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Research Article

The Application of Seepage Flow Prediction in Nuer Dam Based on the Grey Self-Memory Model

Ai-Feng Wang,[1,2] **Xiu-Tao Yang**,[3] **and Da-Hai Guo**[4]

[1]*School of Architecture, Nanyang Institute of Technology, Nanyang, Henan, China 473004*
[2]*Guizhou Provincial Key Laboratory of Rock and Soil Mechanics and Engineering Safety, Guiyang 550025, China*
[3]*Henan Planning Design & Research Institute Co. Ltd.Zhengzhou, Henan, China 450000*
[4]*The Nuer Hydro-Junction Projection and Construction Authority in XinJiang Tarim River Basin, Xinjiang, China 848300*

Correspondence should be addressed to Da-Hai Guo; guodahai5888@163.com

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The accurate time prediction of seepage pressure in the dam has essential significance for the safety of the dam body and the life and property of people. To predict the time sequence of seepage pressure, the grey self-memory model is introduced at first, and its calculative procedure is analyzed. Then, the engineering overview in the Nuer dam is narrated, and the prediction model of seepage pressure in the Nuer dam is established and analyzed based on the grey self-memory theory. Finally, the conclusions are drawn that relatively to GM (1,1), the grey self-memory model has higher accuracy, and it not only can predict the time sequence of seepage pressure in the Nuer reservoir accurately but also provide a new method for the development trend of seepage flow in the hydraulic engineering in the future.

1. Introduction

The dam is the basis of hydroelectric power. Different types of dams have been built continuously since 1949 in China, for example, embankment dams, gravity dams, and arch dams; the total numbers arrive at 100 thousand [1]. These dams have significant influences on the rapid development of the national economy. However, when the dam break occurs, the life of people and property safe at the downwards of the river will be significantly endangered, so the safety of the dam has always become a hot issue [2, 3]. Many factors affect the safety of embankment dam, such as the seepage flow and deformation, especially, the seepage flow is one of the essential factors [4]. According to corresponding statistics, more than 52% of embankment dam crashes originate from seepage damage [5, 6], so the investigation on the seepage flow prediction of embankment dams has excellent significance for the safety of hydraulic engineering [7].

To assure the dam's safety in advance, the prediction of seepage flow in the dam has aroused many researchers' attention [8]. The researchers in many countries have performed plenty of experiments; their investigation results provide the firm basis for the development of seepage flow theory [9]. With the development of mathematics science and computer technology, many methods are provided by many researchers [10] to determine the seepage prediction of dam body; a nonlinear elastic deformation and unsteady seepage coupling model are used by Chen et al. [11] to predict the seepage and deformation process; Larese et al. [12] proposed an improved Navier-Stokes equation to simulate the seepage and free surface flow in the porous embankment dam. The seepage behavior is investigated by Choo et al. [13] in the drainage area about an embankment dam with a centrifugal experiment and numerical simulation. The Monte Carlo simulation and random field theory are used to simulate the seepage of an embankment dam by Tan et al. [14]. Abnormal seepage behavior is detected by comparing the measured and calculated values in the finite element model [15]. Besides, the numerical simulation of seepage flow has always been performed by many researchers [16–18], for example, the finite element method, the finite difference method, and boundary element method [19]; Rafifiezadeh et al. suggested an efficient over relaxation algorithm of block to solve the seepage flow of the dam [20]. In 1988, Kazemzadeh-Parsi et al. [21] provided a new iterative algorithm to predict the variation of seepage flow in the dam. In 2011, Chen [22] suggested a numerical simulation based on the finite element method to solve the complex seepage problem of drainage systems; its results are validated by two other numerical models. Besides, other many methods [23, 24] are also applied to predict the time sequence of seepage flow in the dam body.

The above methods improve the development of seepage flow prediction in the dam, but these models or methods are complex, and many physical parameters are difficult to be obtained. It is inconvenient to apply the actual engineering, so the grey self-memory model is introduced in the paper. The method avoids the collection and treatment of data about the different factors, and it is convenient and practical; the excellent accuracy can be obtained, so it is widely applied to hydraulic engineering.

The paper is organized as follows: In Section 2, the basic theory of grey self-memory is introduced at first. In Section 3, an engineering application example in Nuer dam is analyzed based on the grey self-memory model. In Section 4, conclusions are drawn.

2. The Basic Theory

2.1. The Grey Theory GM (1,1). The seepage time sequence of the dam is affected by many factors, and it has many uncertainties, so the grey theory is applied to analyze it. GM (1,1) approach is used to depict the model of a single sequential dynamic case; it can perform the medium and long prediction for the single factor.

A group of new data series with apparent trends can be generated from the accumulative method of specific data series by using the grey theory. The predictive model is established according to the increasing trend of new data series, then reverse computation is performed by using the method of accumulative decrease, and the final prediction results are obtained.

Its model is established as follows:

(1) It is assumed that there is a group of original datum $x(t), t = 1, 2, \cdots, n$; n is the number of datum, and then, the normalization treatment is performed. It can be expressed as [25]

$$x_t^{(0)} = \frac{x(t)}{x_{\max}}. \tag{1}$$

(2) The sequence $x_t^{(0)}$ is accumulated once, and the result can be obtained as follows:

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

where $x_t^{(1)} = x_1^{(0)}$; $x_t^{(1)} = \sum_{i=2}^{t} x_{\mathrm{i}}^{(0)} = x_{t-1}^{(1)} + x_t^{(0)}$, $t = 2, \cdots, n$.

(3) When new datum sequences are compared with the original ones, their random degree is significantly weakened, and the degree of smoothness increases. Its variable trends can be depicted by the first-order differential equation as follows:

$$dx^{(1)}/dt + ax^{(1)} = u, \tag{3}$$

where a and u can be obtained by using the least square method, namely:

$$[a, \quad u]^T = \left(B^T B\right)^{-1} B^T Y_N, \tag{4}$$

where

$$B = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \cdots & \cdots \\ -\frac{1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix}, \tag{5}$$

$$Y_N = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix}. \tag{6}$$

In Equation (4), let $\mathrm{d}x^{(1)}/dt = F(x, t)$, and then, its differential equation can be expressed as

$$F(x, t) = u - ax^{(1)}. \tag{7}$$

2.2. Self-Memory Model. The above grey differential equation is regarded as the dynamic core. The self-memory model of seepage flow vs. time sequences in the dam is constructed based on the self-memory theory.

For many time sequences $t_i (i = -p, -p+1, \cdots, 0, 1)$, t_0 is the initial time, t_1 is predictive time, and p is backtracking order; memory function $\beta(\mathrm{t})$ is introduced. When $F(x, t)$ is performed weighted integral from t_{-p} to t_1, a difference integral equation can be obtained by using the partial integration and mean value theorem as follows [26]:

$$\beta_{\mathrm{t}} x_t{}^{(1)} - \beta_{\text{-p}} x_{-p}{}^{(1)} - \sum_{i=-p}^{0} x_i^{(1)m} (\beta_{i+1} - \beta_i) = \int_{t_{-p}}^{t_1} \beta(\tau) F\left[x^{(1)}, \tau\right] d\tau, \tag{8}$$

where $x_i^{(1)m} = x^{(1)}(t_m)$, $t_i < t_m < t_{i+1}$. Equation (9) is called as p-order self-memory equation.

It is assumed that approximate value $x_i^{(1)m} = [x_i^{(1)} + x_{t+1}^{(1)}]/2$, and the integral is substituted by using summation, and $\alpha_i = \beta_i/(\beta_1 + \beta_0)(i = -p, \cdots, 0, 1)$; the approximate expression of self-memory equation can be obtained as follows:

$$x_i^{(1)} = \alpha_{-p}\left[x_{-p}^{(1)} - x_{-p+1}^{(1)} + 2F_{-p}\Delta t\right] + \sum_{i=-p+1}^{-1}\left[x_{i-1}^{(1)} - x_{i+1}^{(1)} + 2F_i\Delta t\right]\alpha_i + \left(x_{-1}^{(1)} + 2F_0\Delta t\right)\alpha_0 + x_0^{(1)}\alpha_1, \tag{9}$$

where Δt-sequential time interval; it is selected as 1 in the manuscript, $F_i - F(x, t)$.

If let $A_{-p} = x_{-p}^{(1)} - x_{-p+1}^{(1)} + 2F_{-p}\Delta t$

$$A_i = x_{i-1}^{(1)} - x_{i+1}^{(1)} + 2F_i\Delta t, (i = -p + 1, -p + 2, \cdots, -1) \tag{10}$$

$A_0 = x_{-1}^{(1)} + 2F_0\Delta t$; $A_1 = x_0^{(1)}$; then, Equation (9) can be rewritten as

$$x_i^{(1)} = \alpha_{-p}A_{-p} + \sum_{i=-p+1}^{-1} A_i\alpha_i + A_0\alpha_0 + A_1\alpha_1. \tag{11}$$

Equation (11) is the prediction equation of grey self-memory. The self-memory coefficients α_i of the model can be evaluated by using the least square method; $p + 2$ datum is classified into a group in the sequential expression. (2) Generated by using the sequential addition, the whole $L = n - p$-1 group data is formed by using the sequential addition, then these data are substituted into Equation (12). A $L \times (p + 2)$ matrix can be obtained as follows:

$$X_1^{(1)} = M\alpha, \tag{12}$$

where

$$X_1^{(1)} = \begin{bmatrix} x_{1,1}^{(1)} \\ x_{1,2}^{(1)} \\ \cdots \\ x_{1,L}^{(1)} \end{bmatrix}, \quad \alpha = \begin{bmatrix} \alpha_{-p} \\ \alpha_{-p+1} \\ \cdots \\ \alpha_1 \end{bmatrix}, \tag{13}$$

$$M = \begin{bmatrix} A_{-p,1} & A_{-p+1,1} & \cdots & A_{0,1} & A_{1,1} \\ A_{-p,2} & A_{-p+1,2} & \cdots & A_{0,2} & A_{1,2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_{-p,L} & A_{-p,L+1} & \cdots & A_{0,L} & A_{1,L} \end{bmatrix}. \tag{14}$$

2.3. The Procedure of Grey Self-Memory Model about the Seepage Flow Prediction. Its procedure is listed as follows:

(1) The detailed datum of seepage monitoring about the dam is collected at first. To enhance the predictive precision, the datum of time sequence should have enough length and equal intervals

(2) Based on the above datum, the grey differential equation of time-displacement sequence $(dx^{(1)}/dt) + ax^{(1)} = b$ is established using the grey system theory GM (1,1). It can then reflect the differential equation of nonlinear dynamics about the dynamic evolution characteristics of the system

(3) Grey self-memory model about seepage monitoring is established. When the self-memory principle of the dynamic system is applied, the inversion of procedure (2) is performed to obtain the self-memory equation with the backtracking order P. The self-memory equation is discrete, the memory coefficients are solved by using the least square method based on the corresponding monitoring datum of seepage flow

(4) The prediction is performed based on the above grey self-memory model. It is assumed that the sequence of seepage pressure vs. time is $x(t), t = 1, 2, \cdots, n$; the time length of forecast is $l(l \leq (p + 1) < n)$. The former l monitoring datum is applied to predict the value x_{n+1} at the moment $(n + 1)$ at first; to enhance the accuracy, the actual monitoring data x_{n+1} is inserted into time sequence, and the old monitoring data x_{n+1-l} in the time sequences can be deleted in the former procedure; new time sequences $\{x_{n-l+2}, x_{n-l+3}, \cdots, x_n, x_{n+1}\}$ with the length l are constructed. They are input into the self-memory model; the prediction value x_{n+2} at the moment $(n + 2)$ can be obtained. And the prediction magnitudes of seepage flow at all moments can be obtained

3. Engineering Application Example

3.1. Project Overview. The hydropower project under consideration in this investigation is located on the Nuer River. It is a controlled hydrojunction projection. A water diversion power generation system is located on the left bank; a spillway and a diversion tunnel are located on the right bank. The total capacity of the reservoir is 0.69 billion m^3; its normal water storage level is 2497 m; the dead water level is 2465 m; and the fully installed capacity of the power station is 6.2 MW. The average annual generation over many years is 0.217 billion kW·h [25], and basic information of the dam are shown in Figure 1.

The dam is located in the riverbed. It is an asphaltic concrete-core rockfill dam with a maximum height of 80 m. Low liquid limit eolian silt is covered on the upper of left bank slope; its thickness is about 30~53 m; Pleistocene alluvial sand and gravel are covered on the lower of Pleistocene alluvial gravel. Its thickness is about 5 ~ 6 m; upper limit of weak weathering layer of the conglomerate in the western region is covered with the foundation in left bank core ($0 + 000$~$0 + 040$ m section) [27].

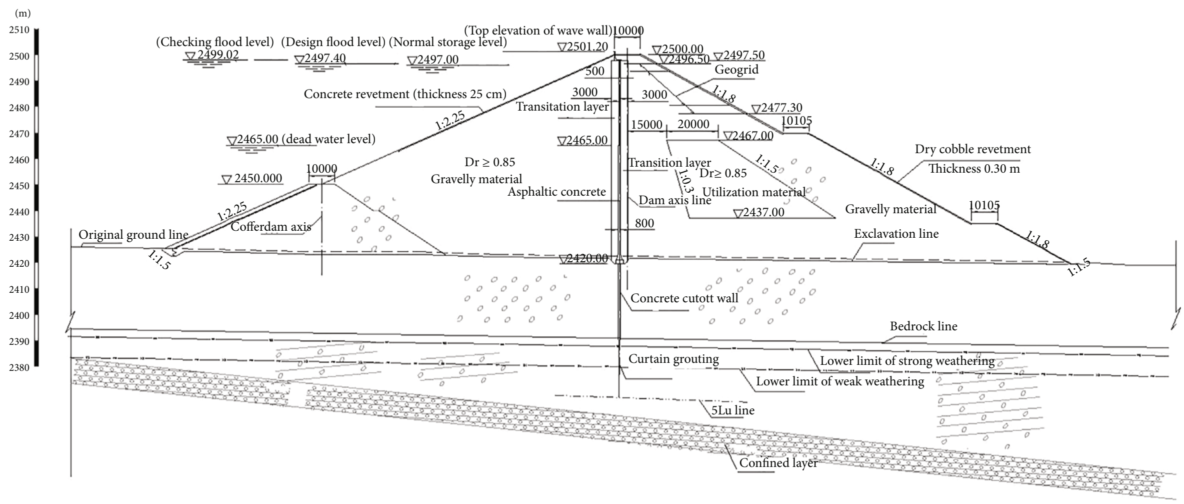

Figure 1: Typical profile of a dam.

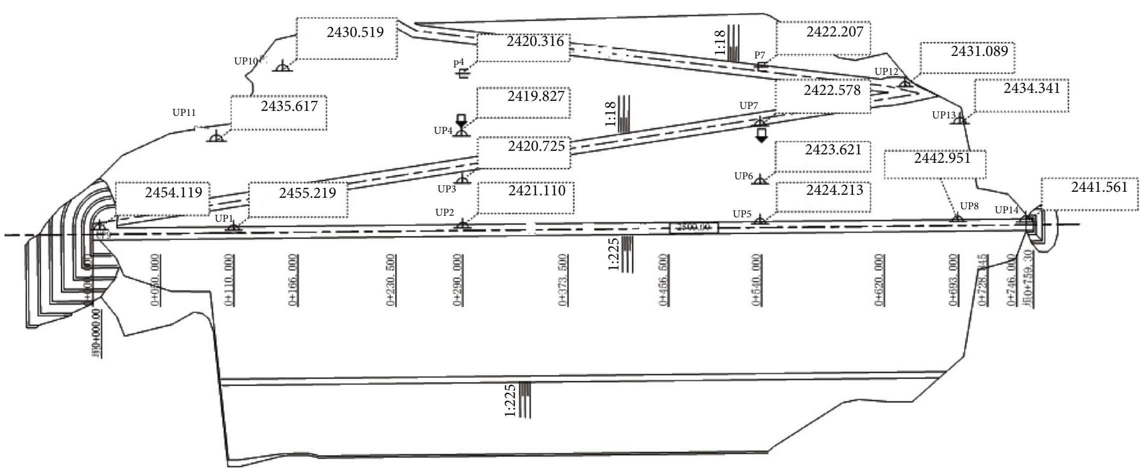

Figure 2: Planar distribution map of seepage monitoring instrument and water level.

To monitor the seepage pressure of Nuer dam, the distribution map of the seepage monitoring instrument is plotted in Figure 2. The distribution map of the monitoring instrument in the cross section 0 + 100 is plotted in Figure 3; the distribution map of the monitoring instrument in the cross section 0 + 290 is plotted in Figure 4.

To establish the seepage flow prediction model, the monitoring reservoir water level and water level of seepage pressure in the dam foundation and body are, respectively, plotted in Figures 5 and 6. Their date is from 2018/08/04 to 2018/12/10. It can be found from Figures 6 to 7 that seepage water level increases as time increases at the initial stage, but it becomes steady at the following settings.

3.2. The Establishment of Grey Self-Memory Model

3.2.1. The Construction of Seepage Prediction Model Frame. The seepage flow has excellent influences on the construction production and safe operation of the dam. And so the construction of the seepage flow prediction model has great significance. The procedure of the seepage flow prediction model of the Nuer dam is plotted in Figure 7.

It can be found in Figure 7 that the original datum of seepage flow in Nuer dam is collected at first; then, the grey model GM (1,1) in the Nuer dam is established; by inversion, the grey self-memory model is constructed about the Nuer dam; secondly, the grey self-memory model is discretized, and the corresponding value at the particular moment is predicted. Finally, the predictive results are compared with monitoring results and the ones of grey theory. Final conclusions are drawn.

3.2.2. The Establishment of Seepage Model in Nuer Dam. According to the relevant datum of monitoring point UP1 at the cross section 0 + 110 in the dam body in Nuer reservoir from 4/8 to 10/12, 2018, the total 129 data is applied to establish the model; 20 data from 9/11 to 28/11, 2018, are used to predict the water head difference from the upstream to downstream.

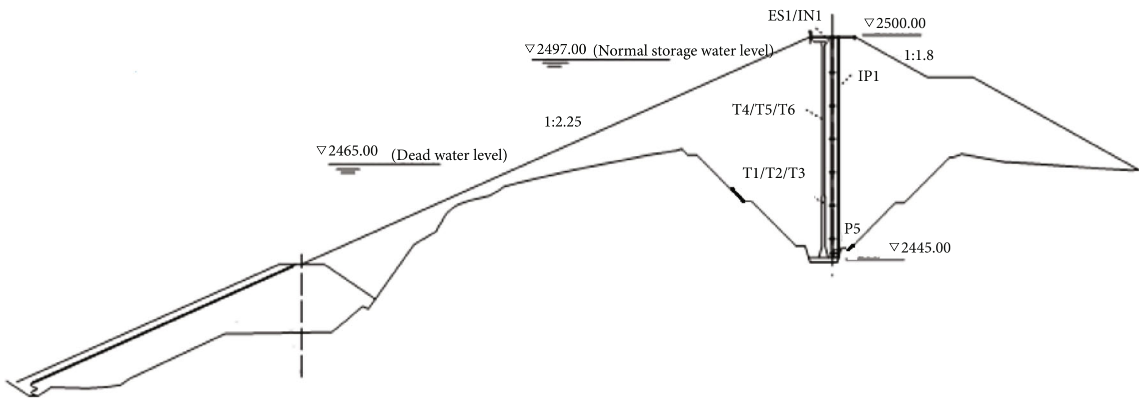

Figure 3: Distribution map of seepage monitoring instrument in the cross section 0 + 100.

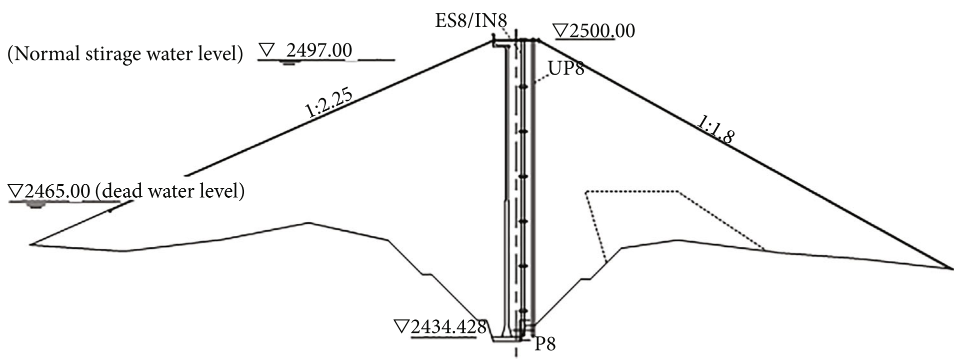

Figure 4: Distribution map of seepage monitoring instrument in the cross section 0 + 290.

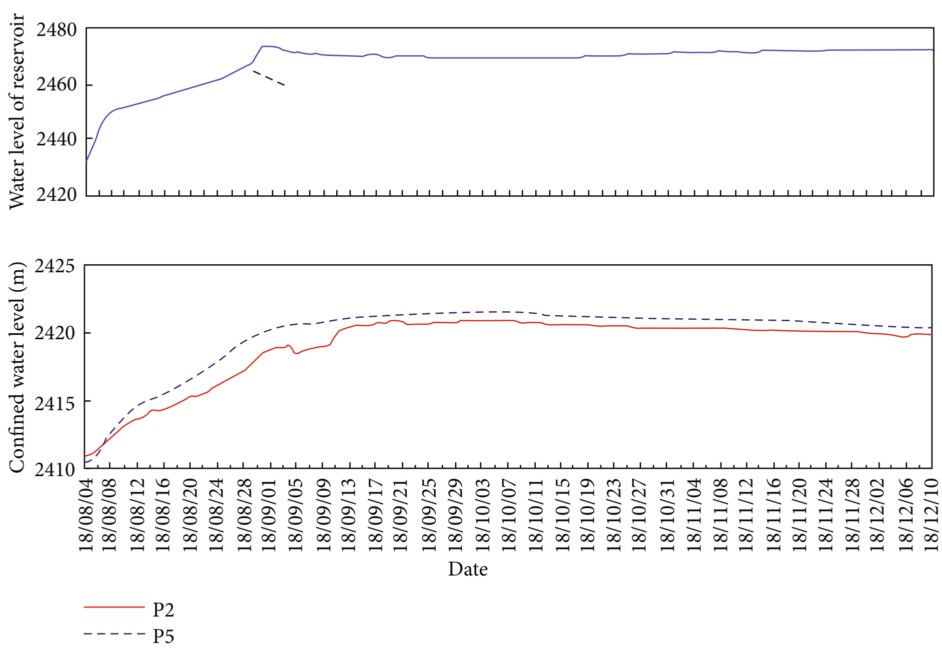

Figure 5: The monitoring reservoir water level and water level of seepage pressure at monitoring point P2 and P5 in the dam foundation.

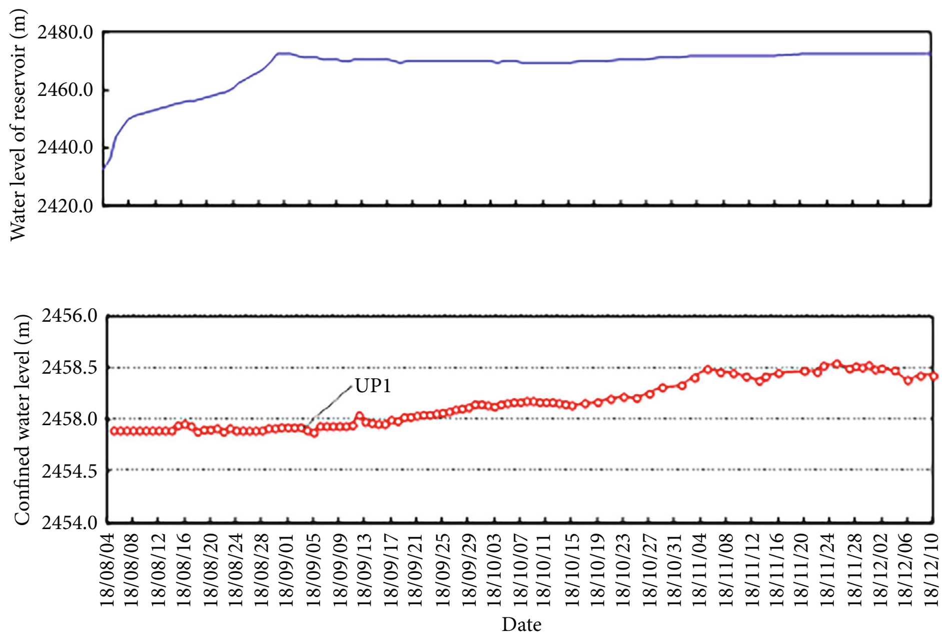

Figure 6: The monitoring reservoir water level and water level of seepage pressure at monitoring point UP1 at the cross section $0 + 110$ in the dam body.

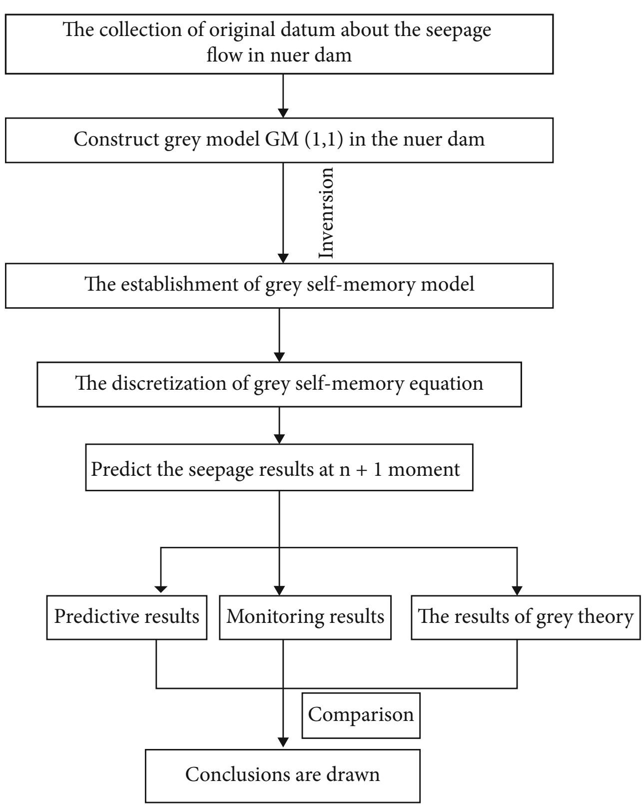

Figure 7: The flowchart of seepage prediction model.

To establish the grey self-memory model, based on the Equations (1)–(5), the differential equation of grey theory can be obtained as follows:

$$F(x, t) = 8.2566 + 0.0077673x^{(1)}. \quad (15)$$

Based on Equation (11), the backtracking order p is selected as 11. Then, the prediction equation of the grey self-memory model can be expressed as

$$x_1^{(1)} = A_{-11}\alpha_{-11} + \sum_{i=-10}^{-1} A_i\alpha_i + A_0\alpha_0 + A_1\alpha_1. \quad (16)$$

According to Equations (11)–(14), the relevant memory parameters of the model can be calculated as: $\alpha_{-11} = -8.658$, $\alpha_{-10} = -8.71$, $\alpha_{-9} = -8.946$, $\alpha_{-8} = 9.388$, $\alpha_{-7} = -9.492$, $\alpha_{-6} = 9.457$, $\alpha_{-5} = -9.257$, $\alpha_{-4} = 9.478$, $\alpha_{-3} = -9.566$, $\alpha_{-2} = 9.683$, $\alpha_{-1} = -9.269$, $\alpha_0 = 8.731$, and $\alpha_1 = -7.332$. The comparison of prediction value and monitoring value is plotted in Figure 8. The calculative results are performed cumulative reduction because the backtracking and accumulative reduction; only the monitoring datum in 17/8-10/12, 2018, is predicted; their error results are shown in Table 1.

Similarly, based on the datum of point P5 in the dam foundation, their comparison between the prediction value and monitoring value is plotted in Figure 9, and the comparison of errors can be shown in Table 2.

Because of the backtracking, the former 13 values are not predicted; only 116 data are analyzed. It can be found in Figures 8 and 9 that there exist sound effects from GM (1,1) and grey self-memory model. Especially for the grey self-memory model, its magnitudes have higher accuracy than the ones obtained from GM (1,1). The predictive characteristics of the grey self-memory model have strong nonlinearity, while GM (1,1) model demonstrates strong linearity. And it can be found in Table 1 that there are four days within the error range of 5%, which accounted for 20% of the total; there are nine days within the error range between 5% and 6%, and it occupied 45%; there are seven days within ones between 6%

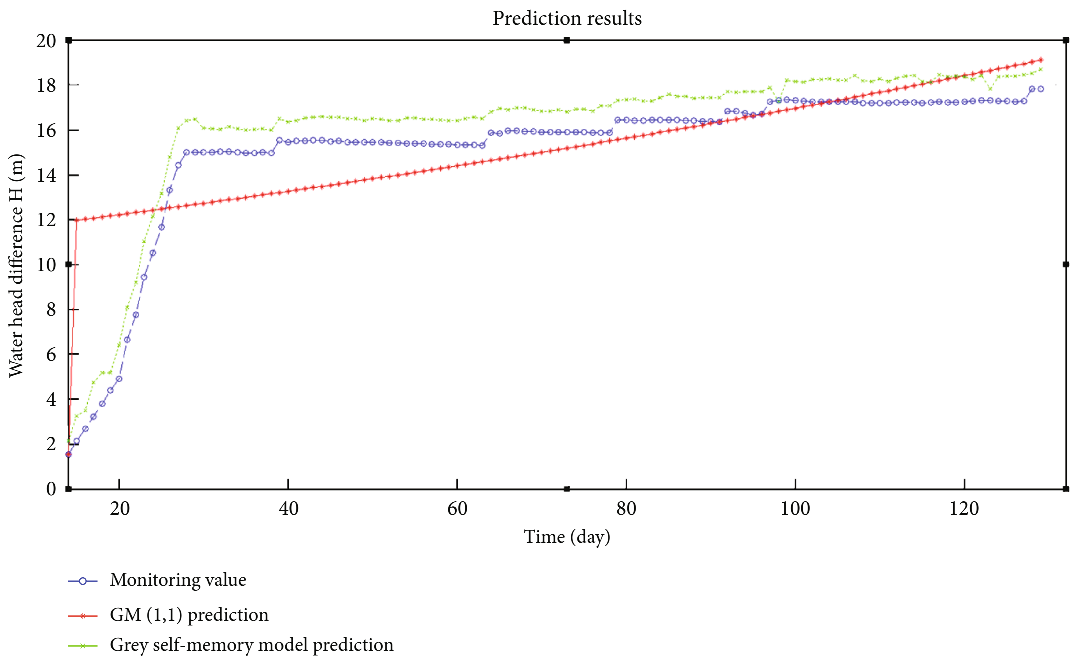

FIGURE 8: The comparison of prediction value and monitoring value at the point UP1.

TABLE 1: The comparison of errors between the monitoring datum and predicting value.

Date	Monitoring value/m	The predicting value/m	The relative error (%)	Date	Monitoring value/m	The predicting value	The relative error (%)
9/11	17.31	17.25	-0.3	19/11	17.19	18.19	5.8
10/11	17.36	18.23	5	20/11	17.19	18.17	5.7
11/11	17.31	18.15	4.9	21/11	17.19	18.27	6.3
12/11	17.30	18.12	4.7	22/11	17.19	18.15	5.6
13/11	17.27	18.25	5.7	23/11	17.22	18.32	6.4
14/11	17.25	18.26	5.9	24/11	17.22	18.41	6.9
15/11	17.25	18.28	6	25/11	17.22	18.43	7.0
16/11	17.25	18.21	5.6	26/11	17.21	18.15	5.5
17/11	17.25	18.22	5.6	27/11	17.24	18.12	5.1
18/11	17.25	18.43	6.8	28/11	17.25	18.45	7

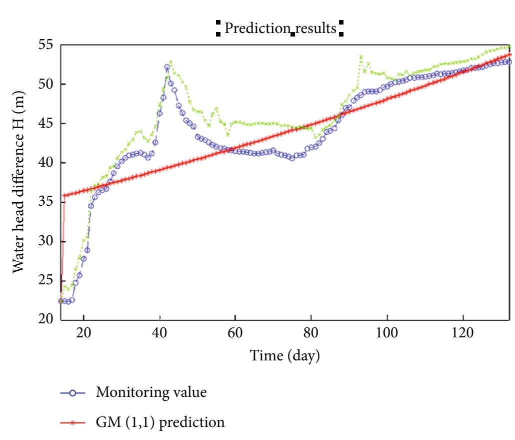

FIGURE 9: The comparison of prediction value and monitoring value at the point P5.

Table 2: The comparison of errors between the monitoring datum and predicting value.

Date	Monitoring value/m	The predicting value/m	The relative error (%)	Date	Monitoring value/m	The predicting value	The relative error (%)
9/11	50.98	51.77	1.5	19/11	51.78	52.92	2.2
10/11	51.02	52.18	2.3	20/11	51.98	53.16	2.3
11/11	51.26	52.22	1.9	21/11	51.99	53.19	2.3
12/11	51.22	52.48	2.5	22/11	52.06	53.38	2.5
13/11	51.26	52.51	2.4	23/11	52.16	53.69	2.9
14/11	51.30	52.52	2.4	24/11	52.31	54.06	3.3
15/11	51.35	52.59	2.4	25/11	52.45	54.17	3.3
16/11	51.41	52.69	2.5	26/11	52.61	54.22	3.1
17/11	51.58	52.78	2.3	27/11	52.65	54.42	3.4
18/11	51.69	52.82	2.2	28/11	52.71	54.56	3.5

and 7%, and it accounted for 45% of the total; their average error is 5.56%; likely, it can be found in Table 2 that all the relative errors are within the ranges of 5%; there are two days within the error ranges of 2%, and it accounted for 10%; there are thirteen days within ones between 2% and 3%, and it accounted for 65%. And there are five days within ones between 3% and 4%, which accounted for 25%; their average error is 2.6%. So conclusions can be drawn that the grey self-memory model can predict the variable law of seepage pressure in the Nuer reservoir accurately and provide a new method for the development trend of seepage flow in hydraulic engineering in the future.

4. Conclusions

(1) The grey self-memory model is a new method in combination with the certainty and uncertainty; its virtues are practical and straightforward because the model is only concerned with the observation sequences of seepage flow monitoring, and other influential factors are not considered. So the grey model GM (1,1) is adopted as the dynamic core; relatively to other methods, the construction of model is simple, and it can be calculated easily

(2) By analyzing the correlated example, the information of many monitoring values is applied fully in the grey self-memory model. The accuracy of prediction can be improved enormously, and better prediction results can be obtained. Conclusions can be drawn that the grey self-memory model can predict the variable law of seepage pressure in the Nuer reservoir accurately and can provide a new method for the development trend of seepage flow in hydraulic engineering in the future

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 they have no conflicts of interest.

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References

[1] J. Bi, P. F. Liu, and F. Gan, “Effects of the cooling treatment on the dynamic behavior of ordinary concrete exposed to high temperatures,” *Construction and Building Materials*, vol. 248, p. 118688, 2020.

[2] X. B. Gu, Q. H. Wu, and Y. H. Zhu, “The experimental investigation on the propagation process of crack for brittle rock similar material,” *Geotechnical and Geological Engineering*, vol. 37, no. 6, pp. 4731–4740, 2019.

[3] H. Shahheydari, E. J. Nodoshan, R. Barati, and M. A. Moghadam, “Discharge coefficient and energy dissipation over stepped spillway under skimming flow regime,” *KSCE Journal of Civil Engineering*, vol. 19, no. 4, pp. 1174–1182, 2015.

[4] Peral, A. Mate, and M. Marco, “Application of data mining techniques to identify relevant keyperformance indicators,” *Computer Standards Interfaces*, vol. 54, no. SI, pp. 76–85, 2017.

[5] Y. Zhao, J. Bi, C. L. Wang, and P. F. Liu, “Effect of unloading rate on the mechanical behavior and fracture characteristics of sandstones under complex triaxial stress conditions,” *Rock Mechanics and Rock Engineering*, vol. 54, no. 9, pp. 4851–4866, 2021.

[6] H. Su, Y. Kang, and H. Z. Sun, “Design of system for monitoring seepage of levee engineering based on distributed optical fiber sensing technology,” *International Journal of Distributed Sensor Networks*, vol. 9, no. 12, 2013.

[7] J. Zhang, J. Wang, and H. Cui, “Causes of the abnormal seepage field in a dam with asphaltic concrete core,” *Journal of Earth Science*, vol. 27, no. 1, pp. 74–82, 2016.

[8] X. B. Gu, J. L. Shao, S. T. Wu, Q. H. Wu, and H. Bai, "The Risk Assessment of Debris Flow Hazards in Zhouqu Based on the Projection Pursuit Classification Model," *Geotechnical and Geological Engineering*, vol. 8, pp. 4–17, 2021.

[9] J. Ren, Z. Z. Shen, J. Yang, and C. Z. Yu, "Back analysis of the 3D seepage problem and its engineering applications," *Environmental Earth Sciences*, vol. 75, no. 2, 2016.

[10] Y. Zhao, C. L. Wang, L. Ning, H. Zhao, and J. Bi, "Pore and fracture development in coal under stress conditions based on nuclear magnetic resonance and fractal theory," *Fuel*, vol. 309, p. 122112, 2022.

[11] Y. Chen, R. Hu, W. Lu, D. Li, and C. Zhou, "Modeling coupled processes of non-steady seepage flow and non-linear deformation for a concrete-faced rockfill dam," *Computers & Structures*, vol. 89, no. 13-14, pp. 1333–1351, 2011.

[12] A. Larese and R. Ross, "Finite element modeling of free surface flow in variable porosity media," *Archives of Computational Methods in Engineering*, vol. 22, no. 4, 2015.

[13] Y. W. Choo, D. H. Shin, S. E. Cho, E. S. Im, and D.-S. Kim, "Seepage behavior of drainage zoning in a concrete faced gravel-fill dam via centrifuge and numerical modeling," *KSCE Journal of Civil Engineering*, vol. 17, no. 5, pp. 949–958, 2013.

[14] X. H. Tan, X. Wang, S. Khoshnevisan, X. Hou, and F. Zha, "Seepage analysis of earth dams considering spatial variability of hydraulic parameters," *Engineering Geology*, vol. 228, pp. 260–269, 2017.

[15] X. B. Gu, Y. Ma, and Q. H. Wu, "The risk assessment of landslide hazards in Shiwangmiao based on intuitionistic fuzzy sets-Topsis model," *Natural Hazards*, vol. 111, no. 1, 2022.

[16] X. P. Zhou, X. B. Gu, M. H. Yu, and Q. H. Qian, "Seismic bearing capacity of shallow foundations resting on rock masses subjected to seismic loads," *KSCE Journal of Civil Engineering*, vol. 20, no. 1, pp. 216–228, 2016.

[17] X. P. Zhou, X. Ji, and Q. H. Qian, "Stability analysis of water front retaining wall subjected to seismic loads using pseudo-dynamic method," *Chinese Journal of Rock Mechanics and Engineering*, vol. 31, no. 10, 2012.

[18] N. Yue, D. Zhang, J. Chen et al., "The development and validation of the inter-wrapper flow model in sodium-cooled fast reactors," *Progress in Nuclear Energy*, vol. 108, pp. 54–65, 2018.

[19] X. B. Gu and Q. H. Wu, "Seismic stability analysis of waterfront rock slopes using the modified pseudo-dynamic method," *Geotechnical and Geological Engineering*, vol. 37, pp. 1743–1753, 2019.

[20] K. Rafiezadeh and B. Ataie-Ashtiani, "Transient free-surface seepage in three-dimensional general anisotropic media by BEM," *Engineering Analysis with Boundary Elements*, vol. 46, 2014.

[21] M. J. Kazemzadeh-Parsi and F. Daneshmand, "Unconfined seepage analysis in earth dams using smoothed fixed grid finite element method," *International Journal for Numerical and Analytical Methods in Geomechanics*, vol. 36, no. 6, 2012.

[22] S. K. Chen, J. Yan, and J. M. Li, "Seepage field 3D finite element simulation of concrete faced rockfifill dam under failure condition of vertical fracture," *Rock Soil Mech*, vol. 32, no. 11, 2011.

[23] J. Chen, Y. Shou, and X. Zhou, "Implementation of the novel perfectly matched layer element for elastodynamic problems in time-domain finite element method," *Soil Dynamics and Earthquake Engineering*, vol. 152, p. 107054, 2022.

[24] T. Fang, Z. Y. Zhang, and X. Wen-Bin, "Analysis of seepage monitoring model for earth-rock dams," *Journal of Heilongjiang Hydraulic Engineering College*, vol. 34, pp. 28–30, 2007.

[25] Y. Xiang, L. Wang, S. Wu, H. Yuan, and Z. Wang, "Seepage analysis of the fractured rock mass in the foundation of the main dam of the Xiaolangdi water control project," *Environmental Earth Sciences*, vol. 74, no. 5, pp. 4453–4468, 2015.

[26] Y. H. Lin, "Applying fuzzy grey modification model on inflow forecasting," *Engineering Applications of Artificial Intelligence*, vol. 25, no. 4, pp. 734–743, 2012.

[27] D. H. Guo, Y. Sun, and X. B. Gu, "Numerical simulation of a 3D seepage field of an asphaltic and concrete core rockfill dam in an arid area," *Geofluids*, vol. 2022, 12 pages, 2022.