# Research on High Slope Deformation Prediction Model based on ARIMA-GRNN

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**Abstract.** In this paper, an autoregressive integral sliding average model (ARIMA) and generalized regression neural network (GRNN) coupled high slope deformation prediction model is proposed, which mainly utilizes the long-term trend fitting ability of the ARIMA model and the short-term data prediction ability of the GRNN to significantly improve the overall prediction performance of the model. The feasibility and effectiveness of the model in practical applications are verified by comparing it with a variety of prediction models. The results show that the ARIMA-GRNN model based on residual correction is better than the traditional model in all assessment indexes, and can provide more accurate and stable prediction of high slope deformation, which provides an important decision support for the fields of geologic disaster management, environmental protection and civil engineering design, and has significant theoretical significance and practical application value.

**Keywords:** high slopes; ARIMA model; GRNN neural network; prediction.

## 1 Introduction

Accurate high slope deformation prediction models can significantly improve the timeliness and accuracy of disaster warnings, providing critical time for preventive measures and emergency response, thus protecting human lives and reducing economic losses. For engineering construction and maintenance, the stability prediction of high slopes is a key safety consideration, and by providing a reliable prediction tool, the engineering design can be optimized to avoid potential engineering disasters [1 ,2]. In this study, a new hybrid prediction model is proposed by combining the ARIMA model and the GRNN neural network, a modeling innovation that not only enhances the understanding of the deformation dynamics of high slopes, but also provides a methodological reference for the prediction of other complex systems. Through the residual correction method, linear and nonlinear analysis techniques can be effectively fused to improve the processing capability of complex data patterns[3,4].



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# 2 Introduction to Algorithms

## 2.1 ARIMA Model

The ARIMA model modeling steps are detailed in the literature [5].

## 2.2 GRNN Neural Network

The GRNN neural network modeling steps are detailed in the literature [6].

# 3 Engineering Applications

The deformation data for monitoring point BD05 is shown in Figure 1.

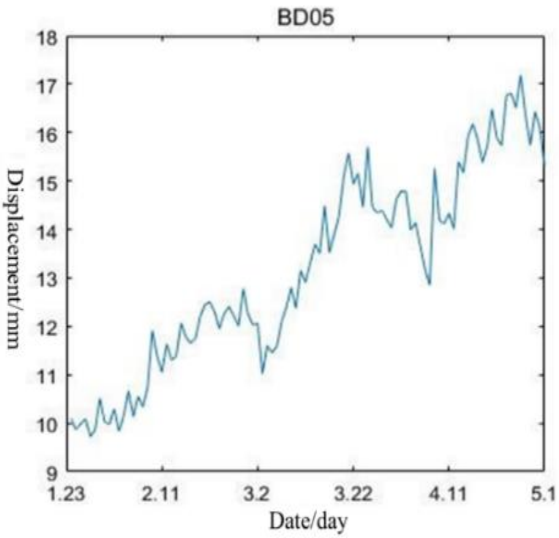


**Fig. 1.** Monitoring data after pre-processing

From the image it can be seen that the BD05 monitoring point exhibits an overall trend upward continuous oscillation. The first 90 periods are used as the training set and the last 10 periods are used as the test set for the model.

## 3.1 ARIMA Prediction Modeling

In this study, SPSS27 was mainly used to analyze the BD05 monitoring data, and before performing the ARIMA prediction model, the data were first observed for seasonal components, and the sequence diagram is shown in Figure 2[7,8].

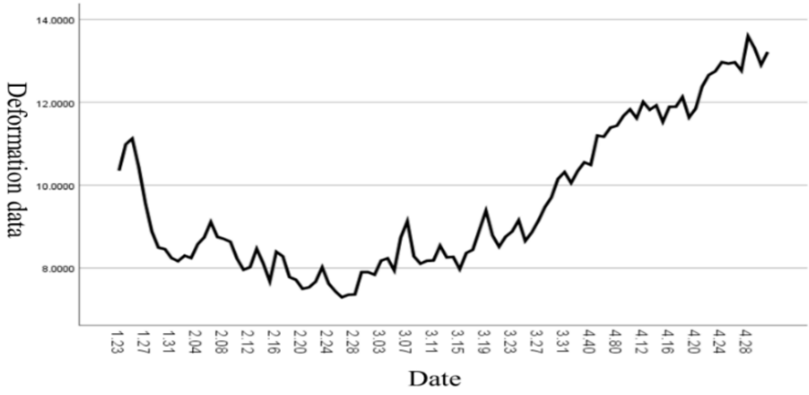


**Fig. 2.** Sequence diagram of monitoring data

From Figure 2, it can be seen that the series has no significant seasonal component, so there is no need to do seasonal decomposition. It can be further analyzed and since the ARIMA model requires the series to be a smooth series, the data is analyzed for smoothness and the autocorrelation plot (ACF) and partial autocorrelation plot (PACF) are shown in Figures 3 and 4:

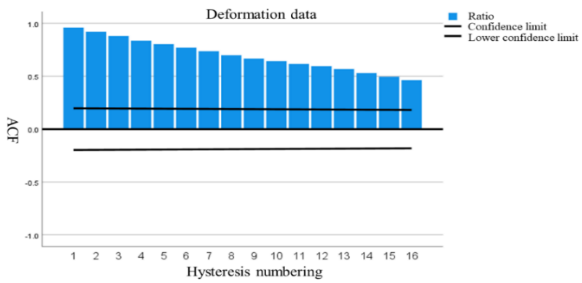


**Fig. 3.** Autocorrelation diagram

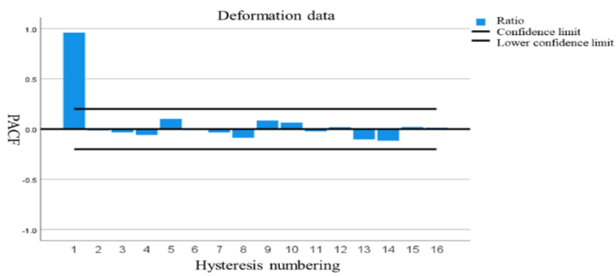


**Fig. 4.** Partial autocorrelation diagram

From the above figure, it can be seen that the serial autocorrelation plot and partial autocorrelation plot are trailing, indicating that the series is non-stationary, so it is necessary to do further analysis through the difference, the first-order difference of the data, plotting the difference sequence graph as shown in Figure 5.

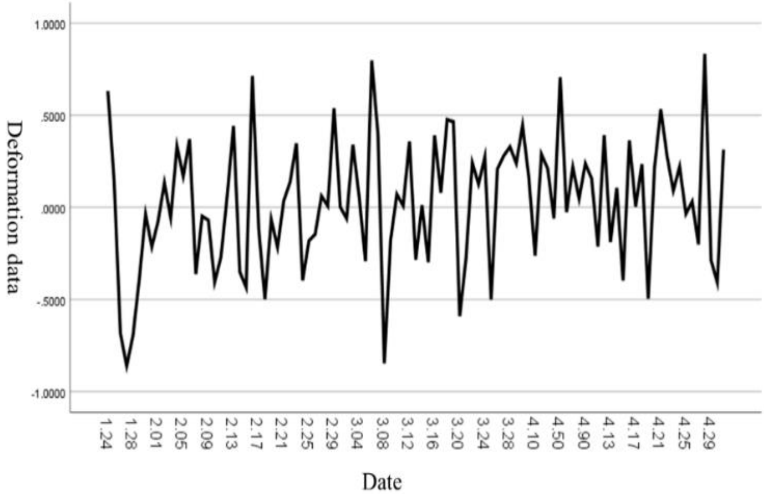


**Fig. 5.** Plot of first-order difference series

From the above figure, it can be seen that the data are basically uniformly distributed above and below the 0 scale, so the difference series can be considered to be smooth. Observe the autocorrelation and partial autocorrelation of the first order difference series, as shown in Fig. 6 and Fig. 7:

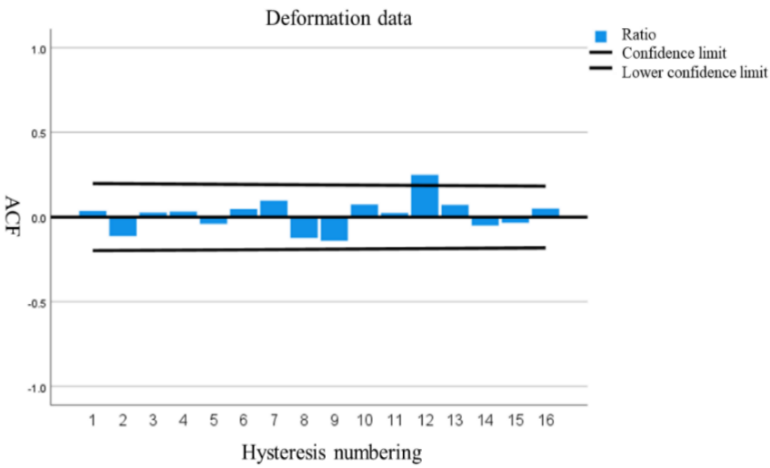


**Fig. 6.** First-order difference sequence ACF plot

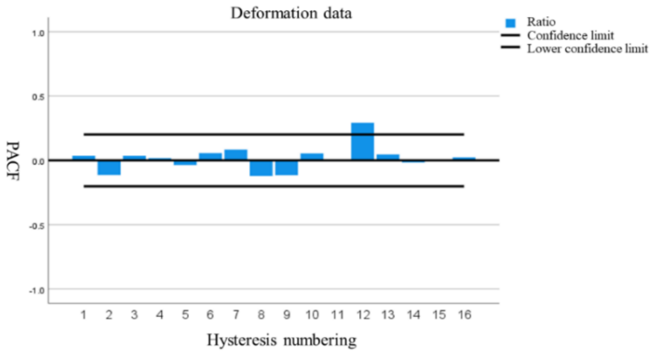


**Fig. 7.** PACF plot of first-order difference series

From the above figure, it can be seen that the ACF and PACF of the first-order difference sequence are trailing, so an ARIMA (p, 1, q) model can be built for the original sequence, and the model is determined to be ARIMA (1, 1, 1) after several repetitive experiments.

### 3.2 Analysis of Forecast Results

In order to test the advancement and feasibility of the ARIMA-GRNN model based on residual correction, the first 90 periods of data from monitoring point BD05 were selected for modeling, and the remaining 10 periods of data were predicted by applying 1) ARIMA model; 2) GRNN neural network; 3) BP neural network; 4) residual-corrected ARIMA-GRNN model; and 5) residual-corrected ARIMA-BP model, respectively. The prediction results and residuals are shown in Figure 8.

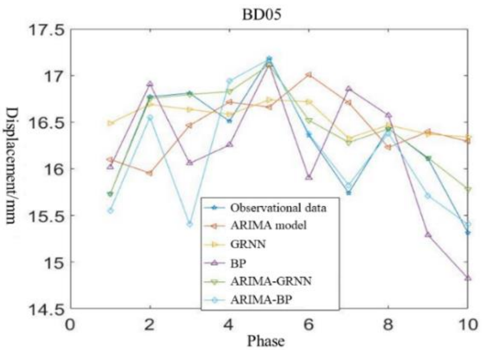


**Fig. 8.** Projected results

Figure 8 demonstrates the performance of five different prediction models on the BD05 dataset, from which it can be observed that there are obvious differences in the prediction accuracy of the models. The prediction results of the ARIMA-BP model and the ARIMA-GRNN model are much more stable and close to the actual observed values, especially in the prediction period between the 6th and 10th period, these two hybrid models show higher prediction accuracy and lower volatility. In contrast, the single ARIMA model and the BP neural network show better accuracy at some time points, but are more volatile and less predictively stable overall.The GRNN neural network performs between the single model and the hybrid model, showing some predictive ability, but does not perform as well as the hybrid model when faced with extreme data points. This suggests that choosing the right model is critical in real-world applications, and that a hybrid model that combines multiple prediction techniques can provide more reliable and stable prediction results.

### 3.3 Accuracy Assessment Criteria

In order to verify the validity of ARIMA-GRNN based model, mean square error (MSE), mean absolute error (MAE), and mean relative error (MRE) are selected as the criteria for accuracy assessment in this paper[9,10].

**Table 1.** Comparison of the accuracy of the models

| Mould | MSE | MAE | MRE |
|---|---|---|---|
| ARIMA-GRNN model with residual correction | 0.0246 | 0.1237 | 0.7092 |
| ARIMA-BP model with residual correction | 0.0288 | 0.1344 | 0.7256 |
| ARIMA model | 0.0311 | 0.1437 | 0.8318 |
| GRNN neural network | 0.0527 | 0.1923 | 1.0806 |
| BP neural network | 0.0709 | 0.2121 | 1.2189 |

From Table 1 it can be seen that the residual corrected ARIMA-GRNN model MSE, MAE and MRE have the lowest values among all the compared models. It can be seen that the model possesses high prediction accuracy and lowest error, and it is feasible to apply it to the study of high slope deformation data.

## 4 Conclusions

In this study, a time series prediction model based on the ARIMA model was firstly established, and the linear trend and periodicity characteristics of the data were successfully identified by analyzing the historical records of the high slope deformation data; then, the accuracy of the prediction model was further improved by introducing the residual correction of the ARIMA model by the GRNN neural network. The ARIMA-GRNN model based on residual correction proposed in this study shows high accuracy and reliability in the prediction of high slope deformation. Through the residual correction technique, this model not only captures the linear relationship in the data, but also effectively simulates the nonlinear dynamics, which is often difficult to achieve when using the ARIMA or GRNN model alone. In the accuracy assessment, the residual-corrected ARIMA-GRNN model outperforms the residual-corrected ARIMA-BP model and the traditional ARIMA model as well as the GRNN neural network, showing lower mean squared error and mean absolute error, which proves its potential in practical applications. The main innovation of this paper is the application of GRNN to residual correction, which not only improves the model's ability to capture nonlinear patterns, but also optimizes the stability and reliability of the prediction results.

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