Risk Forecasting Technology During Construction Period of Water Conservancy and Hydropower Projects Based on Modified Grey Model

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Abstract. The risk forecasting and modeling during the construction period of water conservancy and hydropower projects are solved by including early warning of risk in the grey system problem. In order to mitigate the problem of modeling difficulties caused by short sequence and lack of information, change in the parameter function of the data sequence, mutation and discontinuity of the original monitoring data have been overcome. In addition, the traditional grey prediction model is upgraded to increases the focus on new interest so that the system change trend reflected by modified model is investigated profoundly. Similarly, modified model is built based on time-varying parameters that greatly enhanced the fitting and accuracy of the forecasting model. Its application realms prove that the method is effective and reasonable.

1. Introduction

With the beginning of the twenty-first Century, the energy crisis is becoming sever day by day. As clean and renewable energy, hydropower is attracting great amount of attention. But in the construction of several large water conservancy projects, the safety problems are becoming prominent issue, and major hazardous accidents occur frequently, causing great casualties and economic losses. Traditional safety control technology has been unable to meet the construction safety problem for complex construction projects. The monitoring data of hazard sources in the construction period of water conservancy and hydropower projects usually have the characteristics of short sequence, poor information, mutagenicity, discontinuity and so on. This kind of risk forecasting has the typical characteristics of the grey system [1].

At present, the existed grey prediction model is mainly GM (1,1) model [2,3]. Many scholars in China and abroad have carried out deep research for making GM (1,1) successfully applied to many practical problems, but it also found that this traditional GM (1,1) has its own shortcomings, such as the high requirement of smoothness and growth of original data. It is not reliable enough for medium and long-term prediction. Although the monitoring data of water conservancy and hydropower projects

define obvious grey characteristics, they usually have discontinuity and mutagenicity, also their original data are not smooth. At the same time, with the continuous development of the construction, the original monitoring data are increasing, monitoring and forecasting model demand better adaptability. In addition, forecasting has high requirements for medium and long-term prediction during construction period. These characteristics limit the prediction accuracy of GM (1,1). Therefore, it is necessary to improve the GM (1,1) to better adapt to risk forecasting for the construction of water conservancy and hydropower projects [4,5]. Considering the defects of poor data smoothness, lack of applicability of data growth, low accuracy of medium and long-term prediction, modified grey prediction model is proposed based on the data transformation of the parametric function and the time varying parameters.

2. Modified equal dimension grey model based on time-varying parameters

In order to accurately identify the specific state of hazardous sources during construction process and provide a powerful mathematical tool for the safe construction, a new model based on time-varying parameters is established for the monitoring data of water conservancy and hydropower projects. This paper deals with data smoothing, new model based on time varying parameter also introduces basic process and parameters to be considered [6].

2.1. Data transformation with reference functions and equal dimension

It is known that raw data sequences for water conservancy and hydropower projects construction hazard monitoring are given as:

$$x_0^{(0)} = (x_0^{(0)}(1), x_0^{(0)}(2), \cdots, x_0^{(0)}(k)),$$

The digital features of the data sequence were checked and preliminary data processing were carried out, mainly including the initial gross error processing and translation processing. The purpose is to remove the obvious data error and adjust the original data sequence to non-negative data sequence, respectively.

The data obtained from the non-negative data sequence is transformed as:

$$y^{(0)} = (y^{(0)}(1), y^{(0)}(2), \cdots, y^{(0)}(k)),$$

where, $f(x^{(0)}(k), k) = c^{-k}$ (if c>1) is transformation function and $y^{(0)}(k) = x^{(0)}(k) \cdot a^{-k}$ is smooth data sequence. Besides, different kinds of risk analysis data can be selected according to their requirement.

The impact of modified system was increased and the interference of the system was reduced to result the better system which adapt the latest changes. Consequently, it ensures the stability of original data sequence, speed of the modeling and propose the new modification to remove old system. The new system is introduced as Fig1:

$$x^{(0)} = (\underbrace{x^{(0)}(1),}_{\text{decrease}} x^{(0)}(2), \cdots, x^{(0)}(n-1), x^{(0)}(n), \underbrace{x^{(0)}(n+1)}_{\text{increase}})$$

Figure 1. Equal Dimension.

2.2. Time varying parameters

The GM (1,1) modeling requires a cumulative addition to 1-AGO (Accumulating Generation Operator) while taking dimension data in the above unmodified data sequence in which:

$$y^{(1)}(k) = \sum_{i=1}^{k} y^{(0)}(k) \, ; k = 1, 2, \cdots, n$$

The grey model for a cumulative generating operator is built. Its original form is:

$$y^{(0)}(k) + a y^{(1)}(k) = b \, ; k = 1, 2, \cdots, n$$

where, a is the development coefficient and b is grey actuating quantity.

The above cumulative production operators are transformed as follows:

$$z^{(1)}(k) = \frac{1}{2}(y^{(1)}(k) + y^{(1)}(k-1)) \; ; k = 2,3,\cdots,n$$

Where, $z^{(1)}(k)$, $y^{(1)}(k)$ are adjacent mean generation sequence, Then the basic form and Albinism equation of grey model can be obtained as

$$y^{(0)}(k) + az^{(1)}(k) = b \; ; k = 2,3,\cdots,n$$

$$\frac{dy^{(1)}}{dt} + ay^{(1)} = b$$

It can be proved that the least squares estimation satisfies this model.

$$\hat{a} = [a,b]^T = (B^T B)^{-1} B^T Y$$

Where, $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, Y = \begin{bmatrix} y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(n) \end{bmatrix}$;

The solution of Albinism equation is express in the time response function as.

$$y^{(1)}(t) = (y^{(1)}(1) - \frac{b}{a})e^{-at} + \frac{b}{a}$$

The time response sequence of the Albino equation is

$$\hat{y}^{(1)}(k+1) = (y^{(1)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \; ; k = 1,2,\cdots,n$$

where Reduction value

$$\hat{y}^{(0)}(k+1) = (1-e^a)(y^{(0)}(1) - \frac{b}{a})e^{-ak} \; ; k = 1,2,\cdots,n$$

Where $y^{(0)}(k) = x^{(0)}(k) \cdot c^{-k}$ is inverse transfer function and forecasting formula can be expressed as

$$\hat{x}^{(0)}(k+1) = (1-e^a)(x^{(0)}(1) \cdot c^k - \frac{b}{a} \cdot c^{k+1})e^{-ak} \; ; k = 1,2,\cdots,n$$

The calculation of the subsequent recurrence formula can be facilitated with u=b/a. Now above expression can be rewritten as

$$\hat{x}^{(0)}(k+1) = (1-e^a)(x^{(0)}(1) \cdot c^k - u \cdot c^{k+1})e^{-ak} \; ; k = 1,2,\cdots,n$$

With the adoption of the equal dimension, the introduction of the new information and the elimination of the traditional, the modeling data changes and results in parameters change of the grey model. Then, it is assumed that the parameter sequence $\theta(k)$, in which $k = 1,2,\cdots,n$, is the dimension, the initial value is searched adjacent to the initial value, which makes the prediction error minimum. After the initial value $\theta(1)$ at $[a,\frac{b}{a}]^T$ is obtained with minimum forecasting error, the time-varying parameter is used to pass the parameter. The initial value $\theta(1)$ is achieved using time-varying parameter recursion formula.

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{\delta}{\left\|\nabla_{\hat{\theta}(k-1)} f[k,\hat{\theta}(k-1)]\right\|^2} \cdot \nabla_{\hat{\theta}(k-1)} f[k,\hat{\theta}(k-1)] \cdot \{y(k) - f[Y_{k-1}, U_k, \hat{\theta}(k-1), k]\}$$

where, δ is a constant, $\nabla_{\hat{\theta}(k-1)} f[k,\hat{\theta}(k-1)]$ is a matrix of order m*n which is defined as follows:

$$\nabla_{\hat{\theta}(k-1)} f[k,\hat{\theta}(k-1)] = \frac{\partial}{\partial \theta} f[Y_{k-1}, U_k, \theta, k]_{\theta=\theta(k-1)}$$

$U(k) = \{u(0), u(1), \cdots u(k-1)\}$ are collection of input data sequences. Now we have,

$$\hat{\theta}(k) = \begin{pmatrix} \hat{a}_k \\ \hat{u}_k \end{pmatrix} = \begin{pmatrix} \hat{a}_{k-1} \\ \hat{u}_{k-1} \end{pmatrix} + \frac{\delta}{\alpha_{k-1}^2 + \beta_{k-1}^2} \cdot \begin{pmatrix} \alpha_{k-1} \\ \beta_{k-1} \end{pmatrix} \cdot \{x^{(0)}(k+t-1) - (1-e^{\hat{a}_{k-1}})[x^{(0)}(k) \cdot c^{k-1} - \hat{u}_{k-1} \cdot c^k]e^{(1-k)\hat{a}_{k-1}}\}$$

where,

$$\alpha_{k-1} = [(1-k) \cdot e^{-\hat{a}_{k-1}(k-1)} - (2-k) \cdot e^{-\hat{a}_{k-1}(k-2)}] \cdot [x^{(0)}(k) \cdot c^{k-1} - \hat{u}_{k-1} \cdot c^k]^{;}$$

$$\beta_{k-1} = (e^{\hat{a}_{k-1}} - 1) \cdot c^k \cdot e^{-(k-1) \cdot \hat{a}_{k-1}} ; k = 2, 3, \cdots, n ;$$

Therefore, the estimated value of time-varying parameter series was obtained, and accurate equal dimension grey model was established. This time-varying parameter algorithm reflects the latest feature of new model and improves the precision of parameter calculation. At the same time, the calculation of parameter is less than the traditional model, which reduces the model forecasting error cause due to the parameter error. The forecasting formula of equal dimension grey model based on time-varying parameter estimation value is:

$$\hat{x}^{(0)}(k+1) = (1-e^{\hat{a}_{k+1}})[x^{(0)}(1) \cdot c^k - \hat{u}_{k+1} \cdot c^{k+1}]e^{-k\hat{a}_{k+1}} ; k = 1, 2, \cdots, n$$

With the updating of data sequence, time-varying parameters and latest prediction value is calculated.

3. Example Analysis

The monitoring data of tunnel deformation during the construction period of a water and hydropower project is analyzed. The deformation values of the tunnel are obtained every 10 hours, with 19 sets of data, of which 14 groups are used for modeling, and the 5 groups are used to predict and compare. Because of the lack of other monitoring data, it is impossible to establish a statistical model based on stepwise regression analysis. So, the establishment of neural network model was employed which results in low modeling accuracy due to the small number of samples. Therefore, based on the measured time series of the tunnel displacement, the traditional grey model, equal dimension grey model and the equal dimension grey model based on time varying parameters were established respectively. The parameters of the model are determined: after comparing the results of the trial calculation, the dimension of the equal maintenance model is 7, and the parameter is the most suitable for the selection of the parameter function according to the characteristics of the measured data sequence. The correlation coefficient and standard deviation of the fitting models are shown in table 4.2.1. The measured fitting line is shown in Figure 2, and the measured values and predicted values are shown in Table 2.

Table 1. The model eigenvalue.

Model Parameter	Traditional Grey Model	equal dimension Grey model	equal dimension Grey model base on varying time
R	0.881	0.995	0.998
S	0.667	0.496	0.480
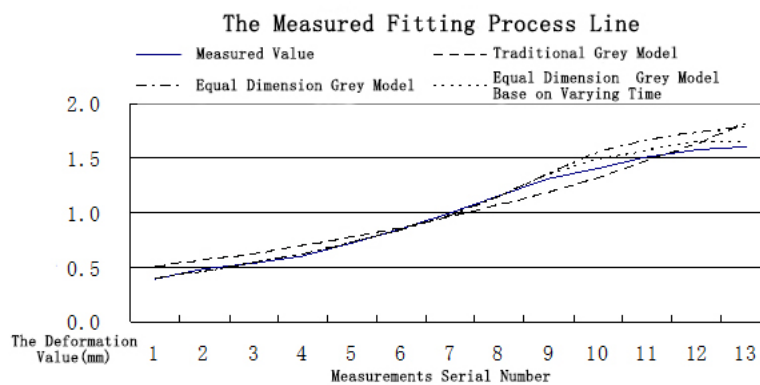
Figure 2. The forecasted values

Table 2. The forecasted values

SN.	Measured value /mm	Traditional Grey Model		Equal Dimension Grey model		Equal Dimension Grey Model Base on Varying Time	
		Forecasted value /mm	error %	Forecasted value /mm	error %	Forecasted value /mm	error %
1	1.63	2.0246	24.2	1.7572	7.8	1.6617	2.0
2	1.65	2.2536	36.5	1.7388	5.4	1.6841	2.1
3	1.67	2.5085	50.2	1.7253	3.3	1.6876	1.1
4	1.68	2.7923	66.2	1.7127	2.0	1.6978	1.1
5	1.69	3.1081	83.9	1.7087	1.1	1.7142	1.4

It can be seen from the above chart that a suitable reference transformation function for the original monitoring value can improve the smoothness of the modelling data, and the application of equal dimension system can recover the shortcomings of the traditional grey model which lack of new information, the medium and long-term prediction.

4. Conclusion

Thus, equal dimension model greatly improves the accuracy of model, fitting and prediction; In terms of the data sequence, it is usually characterized by a larger initial value change and a gradual stabilization in the later period. If the new information system cannot fully be considered to reflect the gradual stability of the tunnel. The forecasted value of the model will be significantly larger and the forecasting accuracy is low. The model can fully absorb the objective information reflected by the new data, and correctly run the monitoring objects with similar features. In addition, the time variant and other

maintenance models are less required, simple calculation and quick operation, which is an effective modeling tool for the risk forecasting of water conservancy and hydropower project construction.

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