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Time-varying identification model for dam behavior considering structural reinforcement

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ABSTRACT

Mathematical relationship model between structural response and its influence factors is often used to identify and assess dam behavior. Under the action of loads, changing material property, structural reinforcement and so on, dam behavior expresses the uncertain variation characteristics. According to the prototypical observations, objective and subjective uncertain information on dam behavior before and after structural reinforcement, support vector regression (SVR) method is combined with Bayesian approach to build the time-varying identification model for dam behavior after structural reinforcement. Firstly, a static SVR model identifying dam behavior is established. Secondly, Bayesian approach is adopted to adjust dynamically the calculated results of static identification model. A method determining the Bayesian prior distribution and likelihood function is developed to describe the objective and subjective uncertainty on dam behavior. Emphasizing the importance of recent information on dam behavior, an algorithm updating in real time the Bayesian parameters is proposed to reflect the characteristic change of dam behavior after structural reinforcement. Lastly, the displacement behavior of one actual dam undergoing structural reinforcements is taken as an example. The identification capabilities of classical statistical model, static SVR model and time-varying model are compared. It is indicated that the proposed time-varying model can provide more accurate fitted and forecasted results, and is more suitable to be used to evaluate the reinforcement effect of dangerous dam.

1. Introduction

Many of 98,000 existing dams in China are in active service under the conditions of low design standard, poor construction quality, serious aging, and other hidden troubles. The massive structural reinforcements of dangerous dams or unsafe dams are being or have been implemented in recent years, which can cause the characteristic change of dam behavior. It is very important for dam safety control to identify accurately dam behavior and assess reasonably the reinforcement validity [1–7]. According to the prototypical observations on deformation, seepage, stress, water level, temperature, rainfall, etc., statistical regression models, which are built using the least squares algorithm, the weighted least squares algorithm, the generalized least squares algorithm and the partial least squares algorithm, are usually regarded as an effective alternative tool for fitting and forecasting dam behavior [8–14]. Genetic algorithm or cointegration theory-based approaches are adopted to enhance the model adaptability and improve the modeling accuracy [2,15–17].

The practice of structural reinforcement or the accompanying modification of monitoring system can cause the interruption, step change or non-stationary change of observed data on dam behavior [2]. For dam engineering serving for many years, it may undergo the structural reinforcements for dam body, dam foundation or reservoir bank in different periods. The structural reinforcements can make the structure and its stiffness change which leads to the reference value variety of time series on observed data. If above data features and structural properties caused by structural reinforcements are not considered in building an identification model for dam behavior, the modeling precision will be influenced, even inaccurate results may be provided. As one alternative solution to the present problem, an approach developing the time-varying identification models for dam behavior is explored in this paper. Prototypical observations on dam behavior before

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and after structural reinforcements, numerical and physical experiment results, and experiential knowledge are taken as the modeling information sources. Support vector regression (SVR) method and Bayesian approach are combined as the modeling tool. It is the core target of this study that the built model can describe the uncertain change of dam behavior after structural reinforcements, and can be used to evaluate the reinforcement validity.

The paper is organized as follows. Based on the prototypical observations on deformation, seepage, stress, water level, temperature, rainfall, etc., a SVR method is introduced to build the static identification model for dam behavior in Section 2. According to new observations, objective and subjective uncertain information on dam behavior, an approach is presented to adjust dynamically the calculated results of static identification model in Section 3. The Bayesian prior distribution and likelihood function, which are characterized by ARMA (Auto-regressive moving average) model, are adopted to describe the objective and subjective uncertainty on dam behavior. A recursive least squares algorithm with forgetting factor is used to implement real time estimation of Bayesian parameters, which make the characteristic change of dam behavior after structural reinforcement be reflected. Section 4 offers an actual case. The displacement behavior of one concrete gravity dam undergoing structural reinforcements is analyzed with three identification models, namely classical statistical model, static SVR model and time-varying model. The fitting and forecasting capabilities of three models are illustrated.

2. Static identification model for dam behavior

2.1. Classical statistical model

To monitor dam safety, some instruments and devices are installed to obtain structural response (effect variable) and environmental, hydraulic, geomechanical information (influence variable). The effect variables include displacement, stress, strain, seepage, etc. The influence variables have water level, temperature (water temperature, air temperature, internal temperature of dam body and dam foundation), sediment pressure, seismic load, etc. The nonlinear functional relationship exists among the effect variable y and the corresponding influence variables ($x_1, x_2, \ldots, x_n$). The concrete gravity dam displacement is taken as an example. It can be treated as the sum of hydrostatic pressure term y_H, temperature term y_T and time effect term y_θ [7,18], namely

$$y = y_H + y_T + y_\theta \tag{1}$$

y_H represents the displacement change caused by the turn and deformation of dam body and its foundation under the action of water load and own weight of dam body. It is mainly related to the upstream reservoir water depth H. y_H of a gravity dam can be written as:

$$y_H = \sum_{i=1}^{3} a_i H^i \tag{2}$$

where a_1, a_2, a_3 are the coefficients.

y_T expresses the displacement caused by the temperature change of dam body concrete and dam foundation rock. When there are enough thermometers installed in dam body and dam foundation, and these thermometers can describe the dam temperature field, y_T can be calculated with Eq. (3). For one concrete dam running for many years, the internal temperature field can be regarded as quasi steady state. If there are not enough temperature observations, y_T can be calculated with Eq. (4).

$$y_T = \sum_{i=1}^{m_1} b_i T_i \tag{3}$$

$$y_T = \sum_{i=1}^{m_2} \left(b_{1i} \sin\frac{2\pi it}{365} + b_{2i} \cos\frac{2\pi it}{365} \right) \tag{4}$$

where T_i represents the observation of the ith thermometer, t denotes the cumulative days from the monitoring day to the beginning day, m_1 is the thermometer number in the dam, m_2 expresses the cycle number taken usually as 1 or 2, which represents annual cycle or semiannual cycle, respectively, $b_1, b_2, \ldots, b_{m1}, b_{11}, b_{12}, \ldots, b_{1m2}, b_{21}, b_{22}, \ldots, b_{2m2}$ are the coefficients.

y_θ is used to represent the creep and plastic deformation of dam body and dam foundation, the autogenous volume deformation caused by dam cracks, and the irreversible displacement. It is described usually with the following logarithmic function and linear function.

$$y_\theta = c_1\theta + c_2 \ln\theta \tag{5}$$

where $\theta = t/100$, c_1 and c_2 are the coefficients.

In the case study of this paper, the following classical statistical model is adopted and the stepwise least squares method is performed.

$$y = a_0 + \sum_{i=1}^{3} a_i H^i + \sum_{i=1}^{2} \left(b_{1i} \sin\frac{2\pi it}{365} + b_{2i} \cos\frac{2\pi it}{365} \right) + c_1\theta + c_2 \ln\theta \tag{6}$$

where a_0 is a constant term.

2.2. Support vector regression model

Support vector machine (SVM) is a new technique solving pattern classification and function approximation problems in many areas [19–23]. As a SVM application for function estimation, support vector regression (SVR) has been used for dam behavior identification [24]. The SVR goal is to find an optimal function $f(x)$ as Eq. (7), which represents the nonlinear mapping relationship between the dependent variable $y \in R$ and the independent variables $x \in R^m$, such as dam displacement variable and corresponding influence variables, from a given training sample data set $\{(x_1,y_1), \ldots, (x_l,y_l)\}$, where m and l represent the number of independent variables and the number of sample data, respectively.

$$f(x) = \langle w, \psi(x) \rangle + b \tag{7}$$

where w represents the weight vector, $\psi(x)$ represents the high-dimensional feature spaces which is nonlinearly transformed from x, $\langle w, \psi(x) \rangle$ denotes the dot product between w and $\psi(x)$, b is a bias.

Optimization of the function as Eq. (7) is equivalent to minimizing the following regularized risk function with the constraints.

$$\begin{aligned} &\min R(w, \xi_i, \xi_i^*) = \min_{w,\xi_i,\xi_i^*} \tfrac{1}{2} w \cdot w + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \\ &\text{s.t.}\, f(x_i) - y_i \leqslant \varepsilon + \xi_i^*,\ i = 1, \cdots, l \\ &\quad f(x_i) - y_i \leqslant \varepsilon + \xi_i,\ i = 1, \cdots, l \\ &\quad \xi_i^*, \xi_i \geqslant 0,\ i = 1, \cdots, l \end{aligned} \tag{8}$$

where C is the regularization constant that determines the trade-off between the empirical risk and the regularization term, ε is a constant called the tube size, ξ_i and ξ_i^* are the slack factors that represent the distance from the actual values to the corresponding boundary values of the ε tube.

The following Lagrangian form is adopted to solve the convex quadratic optimization problem in Eq. (8).

$$\begin{aligned} L(w, b, \xi_i, \xi_i^*, \alpha_i, \alpha_i^*, \gamma_i, \gamma_i^*) &= \tfrac{1}{2} w \cdot w + C \sum_{i=1}^{l} (\xi_i + \xi_i^*) \\ &- \sum_{i=1}^{l} \alpha_i [\xi_i + \varepsilon - y_i + f(x_i)] - \sum_{i=1}^{l} \alpha_i^* [\xi_i + \varepsilon + y_i - f(x_i)] - \sum_{i=1}^{l} (\xi_i \gamma_i - \xi_i^* \gamma_i^*) \end{aligned} \tag{9}$$