safety management, which is conducive to the analysis of slope stability and the prevention of slope safety accidents. Therefore, the forecasting of deep horizontal displacement of slope soil is a very important forecasting problem.

2.2. Time Series Forecasting Analysis

The method of time series forecasting is to regard the historical monitoring data of the deep horizontal displacement of slope soil as the time series of changes, and to forecast the trend and rule of the future evolution of things by building a reasonable time series model, see Figure 1. However, the time series forecasting method is in line with the randomness, time-variability and other characteristics of the deep horizontal displacement evolution of slope soil, and has a high short-term forecasting accuracy. At present, the commonly used time series analysis methods include autoregressive model (AR), sliding average model
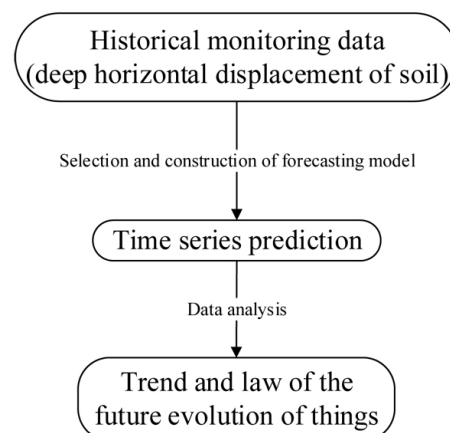

Figure 1. A analysis process of the time series prediction method.

(MA) and autoregressive sliding average model (ARMA), etc., and their theoretical formula [14] is as follows:

The formula of AR(p):

$$x_t = \delta + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + u_t \tag{3}$$

The formula of MA(q):

$$x_t = u + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \tag{4}$$

The formula of ARMA(p, q):

$$
\begin{aligned}
x_t = {} & \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \delta \\
& + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q}
\end{aligned}
\tag{5}
$$

There are two forecasting methods: static forecasting and dynamic forecasting. Static forecasting refers to the forecasting based on the actual value in the original sequence, which can only be used after obtaining the real data. Dynamic forecasting refers to the forecasting of the first phase from the actual value, and then the first phase value is put into the original time series to forecast the value of the second phase together with it, and so on, but for long-term forecasting, it may produce cumulative error.

3. Empirical Analysis of ARIMA Model Based on the Monitoring Value of Deep Horizontal Displacement of Slope Soil

3.1. Problem Description and Model Introduction

In the long-term slope deformation process, the monitored horizontal displacement value of soil depth changes with the seasonal cycle and has a certain increase (or decrease) trend of non-stationary time series. Traditional forecasting methods, such as regression model and gray GM(1,1) model, are applicable to stationary time series, and the forecasting results for such values are not ideal [15]. And C. P. Box and G. M. Jenkins was first put forward the regression sum of moving average model (ARIMA model for short), is a non-stationary time series after d first order difference tranquilization, again to get the stationary time series by using autoregressive (AR(p) process) and moving average (MA(q) process), and through the sample autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PCF), and other data to establish the model of recognition, at the same time also put forward a set of modeling, estimation, inspection and control methods for the [16]. Therefore, it is suitable for forecasting time series problems with periodic fluctuations and trend growth (or decrease). Set $\{H_t\}$ as stationary time series and the mean value is zero, then the first-order autoregressive first-order sliding average model formula of ARMA(1,1) can be expressed as:

$$H_t = \phi H_{t-1} + e_t - \theta e_{t-1} \tag{6}$$

Therefore, the formula of ARMA(p, q) can be expressed as:

$$H_t - \phi_1 H_{t-1} - \cdots - \phi_p H_{t-p} = e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \tag{7}$$

Formula (4) can be abbreviated as:

$$\phi(B)H_t = \theta(B)e_t \tag{8}$$

Among them, e_t represents the white noise parameter, $t = 1, 2, \cdots, p$; ϕ said regression coefficient; θ represents the regression parameter. In the model ARIMA(p, d, q), d represents the difference order. In slope monitoring projects, time series data of deep horizontal displacement of soil are generally unstable, and there are many ways to make the series stable. Difference is one of them, and the modeling process of ARIMA model is almost the same as that of ARMA.

3.2. Build a Model

The data of deep horizontal displacement of slope soil in this paper are obtained from the SQLsever database of *Sichuan Shengtuo Detection co., LTD*. The related slope engineering project is the ladder trough landslide monitoring project of Shuangma village, Shiguan township, Maoxian county. SQLsever database is a high performance and extensible relational database management system designed by Microsoft.

Due to the failure of data acquisition equipment and external environment, data acquisition at some time points is missing. Therefore, in order to reduce the forecasting error, a continuous and stable period of monitoring data was selected for the forecasting experiment.

Randomly selecting 500 - 650 data of a deep horizontal displacement monitoring point in the monitoring project. There are two reasons for the selection of 500 - 650: first, if too little data is taken, the information in the original sequence cannot be fully mined; and if too much data is selected, the sequence interval will be too long, making the early data have little influence on the later forecasting data and causing unnecessary errors. Second, a lot of related time series forecasting literatures are consulted. If the number of original series in the empirical analysis of quarterly data (m = 4, cycle four quarters a year) is between 50 and 100, and the number of monthly data (m = 12, cycle for 1 year and 12 months) is between 250 and 350, the number of original series in the empirical analysis of time data (m = 24, cycle 24 hours a day) is between 500 and 650.

In this paper, from 0 points on August 15, 2018 to 23 points on September 10, 2018, all the whole point data in the direction of "X axis" are selected to form the "H" data set and sequence {H_t}. The data amount is 504, as shown in **Figure 2**. As can be seen from **Figure 2**, "sequence {H_t} is an obvious time series with deterministic trend and periodicity".

According to the above "three criteria", AIC, SC and HQ values with smaller values are better. Based on the unit root test results in **Table 1**, it can be judged that this sequence is a unit root process with no intercept term and no trend term.

It can be seen from **Table 2** that the absolute value of the t-statistic value of the first-order difference ADF test is 18.5774, which is much higher than the t-statistic value of 1.9413 when the significance level is 0.05, so the null hypothesis
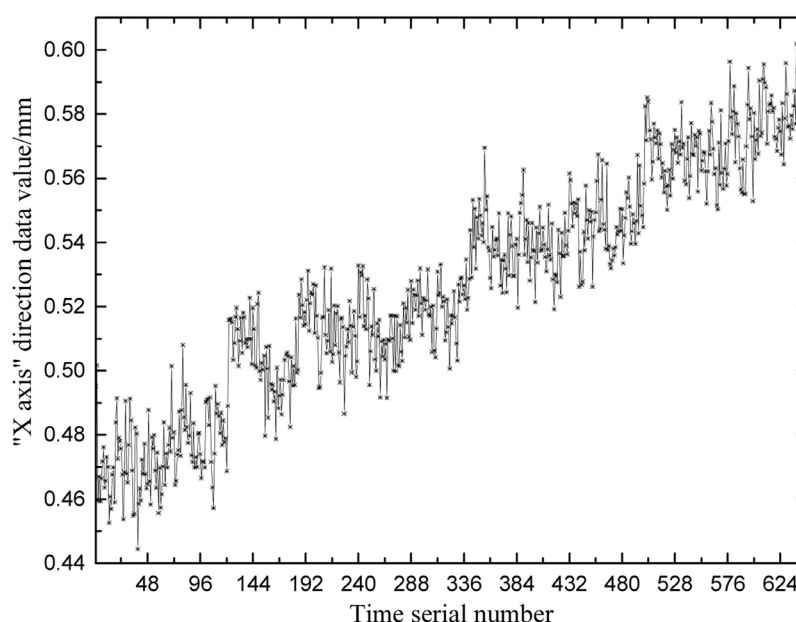
Figure 2. The sequence diagram of the "H" dataset.

Table 1. The unit root test of the first-order difference sequence.

ADF tests the category	AIC	SC	HQ
Intercept, Trend	−6.3234	−6.2818	−6.3073
Intercept	−6.3263	−6.2916	−6.3129
No intercept, No trend	−6.3284	−6.3006	−6.3176

Note: AIC, also known as AIC information criterion, was put forward by Japanese statistician Hiroji Akaike in 1973 [17]. SC refers to Schwartz criterion, also known as BIC. HQ refers to Hannan-Quinn criterion [18].

Table 2. The ADF test of the first-order difference sequence (no intercept term and no trend term.

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	−18.576	0.0000
Test critical Values: 1% level	−2.569	
5% level	−1.941	
10% level	−1.616	

of a unit root exists. And then *P*-value is small. All these indicate that the first-order difference sequence of the original sequence is stable, so $d = 1$.

As can be clearly seen from **Figure 3**, the timing diagram of *DH* fluctuates up and down around a constant value with a small fluctuation range. It can also be seen from **Figure 4** that the autocorrelation coefficient rapidly decays to 0. In summary, the original sequence is stable after the first-order difference, and the second-order difference test is no longer carried out.

As can be clearly seen from **Figure 3**, all *P*-values are less than 0.05 and close to 0, so the original sequence is non-white noise, with a certain correlation and a law to follow. After lag order (lag) is 4, the partial autocorrelation coefficient
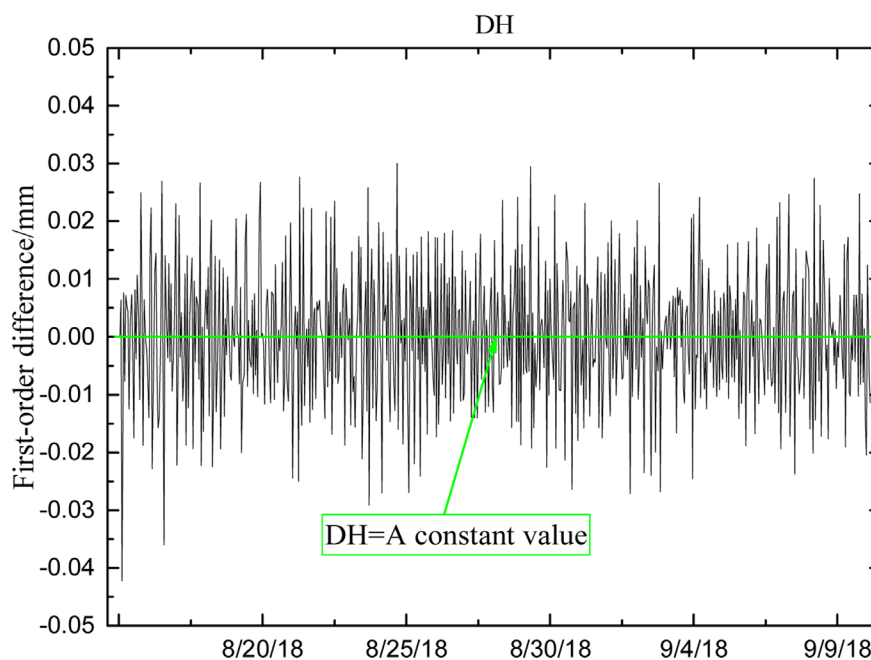
Figure 3. The first-order difference sequence diagram of the "H" dataset.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.394	-0.394	100.94	0.000
		2	-0.053	-0.247	102.80	0.000
		3	0.008	-0.145	102.85	0.000
		4	-0.015	-0.109	103.00	0.000
		5	0.012	-0.062	103.09	0.000
		6	-0.039	-0.089	104.09	0.000
		7	-0.022	-0.108	104.40	0.000
		8	0.057	-0.027	106.53	0.000
		9	-0.064	-0.089	109.23	0.000
		10	0.019	-0.063	109.48	0.000
		11	0.037	-0.006	110.41	0.000
		12	0.023	0.042	110.75	0.000
		13	-0.021	0.020	111.05	0.000
		14	-0.036	-0.028	111.89	0.000
		15	0.012	-0.024	111.99	0.000
		16	-0.001	-0.028	111.99	0.000
		17	-0.022	-0.042	112.30	0.000
		18	0.038	0.008	113.25	0.000
		19	-0.042	-0.041	114.45	0.000
		20	-0.006	-0.058	114.48	0.000
		21	0.034	-0.014	115.26	0.000
		22	-0.019	-0.031	115.51	0.000
		23	-0.007	-0.050	115.54	0.000
		24	0.045	0.016	116.89	0.000
		25	-0.042	-0.023	118.10	0.000

Figure 4. The first-order differential autocorrelation graph.

rapidly approaches to 0, and the first-order difference sequence is preliminarily judged to be the fourth-order truncation of partial autocorrelation, so the AR(4)

model can be tried to fit. When lag = 5, the partial autocorrelation coefficient is at the edge of the confidence band of 2 times the standard deviation, so the AR(5) model can be tried to fit. For lag = 1, the autocorrelation coefficient is not significantly zero, and for lag = 2, 8, it is on the edge of the confidence band of 2 standard deviations, so we can try to fit the MA(1), MA(2) and MA(8) models. Therefore, ARIMA(4,1,1) and ARIMA(5,1,1) can be preliminarily fitted. Finally, it is found that p may be equal to 4 and q may be equal to 1, 2 and 8 according to the model's order determination. Table 3 and Table 4 below are the comparison of estimated results and forecasted parameters of each fitting model respectively.

According to the judgment principle that the P-value is less than the significance level 0.05 and the smaller the result is, the more significant the result is (the model is better), the P-value values of C, AR(p) and MA(q) in Table 3 are compared to obtain the optimal ARIMA(3,1,1) model.

First, according to the "three criteria", AIC, SC and HQ value are relatively low, and the test statistics of each model in Table 4 are compared. It is concluded that ARIMA(3,1,1) has two minimum values (SC and HQ). According to the principle of F distribution, the value of F-statistics is better, and the F statistic of ARIMA(3,1,1) is obviously the largest, and the P-value is also less than the significance level of 0.05. Therefore, ARIMA(3,1,1) was comprehensively judged as the optimal fitting model.

The formula of the model ARIMA(3,1,1) is derived [14] [19] as follows:

1) Because of $W_t = \hat{\alpha} + v_t$ (9)

2) Again,

Table 3. Comparing the *P*-values of the equations.

P-values/(10^{-2})	ARIMA (3,1,1)	ARIMA (4,1,1)	ARIMA (4,1,2)	ARIMA (4,1,8)
C	0	0	0	0
AR(3)	0.12	0.74	0	0.10
AR(4)	-	14.96	0.04	2.88
MA(1)	0	0	81.92	74.08
MA(2)	-	-	0	3.99
MA(8)	-	-	-	8.72

Note: *C* stands for constant; *AR* represents the autoregressive process, and the lag order is denoted in brackets; *MA* represents the sliding average process, and the brackets indicate the lag order.

Table 4. Comparing the precision indexes of various models.

Precision index	ARIMA (3,1,1)	ARIMA (4,1,1)	ARIMA (4,1,2)	ARIMA (4,1,8)
AIC	−6.384	−6.385	−6.382	−6.375
SC	−6.349	−6.343	−6.333	−6.285
HQ	−6.370	−6.368	−6.363	−6.340
F-statistics	62.787	50.921	42.410	21.887
Prob (F-statistics)	0.000	0.000	0.000	0.000

$$\left(1-\hat{\rho}_1 L-\hat{\rho}_2 L^2-\hat{\rho}_3 L^2\right)v_t = \left(1+\hat{\theta}L\right)\hat{e}_t \tag{10}$$

$$1-\hat{\rho}_1 L-\hat{\rho}_2 L^2-\hat{\rho}_3 L^2 \tag{11}$$

3) If you multiply both sides of this equation by 11, you get PI (1):

$$W_t = \left(1-\hat{\rho}_1-\hat{\rho}_2-\hat{\rho}_3\right)\hat{\alpha}+\hat{\rho}_1 w_{t-1}+\hat{\rho}_2 w_{t-2}+\hat{\rho}_3 w_{t-3}+\hat{e}_t+\hat{\theta}L\hat{e}_t \tag{12}$$

4) The formula of ARMA(3,1) model is obtained by substituting the coefficient:

$$\begin{aligned}W_t &= 0.000061+0.381209w_{t-1}+0.147211w_{t-2}+0.127094w_{t-3} \\ &\quad +\hat{e}_t-0.994342\hat{e}_t\end{aligned} \tag{13}$$

5) Then, making the $W_t = h_t - h_{t-1}$, and the formula of ARIMA(3,1,1) model is:

$$\begin{aligned}&\left(H_t - H_{t-1}\right)+0.381209\left(H_{t-2}-H_{t-1}\right) \\ &+0.147211\left(H_{t-3}-H_{t-2}\right)+0.127094\left(H_{t-4}-H_{t-3}\right) \\ &=0.000061+\hat{e}_t-0.994342\hat{e}_t\end{aligned} \tag{14}$$

3.3. Diagnostic Testing of Models

After determining the estimated ARMA model parameters, diagnostic tests are required to verify the adaptability of the fitting model. In this paper, Eviews time series analysis software is used to establish the autocorrelation graph of the residual error, and the residual error is tested by pure randomness. **Figure 5** below is the result of ARIMA(3,1,1).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.008	-0.008	0.0448	
		2	-0.020	-0.020	0.3116	
		3	-0.029	-0.029	0.8389	
		4	0.025	0.024	1.2380	
		5	0.026	0.026	1.6939	0.193
		6	-0.020	-0.020	1.9641	0.375
		7	0.003	0.005	1.9705	0.579
		8	0.064	0.064	4.6530	0.325
		9	-0.014	-0.015	4.7738	0.444
		10	0.053	0.056	6.6075	0.359
		11	0.089	0.095	11.778	0.108
		12	0.063	0.063	14.368	0.073
		13	0.002	0.009	14.371	0.110
		14	-0.032	-0.022	15.028	0.131
		15	-0.000	-0.005	15.028	0.181
		16	0.016	0.006	15.199	0.231
		17	-0.004	-0.004	15.210	0.294
		18	0.011	0.007	15.297	0.358
		19	-0.035	-0.044	16.106	0.375
		20	-0.004	-0.016	16.117	0.445
		21	0.029	0.018	16.666	0.477
		22	-0.008	-0.022	16.705	0.543
		23	0.001	-0.011	16.706	0.610
		24	0.047	0.049	18.215	0.573
		25	0.000	0.004	18.215	0.635

Figure 5. Residual correlation graph of the ARMA(3,1,1) model.

As can be seen from **Figure 5**, the autocorrelation function values are almost within the confidence region of 0.95. Secondly, all *P*-values are greater than 0.05, indicating that the residuals are white noise and purely random. According to ARIMA(3,1,1) model fitting **Figure 6**, the fitting effect is good. By comprehensive judgment, the fitted ARIMA(3,1,1) model is effective.

3.4. Application of Models

In order to verify the applicability of the fitting model, the model ARIMA(3,1,1) is used for forecasting. The dynamic forecasting was carried out first, and the results are shown in **Figure 7** below.

The forecasted results were stored in the *DH* sequence to make the dynamic forecasting fitting diagram of *DH* and *DHF*, as shown in **Figure 8**. As can be seen from the figure, the trend line of dynamic forecasting results is basically a straight line without obvious fluctuation, indicating that the dynamic forecasting effect of this model is not good.
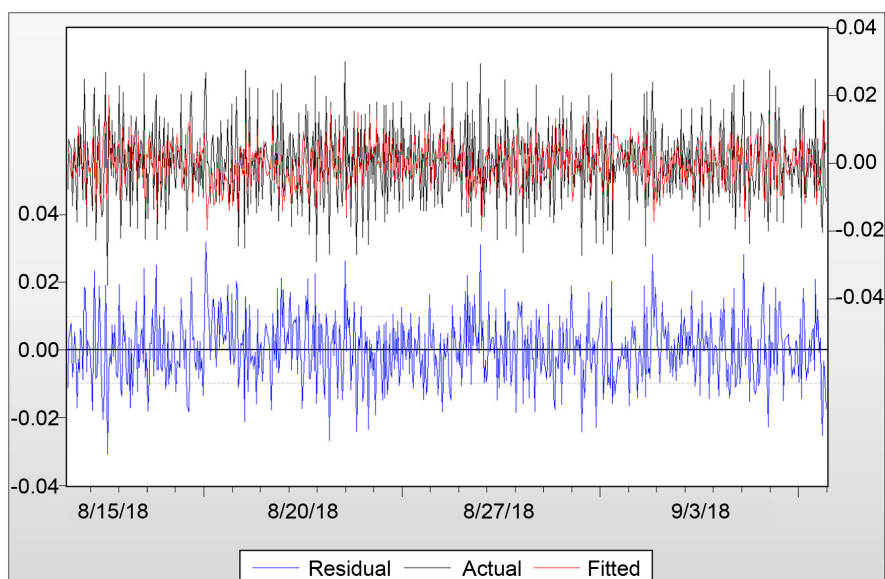
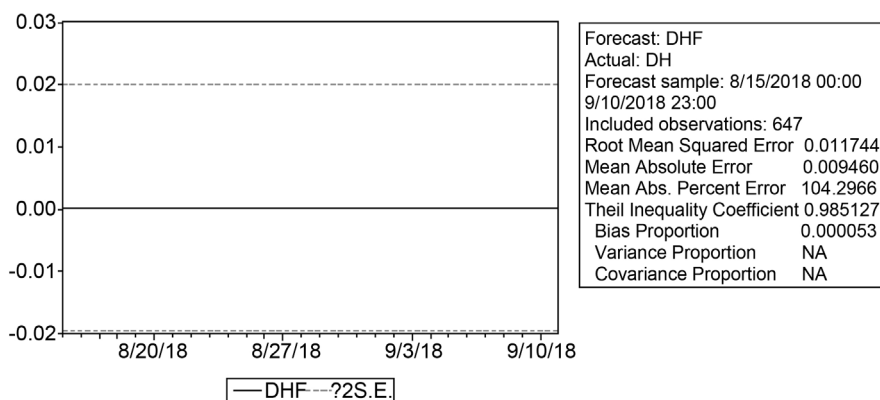

Figure 6. The fitting graph of the ARMA(3,1,1) model.

Figure 7. The sequence dynamic forecasting graph.
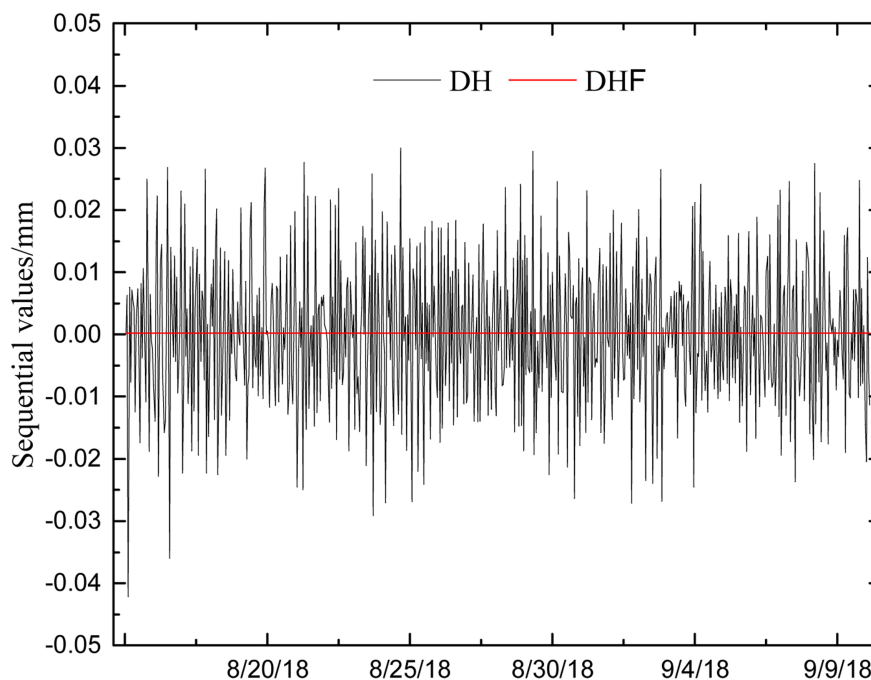
Figure 8. The dynamic forecasting fitting graph.

Secondly, the static forecasting is carried out, and its short-term forecasting can only be carried out step by step. The forecasting results are shown in **Figure 9**, which shows that the static forecasting effect of this model is quite ideal.

The forecasted values were stored in the *DH* sequence to make the static forecasting fitting graph for *DH* and *DHF*, as shown in **Figure 10** below. It can be seen from the figure that the static forecasting effect of the model is better.

According to the existing forecasting value in *DHF*, the model ARIMA(3,1,1) formula can be used to deduce the forecasted value of the first phase reversely, and the forecasted value can be integrated into the original sequence, the same process can be used to obtain the forecasted value of the second phase, and so on until the $m(m = 24)$ phase. Therefore, the limitations of the model for long-term forecasting are shown in **Table 5**.

where, the average relative error $\bar{e}$ is,

$$\bar{e} = \frac{1}{n}\sum_{i=1}^{24}\frac{|h_i - h_i'|}{h_i} \approx 1.73\%$$

where, h_i and h_i' represent the actual value and the forecasted value respectively; *i* represents the number of forecasting periods, $i = 1, 2, \cdots, 24$; $n = 24$.

As can be seen from **Table 5**, the absolute error is relatively small, while the relative error is only 1.73%. In **Figure 11**, the forecasted results are all within the confidence interval of 0.95, and are basically consistent with the change trend of the actual value curve. Therefore, it is not difficult to draw the following conclusions from the forecasting results of the fitting model:

1) ARIMA model is feasible as a short-term forecasting model for deep horizontal displacement of slope soil. It can be seen from the forecasting fitting effect
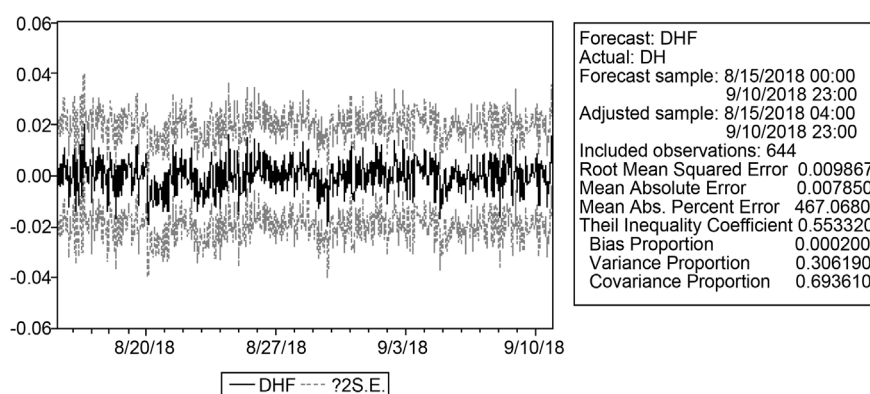
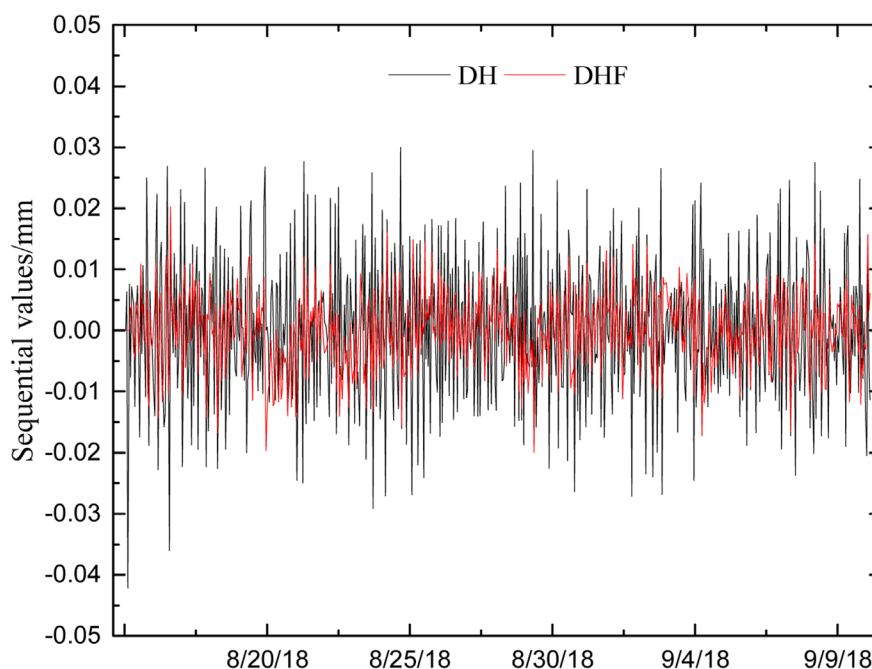Figure 9. The sequence static forecasting graph.

Figure 10. The static forecasting fitting graph.

diagram that the fitting effect is good, indicating that the original sequence contains the information of the "X-axis" direction of the deep horizontal displacement of the slope soil, and it is not difficult to see that the static forecasting effect is far better than the dynamic forecasting.

2) It is easy to generate the cumulative error when the static forecasted value is calculated by the model back-stepping. It is not difficult to see from the forecasting results of ARIMA(3,1,1) in Table 5 that the average forecasting error of the first eight stages is about 0.69%, the average forecasting error of the middle eight stages is 0.89%, and the average forecasting error of the last eight stages is much larger than that of the first two stages, which is 1.41%. This is because in order to forecast the second phase, the forecasted value of the first phase must be used for back-analysis, rather than the calculation of the real value of the first phase, and so on, so it is easy to produce cumulative error. This feature of static
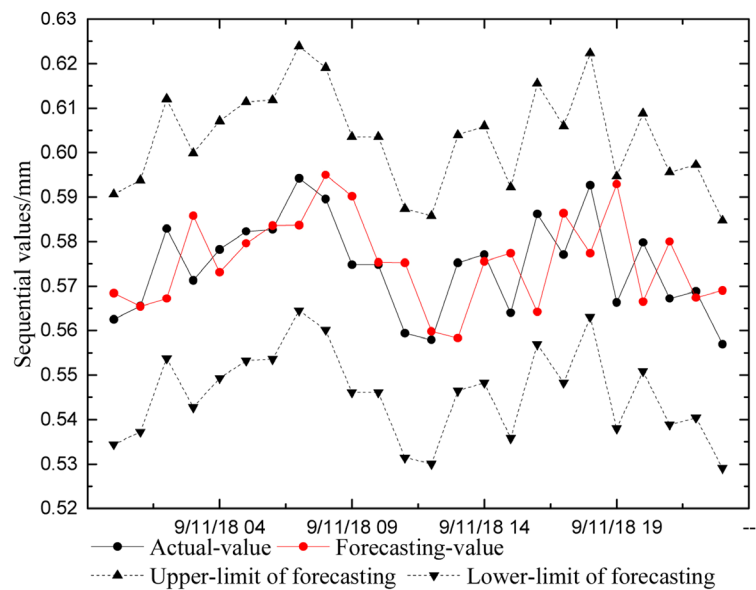
Figure 11. The static forecasting result.

Table 5. The forecasting results of model of ARMA(3,1,1).

Time serial number	Actual value/(10^{-2}·mm)	Forecasting value/(10^{-2}·mm)	Absolute error (%)	Relative error (%)
1	56.25	56.84	0.59	1.05
2	56.55	56.54	0.01	0.02
3	58.29	56.72	1.57	2.69
4	57.13	58.58	1.45	2.54
5	57.82	57.31	0.51	0.89
6	58.23	57.96	0.27	0.47
7	58.27	58.36	0.09	0.15
8	59.42	58.37	1.05	1.77
9	58.96	59.50	0.54	0.92
10	57.48	59.02	1.55	2.69
11	57.48	57.53	0.06	0.10
12	55.94	57.52	1.59	2.84
13	55.79	55.98	0.19	0.33
14	57.52	55.83	1.69	2.94
15	57.71	57.55	0.16	0.28
16	56.40	57.74	1.35	2.39
17	58.62	56.42	2.19	3.74
18	57.71	58.64	0.93	1.60
19	59.27	57.74	1.53	2.58
20	56.63	59.29	2.66	4.69
21	57.98	56.65	1.32	2.29
22	56.72	58.00	1.28	2.26
23	56.88	56.74	0.14	0.25
24	55.69	56.90	1.21	2.17
	Mean relative error			1.73

Note: the forecasted time is "2018-09-11 00-2018-09-11 23", corresponding to the time serial number; Absolute-error = |Actual-value − Forecasted-value| * 100%; Relative error = (Absolute-error/Actual-value)*100%. The actual value comes from the SQLsever database of Sichuan Shengtuo detection co., LTD.

forecasting is not conducive to long-term forecasting, but overall, the relative error and average relative error of the forecasting results of the fitting model in this paper show that the absolute error of these 24 periods is very small, and the forecasting effect is relatively ideal.

3) The characteristic of time series forecasting itself is to extract useful information from the historical data of things to forecast their future development or trend. In this paper, other factors affecting the deep horizontal displacement of soil are only reflected by random terms, which is also a defect of the fitting model. In the empirical analysis, other factors affecting the deep horizontal displacement of soil cannot be controlled. Therefore, when selecting data, it is necessary to avoid major fluctuations caused by earthquakes and artificial construction as far as possible, so as to reduce the forecasting error.

4. A New Method for the Forecasting and Management of Slope Stability

Combined with the results of the whole empirical analysis, a theoretical method suitable for the forecasting and management of slope stability is proposed, which is a short-term static forecasting method of deep horizontal displacement of soil based on ARIMA model (ARIMA-soil displacement forecasting method), as shown in Figure 12.

ARIMA-soil displacement forecasting method, relies on the historical data of deep horizontal displacement monitoring of slope soil, builds ARIMA model by analyzing the original sequence, and makes short-term static forecasting. If the analysis results of the first phase forecasting are not harmful to the slope stability, the results of the first phase forecasting will be put into the original sequence for the second phase forecasting, and so on. On the other hand, if the analysis results of a certain period are not favorable to the slope stability, the monitoring should be strengthened and emergency measures should be prepared in advance. The application of this method can provide more basis for slope stability analysis and prevent slope safety accidents.

5. Conclusions

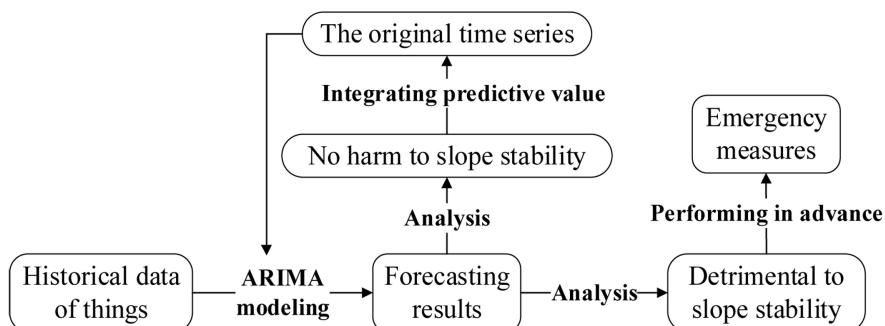The forecasting of deep horizontal displacement of slope soil is a challenging

Figure 12. The workflow of the forecasting method.

problem, but the forecasting of time series has always been considered as an effective means for statistical forecasting of trend growth (decrease) and time-varying fluctuation series. Because time series forecasting has a good short-term forecasting effect, although this paper only carries out short-term static forecasting of ARIMA model for time series of deep horizontal displacement of soil, theoretically time series can achieve long-term dynamic forecasting. In the empirical analysis of this paper, it can be seen from Figure 10 that the static forecasting results have a good fitting effect. It can be seen from Table 5 that both the absolute error and the average error obtained by the model forecasting are small. All these indicate that the ARIMA model is feasible as a short-term forecasting model for deep horizontal displacement of slope soil. Therefore, the use of the model ARIMA has certain reference value for this paper to seize the implementation opportunity of slope quality and safety management measures, analyze slope stability and prevent slope accidents.

Due to the time limitation, this paper only makes empirical analysis on the changes of some historical monitoring data of the deep horizontal displacement of slope soil, and when the sample data are changed, the structural parameters of the fitting model will also change accordingly, which indicates that the model is very sensitive to the changes of samples. At the same time, from the perspective of short-term static forecasting results, the fitting model still has the characteristics of short-term stability for the fluctuation pattern of soil displacement forecasting, but the forecasting accuracy also changes with the change of samples, so the conclusion may lack universality. In general, when using the ARIMA model to forecast the deep horizontal displacement of slope soil, it is better to forecast the historical data with stable development and change, no severe construction and large abnormal fluctuation caused by external factors such as emergencies. Finally, in order to better connect the empirical analysis conclusion with the slope management work, a new applied method of slope quality safety monitoring management, to ARIMA-soil displacement forecasting method is proposed.

In conclusion, this paper uses the ARIMA model and historical displacement value as sequence data to make short-term forecasting of the next 24 displacements, hoping that the results will be helpful for slope managers to strengthen slope safety management and prevent slope accidents. In addition, other forecasting methods can be considered to strengthen the attention to various influencing factors, such as slope structure, weather change, engineering construction, etc. Often these unstable factors also have important application value for the long-term trend of the deep horizontal displacement of slope soil.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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