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Accident prediction of project construction based on gray system theory

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ABSTRACT

In engineering practice, security incident in real terms is a gray system, so it is possible to predict the accident using gray system theory. In this article, we established the prediction model for pit deformation based on gray system theory, and predicted the pit deformation in future adopting actual project monitoring data. The results are in good agreement with the measured values, indicating the prediction model has good accuracy and has positive significance in guiding informationizaton construction of excavation engineering. We establish the metabolism model to improve the accuracy of the prediction model. Practice has shown that the accuracy of the metabolism model is higher than that of the old information model; the predicted results are consistent with the measured data.

KEYWORDS

Gray system; Security incident; Prediction.

INTRODUCTION

Safety prediction can be divided into macro-forecast and micro-forecast according to objects to be predicted. Macro forecast mainly studies the trends of safety accidents of an enterprise or department; micro-forecast researches the dangerous source, the probability of accidents and their risk degree of a specific system[1]. Currently, engineering safety incidents are predicted mainly using m method and finite element method[2]. Because of the difference between the ideal model and the actual working conditions as well as the calculation parameter is difficult to correctly determine, the calculated value is different to that of the actual situation. Therefore, it is essential to find a more effective prediction method for engineering safety incidents, which is able to predict the new developments that may occur in the next phase of construction according to the measured information of the site, and provide reliable information for optimized design and reasonable construction during the construction process. A variety of forecasting models and methods are used: traditional gray prediction, time series analysis (AR method, ARMA method, NAR method, TAR method, NARMA method and SMD method) and genetic-neural network method combining the nonlinear mapping ability of artificial neural networks with the global random search capability of genetic algorithm[3]. But most of these methods are limited to single point modeling and forecasting, that is, the model is established based on the early measured deformation data of a single monitoring point of the construction projects to obtain the subsequent forecast on this point; this prediction model is only a partial study, and cannot take into account the interaction between the monitoring points, and cannot fully take advantage of the relative information of the monitoring points[4]. In engineering practice, a safety accident on a monitoring point is not isolated, but be influenced by other monitoring points and affect the safety of other monitoring points. Therefore, the trend and regularity of the project should be described as a whole from the viewpoint of observing system. The whole observation data should be handled correctly, to establish a reasonable model to make an accurate prediction of the accident. The multi-variable gray prediction model introduced in this paper is based on this thought. On the basis of the traditional model, considering the interaction between n points, establish n-order ordinary differential equations by extension; taking the MATLAB software as computing platforms, export the multi-variant gray model, thus achieving the modeling of multi-point prediction model. In this work, we established the multi-variable gray forecast model based on the real-time monitoring data of a construction project, to accurately predict the possible accident, which plays an active role in guiding informationizaton construction and avoiding project risks. The work implements macro forecast on construction work accident and predictive analysis using grey system theory.

CONSTRUCTION ACCIDENT PREDICTION MODELS BASED ON GRAY SYSTEM THEORY

Gray system theory is a theory exerting features of both hard and soft science proposed by Professor Deng Julongin the early 1980s[5]. According to this theory, systems with entirely clear information are defined as white system, systems with entirely unclear information are defined as black system, and systems with part clear and part unclear information are defined as gray system. The gray forecast mainly includes series prediction, interval prediction, disaster prediction, topology prediction and system prediction[6]. These prediction methods have been widely used in practice. The following is a brief introduction to the basic principles of the gray prediction:

Step 1: level compare examination, modeling feasibility analysis: Create the original data series based on the calendar year accident sample data of the analysis object (such as the total accidents, industrial accidents or corporate accidents):

$$x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\} \quad \textbf{(1)}$$

Check the level compare $\sigma^0(k)=\frac{x^{(0)}(k\text{-}1)}{x^{(0)}(k)}(k=1,2,\cdots,n)$, if $\sigma^0(k)\in(e^{-\frac{2}{n+1}},e^{\frac{2}{n+1}})$, then $\mathrm{GM}(1,1)$ modelling is feasible for $x^{(0)}$.

Step 2:carry out cumulative processing on the above-described series according to formula (2):

$$x^{(1)}(k)=\sum_{j=1}^{k}x^{(0)}(j)\quad(k=1,2,\cdots,n) \tag{2}$$

Generate sequences:

$$x^{(1)}=\left\{x^{(1)}(1),x^{(1)}(2),x^{(1)}(3),\cdots,x^{(1)}(n)\right\} \tag{3}$$

Step 3:establish the equation with white form, namely the first order differential equation corresponding to the $\mathrm{GM}(1,1)$ model:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b \tag{4}$$

Here a is the development factor, b is the grey action quantity; both a and b are coefficients to be determined.

Step 4:obtain the coefficient vector of differential equations by the method of least squares:

$$\bar{a}=\begin{bmatrix}a\\b\end{bmatrix}=(B^TB)^{-1}B^TY_N \tag{5}$$

Where : $Y_N=\left\{x^{(0)}(2),x^{(0)}(3),x^{(0)}(4),\cdots,x^{(0)}(n)\right\}$ **(6)**

$$B=\begin{bmatrix}-\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2)) & 1\\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3)) & 1\\ \vdots & \vdots\\ -\frac{1}{2}(x^{(1)}(n\text{-}1)+x^{(1)}(n)) & 1\end{bmatrix} \tag{7}$$

Step 5: solve the differential equations, obtain the prediction model:

$$\hat{x}^{(1)}(k+1)=(x^{(0)}(1)\text{-}\frac{b}{a})e^{-ak}+\frac{b}{a}\quad(k=1,2,\cdots,n\text{-}1) \tag{8}$$

Step 6: restore the original sequence prediction results by regressing the generated model:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)\text{-}\hat{x}^{(1)}(k)=(1\text{-}e^{a})(x^{(0)}(1)\text{-}\frac{b}{a})e^{-ak} \tag{9}$$

Step 7:compare the calculated values and the original sequence actual values , calculate the residuals:

$$\varepsilon^{(0)}(k)=x^{(0)}(k)\text{-}\hat{x}^{(0)}(k)\quad(k=1,2,\cdots,n) \tag{10}$$

Step 8:check the accuracy of model $\mathrm{GM}(1,1)$:

Calculate the average of the original sequence:

$$\overline{x}=\frac{1}{n}\sum_{k=1}^{n}x^{(0)}(k) \quad (11)$$

Calculate the variance of the original sequence:

$$S_1^2=\frac{1}{n}\sum_{k=1}^{n}(x^{(0)}(k)-\overline{x})^2 \quad (12)$$

Calculate the average of the residuals:

$$\overline{\varepsilon}=\frac{1}{n}\sum_{k=1}^{n}\varepsilon^{(0)}(k) \quad (13)$$

Calculate the variance of the residuals:

$$\varepsilon_1^2=\frac{1}{n}\sum_{k=1}^{n}(\varepsilon^{(0)}(k)-\overline{\varepsilon})^2 \quad (14)$$

Calculate the posterior error ratio C and small error probability P :

$$C=\frac{S_2}{S_1} \quad (15)$$

$$P=P\left\{\left|\varepsilon^{(0)}(k)-\overline{\varepsilon}\right|<0.6745S_1\right\} \quad (16)$$

It is also possible to adopt "residual test," which is a point-by-point test method. Set the relative error Δ_k , average relative error $\Delta_{(avg)}$ and accuracy P^0 as follows:

$$\Delta_k=\frac{|\varepsilon(k)|}{x^{(0)}(k)}\times 100\%=\frac{\left|x^{(0)}(k)-\hat{x}^{(0)}(k)\right|}{x^{(0)}(k)}\times 100\% \quad (17)$$

$$\Delta_{(avg)}=\frac{1}{n-1}\sum_{k=2}^{n}|\Delta_k| \quad (18)$$

$$P^0=(1-\Delta_{(avg)})\times 100\% \quad (19)$$

According to the values of C , P , Δ_k and P^0 , the accuracy can be divided into 4 classes, the criterion of each class are shown in TABLE 1.

TABLE 1: Prediction accuracy class

Prediction accuracy	good	Qualified	Unqualified
C	$C\le 0.35$	$0.35<C\le 0.5$	$0.5<C$
P	$P\ge 0.95$	$0.95>P\ge 0.8$	$0.8>P$
Δ_k	$\Delta_k\le 1\%$	$1\%<\Delta_k\le 5\%$	$5\%<\Delta_k$
P^0	$P^0\ge 99\%$	$99\%>P^0\ge 95\%$	$95\%>P^0$

In the actual modelling, it is not necessary to use all the original data sequence for modelling. A model can be established taking only part of the original data sequence. Generally used models include full data model, new information model and metabolism model, defined as follows: Set the original data sequence as:

$$x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\} \quad \textbf{(20)}$$

The $\mathrm{GM}(1,1)$ model established by $x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\}$ is named as the full data model;

$x^{(0)}(n+1)$ indicates the newest information, substitute $x^{(0)}(n+1)$ into $x^{(0)}$, then the resulted model is called the new information model established by $x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\}$;

Introduce the newest information $x^{(0)}(n+1)$, remove the old information $x^{(0)}(1)$, then the resulted model is called the metabolism model established by $x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\cdots,x^{(0)}(n)\right\}$.

APPLICATION OF THE GRAY PREDICTION MODEL

Overview on the project

A building's total gross floor area is 10,000 m^2, the pit area is approximately 3000$m^2$the circumference of the pit is about 270 m and the excavation depth is 7.0m. The foundation pit support of this project takes the pattern of bored piles plus single layer reinforced concrete support, and deep mixing pile sealing. Due to the deformation of the pit needs to be monitored during the excavating process, monitoring points are set to monitor the horizontal displacement of the support structure, settlement deformation of the buildings near the pit, settlement of the support column pile in the pit, deep horizontal displacement, supporting axial force and the structure envelope pile stress. Select the horizontal displacement data measured at monitoring point 6 to implement the prediction. The monitoring data is the horizontal displacement of the top ring beam, monitoring interval is two days, and the monitoring data are shown in TABLE 2.

The establishment of the model

The prediction model can be built according to the steps described in section 2 of this article. Since the interval of monitoring time of the raw data in this example is of the same, it needs not to be linear interpolated. Accumulating the original data in TABLE 2, we can get:

$$x^{(1)}(k)=\left\{3.0,7.9,12.9,18.8,26.5,34.2,41.0\right\} \quad \textbf{(21)}$$

Where: $x^{(0)}(k)=\left\{3.1,4.9,5.5,6.2,6.7,7.2,7.8\right\}$ **(22)**

The value of B and Y_N can be calculated using formula (5). Carry out the calculation of transpose, product and inversion on B and Y_N, we obtain the coefficient vector $\bar{a}=\left[a,b\right]^T=\left[\text{-}0.0773,4.6575\right]^T$, thus we determine the values of a and b (-0. 0773and 4.6575 respectively). Substitute a and b into formula (8) and (9), we get the prediction model:

$$\hat{x}^{(1)}(k+1)=63.362e^{0.0773}\text{-}61.124 \quad \textbf{(23)}$$

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)\text{-}\hat{x}^{(1)}(k) \quad \textbf{(24)}$$

The prediction results are shown in Figure 2. The a posteriori error ratio $C=0.12$, the accuracy class is good; the small error probability $P=1$, the accuracy class is good; the average relative error $\Delta_{(avg)}=0.024$, the accuracy class is qualified. Now carry out the prediction on the horizontal displacement of the next four time points using the model, the predicted value and the measured value are shown in TABLE 3. The average relative error of the predicted value is 9.75%, we can infer the accuracy of the predicted value is good according to TABLE 2. Figure 1 shows the contrast curve of the measured deformation value and the predicted deformation value; Figure 2 shows the contrast curve of the measured deformation rate and the predicted deformation rate. From the two figures we learn that the measured curves are basically consistent with the predicted curves, indicating the accuracy of this model is good; the predicted deformation rate does not exceed the allowed value of 2mm/d, indicating the model is feasible to predict the short-term horizontal displacement.

TABLE 2: Monitoring values and predicted results of horizontal deformation

Time serial number	1	2	3	4	5	6	7
Measure time	12.5.1	12.5.3	12.5.5	12.5.7	12.5.9	12.5.11	12.5.13
Raw data	2.9	4.9	5.3	6.2	6.8	7.5	7.6
Predictive value	2.9	5.07	5.23	6.09	6.75	7.63	7.69
Relative error	0	0.0347	0.0132	0.0177	0.0074	0.0173	0.0118

TABLE 3: Predict results of later stage

Time serial number	8	9	10	11
Time	12.5.15	12.5.17	12.5.19	12.5.21
Predictive value	8.10	8.77	9.56	10.23
Measured value	7.68	8.05	8.79	9.21
Predictive deformation rate	0.30	0.35	0.38	0.41
Measured deformation rate	0.21	0.21	0.22	0.21

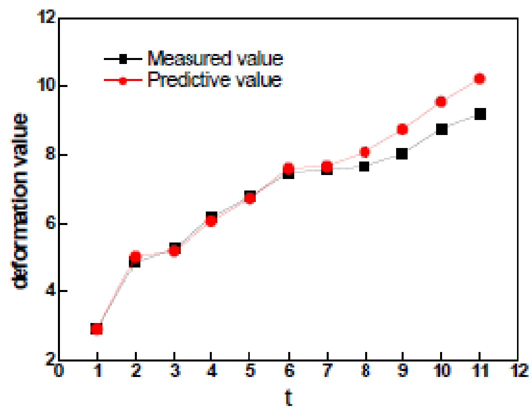

Figure 1: Contrast curves of measured and predicted results of horizontal deformation

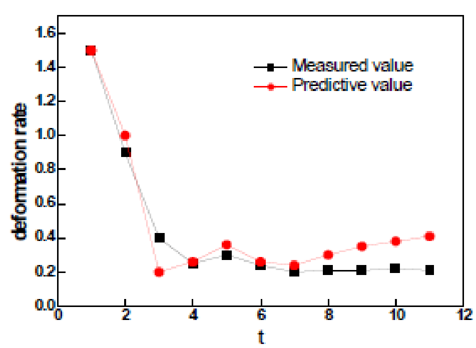

Figure 2: Contrast curves of measured and predicted results of horizontal deformation rate

Comparison between short-term and long-term predictions

In the above we predicted the future four time points using this model, and obtained relatively higher prediction accuracy. Here we carry out prediction at the 5th, 6th and 7th time points, and the prediction results are shown in TABLE 4. Know from TABLE 4, all the relative errors of the prediction values at the 5th, 6th and 7th time points exceed 15%, and the average relative error is 20%. This prediction is feasible, but the accuracy is much lower; as time goes on, the error will be gradually increased. Therefore, the use of this model should be limited in a short period ahead.

TABLE 4: Predict results of later stage

Time serial number	12	13	14
Time	12.5.23	12.5.15	12.5.27
Predictive value	11.05	11.87	12.96
Measured value	9.3	9.5	9.8
Relative error	0.158	0.200	0.244

Comparison between old Information Model and metabolism model

As time goes by, the old data is increasingly not adapted to the new situation, which means that the significance of the old data decreases over time. Therefore, when supply a new information, get rid of one or a few old information using some kind of measure criterion at the same time, so that make timing sequences keep to be a raw data not increasing with time, and this model is called metabolism s model. The horizontal displacement data of the 13th monitoring point of this pit are shown in TABLE 5. First, the prediction is carried out using the old information model, and the predicted results are shown in TABLE 5. From TABLE 5, we can learn that, the relative error of the predicted results at the 5th and 6th time points of the metabolism model is smaller than that of the old information model, indicating the accuracy of the metabolism model is higher than the old information model. Therefore, for situations with stepwise horizontal displacement curves, the metabolism model can be adopted to carry out the prediction, which takes into account some random disturbance factors, and the modelling sequence can reflect the characteristics of the displacement mutation more effectively.

TABLE 5: Predicted results of old information model

Time serial number	1	2	3	4	5	6
Raw data	28.75	32.52	33.20	33.85	36.75	38.72
Predictive value	28.75	32.15	33.41	34.81	36.23	37.63
Relative error %	——	——	——	——	1.41	2.82

CONCLUSIONS

We in this work establish a pit deformation prediction model to predict the deformation and deformation rate of the foundation pit. The results show that the error of the predicted value is very small, and the curves of measured results and predicted results are basically the same, indicating the accuracy of the prediction model is relatively higher.

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