


Research Article

A Discrete-Time Model-Based Method for Predicting Settlement of Geotechnical Foundations in Buildings

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The selection of a single prediction method is difficult to adapt to the actual engineering situation in the construction geotechnical foundation's settlement prediction. This article proposes a modified optimized comprehensive prediction model to independently mine the construction geotechnical foundation settlement monitoring data from different angles. The proposed model analyzes the construction geotechnical foundation settlement's change law and realizes the comprehensive prediction of construction geotechnical foundation settlement. Initially, the preliminary integrated discrete-time prediction model is established based on the combination of the hyperbolic method and the GM (1, 1) model's modeling mechanism. The GM (1, 1) modeling mechanism is based on the idea of arithmetic weighted average combination. Then the real-time correction weight coefficients are constructed and the real-time correction amount is calculated to modify the initial integrated prediction model. The modified optimized integrated prediction model is established too. Finally, the modified optimized integrated prediction model is utilized to predict the settlement of building geotechnical foundations. The experimental results of A-Ma city project, China show that the modified optimized integrated prediction model has better prediction accuracy and has universal applicability than the hyperbolic method and GM (1, 1) in the prediction of foundation settlement of building geotechnical foundations. It can effectively reduce the prediction error after the combination of single methods.

1. Introduction

Construction operations upon unstable foundations are becoming increasingly common as the scope of urban construction continues to grow. The failure to provide adequate supervision in the geological survey, design, construction, monitoring and other areas may result in mishaps. These catastrophes include uneven settlement of foundations, cracking of walls, and tilting of buildings [1–3]. It is possible that the aforesaid scenario will occur and the structure will be demolished without any prior planning that will result in several difficulties including resource waste and environmental degradation [4–7]. The deformation of the foundation will have a direct impact on the safety of the superstructure as well as its ability to function normally. The settlement of the rock-soil foundation of the building will

not only have an impact on the structural integrity of the building, but it will also raise safety concerns. It is possible to control engineering difficulties in advance by using settlement prediction results for building rock and soil foundations. This can help to minimize safety mishaps as well as property losses. The results of settlement prediction can also be used to guide later construction.

In today's world, settlement prediction of building rock and soil foundations is primarily divided into two categories. The first category is to predict the actual situation based on the principle of soil mechanics. In this category, most of the results are unable to describe the actual settlement accurately because of the large difference between a model and the actual situation [8, 9]. The other category is to excavate the settlement. Predictions are made using the quantitative change law that is used in a variety of ways. The most

common are the grey theory, the hyperbolic approach, and the exponential curve method [7, 10–13]. Building geotechnical settlement results show that the grey theory and hyperbolic method have good prediction effects for soft soil settlement prediction. However, the prediction accuracy will be subject to assumptions condition affects in the future because both grey theory and hyperbolic method predict under certain assumptions. It is important to keep in mind while utilizing the single-item technique to anticipate the settlement of soft soil is the matching between that method and the real phenomena. The prediction findings will be difficult to utilize to guide actual engineering if it is not taken into consideration. Combined forecasting is a way of mining sample data information from numerous aspects by combining separate single forecasting methods [14]. This method can effectively reduce forecasting mistakes by mining information from multiple aspects independently [15, 16].

The modeling mechanism of the hyperbolic technique and GM (1, 1) is explored in detail in this study. The hyperbolic method and GM (1, 1) are merged using the arithmetic weighted combination approach to achieve the best results. In this section, we revise the preliminary comprehensive prediction model and the revised and optimized comprehensive prediction model is established to predict the settlement of the rock-soil foundation of the building. An engineering example is provided for verification of the comprehensive prediction model [17–19].

The rest of the paper is presented as follow. The proposed discrete-time forecasting model is presented in Section 2. The experimental results and discussion is provided in Section 3. Finally, the paper is concluded in Section 4.

2. Proposed Discrete-Time Forecasting Model

The modeling principle of the discrete-time prediction model is primarily divided into two major parts. One is based on the arithmetic average weighted combination method to combine the predicted value of hyperbolic subsidence and the predicted value of GM (1, 1) settlement to achieve the comprehensive predicted value of the settlement and the actual monitoring value. The second is based on the arithmetic average weighted combination method to combine the predicted value of GM (1, 1) settlement and the actual monitoring value to achieve the comprehensive predicted value. To begin with, it is presumed that the total prediction error of the combined settlement value is the smallest. Secondly, it is presumed that the total fluctuation of the combined predicted value of the settlement and actual monitoring value is the smallest. Thirdly, it is presumed that the predicted value of each combination is revised to bring the predicted value of each combination as close as possible to the actual monitoring value. Building a discrete-time forecasting model is separated into two steps. The first step is building a preliminary comprehensive forecasting model, then building a revised and optimized comprehensive forecasting.

2.1. GM (1, 1) Model Description. Let the original data sequence $X = (x(1), x(2), \dots, x(n))$, and let

$$XD = (x(1)d, x(2)d, \dots, x(n)d), \quad (1)$$

where $x(1), x(2), \dots, x(n)$ are the specific values of each element of the original data sequence and $x(1)d, x(2)d, \dots, x(n)d$ are the original data. The specific value of each element of the sequence after the buffer operator is applied, where

$$x(k)d = \frac{1}{n-k+1} [x(k) + x(k+1) + \dots + x(n)]. \quad (2)$$

Let the original data sequence of n elements be $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, first perform the weakening buffer operator processing on the original sequence and then linearize the obtained sequence $P^{(0)}$ transformation. The linear transformation function used is $y = 0.5P^{(0)}(n) + R$ (R is a constant), then the final new sequence is

$$M^{(0)} = (M^{(0)}(1), M^{(0)}(2), \dots, M^{(0)}(n)). \quad (3)$$

Accumulate (1-AGO) the obtained new sequence $M^{(0)}$ once to get the sequence $M^{(1)}$

$$M^{(1)} = (M^{(1)}(1), M^{(0)}(2), \dots, M^{(1)}(n)), \quad (4)$$

where $M^{(1)}(k) = \sum_{i=1}^k M^{(0)}(i)$, $k = 1, 2, \dots, n$.

Calculate the immediate mean generation sequence of $M^{(1)}$ to get the background value sequence $Z^{(1)}$.

$$Z^{(1)}(k) = 0.5M^{(1)}(k) + 0.5M^{(0)}(k-1), \quad k = 2, 3, \dots, n. \quad (5)$$

According to the grey theory, the whitening differential equation for establishing the GM (1, 1) model is as follows

$$\frac{dM^{(1)}(t)}{dt} + aM^{(1)}(t) = b, \quad (6)$$

where a is the development coefficient and b is the ash action.

The least squares estimate of the grey GM (1, 1) model parameter column $u = (a, b)^T$ is

$$u = (a, b)^T = (B^T B)^{-1} B^T M, \quad (7)$$

where

$$B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix}, \quad (8)$$

$$M = \begin{pmatrix} M^{(0)}(2) \\ M^{(0)}(3) \\ \vdots \\ M^{(0)}(n) \end{pmatrix}.$$

The parameters “ a ” and “ b ” obtained from equation (7) are brought into equation (6), and the model time response equation of equation (9) is obtained after solving the differential equation.

$$M^{(1)}(k+1) = \left[M^{(0)}(1) - \frac{b}{a} \right] e^{-ab} + \frac{b}{a}, \quad k = 1, 2, \dots, n-1. \quad (9)$$

According to equation (10), the result of equation (9) is reduced by IAGO once to get the prediction result $M^{(0)}$

$$M^{(0)}(k+1) = M^{(1)}(k+1) - M^{(1)}(k). \quad (10)$$

Because the linear transformation is performed on the sequence obtained after the buffer operator acts, it is necessary to restore the obtained result $M^{(0)}$ to obtain the final simulated value.

2.2. Construction of Preliminary Comprehensive Prediction Model. The construction of the preliminary comprehensive prediction model is elaborated in this section. This model is composed of different steps. The model is used to predict the construction properties. The detail about the step are provided in detail.

- (1) Using the GM (1, 1) model and the hyperbolic method for prediction, the predicted values $M^{(1)}$, $M^{(2)}$, of the settlement of soft soil foundation can be obtained respectively.
- (2) Since the arithmetically weighted average combination can achieve better prediction accuracy, this paper adopts the arithmetically weighted average combination to forecast:

$$M^{(0)}(k) = \omega_1 \times M^{(1)}(k) + \omega_2 \times M^{(2)}(k), \quad (11)$$

where $M^{(1)}(k)$ represents the subsidence predicted by the grey theory; $M^{(2)}(k)$ represents the subsidence predicted by the hyperbolic method. In addition, $M^{(0)}(k)$ represents the subsidence predicted by the preliminary comprehensive prediction model and ω represents Preliminary combination weight coefficient, an $\omega_1^2 + \omega_2^2 = 1$.

- (3) The following objective function is constructed to characterize the total difference between the predicted value of the settlement combination and the actual monitoring value. ω_1 and ω_2 corresponding to the minimum value of the objective function are the initial combination weight coefficient values.

$$\begin{aligned} \min \sum_{k=1}^n F(k) &= \sum_{k=1}^n \left(\frac{M^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right) \\ &= \sum_{k=1}^n \left(\frac{\omega_1 \times M^{(1)}(k) + \omega_2 \times M^{(2)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right), \end{aligned} \quad (12)$$

where $x^{(0)}(k)$ represents the actual monitored settlement value at each moment. By debugging ω_1 and ω_2 , making the above formula get the minimum value and output the value of ω_1 and ω_2 as the value of the combined weight coefficient of the preliminary comprehensive prediction model.

2.3. Development of Discrete-Time Prediction Models. The central concept of comprehensive forecast value correction is to create real-time correction weight coefficients and utilize real-time correction values to correct comprehensive forecast values. This is performed to reduce the predicted discrepancy between comprehensive forecast value and real monitoring value. The development of the discrete-time prediction models is described in this step. It involves three activities.

2.3.1. Determination of Real-Time Correction Weight Coefficient. This is because each single prediction technique uses past monitoring data from a different perspective and is independent of the application of historical monitoring data, which explains why the combination of single prediction methods can improve the prediction performance of the model. It is necessary to quantify the amount of independent information contained in the data. The real-time correction weight coefficient increases in direct proportion to the amount of independent information contained in the data. There are two main aspects to consider when measuring the independent information contained in the data: first, the resolution coefficient, which is used to measure the effective information between the predicted value of the hyperbolic subsidence, the predicted value of GM(1, 1), and the actual monitoring data; and second, the resolution coefficient, which is used to measure the effective information between the predicted value of the hyperbolic subsidence, the predicted value of GM(1, 1) and the actual monitoring data. The correlation coefficient, on the other hand, is used to determine the degree of overlap in information consumption between the expected value of hyperbolic subsidence and the predicted value of GM (1, 1), which is the second step. The following is the formula for calculating the real-time corrective weight coefficient in this case:

$$p^{(i)}(k) = \frac{M^{(i)}(k) |\xi^{(i)}k - \rho_{12}|}{\sum_{i=1}^2 M^{(i)}(k) |\xi^{(i)}k - \rho_{12}|}, \quad (13)$$

where $\xi^{(i)}k$ represents the resolution coefficient corresponding to the predicted value of the i th method at time k ; $M^{(i)}$ represents the settlement amount obtained by the single prediction method; ρ_{12} is the predicted value of the hyperbolic method settlement and the GM(1, 1) settlement. The correlation coefficient between predicted values, the resolution coefficient and the correlation coefficient are all commonly used physical quantities.

The real-time correction weight coefficients $P_1(k)$ and $P_2(k)$ of GM (1, 1) and hyperbolic method can be obtained respectively from the above formula, and the idea of the curve fitting method in settlement prediction can be used for reference 13. By fitting the modified weight coefficient data,

the hyperbolic method and GM (1, 1) corresponding to the real-time modified weight coefficient variation with time k can be obtained, and the real-time modified weight coefficient can be predicted by this functional formula.

2.3.2. Combined Forecast Values. The real-time correction amount of the combined forecast value can be obtained by corresponding to the real-time correction coefficient, the preset value of the hyperbolic method settlement, and the predicted value of GM (1, 1) settlement:

$$\Delta = (M_0^{(n)}(k) - M^{(1)}(k))p_1(k) + (M_0^{(n)}(k) - M^{(2)}(k))p_2(k), \quad (14)$$

where $M_0^{(n)}(k)$ is the fitting function of the actual foundation settlement data curve; $M^{(1)}(k)$ is the predicted settlement value of GM(1, 1); $M^{(2)}(k)$ is the predicted settlement value of the hyperbolic method; $p_1(k)$ and $p_2(k)$ are the real-time correction weight coefficients of GM(1, 1) and hyperbolic method, respectively.

2.3.3. Real-Time Values Utilization. Use the obtained real-time correction to correct the predicted value of combined settlement:

$$M_0^\Delta(k) = M^{(0)}(k) + \Delta, \quad (15)$$

where $M^{(0)}(k)$ represents the settlement amount predicted by the preliminary comprehensive prediction model; $M_0^\Delta(k)$ represents the settlement prediction value of the revised and optimized combined prediction model. By solving the model, the settlement amount predicted by the revised optimal combination can be obtained, and the prediction result of the revised optimal combination can be compared with the actual monitoring value, the settlement prediction result of the hyperbolic method, and the GM (1, 1) settlement prediction result.

3. Results and Discussion

The results of engineering examples and an explanation of the findings are presented in this section. The A-Ma City project is utilized to realize the proposed model. The results of the A-Ma City project illustrate that the adapted optimized mode of prediction has better accuracy than the hyperbolic method and GM (1, 1) in the prediction of foundation settlement of building geotechnical foundations. It can effectually decrease the error of prediction after the combination of single methods. Moreover, it is universally applicable.

3.1. A General Outline of the Project. A-Ma City's core area has been subjected to a thorough assessment of data about land reclamation, inner bay coast protection, and road foundation treatment projects to determine the feasibility of the model in a realistic setting. Silty clay, powdery clay, and partly muddy medium sand are used as the construction geotechnical foundation when building an infrastructure

project in A-Ma City's central business district. However, the thickness of the construction geotechnical layer is unevenly distributed. The engineering geological conditions are poor and the foundation settlement has a significant impact on the project.

3.2. The Outcome of the Calculation. The measured data of ZH KO +300 and DH K3 +800 monitoring points of A-Ma City core area reclamation, inner bay shore protection, and road foundation treatment project were selected as samples using the modified optimization integrated prediction model. The sample data was analyzed and predicted using the modified optimization integrated prediction model are shown in Table 1.

The predicted settlement values of monitoring points ZH K0 +300 and DH K3 +800 were calculated according to GM (1, 1) and hyperbolic method modeling steps. The predicted results are shown in Table 2.

The real-time correction weight coefficients of ZH KO +300 and DHK3 +800 monitoring points are calculated using equation (3) for each prediction period. It was fit for the real-time correction weight coefficients of ZH KO +300 and DH K3 +800 monitoring points to obtain the expressions of real-time correction weight coefficients respectively. The ZH K0 +300 and DH K3 +800 are calculated using the following formulas:

$$\begin{aligned} \text{For ZH K0 +300: } & p_1(k) = 0.4621 + 0.0963 \sin(k - 5.0605/0.001366) \\ \text{For DH K3 +800: } & p_1(k) = 0.5688 + 0.0951 \sin(k - 1.9861/3.546810) \end{aligned}$$

The inclusive estimation of foundation settlement at monitoring points ZH K0 +300 and DH K3 +800 is carried out using equations (14) and (15). The prediction results of the modified and optimized comprehensive prediction model are shown in Table 3.

Comparing the predicted settlement values of ZH KO +300 and DH K3 +800 monitoring points obtained by the three methods, it can be found that the predicted settlement values obtained by the proposed prediction model are closer to the real monitoring data. The proposed prediction model can more truly reflect the change of settlement of building geotechnical foundations than the two methods of hyperbolic method and GM (1, 1). The comparison between the calculated and measured displacement values is shown in Figures 1 and 2.

3.3. Model Applicability Analysis. The sensitivity analysis of the prediction model proposed in this paper should be carried out to verify the applicability of the modified optimized integrated prediction model. The difference range of the monitoring data at the monitoring point ZH KO +300 is set to 10% considering the variance of the actual data of the building geotechnical foundation settlement monitoring. Therefore, the input value of the modified optimized integrated prediction model is between 90% and 110% of the reference value. The sensitivity analysis results are compared

TABLE 1: Actual settlement of monitoring point ZH K0 +300 and DH K3 +800.

Number	1	2	3	4	5	6	7
Time/d	0~60	60~120	120~180	180~240	240~300	300~360	360~420
ZH K0 +300 settling volume/mm	79.31	68.54	55.36	48.56	44.37	37.41	36.84
DH K3 +800 settling volume/mm	92.22	84.33	75.46	57.18	47.35	34.48	31.52

TABLE 2: Settlement prediction results of GM (1, 1) and hyperbolic model.

Number	ZH K0 +300			DH K3 +800		
	True (mm)	GM (1, 1) (mm)	Hyperbolic (mm)	True (mm)	GM (1, 1) (mm)	Hyperbolic (mm)
2	68.54	64.96	67.12	84.33	86.78	79.91
3	55.36	57.21	57.63	75.46	70.79	66.65
4	48.56	50.38	50.02	57.18	57.74	56.43
5	44.37	44.37	43.83	47.35	47.1	48.40
6	37.41	39.07	38.71	34.48	38.42	41.96
7	36.84	34.41	34.45	31.52	31.34	36.73

TABLE 3: Comparison of settlement prediction results of monitoring points.

Number	ZH K0 +300			DH K3 +800		
	True (mm)	Our (mm)	Error (%)	True (mm)	Our (mm)	Error (%)
2	68.54	69.64	-1.60	84.33	87.14	-3.33
3	55.36	55.54	-0.33	75.46	77.05	-2.11
4	48.56	48.38	0.37	57.18	58.65	-2.57
5	44.37	44.14	0.52	47.35	46.91	0.93
6	37.41	37.24	0.45	34.48	33.33	3.34
7	36.84	36.86	-0.05	31.52	30.86	2.09

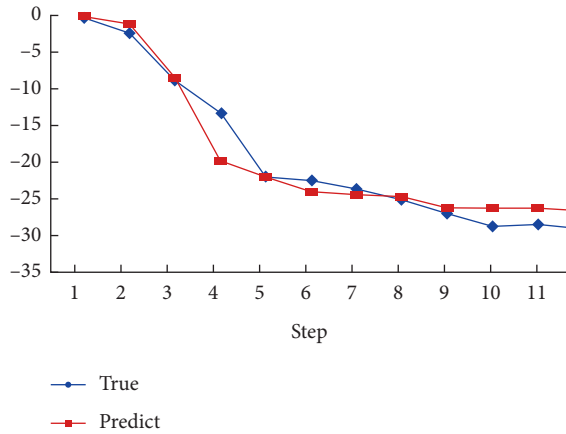


FIGURE 1: Comparison of calculation results with monitoring values.

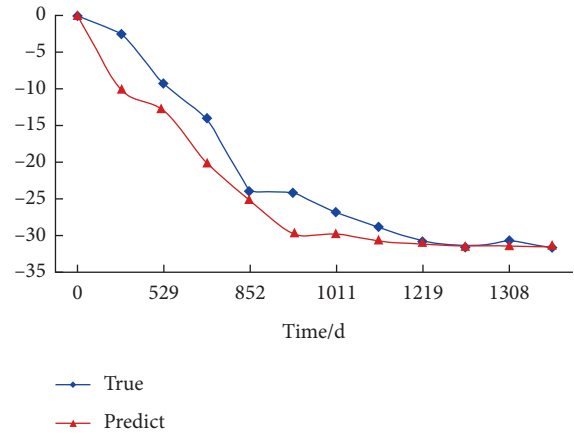


FIGURE 2: Comparison of calculation results with monitoring values.

with hyperbolic method and the grey GM (1, 1). The results of sensitivity analysis of hyperbolic method were compared and shown in Figures 3 to 7. A sensitivity study of ZH KO +300 monitoring points was carried out over five time periods of 120–180 d, 180–240 d, 240–300 d, 300–360 d, and 360–420 d. It can be seen that the prediction straight of the GM (1, 1) and hyperbolic method in the five plots is located on the same side of the actual monitoring value in Figure 3.

The accuracy of this specific model is better than that of the GM (1, 1) and hyperbolic method respectively. The predicted values of building foundation settlement in the five

time periods of the prediction model proposed in this paper are approximately linearly changed when the original sample data changes from 90 percent to 110 percent according to Figures 3 to 7. Figure 4 shows the sensitivity analysis results in 180~240 d and the sensitivity analysis results in 240~300 d is shown in Figure 5.

The results show that the proposed model has decent steadiness and does not vary the applicability of the model as a result of the variation in the original data. A reasonable arrangement of applicability occurs for the proposed prediction model in the field of building foundation settlement

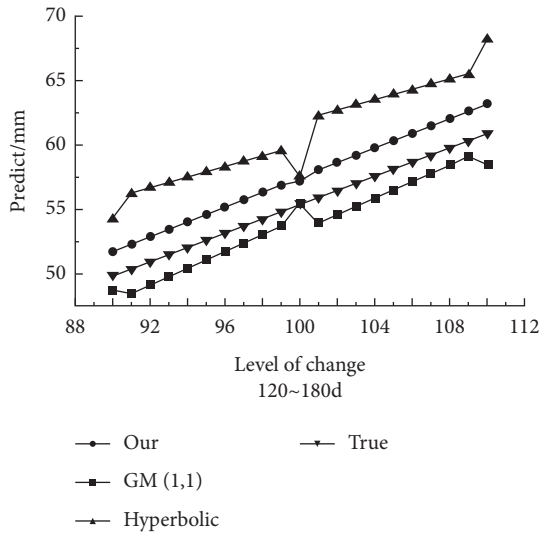


FIGURE 3: Sensitivity analysis results in 120~180 d.

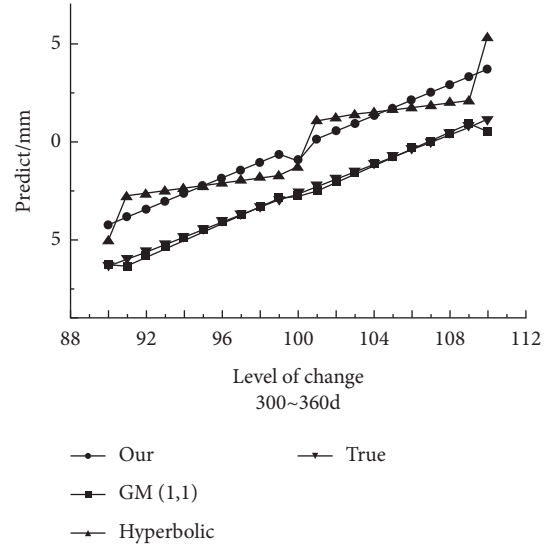


FIGURE 6: Sensitivity analysis results in 300~360 d.

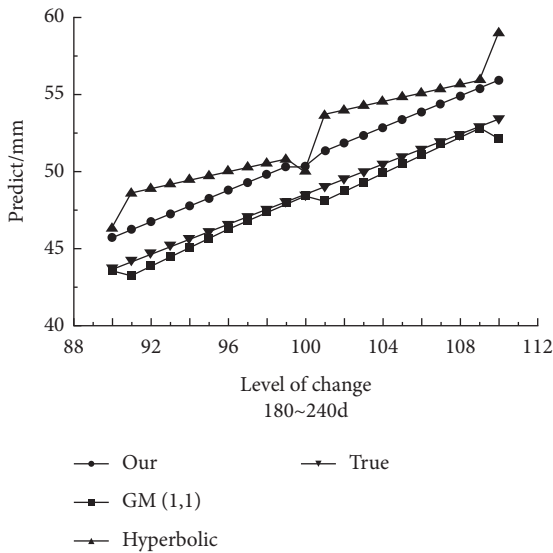


FIGURE 4: Sensitivity analysis results in 180~240 d.

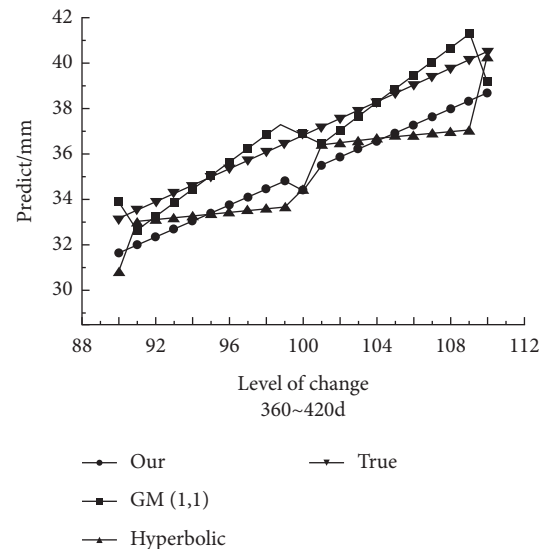


FIGURE 7: Sensitivity analysis results in 360~420 d.

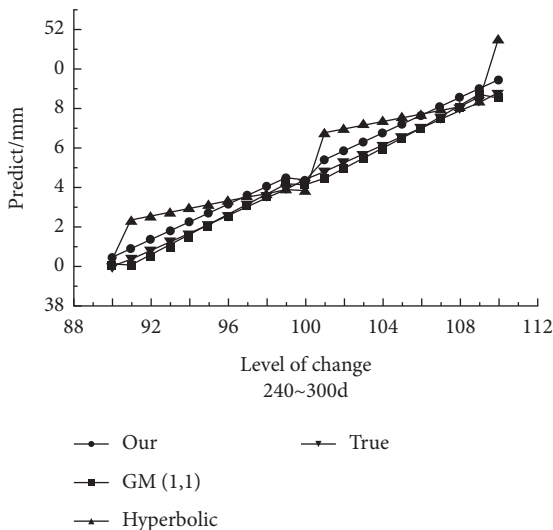


FIGURE 5: Sensitivity analysis results in 240~300 d.

prediction. Building rock settling might be predicted with realistic accuracy using the proposed prediction model. Results of sensitivity analysis reveal that both the prediction models (GM (1, 1) and the hyperbolic approach) are essentially linear in their predictions of soft ground settlement over a five-year time span. In soft ground settlement prediction, since GM (1, 1) and hyperbolic method are both more perfect classical prediction methods, and because GM (1, 1) and hyperbolic method have high prediction stability, it follows that the modified optimized integrated prediction model will also have high prediction stability.

4. Conclusion

The settlement of building geotechnical foundations at the monitoring points ZH KO +300 and DH K3 +800 of the

reclamation in this research. The inner bay shore protection and road foundation treatment project in the core area of A-Ma City was predicted. The results were compared to actual measured data. The proposed work is the definition of real-time correction coefficient. We develop a discrete-time prediction model based on the real-time correction coefficient. The discrete-time prediction model is applied to predict the settlement of construction foundations. The settlement values predicted by GM (1, 1) and the hyperbolic method can significantly improve the prediction accuracy after they are combined with other single prediction methods. The proposed model improves the prediction accuracy regardless of whether the settlement values are located on the same side or the other side of the actual monitoring values based on the discrete-time prediction model. The findings of the sensitivity analysis revealed that the suggested model has excellent prediction stability and universal applicability in the prediction of settlement of building geotechnical foundations when compared to standard algorithms such as the GM (1, 1) and hyperbolic technique.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that no conflicts of interest.

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