Research and Application of RBF Neural Network-based Osmotic Pressure Forecast Model for Concrete-Faced Rockfill Dam

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Abstract: To realize real-time forecast and early-warning of osmotic pressure of concrete-faced rockfill dams, this research analyses factors that influence fluctuation of osmotic pressure and builds a statistical model for the osmotic pressure. A three-layer RBF neural network-based osmotic pressure forecast model for the concrete-faced rockfill dam is built with the 16 standardized variables as input-layer factors and the osmotic pressure as the output-layer factor. With 12 groups of actually-measured data from different sections of the dam as samples, this research analyses the fitting and forecast accuracy of the model via SPSS and the RBF neural network. In light of actual engineering demand, the model is applied to the 3D visual monitoring information system, and with the early-warning indicators determined, it can realize real-time monitoring.

1. Introduction

The concrete-faced rockfill dam is a kind dam with rockfill as the supporting structure and with concrete panels as the impermeable structure on the upper-stream part. As the materials for this kind of dam are usually drawn locally, it has such advantages as low requirements for the dam foundation, high stability and economic efficiency, so it has become a highly competitive type of stone dam [1~2]. Yet, judging from the operation of built dams, despite the great popularity of the concrete-faced rockfill dam, it has problems like rockfill disengagement, rockfill cracking and rupture of the water-proof structure, all of which may lead to larger seepage and threaten the safety of the dam[3].

Seepage is a major concern for safety of dams, so seepage detectors are often installed in dam-building projects to realize monitoring, and analysis of osmotic pressure monitoring results and field inspection are conducted to detect anomalies in the operation of the dam. To master the law of osmotic pressure fluctuation in the dam, materials obtained from actual measurement are applied to mathematical models to realize forecast and analysis. Xu Tiankai[4] and et al. analyzed the lagged effect of the reservoir’s water level and precipitation on seepage of the concrete-faced rockfill dam and, in light of the dam-building features of the deep overburden concrete-faced rockfill dams, built a self-adaptive genetic algorithm-based safety monitoring model with consideration of the lagged effect to monitor the seepage of deep overburden concrete-faced rockfill dam.

Characterized by such advantages as strong classification ability, approximation ability and high learning efficiency as well as no risk of regional optimization, RBF neural network has been widely

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used. Huang Ming [5] and et al., with RBF neural network as the modelling tool, built a model to monitor osmotic pressure and precipitation to conduct fitting and forecast for the osmotic pressure changes on the high slope under precipitation. Besides, RBF neural network has also shown good performance when applied to monitoring of coal and gas outburst intensity [6] and forecast of urban water usage [7].

With the concrete-faced rockfill dam building project at the reservoir of Hekou village as the research target, this research analyzes the factors that influence the osmotic pressure changes and builds a statistical model with four determining factors: water pressure, temperature, time and precipitation. With a total of 16 variables taken as input-layer factors after standardization and the osmotic pressure as the output-layer factor, a three-layer RBF neural network-based statistical model is built to monitor the osmotic pressure of the concrete-faced rockfill dam. With the data about the dam foundation, the dam body, the cutoff wall and the surrounding dam achieved through actual measurement, the accuracy of the forecast model is tested and the test shows a good result. The model is applied to the 3D visual monitoring information system, and with the early-warning indicators determined, it can realize real-time monitoring, forecast and early-warning of the osmotic pressure of the dam. The result of this research can be used as reference for similar engineering projects.

2. Building of the Osmotic Pressure Forecast Model

The osmotic pressure are mainly subject to influence of the water level, temperature, time and precipitation[8]. The following statistical model is used in analysis:

\[ H = H_h + H_T + H_0 + H_r \]  

where:  
- \( H \) is the osmotic pressure fitting value,  
- \( H_h \) the component of water level,  
- \( H_T \) the component of temperature,  
- \( H_0 \) the component of time of seepage and  
- \( H_r \) the component of precipitation of seepage.

The 3-layer RBF neural network composed of an input layer, a hidden layer and an output layer is used herein. Factors on the input layer include the water level component, temperature component, time component and precipitation component. According to analysis of the lagged effect based on materials obtained from actual measurement, the number of lagged days of the osmotic pressure is within 60 days, so the selected water level components are \( H_1, H_{1-2}, H_{1-5}, H_{1-15}, H_{1-30}, H_{1-60} \). The selected precipitation components are the precipitation on the exact monitoring day and average precipitation within 15 days before the monitoring day, hence \( R_1, R_{1-2}, R_{1-7}, R_{1-8}, R_{1-15} \). The two selected time components are \( \theta \) and \( \ln \theta \). According to Equation (4), when \( i \) is valued at 1 and 2 respectively, the temperature component can be divided into 4 factors.

In summary, the statistical model for osmotic pressure is:

\[ H = H_h + H_T + H_0 + H_r \]

\[ + a_0 H_1 + a_1 H_{1-2} + a_2 H_{1-5} + a_3 H_{1-15} + a_4 H_{1-30} + a_5 H_{1-60} \]

\[ + b_{11} \left( \frac{2\pi t}{365} - \sin \frac{2\pi t}{365} \right) + b_{21} \left( \frac{2\pi t}{365} - \cos \frac{2\pi t}{365} \right) \]

\[ + b_{12} \left( \frac{4\pi t}{365} - \sin \frac{4\pi t}{365} \right) + b_{22} \left( \frac{4\pi t}{365} - \cos \frac{4\pi t}{365} \right) \]

\[ + c_1 (\theta - \theta_0) + c_2 (\ln \theta - \ln \theta_0) + d_1 R_1 + d_2 R_{1-2} + d_3 R_{1-7} + d_4 R_{1-15} \]

Where \( H \) refers to the water level in the upper stream on the monitoring day; \( H_{i-j} \) refers to the water level in the upper stream from the \( i \)th day to the \( j \)th day before the monitoring day; \( d_0 \) and \( d_m \) represent the regression coefficients of the water level component (\( m=1,2,3,4,5 \)).

Where \( t \) represents the number of days between the monitoring day and the first measurement day; \( t_0 \) represents the number of days between the first monitoring day in the sequence of the model and the first measurement day; \( b_0 \) and \( b_2 \) represent the regression coefficients of temperature
(i=1,2).
    
Where $\theta$ stands for the result of 100 divided by the number of days $t$ between the monitoring day and the first measurement day; $\theta_0$ refers to the result of 100 divided by the number of days $t_0$ between the first monitoring day in the sequence of the model and the first measurement day; $c_1$ and $c_2$ are the regression coefficients for the component of time.

Where $R_t$ stands for the precipitation on the exact monitoring day; $\bar{R}_{ij}$ refers to the average precipitation from the $i$th day and $j$th day before the monitoring day; $d_0$ and $d_k$ are the regression coefficients of the component of precipitation.

3. Application in Actual Engineering Case

3.1. Analysis of Accuracy of the Osmotic Forecast Model

The dam of the reservoir in Hekou village is a concrete-faced rockfill dam, the maximum height of which is 122.5m, the altitude of its top 288.5m, the length of its top 530.0m and the width of its top 9.0m. The dam is built on the deep overburden foundation, the maximum depth of which is 40m. To monitor the osmotic pressure of the dam, 106 osmometers are installed around the foundation and main body of the dam as well as the cutoff wall. To monitor the seepage conditions of the surrounding dam, 17 sets of piezometers are installed, and all monitoring data of the detection instruments are obtained in real time and automatically. The hydrological measuring and reporting system can realize automatic monitoring and data collection of the water level and precipitation of the reservoir.

To study the fitting and forecast function of the osmotic pressure forecast model, three samples are selected respectively from each of the following parts: the dam foundation, the cutoff wall, the surrounding dam and the main body of the dam, to test the model’s accuracy. The time of sample collection is from May 27th, 2016 to March 11th, 2018, each sample containing 450 pieces of data. Statistics of the model’s forecast accuracy is shown in Table 1, and the actual monitoring value-forecast value comparison hydrographs for typical monitoring sites are shown in Fig.1 ~Fig.4. From the tables and figures, the following results can be observed:

1) The association coefficient between the forecast value and the actual monitoring value in each part is above 0.9, and the coefficient of determination is above 0.85. In general, it shows strong association and the changes in the forecast data and in the actual monitoring data are consistent. The association coefficient for osmotic pressure forecast in the dam foundation is slightly smaller than those for other parts because the influence of the reservoir’s water level on the osmotic pressure changes is relatively small, and in particular, the correlation between the osmotic pressure of the dam foundation behind the cutoff wall and the reservoir’s water level is not obvious.

2) The root-mean-square errors for all parts are between 1.04 and 4.32, and the mean square errors fall into the range from 0.68kPa to 2.36kPa. The error is small and hence the forecast accuracy is high. According to the collected data, the forecast error for the dam foundation is smaller than that for the cutoff wall and the surrounding dam. As the osmotic pressure of the dam foundation is under 100kPa, with the pressure for some parts being zero or even negative; in contrast, the osmotic pressure for the monitoring sites before the cutoff wall and on the surrounding dam are mostly above 100kPa, and the forecast error for the dam foundation is relatively high. Therefore, though the forecast error for the dam foundation is small, the association coefficient is small.

3) The absolute errors for both the sample fitting forecast data and the actual monitoring data are lower than the double of the standard deviation of the fitting forecast data. According to the hydrographs, the forecast data are consistent with the data achieved through actual measurement in spite of some minor fluctuations, and the overall trend remains the same. Analysis above shows that this model well reflects the trend of osmotic pressure changes in different parts of the concrete-faced rockfill dam and demonstrates high accuracy. It can be applied in software for secondary development to realize real-time forecast.
### Table 1: Accuracy Analysis of RBF Neural Network Osmotic Pressure Forecast Model

| Index                              | Dam foundation | Cutoff wall | Dam body | Surrounding dam | Average |
|------------------------------------|----------------|-------------|----------|-----------------|---------|
| Association coefficient            | 0.92           | 0.99        | 0.97     | 0.99            | 0.97    |
| Coefficient of determination $R^2$ | 0.85           | 0.97        | 0.94     | 0.98            | 0.94    |
| Root-mean-square error (RMSE)      | 1.04           | 3.69        | 1.10     | 4.32            | 2.54    |
| Mean square error (MSE) (kPa)      | 0.73           | 1.61        | 0.68     | 2.36            | 1.34    |

**Fig. 1** Actual measurement data – forecast data comparison by Osmometer P5-14 in dam foundation

**Fig. 2** Actual measurement data – forecast data comparison by Osmometer P5-82 in cutoff wall

**Fig. 3** Actual measurement data – forecast data comparison by Osmometer P5-37 in dam body
3.2. Osmotic Monitoring Early Warning

With the concrete-faced rockfill dam in Hekou village as the study case, a 3D visual safety monitoring information system based on domain drive is built to conduct 3D simulation and present the safety information of the structure under different engineering conditions in a direct way. The system categorizes, stores and manages the monitoring data, and four libraries – the professional knowledge library, the original data library, the re-organization library and the model library, composes the major data sources for the monitoring and early-warning system. On that basis, the model realizes such main functions as production of analysis charts of the dam’s features, online data monitoring and over-limit early-warning information release. It can fulfill measuring data transformation of the online monitoring data, marking of gross error detecting data, recognition of measurement anomalies and batch output of data analysis charts.

According to the result of 3.1, the monitoring information system early-warning index is set as follows:

(1) When $|\hat{H} - H| < 2S$, the monitoring data are normal;
(2) When $2S < |\hat{H} - H| \leq 3S$, the system conducts tracking monitoring, and it labels the result as normal if no trend of changes shows, otherwise labels it as abnormal and analyzes causes;
(3) When $|\hat{H} - H| > 3S$, the measurement data are abnormal and the system analyzes the causes.

As mentioned above, $H$ is the actual measurement value of osmotic pressure, $\hat{H}$ the calculated value worked out by the model and $S$ the standard deviation of the forecast value.

The steps through which the monitoring information system realizes forecast and early-warning are as follows:

(1) The monitoring sites are selected on the window of “Digital Model” and the RBF neural network forecast model is built;
(2) During real-time monitoring, the system calls the measured data of osmotic pressure and the
data of water level and precipitation of the reservoir for calculation, and meanwhile works out the actual measurement data – forecast data comparison hydrograph, as presented in Fig. 5.

(3) When the osmotic pressure of the monitoring sites exceeds the warning limit, the early-warning prompt box will pop up automatically with the latest warning information;

(4) When the early-warning information occurs, in-depth analysis will be conducted in light of the monitoring data from different regions and on-site inspections to provide support for users to make highly efficient decisions.

4. Conclusion
(1) Through analysis of the contributing factors and mathematical formulas of the osmotic pressure of the concrete-faced rockfill dam, an RBF neural network-based osmotic pressure statistical model is built to realize forecast of osmotic pressure changes of the dam. The result of the osmotic pressure analysis shows that the forecast data are consistent with the actual measurement data and they present consistent trends; besides, the forecast accuracy is high and this method can be used to osmotic pressure forecast of the dam;

(2) Based on the research result of osmotic pressure forecasting, the early-warning indicators are determined, and the early-warning module is built on the 3D visual safety monitoring information system, which realizes real-time monitoring, forecast and early-warning of the osmotic pressure of the dam and increases management efficiency. Thus, the research result herein can provide reference for similar engineering projects.

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