Back analysis of permeability coefficient of earth-rock dam based on EMD-RVM

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Abstract. Since contemporary information-retrieval systems rely heavily on the content of titles and abstracts to identify relevant articles in literature searches, great care should be taken in constructing both. Since the permeability coefficient of the dam material of the earth-rock dam directly affects the seepage flow of the dam, in order to improve the accuracy of retrieving the permeability coefficient from the measured value of the seepage flow, the empirical mode decomposition method (EMD) is used to monitor the actual seepage flow of the weir. After decomposition, multiple sets of intrinsic modal functions (IMF) were generated to fit the relationship between water level and seepage flow; then the finite element software was used to calculate the seepage flow corresponding to the randomly distributed infiltration parameters at different water levels in order to the RVM model performs inverse analysis on the permeability coefficient. The training sample group is constructed by finite element calculation, the calculated seepage volume of the sample group is used as the input value, and the corresponding permeability coefficient is used as the output value. Based on EMD-RVM, a nonlinear mapping relationship between the permeability coefficient and seepage volume of each section of the face rockfill dam is established. Using the model inversion, the results show that the EMD-RVM model has high inversion accuracy and is significantly higher than the conventional RVM model and GA-BP model. The infiltration pressure of the face rockfill dam can be calculated from the inversion result of the permeability coefficient, and the error with the measured value is small, which verifies the feasibility of the model.

1. Introduction

Earth-rock dams are widely used in the field of dam engineering due to their economic advantages, simple construction techniques, and strong adaptability to terrain and geology. In the three investigation reports of the International Dam Commission[1], the number of earth-rock dam failures accounted for 70% of the total. Among them, about 25% of the earth-rock dam failures were caused by the seepage and destruction of the dam body. Concrete face rockfill dam is an important dam type of earth-rock dam, and the safety of seepage is very critical to the safe operation of face rockfill dam. In order to ensure the seepage safety of the rockfill dam during operation, it is necessary to monitor the seepage of the rockfill dam in combination with the monitoring data. The seepage monitoring of the rockfill dam during operation generally includes the seepage flow behind the dam and the seepage pressure head in the dam. These two types of monitoring data are a direct characterization of the dam's operating behavior[2]. However, the monitoring data cannot be directly used as the criterion for dam seepage safety, and it can be judged only by techniques such as dam seepage field analysis. The analysis of the seepage field of the rockfill dam is inseparable from the calculation of the permeability coefficient of the dam material.
in each section of the actual dam body[3]. Therefore, the use of rockfill dam seepage monitoring data to obtain the permeability coefficients of various sections of the dam body in order to improve the reliability of the rockfill dam seepage field analysis is of great practical significance for the accurate evaluation of the dam seepage safety situation.

Due to influencing factors such as weak rainfall, changing water level, and aging deformation of the dam body, the monitoring data of seepage in rockfill dams are generally non-linear and non-stationary, so it is better to study the seepage monitoring data and accurately invert difficult. At present, in order to solve the problems of overfitting and non-unique results of rockfill dam permeability coefficient inversion, intelligent algorithms are widely used in inversion analysis. For example, Shen Yuyang and others proposed the thinking evolution algorithm to optimize the penetration parameter inversion method of the BP neural network to improve the global optimization accuracy, but the algorithm still relies heavily on the initial value[4]; Ma Chunhui and others proposed a hybrid genetic algorithm and multi-output kernel Correlation vector machine-based adaptive inversion method of rockfill dam material parameters improves the adaptability of the algorithm[5]; Cui Zhiwei et al. introduced the AHP-GA algorithm to solve the problem that the rockfill dam permeability parameter inversion results are not unique[6]. Whether it is a traditional algorithm or an intelligent optimization algorithm, there are many problems. In the parameter inversion analysis of the face rockfill dam, the selection of the initial value of the parameter greatly affects the accuracy of the inversion result, and the algorithm is poorly robust. In addition, when performing multi-parameter inversion, the algorithm iteration is too complicated and the convergence is slow. The inversion results are often easy to fall into the local minimum and the inversion accuracy is low. The inversion algorithm needs to be improved in theoretical research and application. Therefore, this paper constructs an empirical mode decomposition (EMD) inversion model based on correlation vector machine theory (RVM) to solve the above problems. Huang[7] et al. proposed an empirical mode decomposition algorithm in 1998 to solve the pulsating time series analysis problem. At present, EMD has been applied to many industries such as environment, hydrology, chemistry, earthquake, etc., but little research has been done in the inversion of permeability coefficient of rockfill dams[8-11]. Compared with the support vector machine (SVM) of the traditional permeability coefficient inversion model, the related vector machine theory (RVM) model established by Tipping[12] not only solves the problem of low structural sparsity of the former, but also simplifies the kernel function. Calculation procedures. In view of this, this paper combines the EMD decomposition method and RVM models, adopts the advantages of each method, establishes the EMD-RVM dam permeability coefficient inversion model, greatly improves the inversion accuracy, and strengthens the model's applicability.

2. Inversion model of permeability coefficient of rockfill dam

2.1. The principle of EMD

Empirical mode decomposition (EMD) can solve the problem of signal smoothing. The general condition of signal smoothing is that the number of upper (lower) zero crossings of the original signal sequence is at least 2 less than the number of extreme values[13]. The smoothing process is to decompose the original data sequence to obtain the components $imf_1$, $imf_2$, ..., $imf_n$ and residual $r_n$. The components obtained by the decomposition should conform to[14]: the number of zero points and the number of extreme points of the sequence are equal or different by one; the envelope of the sequence is symmetrical about the t-axis, and the mean value of each component is zero. The principle of data smoothing is as follows:

(1) For a signal sequence $y(t)$, the upper and lower envelopes can be obtained by the cubic spline difference function according to its extreme point, and recorded $m_i(t)$ as the average of the upper and lower envelopes, which is the first IMF of the original sequence Weight:

$$h_i(t) = y(t) - m_i(t)$$ (1)
 Generally speaking, the first screening $h_1(t)$ does not meet the characteristics of the IMF component, but a theoretical component. Because in the calculation process, these new extreme points were not found in the previous calculation, and should be found in the next calculation process, so cyclic filtering is used to eliminate modal waveform superposition and make the component waveform more about the t-axis Symmetry[15]. Therefore, $h_1(t)$ as a new data sequence $y(t)$, it is sifted through $k$ times until it meets the conditions to obtain $h_{k1}(t)$. Taking the new original data calculation sequence $r_1(t)$ and looping the above steps $m$ times, you get $m$ IMF components:

$$r_1(t) = r_1(t) - f_1(t)$$

$$\vdots$$

$$r_m(t) = r_{m-1}(t) - f_m(t)$$

(3) If the residual is monotonic or meets the error limit, the decomposition ends, so $y(t)$ is:

$$y(t) = \sum_{i=1}^{m} f_i(t) + r_m(t)$$

(4) In order to decompose the components in accordance with the actual physical meaning, the standard deviation $SD$ of the two adjacent screening results is used as the screening stop criterion[16], and the $SD$ calculation formula is:

$$SD = \frac{1}{k-1} \sum_{k=1}^{2} \left( \frac{h_{k1}(t) - h_{k}(t)}{h_{k1}(t)} \right)^2$$

Where $A$ is the length of the original sequence; $SD$ is generally between 0.2 and 0.3, in order to ensure the stability of the component, $SD$ takes 0.3.

2.2. Principle of correlation vector machine algorithm (RVM)

The data sequence group is $\{y_n, t_n\}_{n=1}^N$, which can be expressed as:

$$t_n = u(y_n, w) + \varepsilon_n$$

Where Gaussian noise $\varepsilon_n$ with zero mean is independent of each other, and the variance is $\sigma^2$. $u(y; w)$ can be expressed as:

$$u(y; w) = \sum_{n=1}^{N} \alpha_n K(y, y_n) + \omega_0$$

Where $y$ is the monitored seepage flow; $u$ is the permeability coefficient of the dam structure to be inverted; $\omega_n$ is the weight; $w$ is the parameter vector; $N$ is the number of samples; $K(y, y_n)$ is the kernel function.

Set $t_n$ as an independent distribution, the complete probability of the data sequence is:

$$p(t | w, \sigma^2) = (2\pi \sigma^2)^{-N/2} \exp \left\{ -\frac{1}{2\sigma^2} \| t - \Phi w \|^2 \right\}$$

Where $w = (\omega_0, \omega_1, \ldots, \omega_N)^T$, $t = (t_1, \ldots, t_N)^T$, $\Phi = [\phi(y_1), \ldots, \phi(y_N)]$ are the matrix of $N \times (N + 1)$, and $\phi(y_n) = [1, K(y_n, y_1), K(y_n, y_2), \ldots, K(y_n, y_N)]^T$. 


However, when the parameters in the training sequence increase, the maximum likelihood estimation of $\sigma^2$ and $w$ will overfit. In order to avoid this phenomenon, this paper combines the principle of SVM and adds constraints to some parameters[17]. Therefore, the parameters $\omega_i$ follow a Gaussian distribution with mean zero:

$$p(w|\alpha) = \prod_{i=1}^{N} N(\omega_i | 0, \alpha^{-1})$$  \hspace{1cm} (9)

Where the hyperparameters $\alpha$ follow the prior distribution.

By calculating the hyperparameter and noise variance through the fast sequence sparse Bayesian algorithm, the model Gaussian kernel function is[18]:

$$K(y, y_i) = \exp(-g\|y - y_i\|^2)$$  \hspace{1cm} (10)

2.3. Construction of inversion model for permeability coefficient of rockfill dam

Based on EMD-RVM model, an inversion model of permeability coefficient of CFRD is constructed, which bears the nonlinear mapping relationship between seepage flow and permeability coefficient. Using this mapping relationship and the actual flow monitoring value, the parameter inversion of the permeability coefficient of each partition of the dam body can be well carried out, and the specific inversion model is shown in Figure 1.

![Figure 1 EMD-RVM permeability coefficient inversion model](image_url)

3. Case study

3.1. Finite element seepage calculation model
Taking a concrete face rockfill dam as an example, the maximum height of the dam is 120m, the seepage three-dimensional finite element calculation model of the dam engineering area is shown in Figure 2. The calculation model covers an area of 1.5 times of dam height for the left and right banks, and one time of dam height for bedrock, front and back of dam. The model includes the main boundary of the seepage field that can affect the calculation domain, as well as the panel, cushion, transition layer, main rockfill area, secondary rockfill area, peripheral joints, toe board, curtain, water measuring weir, rock mass, etc. The whole model has 64122 units and 68275 nodes, as shown in Figure 2. In the design stage of the dam, the permeability test of dam materials in each zone is carried out, and the permeability coefficient of cushion is about $5 \times 10^{-6} \text{cm/s}$, which is about 4 orders of magnitude larger than that of face slab; the permeability coefficient of transition layer is about $5 \times 10^{-4} \text{cm/s}$; the permeability coefficient of secondary rockfill is about $4 \times 10^{-2} \text{cm/s}$. Considering that the permeability coefficient of transition layer, secondary rockfill and cushion is 4-8 orders of magnitude different from that of the face slab, its numerical value has little influence on the seepage field, so the permeability coefficient of these dam materials is taken as the fixed value in inversion, and the comprehensive permeability coefficient of the face slab, curtain, bedrock and cushion are taken as the inversion parameters.

![Figure 2. Three-dimensional finite element calculation model of rockfill dam seepage](image)

3.2. Inverse calculation of permeability coefficient

The measured seepage flow of the face rockfill dam is mainly affected by the upstream and downstream water levels, rainfall infiltration and other factors. In order to eliminate the influence of rainfall on the seepage flow, at least 7 days of no rainfall conditions were selected for inversion analysis. Select the measured data from September 9, 2013 to November 10, 2013, from October 22, 2016 to December 30, 2016 and from October 6, 2014 to December 15, 2014 as the calculation inversion group, select the infiltration monitoring data from October 7, 2017 to November 5, 2017 as the model verification group. First, use the finite element program of the saturated-unsaturated seepage field to generate learning samples, and set the possible range of the parameters to be inversed according to experience. The value ranges of $k_1$, $k_2$, $k_3$, and $k_4$ are: $8 \times 10^{-9}$ ~ $1.5 \times 10^{-10} \text{cm/s}$, $1 \times 10^{-9}$ ~ $1.5 \times 10^{-11} \text{cm/s}$, $1.2 \times 10^{-7}$ ~ $2.0 \times 10^{-8} \text{cm/s}$, $4.5 \times 10^{-6}$~$2.0 \times 10^{-7} \text{cm/s}$. Within the parameter range, 60 sets of parameter values were randomly given according to the uniform distribution. The finite element positive analysis is used to calculate the seepage flow at different water levels, so as to construct 60 sets of learning samples, which are denoted as $F$. Through the learning of the training sample, the calculated seepage flow in the learning sample is used as the input value, and the corresponding permeability coefficient is used as the output value. Based on the EMD-RVM, the non-linear mapping relationship between the permeability coefficient and the seepage flow of the panel rockfill dam is established.

Take the seepage monitoring data from October 7, 2017 to December 21, 2017 to fit the relationship between water level and seepage flow. For the data smoothing process, based on EMD decomposition
and reorganization, three IMF components and one residual component can be obtained. The decomposition results are shown in Figure 3. The relationship between water level and seepage flow is shown in Figure 4.

![EMD decomposition component results](image1)

![Fitting diagram of water level and seepage flow](image2)

The relevant parameters of the RVM model constructed are shown in Table 1.
Table 1. Values of model inversion parameters

| Parameter                  | Inertia factor $\omega$ | The kernel parameters $g$ | Learning factor $C_1$ | Learning factor $C_2$ | Position factor of the nuclear function $\nu$ | Speed factor $\gamma$ |
|----------------------------|-------------------------|----------------------------|------------------------|------------------------|---------------------------------------------|------------------------|
| Value                      | 0.25–0.75               | 0.01–1.0                   | 1.3–2.4                | 1.55–2.45              | 0.01                                        | 1.00                   |

The finite element software can batch calculate the seepage flow corresponding to the randomly generated permeability coefficient set. There are 60 groups in the set. And then the RVM model can fit the implicit relationship between the seepage flow and the permeability coefficient, and the comparison between the RVM model fitting value and the design permeability coefficient value is inverse. After calculating the error value, and then correcting the inversion results, the final inversion results $k_1$, $k_2$, $k_3$, and $k_4$ of the permeability coefficients of each section of the face rockfill dam can be obtained. In order to verify the feasibility of this model, the inversion results of RVM model and traditional GA-BP model are given in Table 2.

Table 2. Inversion values of permeability coefficients of different sections of face rockfill dam with different methods

| Permeability coefficient (cm/s) | $k_1$ | $k_2$ | $k_3$ | $k_4$ |
|-------------------------------|-------|-------|-------|-------|
| EMD-RVM                       | 1.23E-10 | 1.07E-10 | 1.50E-07 | 5.34E-06 |
| RVM                           | 1.26E-10 | 1.08E-10 | 1.64E-07 | 4.89E-06 |
| GA-BP                         | 1.13E-10 | 9.08E-11 | 1.61E-07 | 6.42E-06 |

3.3. Verification results and error analysis
Based on the three groups of permeability coefficients of emd-rvm inversion model, RVM model and GA-BP model, the corresponding calculated seepage flow from October 7, 2017 to December 21, 2017 is calculated by using the finite element method. The calculation results of seepage flow of three models and the corresponding average residual results are shown in Figure 5 and Figure 6. The average residuals of the corresponding seepage flow are 0.103L/s, 0.088L/s and 0.034L/s, respectively, calculated by the permeability coefficient inversely by GA-BP model, RVM model and EMD-RVM model.
In order to further verify the feasibility of the EMD-RVM inversion model, the infiltration pressure of the dam was calculated by inversion of the permeability coefficient. The P3 osmotic pressure monitoring value with good measured value law is selected and compared with the corresponding osmotic pressure value obtained by finite element calculation of different inversion models. The results are shown in Figure 7 and Figure 8 below. The average residual pressure of osmotic pressure is 2.54kPa, 1.75kPa, 0.92kPa. To sum up, the inversion effect of EMD-RVM model is better than that of RVM model and GA-BP model.
4. Conclusion

In order to solve the non-stationary and non-linear problem of seepage inversion data of face rockfill dam, this paper constructs the EMD-RVM face rockfill dam permeability coefficient inversion model. The main conclusions are as follows:

(1) Taking the actual measured data of the seepage of a concrete face rockfill dam as an example, based on the RVM theory inversion, after using the EMD method to stabilize the data, several IMF components and a residual difference component are obtained, the relationship between the water level and the seepage flow is fitted, and then used The RVM model establishes a mapping relationship between the randomly generated permeability coefficient set and the finite element calculated seepage flow set, and finally calculates the residual difference component to obtain the error value to obtain the final inversion result. Through the example inversion and verification results, the EMD-RVM inversion model is feasible in engineering applications, with high operability and accuracy.

(2) By comparing with the inversion results of the single RVM model and GA-BP model, it can be seen that the EMD-RVM model has higher inversion accuracy, indicating that the model inverts the permeability coefficient of the face rockfill dam Has high reliability.

(3) In the inversion process of the concrete face rockfill dam, because there are few measured values of the weir behind the dam that is not affected by rainfall, the analysis data is not much, which affects the accuracy of the inversion result. Rainfall should also be considered in the future Research on the inversion of permeability coefficient in complex situations.

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