Research Article

Crack-Considered Elastic Net Monitoring Model of Concrete Dam Displacement

Jiingmei Zhang 1,2,3 and Chongshi Gu 2

1 College of Water Conservancy and Environmental Engineering, Zhejiang University of Water Resources and Electric Power, Hangzhou 310018, China
2 State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Hohai University, Nanjing 210098, China
3 Key Laboratory for Technology, Rural Water Management of Zhejiang Province, Zhejiang University of Water Resources and Electric Power, Hangzhou 310018, China

Correspondence should be addressed to Jiingmei Zhang; zhangjm@zjweu.edu.cn

Received 19 August 2021; Accepted 19 October 2021; Published 11 November 2021

Academic Editor: Lei Hou

Copyright © 2021 Jiingmei Zhang and Chongshi Gu. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Displacement monitoring data modeling is important for evaluating the performance and health conditions of concrete dams. Conventional displacement monitoring models of concrete dams decompose the total displacement into the water pressure component, temperature component, and time-dependent component. And the crack-induced displacement is generally incorporated into the time-dependent component, thus weakening the interpretability of the model. In the practical engineering modeling, some significant explaining variables are selected while the others are eliminated by applying commonly used regression methods which occasionally show instability. This paper proposes a crack-considered elastic net monitoring model of concrete dam displacement to improve the interpretability and stability. In this model, the mathematical expression of the crack-induced displacement component is derived through the analysis of large surface crack's effect on the concrete dam displacement to improve the interpretability of the model. Moreover, the elastic net method with better stability is used to solve the crack-considered displacement monitoring model. Sequentially, the proposed model is applied to analyze the radial displacement of a gravity arch dam. The results demonstrate that the proposed model contributes to more reasonable explaining variables’ selection and better coefficients’ estimation and also indicate better interpretability and higher predictive precision.

1. Introduction

Structural safety monitoring of concrete dams depends on visual observation and monitoring data analysis with the purpose of, as early as possible, identifying eventual anomalous behavior which could deteriorate the dam. The analysis results can help the dam administrative department take corresponding measures to eliminate the impact of abnormal behavior [1]. Displacement monitoring data have been widely acknowledged as a significant source for the performance and health condition assessments of concrete dams [2] because it directly reflects the structural behavior. Therefore, various monitoring models have been built to explain and predict the dam displacement which is influenced by many factors such as hydrostatic pressure, concrete temperature, and time effect [3]. The hydrostatic-season-time (HST) model is commonly used to interpret dam deformation [4]. Wu et al. [5] discussed the factor selection of displacement statistical models for concrete dams. Rocha [6] introduced the multiple linear regression (MLR) model to analyze the deformation behavior of concrete dams. Based on the assumption that the residual error sequence of MLR models is uncorrelated and that multicollinearity does not exist among those explanatory variables, the optimal unbiased estimates of MLR model coefficients can be obtained using the least-squares method [7]. If some explanatory variables are linearly related, the stepwise least square regression (SLSR) method can be used to estimate model coefficients with multicollinearity considered. To date, HST models have been used to analyze the monitoring data of
many dams, and various methods have been proposed to obtain the specific expressions and coefficients of practical models [8–16].

Traditional displacement monitoring model research studies focused on model calculation [17], but ignored key factor selection. However, many cracks exist in a lot of concrete dams which have been operating for years [18]. A mouth opening degree of a large surface crack varies regularly with the external loads, and the opening degree variations directly affect the concrete dam displacement [19, 20]. Crack-induced displacement is incorporated into the time effect component of those classical models, so the accuracy and interpretability of those models are weakened somewhat. It is necessary to analyze a large surface crack’s effect on concrete dam displacement, and a crack-considered monitoring model is yet to be built to improve interpretability.

The original theoretical displacement monitoring model of concrete dams conservatively includes as many explaining variables as possible to minimize the model deviation caused by the lack of important explaining variables. However, the actually applied model only needs those explaining variables which have a closer relationship with the explained response to improve its interpretability and predictive precision. Stepwise regression combined with AIC or BIC criterion has been generally used to select the optimal model. However, it has some inevitable drawbacks. Breiman [21] pointed out that the stepwise regression method is unstable when applied to select the actual model. And Fan et al. [22] indicated that a random error exists in the calculation process of stepwise regression and the theoretical nature of the method is difficult to study. In order to solve the above problems, Breiman [23] puts forward the nonnegative garrote method based on penalized least squares to get the actual interpretable model. Combining the nonnegative garrote method and bridge regression proposed by Frank [24], Tibshirani [25] proposed the Lasso (least absolute shrinkage and selection operator) method to select the explaining variables. Efron et al. [26] put forward the least angle regression algorithm to promote the practical application of the Lasso method. The Lasso method is being carried out in many fields [27–31], including statistics, engineering, biology, and information science.

The Lasso method excessively shrinks the coefficients, which have larger absolute values sometimes, resulting in a larger model error in some cases. In view of this, Fan and Liu [22] proposed the SCAD method, and Zou [32] presented the adaptive Lasso method to solve the deficient coefficient shrinkage problems in some situations. Zou and Hastie [33] introduced the quadratic penalty of coefficients into the Lasso method and put forward the another improved Lasso method called the elastic net method. The elastic net method can select significant explaining variables and estimate the corresponding coefficients simultaneously. Moreover, the method moderately shrinks the coefficients. The elastic net method with better stability is more suitable to solve the displacement monitoring model.

This article is organized as follows. In Section 2, large surface crack’s effect on the concrete dam displacement is analyzed theoretically and then the crack factor is introduced to develop a theoretical crack-considered monitoring model of concrete dam displacement. In Section 3, the elastic net method with better stability is used to solve the crack-considered displacement monitoring model. In Section 4, the proposed model is applied to analyze the radial displacement of a gravity arch dam, and the analysis results demonstrate better interpretability and higher predictive precision. Concluding remarks complete the paper in Section 5.

2. Theoretical Model Development

Traditional concrete dam displacement monitoring models divide the displacement response into the hydrostatic pressure component, temperature component, and time effect component, which can be expressed as follows:

\[ \delta = \delta_H + \delta_T + \delta_H + \epsilon, \]  \hspace{1cm} (1)

where \( \delta \) represents the concrete dam displacement response, \( \delta_H \) denotes the displacement caused by hydrostatic pressure, \( \delta_T \) indicates the displacement caused by temperature, \( \delta_H \) refers to the displacement caused by the time effect, and \( \epsilon \) means the random error term.

Based on the dam engineering theory and engineering mechanics, the mathematical expressions for each component of the concrete dam horizontal displacement response in equation (1) have been deduced [6].

2.1. Hydrostatic-Pressure Component. The hydrostatic-pressure-induced horizontal displacement of any point in a concrete dam consists of three parts [34] which can be expressed as follows:

\[ \delta_H = \delta_{1H} + \delta_{2H} + \delta_{3H}. \]  \hspace{1cm} (2)

The first part \( \delta_{1H} \) comes from the dam body deformation caused by the reservoir water pressure. The second part \( \delta_{2H} \) is derived from the foundation deformation induced by reservoir water pressure. The third part \( \delta_{3H} \) is from foundation surface rotation caused by reservoir water gravity.

For the gravity dam, the cross section can be simplified as a triangular wedge with a vertical upstream surface and the dam can be simplified as a cantilever beam fixed on the foundation, as shown in Figure 1. The following explanation can be obtained through the mechanical relationship between the water level and dam deformation. Reservoir water pressure on the beam has a linear correlation with water depth. The water pressure to the dam body causes the horizontal displacement \( \delta_{1H} \):

\[ \delta_{1H} = \frac{P}{2} \cdot \frac{b}{c} \cdot \frac{y}{c} \hspace{1cm} (3), \]
where \( H \) is the upstream water level, \( h \) is the height of the dam, \( m \) is the downstream slope, \( d \) is the distance between the observation point and the dam crest, \( E_c \) and \( G_c \) are the elastic modulus and shear modulus of dam concrete, respectively, and \( c_0 \) is the water density.

The effect of reservoir water pressure is transferred by the cantilever beam to the foundation. The water pressure to the bottom of a dam causes the horizontal displacement \( \delta_{2H} \):

\[
\delta_{2H} = \frac{c_0}{E_r m^2} \left[ (h - d)^2 + 6(h - H) \left( d \ln \frac{h}{d + h} + 6(h - H)^2 \left( d \ln \frac{h}{d + h} + 1 \right) - \frac{(h - H)^3}{h^2 d} (h - d)^2 \right) \right]
\]

where \( E_r \) and \( \mu_r \) are elastic modulus and Poisson’s ratio of the dam foundation, respectively.

The topography and geological conditions of the reservoir area are complex, so a strict derivation for the mathematical expressions of \( \delta_{3H} \) is difficult. Here, vertical reservoir water pressure is regarded as acting uniformly on an infinite elastic body surface with the assumption that the reservoir bottom near the dam is horizontal and has a certain width. The horizontal displacement \( \delta_{3H} \) caused by the rotation of dam foundation is, approximately, as follows:

\[
\delta_{3H} = aH,
\]

where \( a \) is the rotation angle of the dam foundation surface at the dam heel.

From the above analysis, it can be found that \( \delta_{1H} \) of the gravity dam is derived to have a linear relation with \( H, H^2, \) and \( H^3 \). And \( \delta_{2H} \) is linearly related with \( H^2 \) and \( H^3 \). For the arch dam, reservoir water pressure on the upstream surface is borne by both the horizontal arch and the vertical cantilever beam which are simplified in its structural analysis, so the water pressure distribution on the beam is nonlinear. Water pressure on the beam for the arch dam has a quadratic relation with water depth \( H \). Thus, \( \delta_{1H} \) of the arch dam has a linear relation with \( H^2, H^3, \) and \( H^4 \), and \( \delta_{2H} \) is linearly related with \( H^3 \) and \( H^4 \). In addition, \( \delta_{3H} \) is approximately considered to be proportional to \( H \). Therefore, the mathematical expression for the hydrostatic-pressure-induced

\[
\begin{align*}
&\text{Figure 1: Influence of hydraulic pressure on the horizontal displacement of a dam. (a) }\delta_{1H} \quad \text{(b) }\delta_{2H} \quad \text{(c) }\delta_{3H}.
\end{align*}
\]
horizontal displacement of any point in a concrete dam can be expressed as follows:

\[ \delta_H = \sum_{i=1}^{m_1} a_i H^i, \]  

where \( a_i \) stands for the coefficients corresponding to the hydrostatic-pressure component and \( m_1 \) takes 3 and 4, respectively, for the gravity dam and the arch dam.

2.2. Temperature Component. The temperature component of concrete dam displacement is mainly caused by the temperature variation of dam concrete and bedrock, so the measurements of the thermometers buried in the dam body and foundation are selected as temperature factors. However, the number of thermometers embedded in many dams is small and some thermometers have been failed after years of operation. Besides, the dam temperature field tends to be quasi-steady over time, so the temperature of any point in the dam is approximately considered to be periodic [35]. Thus, the temperature component can be simply represented by some periodic functions as follows:

\[ \delta_T = \sum_{i=1}^{m_2} \left( b_{1i} \sin \frac{2\pi t}{365} + b_{2i} \cos \frac{2\pi t}{365} \right), \]  

where \( t \) denotes the accumulated days from the initial measured day to the observation day, \( b_{1i} \) and \( b_{2i} \) represent the corresponding regression coefficients, and \( m_2 \) refers to the cycle parameter which takes 1 for a year cycle and 2 for half a year cycle, and so on.

2.3. Time Effect Component. The time effect component of concrete dam displacement comes from many aspects, including creep and plastic deformation of dam concrete and bedrock, irreversible deformation caused by long-term adverse loads, and self-grown volume deformation [14]. In general, time effect displacement changed dramatically during initial water impoundment and then gradually steadily over time. For the concrete dam operating for years, by analyzing the developing trend of displacement observations and the remaining value \( \delta - \delta_H - \delta_T \), the expression of \( \delta_0 \) can be determined reasonably as follows:

\[ \delta_0 = c_1 \theta + c_2 \ln \theta, \]  

where \( c_1 \) and \( c_2 \) indicate the corresponding regression coefficients and \( \theta = t/100 \) and \( t \) has the same meaning with that in equation (7).

2.4. Crack Component. The mouth opening degree of some large surface cracks, such as horizontal surface cracks and longitudinal ones, varies regularly with the external loads, including hydrostatic pressure and temperature. The opening degree variations of these cracks obviously affect the concrete dam displacement. Herein, we take a horizontal surface crack as an example to analyze the crack’s effect on the dam displacement.

Assuming the concrete dam body is rigid, without considering water pressure, Figure 2 shows the effect of large surface crack on the dam horizontal displacement. The rotation angles \( \alpha \) and \( \beta \) are deemed approximately equal (\( \sin \alpha = \sin \beta \)); thus equations (9) and (10) can be approximately given:

\[ \frac{\delta_{AI}}{l_A} = \Delta K \frac{l_A}{l_K}, \]  

\[ \delta_{AI} = \Delta K \frac{I_A}{l_K}, \]  

where \( l_A \) and \( l_K \) indicate the distances shown in Figure 2, \( \Delta K \) represents the opening degree variation of the crack, and \( \delta_{AI} \) denotes the horizontal displacement of point A. For a specific point A, \( l_A/l_K \) is the deemed constant; then, the crack-induced displacement can be approximately expressed as follows:

\[ \delta_K = \sum_{i=1}^{m_3} d_i K_i, \]  

2.5. Theoretical Crack-Considered Monitoring Model of Concrete Dam Displacement. Integrating the above four components, including the hydrostatic-pressure component, temperature component, time effect component, and crack component, the theoretical crack-considered monitoring model of concrete dam displacement can be expressed as follows:

\[ \delta = a_0 + \sum_{i=1}^{m_1} a_i H^i + \sum_{i=1}^{m_2} \left( b_{1i} \sin \frac{2\pi t}{365} + b_{2i} \cos \frac{2\pi t}{365} \right) + c_1 \theta + c_2 \ln \theta + \sum_{i=1}^{m_3} d_i K_i + \varepsilon, \]
where \( a_0 \) denotes the constant term, \( \varepsilon \) indicates the random error term, and the other symbols have the same meanings with those in the above equations.

3. Practical Model Solution

3.1. Elastic Net. Given a linear regression with standardized predictors \( x_{ij} \) and centered response values \( y_i \), for \( i = 1, 2, \ldots, N \) and \( j = 1, 2, \ldots, p \), letting \( \beta = (\beta_1, \ldots, \beta_p)^T \), the lasso estimate \((\tilde{\alpha}, \tilde{\beta})\) is defined by the following equation:

\[
(\tilde{\alpha}, \tilde{\beta}) = \text{arg min} \left\{ \sum_{i=1}^{N} \left( y_i - \alpha - \sum_{j} \beta_j x_{ij} \right)^2 \right\}, \quad \text{subject to } \sum_{j} \beta_j^2 \leq t. \tag{13}
\]

For all \( t > 0 \), the solution for \( \alpha \) is \( \overline{y} \). Assuming without loss of generality that \( \overline{y} = 0 \) and hence omitting \( \alpha \), the lasso solves the \( L_1 \)-penalized regression problem of finding \( \beta \) to minimize

\[
\sum_{i=1}^{N} \left( y_i - \sum_{j} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{P} |\beta_j|, \tag{14}
\]

where \( \lambda_1 \) and \( \lambda_2 \) represent the penalty parameters and \( \lambda_1, \lambda_2 \geq 0 \). \( \lambda_1 \) takes 0 for the ridge regression estimate. The Lasso estimate is given when \( \lambda_2 \) takes zero.

Asymptotics for Lasso-type estimators has been analyzed by Knight and Fu [36]. However, the Lasso method shrinks all the coefficients to the same degree resulting in a large model error, and the Lasso method does not have oracle properties. In comparison, improved lasso methods including the elastic net method commonly have oracle properties, that is, the optimal model obtained by elastic net has the following properties.

The Lasso method is actually to optimize a function with loss item \( \sum_{i=1}^{N} (y_i - \sum_j \beta_j x_{ij})^2 \) and penalty item \( \lambda \sum_{j=1}^{P} |\beta_j| \). The improved Lasso methods were given by changing the penalty function item. Among these improved lasso methods, the elastic net estimate \( \hat{\beta} \) is defined as follows:

\[
\hat{\beta} = \text{arg min} \left\{ \sum_{i=1}^{N} \left( y_i - \sum_{j} \beta_j x_{ij} \right)^2 + \lambda_1 \sum_{j=1}^{P} |\beta_j| + \lambda_2 \sum_{j=1}^{P} \beta_j^2 \right\}, \tag{14}
\]
\[
\lim_{n \to \infty} P\{\{ i \mid \hat{\beta}_i(\eta) \neq 0 \} = A \} = 1,
\]
\[
\sqrt{n} (\hat{\beta}(\eta) - \beta_A) \to \mathcal{N}(0, \Sigma),
\]
where \( \Sigma \) stands for the covariance of real model parameters. The oracle properties are also referred to as super-efficiency in the parameter estimation.

\[
\delta_i = \alpha + \sum_j \beta_j x_{ij} + \epsilon,
\]
\[
x_i = (x_{i1}, x_{i2}, \ldots, x_{im})
\]
\[
= (H_1, \ldots, H_m, \sin \frac{2\pi t}{365}, \ldots, \sin \frac{2\pi n t}{365}, \cos \frac{2\pi t}{365}, \ldots, \cos \frac{2\pi n t}{365}, \theta, \ln \theta, K_1, \ldots, K_m)^T,
\]
\[
\bar{a} = a_0,
\]
\[
\bar{\beta} = (\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_n) = (a_1, \ldots, a_m, b_1, \ldots, b_{m_1}, \ldots, b_{m_2}, c_1, \ldots, c_{m_2}, d_1, \ldots, d_{m_2})^T,
\]
\[
(\bar{a}, \bar{\beta}) = \arg \min \left\{ \sum_{i=1}^N \left( \delta_i - \alpha - \sum_j \beta_j x_{ij} \right)^2 + \lambda_1 \sum_{j=1}^p |\beta_j| + \lambda_2 \sum_{j=1}^p \beta_j^2 \right\},
\]
where \((\bar{a}, \bar{\beta})\) represents the elastic net estimator of the model coefficients, \(N\) denotes the number of observations, and \(n\) indicates the number of explaining variables.

Determination of penalty parameters \(\lambda_1\) and \(\lambda_2\) is critical in the model solution. In general, \(n\)-fold cross validation [37] is applied to determine penalty parameters. The following equations briefly introduce the \(n\)-fold cross validation.

Suppose \(T\) represents the complete dataset, \(T - T^n\) represents the training set, and \(T^n\) represents the testing set, where \(n=1, 2, \ldots\). For each \(\lambda_1, \lambda_2\) and \(n\), the estimate \((\bar{a}, \bar{\beta})^{(n)}(\lambda_1, \lambda_2)\) of \((a, \beta)\) can be obtained from the training set \(T - T^n\). Then, the standard \(CV(\lambda_1, \lambda_2)\) of \(n\)-fold cross validation can be given as follows:

\[
CV(\lambda_1, \lambda_2) = \sum_{n=1}^N \sum_{(y_k, x_k) \in T^n} \left( y_k - \bar{a} - \bar{x}_k \bar{\beta}^{(n)}(\lambda_1, \lambda_2) \right)^2.
\]

The estimator \(\hat{\lambda}_1, \hat{\lambda}_2\) of the penalty parameters can be obtained as follows:

\[
\hat{\lambda}_1, \hat{\lambda}_2 = \arg \min [CV(\lambda_1, \lambda_2)].
\]

Figure 3 shows how to solve the elastic net crack-considered monitoring model of concrete dam displacement.

### 4. Project Case Application

#### 4.1. Displacement Model Development

The crest horizontal displacement of a concrete dam is analyzed by the elastic net crack-considered monitoring model. This dam is a concrete gravity arch dam, as shown in Figure 4, located in the east of China. Its maximum height is 76.3 m, and it has 28 sections. The dam was constructed in three phases. The concrete lift in Phase II was poured in such a hurry that its shrinkage distortion was restrained by the concrete in Phase I, resulting in a horizontal crack in the longitudinal direction at the interface. A large vertical crack in the longitudinal direction also exists in the dam crest. The dam crest radial displacement monitoring data in dam section No. 26 from May 8, 2013, to July 25, 2019, are analyzed. The monitoring data provided in the supplementary material “Monitoring data of dam section No. 26 pdf” were obtained from the pendulums buried in the dam, as shown in Figure 5 and Figure 6. The elevation in Figure 6 is in meters.

According to the elastic net crack-considered model, with the actual project situation considered, the radial displacement monitoring model of the dam crest is obtained as follows:

3.2. Practical Elastic Net Crack-Considered Monitoring Model of Concrete Dam Displacement. Combining with the elastic net method with better stability, moderate coefficients’ shrinkage, and oracle properties, the practically applied elastic net crack-considered monitoring model of concrete dam displacement is obtained as follows:
Input the measured data of the displacement, environmental variables and crack opening degree of concrete dam

Establish the theoretical crack-considered monitoring model of concrete dam displacement
\[ \delta_i = \alpha + \sum_j \beta_j x_{ij} + \epsilon \]

Estimate \((\hat{\alpha}, \hat{\beta})^{(n)}(\lambda_1, \lambda_2)\) with the initial penalty parameter \(\lambda_1, \lambda_2\) given by using the training set \(T^T\)

Calculate the standard \(CV(\lambda_1, \lambda_2)\) of \(n\)-fold cross validation by using the testing set \(T^n\)
\[ CV(\lambda_1, \lambda_2) = \frac{1}{n} \sum_{\nu=1}^{n} \sum_{\nu \in T^\nu} (y_k - \hat{\alpha} - x_k^T \hat{\beta}^{(\nu)}(\lambda_1, \lambda_2))^2 \]

Adjust the penalty parameter

\(CV(\lambda_1, \lambda_2) \leq CV_m\) \(\Rightarrow\) YES

Obtain the elastic net estimate with the ultimate \(\hat{\lambda}_1, \hat{\lambda}_2\)
\[ (\hat{\alpha}, \hat{\beta}) = \arg \min \left( \sum_i (\delta_i - \alpha - \sum_j \beta_j x_{ij})^2 + \hat{\lambda}_1 \sum_j \beta_j^2 + \hat{\lambda}_2 \sum_j \beta_j^2 \right) \]

Output the practically-applied elastic net crack-considered monitoring model of concrete dam displacement
\[ \delta_i = \hat{\alpha} + \sum_j \hat{\beta}_j x_{ij} + \epsilon \]

End

Figure 3: The practical elastic net crack-considered monitoring model establishment of concrete dam displacement.

Figure 4: Aerial view of the gravity arch dam.
\[ \delta = \tilde{\delta} + \epsilon \]
\[ = a_0 + \sum_{i=1}^{4} a_i T^i + \sum_{j=1}^{2} (b_{ij} \sin \frac{2\pi it}{365} + b_{2j} \cos \frac{2\pi it}{365}) + c_1 \theta + c_2 \ln \theta + d_1 K_1 + d_2 K_2 + \epsilon, \]

\[ \bar{\alpha} = a_0, \]

\[ \bar{\beta} = (a_1, a_2, a_3, a_4, b_{11}, b_{12}, b_{21}, b_{22}, c_1, c_2, d_1, d_2)^T, \]

\[ (\bar{\alpha}, \bar{\beta}) = \arg \min \left\{ \text{subject to} \right\} \sum_{i=1}^{N} (\delta - \tilde{\delta})^2 + \lambda_1 \sum_{j=1}^{P} |\beta_j| + \lambda_2 \sum_{j=1}^{P} \beta_j^2 \right\}.
where $K_1$ represents the opening degree of the vertical crack described above, $K_2$ indicates the opening degree of the horizontal crack described above, and the other symbols refer to the meanings of those variables in the aforementioned equations.

The recorded water level curve of the reservoir is shown in Figure 7. Figure 8 displays the opening degree curves of the two cracks mentioned above.

5. Results and Discussion

The radial displacement monitoring data from May 8, 2013, to December 31, 2018, were used to establish the monitoring model. Tables 1 and 2 show the results obtained by different models. In Table 2, $R$ stands for the multiple correlation coefficient. Larger the multiple correlation coefficient, better the fitted effect. In Table 2, $S$ means standard deviation. Smaller standard deviation represents better fitted effect. $R$ and $S$ are defined as follows:

$$R = \frac{\sum_{i=1}^{N}(\delta_i - \bar{\delta})(\delta_i - \bar{\delta})}{\sqrt{\sum_{i=1}^{N}(\delta_i - \bar{\delta})^2(\delta_i - \bar{\delta})^2}},$$

(20)

$$S = \sqrt{\frac{\sum_{i=1}^{N}(\delta_i - \bar{\delta})^2}{N - 1}}.$$

Figures 9–12 give comparisons between measured displacement curves and fitted ones obtained by four different models. Displacement components extracted by the crack-considered elastic net model are given in Figure 13. Figures 14 and 15 show comparisons between fitted displacement residual curves obtained by different models. Comparisons of these tables and figures indicate the following analysis result.

1. The multiple correlation coefficient $R$ (0.961) of the crack-unconsidered stepwise model is smaller than that (0.975) of the crack-considered stepwise model. The standard deviation $S$ (0.218) of the crack-unconsidered stepwise model is larger than that (0.199) of the crack-considered stepwise model. For models obtained by the elastic net method, $R$ (0.964) of the uncrack-considered model is smaller than that (0.978) of the crack-considered model and $S$ (0.215) of the uncrack-considered model is larger than that (0.193) of the crack-considered model. These results show that the crack-considered models have a better fitting effect than the crack-unconsidered ones.

2. The values of the coefficient $d_i$ are positive for both the crack-considered stepwise model and the crack-considered elastic net model, which means that the dam crest displacement is positively correlated with the vertical crack opening degree, that is, the opening of the vertical crack contributes to the downstream displacement of the dam crest. Meanwhile, the negative values of $d_i$ obtained by the two crack-considered models indicate that the opening of the horizontal crack contributes to the upstream displacement of the dam crest. It can also be seen from Figure 13 that the crack components account for considerable proportions in the dam crest displacement. Therefore, it is necessary to extract the crack component separately to explain the variation behavior of the dam displacement, that is, the crack-considered model has better interpretability.

3. For crack-unconsidered models, $R$ (0.961) and $S$ (0.218) of the stepwise regression model are approximately equal with those (0.964 and 0.215) of the elastic net model. Meanwhile, the crack-considered models also have the same comparison result. These results indicate that the elastic net models have approximately equal fitting effect with the stepwise regression models.

4. The zero-value coefficient items of the crack-considered stepwise model are different with those of the crack-unconsidered stepwise model. For the elastic net models, the zero-value coefficient items of the crack-considered model are consistent with those of the crack-unconsidered model. The results reveal that the stability of the elastic net models is superior to that of the stepwise regression models.

5. For stepwise regression models, the zero-value coefficients of the crack-unconsidered model include all-time effect coefficients ($c_1$ and $c_2$), that is, the time effect is regarded not to contribute to the displacement. However, it is confirmed that the time effect component cannot be a zero value by analyzing the measured series and referring to general engineering experience. The time effect component obtained by the elastic net models is not a zero value. The results imply that the elastic net models have better interpretability than the stepwise regression models.

In order to evaluate the forecast effect of the monitoring model, the radial displacement monitoring data from January 1, 2019, to July 25, 2019, were used as predictive samples. Figures 16 and 17 give comparisons between measured displacement residual curves and predicted ones obtained by different models. Figure 18 displays a comparison between the measured displacement curve and the predicted one obtained by the crack-considered elastic net model. Table 2 shows the predictive effect ($R_{pre}$ and $S_{pre}$) of different models. $R_{pre}$ and $S_{pre}$ are multiple correlation coefficient and standard deviation, respectively, representing the predicted goodness. Through comparison from the table and figures, the following analysis result can be obtained.

1. The predictive multiple correlation coefficient $R_{pre}$ (0.961) of the crack-unconsidered stepwise model is smaller than that (0.975) of the crack-considered stepwise model. The standard deviation $S_{pre}$ (0.224) of the crack-unconsidered stepwise model is larger than that (0.201) of the crack-considered stepwise model. The elastic net models also have the same comparison result. These results show that the crack-considered models have a better predictive effect than the crack-unconsidered models.
Figure 7: Water level measurements.

Figure 8: Opening degree measurements of the vertical crack $K_1$ and the horizontal crack $K_2$.

Table 1: Regression coefficients of four different models.

| Coefficients | Method          | Crack-unconsidered | Crack-considered | Crack-unconsidered | Crack-considered |
|--------------|-----------------|--------------------|------------------|--------------------|------------------|
| $a_0$        | Crack-unconsidered | -0.707             | -0.733           | -0.749             | -0.721           |
| $a_1$        | Crack-considered  | -218.0             | -172.0           | 0.270              | 0.225            |
| $a_2$        | Crack-unconsidered | 5.490              | 4.320            | 0.000              | 0.000            |
| $a_3$        | Crack-considered  | -0.061             | -0.048           | 0.000              | 0.000            |
| $a_4$        | Crack-unconsidered | 0.000              | 0.000            | 0.000              | 0.000            |
| $b_{11}$     | Crack-unconsidered | -0.546             | -0.714           | -0.556             | -0.733           |
| $b_{12}$     | Crack-considered  | -1.190             | -1.290           | -1.200             | -1.340           |
| $b_{21}$     | Crack-unconsidered | -0.332             | -0.234           | -0.340             | -0.227           |
| $b_{22}$     | Crack-considered  | -0.142             | -0.094           | -0.148             | -0.080           |
| $c_1$        | Crack-unconsidered | 0.000              | -0.248           | 0.000              | -0.094           |
| $c_2$        | Crack-considered  | 0.000              | 33.80            | 0.104              | 12.60            |
| $d_1$        | Crack-unconsidered | —                  | 2.130            | —                  | 2.120            |
| $d_2$        | Crack-unconsidered | —                  | -0.448           | —                  | -0.564           |

Table 2: Fitted goodness of four different models.

| Method          | $R$  | $S$ (mm) | $R_{pre}$ | $S_{pre}$ (mm) |
|-----------------|------|----------|-----------|----------------|
| Stepwise        |      | Crack-unconsidered | 0.961    | 0.218          | 0.961 | 0.224 |
| Crack-considered | 0.975 | 0.199     | 0.975 | 0.201 |
| Elastic net     |      | Crack-unconsidered | 0.964    | 0.215          | 0.964 | 0.203 |
| Crack-considered | 0.978 | 0.193     | 0.978 | 0.174 |
Figure 9: Measured displacement curve and fitted curve of the crack-unconsidered stepwise model.

Figure 10: Measured displacement curve and fitted curve of the crack-considered stepwise model.

Figure 11: Measured displacement curve and fitted curve of the crack-unconsidered elastic net model.

Figure 12: Measured displacement curve and fitted curve of the crack-considered elastic net model.
**Figure 13:** Displacement components extracted by the crack-considered elastic net model.

**Figure 14:** Fitted displacement residual curves of two different elastic net models.

**Figure 15:** Fitted displacement residual curves of two different crack-considered models.

**Figure 16:** Predicted displacement residual curves of the elastic net models.
For the crack-considered models, $R_{pre} (0.975)$ of the stepwise regression model is approximately equal with that (0.978) of the elastic net model, while $S_{pre} (0.174)$ of the elastic net model is smaller than that (0.201) of the stepwise regression model. The results indicate that the elastic net models have a better predictive effect than the stepwise regression models.

6. Conclusions

This study was devoted to establish and solve the crack-considered elastic net monitoring model of the concrete dam displacement. The main conclusions are as follows:

(1) Concrete dam safety operation and management need analysis and forecast on the dam displacement monitoring data. By inputting displacement monitoring data into theoretical monitoring models, the final actually applied monitoring and forecasting models can be obtained to interpret and predict the work behavior of concrete dams.

(2) Crack-induced displacement in classical displacement monitoring models is incorporated into the time effect component so that the accuracy and interpretability of those models are weakened somewhat. In this paper, the crack factor was introduced into the model to be an independent crack component. Through the theoretical analysis of large surface crack’s effect on the concrete dam displacement, a mathematical expression of the crack-induced displacement component was derived, and the theoretical crack-considered monitoring model of the concrete dam displacement was built to improve the interpretability of the model.

(3) The theoretical monitoring model of the concrete dam displacement conservatively includes as many explaining variables as possible to minimize the model deviation. However, the actually applied model only needs those explaining variables which have a closer relationship with the explained response to improve its interpretability and predictive precision. Conventional stepwise regression methods used in variable selection have instability in some cases. The elastic net method with better stability and moderate coefficient shrinkage was used to develop the practically applied crack-considered elastic net monitoring model of concrete dam displacement. The proposed model gives more reasonable factors and parameter estimation.

(4) Study on the crack-considered elastic net monitoring model of concrete dam displacement has been conducted tentatively in the paper, and a project case exhibits better interpretability and higher prediction accuracy of the proposed model. Furthermore, the thought and method of establishing the crack-
considered elastic net model can also be introduced to the deterministic model and hybrid model of concrete dams.

Data Availability

The data used to support the findings of this study are from a large water conservancy project and not suitable to upload to the network. The data are included within the Supplementary Information files.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors thank the Dam Safety Research Group of Hohai University for the monitoring data. This research was supported by the Science and Technology Project of Zhejiang Water Resources Department, the Research Development Support Project of Zhejiang University of Water Resources and Electric Power (88106003136), National Natural Science Foundation of China (51739003), and National Key R&D Program of China (2018YFC0407104).

Supplementary Materials

The monitoring data of dam section No. 26.pdf provide the dam crest radial displacement monitoring data in dam section No. 26 from May 8, 2013, to July 25, 2019. (Supplementary Materials)

References

[1] R. Zinno and S. Artese, "Innovative methods and materials in structural health monitoring of civil infrastructures," Applied Sciences, vol. 11, no. 3, Article ID 11033140, 2021.

[2] Y. Hu, C. Shao, C. Gu, and Z. Meng, "Concrete dam displacement prediction based on an ISODATA-GMM clustering and random coefficient model," Water, vol. 11, no. 4, Article ID 1104714, 2019.

[3] J. Mata, "Interpretation of concrete dam behaviour with artificial neural network and multiple linear regression models," Engineering Structures, vol. 33, no. 3, pp. 903–910, 2011.

[4] S. Gamse, W.-H. Zhou, F. Tan, K.-V. Yuen, and M. Oberguggenberger, "Hydrostatic-season-time model updating based on the Bayesian model class selection," Reliability Engineering & System Safety, vol. 169, pp. 40–50, 2018.

[5] Z. Wu, C. Shen, and H. Ruan, "Factor selection of displacement statistical models for concrete dams," Journal of Hohai University, vol. 06, pp. 1–9, 1988.

[6] M. Rocha, A quantitative method for the interpretation of the results of the observation of dams, VI Congress on Large Dams, New York, NY, USA, 1958.

[7] F. Li, Z. Wang, and G. Liu, "Towards an Error Correction Model for dam monitoring data analysis based on Cointegration Theory," Structural Safety, vol. 43, pp. 12–20, 2013.

[8] Q. Ren, M. Li, H. Li, L. Song, W. Si, and H. Liu, "A robust prediction model for displacement of concrete dams subjected to irregular water-level fluctuations," Computer-Aided Civil and Infrastructure Engineering, vol. 36, no. 5, pp. 577–601, 2021.

[9] S. Chen, C. Gu, C. Lin, K. Zhang, and Y. Zhu, "Multi-kernel optimized relevance vector machine for probabilistic prediction of concrete dam displacement," Engineering with Computers, vol. 37, no. 3, pp. 1943–1959, 2021.

[10] B. Wei, B. Liu, D. Yuan, Y. Mao, and S. Yao, "Spatiotemporal hybrid model for concrete arch dam deformation monitoring considering chaotic effect of residual series," Engineering Structures, vol. 228, Article ID 114888, 2021.

[11] X. Shu, T. Bao, Y. Li, J. Gong, and K. Zhang, "VAE-TALSTM: a temporal attention and variational autoencoder-based long short-term memory framework for dam displacement prediction," Engineering With Computers, 2021.

[12] M. Li, Y. Shen, Q. Ren, and H. Li, "A new distributed time series evolution prediction model for dam deformation based on constituent elements," Advanced Engineering Informatics, vol. 39, pp. 41–52, 2019.

[13] B. Ahmed, K. M. Mustapha, and S. David, "Analysis of dam behavior by statistical models: application of the random forest approach," KSCE Journal of Civil Engineering, vol. 23, no. 11, pp. 4800–4811, 2019.

[14] H. Su, Z. Wen, X. Yan, H. Liu, and M. Yang, "Early-warning model of deformation safety for roller compacted concrete arch dam considering time-varying characteristics," Composite Structures, vol. 203, pp. 373–381, 2018.

[15] B. Dai, C. Gu, E. Zhao, and X. Qin, "Statistical model optimized random forest regression model for concrete dam deformation monitoring." Structural Control and Health Monitoring, vol. 25, no. 6, Article ID e2170, 2018.

[16] A. De Sortis and P. Paoliani, "Statistical analysis and structural identification in concrete dam monitoring," Engineering Structures, vol. 29, no. 1, pp. 110–120, 2007.

[17] L. Pierre and L. Martin, "Hydrostatic, temperature, time displacement model for concrete dams," Journal of Engineering Mechanics, vol. 133, no. 3, pp. 267–277, 2007.

[18] E. Zhao and B. Li, "Evaluation method for cohesive crack propagation in fragile locations of RCC dam using XFEM," Water, vol. 13, no. 1, Article ID 13010058, 2021.

[19] B. Xu, Z. Li, and J. Zhao, "Unit root analysis method of actual crack behavior of the concrete dam based on residuals of the monitoring model," Advances in Civil Engineering, vol. 2020, Article ID 8149658, 2020.

[20] J. Hu and S. Wu, "Statistical modeling for deformation analysis of concrete arch dams with influential horizontal cracks," Structural Health Monitoring, vol. 18, no. 2, pp. 546–562, 2019.

[21] L. Breiman, "Heuristics of instability and stabilization in model selection," The Annals of Statistics, vol. 24, no. 6, pp. 2350–2383, 1996.

[22] J. Fan and R. Li, Variable Selection via Penalized Likelihood, UCLA, California, LA, USA, 1999.

[23] L. Breiman, "Better subset regression using the nonnegative garrote," Technometrics, vol. 37, no. 4, pp. 373–384, 1995.

[24] E. F. Lindo and H. F. Jerome, "A statistical view of some chemometrics regression tools," Technometrics, vol. 35, no. 2, pp. 109–148, 1993.

[25] R. Tibshirani, "Regression shrinkage and selection via the lasso," Journal of the Royal Statistical Society: Series B (Methodological), vol. 58, no. 1, pp. 267–288, 1996.

[26] B. Efron, T. Hastie, I. Johnstone, and R. Tibshirani, "Least angle regression," The Annals of Statistics, vol. 32, no. 2, pp. 407–451, 2004.
[27] Y. Chen, M. G. Tsionas, and V. Zelenyuk, “LASSO+DEA for small and big wide data,” Omega, vol. 102, Article ID 102419, 2021.
[28] M. Kuismin and M. J. Sillanpää, “MCPeSe: Monte Carlo penalty selection for graphical lasso,” Bioinformatics, vol. 37, no. 5, pp. 726–727, 2021.
[29] A. D. Mehr and A. H. Gandomi, “MSGP-LASSO: an improved multi-stage genetic programming model for streamflow prediction,” Information Sciences, vol. 561, pp. 181–195, 2021.
[30] S. Jokubaitis, D. Celov, and R. Leipus, “Sparse structures with LASSO through principal components: forecasting GDP components in the short-run,” International Journal of Forecasting, vol. 37, no. 2, pp. 759–776, 2021.
[31] R. Tibshirani, “Regression shrinkage and selection via the lasso: a retrospective,” Journal of the Royal Statistical Society: Series B (Statistical Methodology), vol. 73, no. 3, pp. 273–282, 2011.
[32] H. Zou, “The adaptive lasso and its oracle properties,” Journal of the American Statistical Association, vol. 101, no. 476, pp. 1418–1429, 2006.
[33] H. Zou and T. Hastie, “Regularization and variable selection via the elastic net,” Journal of the Royal Statistical Society: Series B (Statistical Methodology), vol. 67, no. 2, pp. 301–320, 2005.
[34] B. Wei, L. Chen, H. Li, D. Yuan, and G. Wang, “Optimized prediction model for concrete dam displacement based on signal residual amendment,” Applied Mathematical Modelling, vol. 78, pp. 20–36, 2020.
[35] J. Mata, A. Tavares de Castro, and J. Sá da Costa, “Time-frequency analysis for concrete dam safety control: correlation between the daily variation of structural response and air temperature,” Engineering Structures, vol. 48, pp. 658–665, 2013.
[36] K. Knight and W. Fu, “Asymptotics for lasso-type estimators,” The Annals of Statistics, vol. 28, no. 5, pp. 1356–1378, 2000.
[37] P. Zhang, “Model selection via multifold cross validation,” The Annals of Statistics, vol. 21, no. 1, 1993.