Seepage forecast model based on time-series cubic exponential smoothing method

Xufeng Wang*, Xushun Fang, Jianfeng Jin, Hongyan Bao, Xiaoji Wang, Chao Gao, Hongxia Liu

1The management office of the Hangzhou Xianlin reservoir Hangzhou, Zhejiang 310012, China
2Nanjing Hydraulic Research Institute, Nanjing, Jiangsu 210024, China

*Corresponding author’s e-mail: 759983358@qq.com

Abstract: Seepage monitoring is a vital part of daily management of dams. However, the seepage data are non-linear which is hard for administrators to use. This paper uses time-series along with the cubic exponential smoothing method to analyse the past monitoring data and get a forecast model. As the data accumulate, the model evolve and form a more precise model. Two year’s seepage monitoring data are analysed of Xianlin Dam with this method and the result of the contrasted data turned out to be well simulated.

1. Introduction
Seepage monitoring is of great importance in the daily monitoring of dams. Many disasters occurred because of ignorance on the seepage monitoring. Unlike displacement, data of seepage are non-linear and change with time as well as the water level of the reservoir. A useful model is an important part of daily monitoring. Most model used in this situation is least square method. However, as pointed above, data in this situation is non-linear, thus least square method as well as function simulation method has much error. Besides, the environment variables have great impact on the seepage. It may vary more in some extent. As variables such as temperature, humidity and water table are too much to consider, and result-oriented methods should be taken into consideration in this situation. All the components that attribute to the change of the seepage give a similar vibration, which indicates that these vibrations could be solved with mathematical methods.

As mathematical methods evolve these years, high-level algorithm helps us to build up-to-date model in this situation. Time series method is a statistic model used in the forecasting trend as well as the quantity of physical parameters. Time-series method is a statistical method, which intends to forecast the future data with the past data as well as trend.

2. Methodology
Time series method uses known data to analyze trend as well as rules to forecast future trends and data. With additional data input into the database, model could be trained to evolve. Since the environment changes over time, this methodology is suitable in this situation.

First, data should be decomposed. It is vital to determine whether the series are stationary or non-stationary series. In the dam monitoring, if we take the construction period into consideration, the series should be increasing non-stationary series since the data changes much after the water is put into the reservoir. To make it simple, we only consider the operation period, which make the series a seasonal
stationary series.

Time series model has four main components: trend (T), seasonal fluctuation (S), the cyclicity (C) and the irregular variations (I). We can combine these components together with several methods. To make the trend more clear, we use times model which is times all the components together to get the full model.

\[ y_t = T_t \cdot S_t \cdot C_t \cdot I_t \]

In the dam monitoring, the seepage has some trend and is remarkable seasonal. Thus, we should take the trend and seasonal fluctuation into consideration. Therefore, the general model changes into the equation below.

\[ y_t = T_t \cdot S_t \cdot C_t \]

Inside the model, we use the cubic exponential smoothing method to analyze the data and forecast the trend of the seepage. The \( \alpha, \beta \) and \( \gamma \) are parameters used which has value between 0 and 1. The equations are shown below. The initial data has little impact in the whole model so we choose the 0 for all the parameters and then computer until it converge.

\[
s_i = \frac{x_i}{p_t} - k + (1 - \alpha)(s_i - 1 + t_i - 1)
\]

\[
t_i = \beta(s_i - s_{i-1}) + (1 - \beta)t_{i-1}
\]

\[
p_t = \gamma\frac{x_i}{s_i} + (1 - \gamma)p_i - k
\]

\[
x_i + h = (s_i + ht_i)p_t - k + (h \mod k)
\]

Errors are evaluated by the residual error and the variance.

\[ E(R_t) = \sigma \]

3. Numerical example

In this paper, we use Xianlin reservoir as an example to test this model. As illustrated in the figure 1, the Xianlin reservoir contains dam seepage monitoring equipment. We take 12 seepage instruments to test the model.

Fig.1 Plane layout of measurement points
To examine the anti-seepage ability of the dam, osmometers are installed inside the dam. Osmometers are placed in the largest section of the dam. Eight osmometers are placed inside the dam to monitor the seepage situation inside the dam. Besides, a measuring weir is installed behind the dam to monitor the seepage amount through the dam body. All the data can be transmitted to the monitor system wirelessly for the administrative.
Data has been collected since 2015. We take 10 instruments and 2-year period to simulate and the result is shown below.

Fig. 2 Result contrast of seepage instruments

As illustrated in the figure, the precast data fits well with the original data. In the first period, which the water level is low, the data is somewhat randomly and the precast data has larger error. When it comes to the operation period when the water level is high, the periodical character comes to show up. Then the error is calculated in such situation. The error stays in a relatively low situation, which indicate the result fit well with the monitoring data.

4. Conclusion

This paper uses time-series along with the cubic exponential smoothing method to analyze the past monitoring data and get a forecast model. As the data accumulate, the model evolve and form a more precise model. Two year’s seepage monitoring data are analyzed of Xianlin Dam with this method and the result of the contrasted data turned out to be well simulated.

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