Study on safety monitoring model of crack opening displacement for high-pile wharf

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Abstract. Safety monitoring is an important measure for the safe operation of water conservancy projects. The monitoring model plays an important role in monitoring data analysis, widely used in reservoirs and dams. However, relevant theories and studies are rarely applied in port terminals. Since high-pile wharves are different from reservoirs or dams in working environment and working behaviour, it is necessary to develop a monitoring model for high-pile wharves considering the working characteristics. In this paper, it was proposed that principal effect factors of crack opening displacement of high-pile wharves were temperature component, wind component, heap load component, and time effect, according to the change law of dependent and independent variables. The expressions of these factors were given. On the basis of it, the statistical model and Least Squares Support Vector Machine (LS-SVM) model of crack opening displacement (COD) was established respectively. The evaluation method for these models was developed. Models were used in fitting and prediction with data series of COD of a high-pile wharf to verify the effectiveness and reasonableness. The results showed that the proposed models with high precision and certain prediction ability can provide scientific principles for data analysis and safety monitoring of high-pile wharves.

1. Introduction

Safety monitoring model is the main tool for quantitative analysis of safety monitoring. It quantitatively describes the relationships between the effects and the factors, and reveals the variation laws of the effect variables. It could also forecast the development of structural behavior of buildings, which has been widely used in reservoir dam and its foundation, slope engineering and so on, and has achieved good social benefits [1-5]. However, the research on the safety monitoring model of port wharf is rarely reported, which is mainly because the layout of safety monitoring instruments for port terminals is far less complete than that in reservoir dams. Even though the consciousness of security monitoring is enhanced in recent years, and researches [6-9] on safety monitoring for some ports have been conducted, there still need further study on the port safety monitoring. High-pile wharves are suitable for soft ground and have made important contributions to the national economy. As enduring the test of the natural environment all the year round, they are prone to appear cracks by the factors such as foundation settlement, climate change, erosion and overloading [10-14]. However, what are the main factors and their influencing mechanisms to the cracks? And which model should be adopted to analyse that? Studies on these are crucial to the safe operation of port wharves. The measured data series of COD are the macroscopic reflection of crack change in port wharves. Thus, the qualitative-
analysis results of its process lines and eigenvalues are obtained first in this paper. Secondly, combined with existing national or industry norms [15-18], the main influencing factors of cracks are discussed, and the expressions are constructed in high-pile wharf. Finally, the safety model for COD of port wharf is built.

2. Monitoring model factors of fracture opening displacement in high-pile wharf

2.1. Qualitative analysis

The qualitative analysis methods mainly include the process diagram method and the characteristic value statistics method. In process graph method, corresponding factors and their influence degree on the effect quantity are analysed by respectively making time-variation process lines of the cause quantity and effect quantity. Figures 1 and 2 are respectively the time-variation process lines of the COD and environmental variables for typical measuring point in a high-pile wharf.

![Figure 1. Process lines of COD.](image1)

![Figure 2.](image2)

(a) Process line of temperature, (b) Process line of terminal load and (c) Process line of wind speed.
According to the time-variation process lines of COD and environmental variable, the cracks in high-pile wharves are mainly affected by temperature, wharf load and wind load, especially by temperature and wharf load. Generally, the COD decreases at high temperature or low wharf load, and increases at lower temperature or larger wharf load. Besides, the COD will produce time-effect deformation due to the sea water erosion, reinforced concrete creep and periodic wave pressure.

2.2. Statistical model of COD for high-pile wharf

According to the above qualitative analysis in section 1.1, the COD of high-pile wharves are mainly composed of temperature, wharf load and time-effect components, which is:

$$\delta = \delta_T + \delta_w + \delta_p + \delta_\theta$$

(1)

in which, $\delta$ — COD; $\delta_T$ — Temperature component; $\delta_w$ — Wind pressure component; $\delta_p$ — Wharf stacking component; $\delta_\theta$ — Time-effect component.

2.2.1. Temperature component ($\delta_T$). The formation and expansion of concrete cracks are very sensitive to the changes in temperature, and the temperature component is precisely the concrete deformation of the wharf structure caused by the changes in temperature. This component has a great influence on the total deformation of wharf cracks. Seen from the analysis of mechanical mechanism, the thermometer value in the wharf concrete should be selected as the factor. The measured values could reflect the temperature field with enough thermometers placed inside the wharf. If no or only a few thermometers are placed inside the wharf, air temperature data could be used when it is available.

According to the theory of elasticity, under the action of temperature change, the crack opening and closing degree of wharf is related to the first power of thermometer measurement, and its expression is as follows:

$$\delta_T = \sum_{i=1}^{k} a_i T_i$$

(2)

in which, $T_i$ — Measurement of the number $i$ thermometer, $a_i$ — Regression coefficient of temperature factor, $k$ — The number of thermometers, when only air temperature data are available, is taken as 1.

When the temperature changes periodically, the harmonic factor can be used as the temperature component to simplify the expression, and its expression can be expressed as:

$$\delta_T = \sum_{i=1}^{2} (a_i \sin \frac{2\pi i t}{365} + a_{2i} \cos \frac{2\pi i t}{365})$$

(3)

in which, $i=1 \sim 2$, $i=1$ represents an annual cycle, $i=2$ represents a cycle of half a year; $t$ — Number of days counted from the beginning of the observation day.

2.2.2. Wind pressure component ($\delta_w$). The expression of wind pressure component of COD is obtained from engineering mechanics knowledge and port engineering load code [15], which is related to the second power of wind speed on the acting face, that is:

$$\delta_w = bv^2$$

(4)

in which, $v$ — Wind velocity values perpendicular to the action surface; $b$ — Regression Coefficient of Wind Pressure Factor.

2.2.3. Wharf stacking component ($\delta_p$). The load component expression of COD is derived from the load code of port engineering [15] by means of load analysis, which is related to the first order of loading amount of wharf, that is:
\[ \delta_P = cP \]  

In which, \( P \) — wharf stacking load; \( c \) — regression coefficient for the COD component of wharf stacking load.

2.2.4. Time-effect component (\( \delta_\theta \)). The expression of time-effect component of COD is mainly based on the theory of safety monitoring of hydraulic structures, which varies greatly in the initial stage of operation and tends to be stable with the operation of buildings, and the polynomial and logarithmic time-effect factor are selected as the time-effect components:

\[ \delta_\theta = d_1 \theta + d_2 \ln \theta \]  

In which, \( d_1 \sim d_2 \) — regression coefficient for the time-effect component; \( \theta \) — Number of days counted from the beginning of the observation day multiply 0.01.

3. Establishment of the COD monitoring model for high-piled wharf

Establishing statistical model is a general method for monitoring data analysis, and LS-SVM model shows strong robustness [19] when dealing with non-linear problems. Therefore, this paper mainly establishes statistical model and LS-SVM model of the COD for high-pile wharves.

3.1. Statistical model

Substitute the expression of each factor into formula (1), that is:

\[ \delta = aT + b\theta^2 + cP + d_1 \theta + d_2 \ln \theta \]  

or

\[ \delta = \sum_{i=1}^{2} \left( a_{0i} \sin \frac{2\pi it}{365} + a_{2i} \cos \frac{2\pi it}{365} + b \theta^2 + cP + d_1 \theta + d_2 \ln \theta \right) \]  

(7)

In practical modelling, in order to avoid the influence of initial factors, the relative value is selected to establish the model, and then the statistical model expression of COD is as follows.

\[ \delta - \delta_0 = a(T - T_0) + b(\theta^2 - \theta_0^2) + c(P - P_0) + d_1(\theta - \theta_0) + d_2(\ln \theta - \ln \theta_0) \]  

(a)

or

\[ \delta - \delta_0 = \sum_{i=1}^{2} \left( a_{0i} \sin \frac{2\pi it}{365} - a_{2i} \cos \frac{2\pi it}{365} + a_{0i} \sin \frac{2\pi it}{365} - a_{2i} \cos \frac{2\pi it}{365} + b(\theta^2 - \theta_0^2) + c(P - P_0) + d_1(\theta - \theta_0) + d_2(\ln \theta - \ln \theta_0) \right) \]  

(b)

(8)

In which, \( \delta_0, T_0, \theta_0, P_0 \) are corresponding monitoring values of effect and factors on the initial monitoring date. \( a \) (or \( a_{0i}, a_{2i} \)), \( b \), \( c \), \( d_1 \), \( d_2 \) are regression coefficients, which are usually obtained by multiple regression or stepwise regression, and the stepwise regression equation contains only significant factors.

3.2. LS-SVM model

In the LS-SVM model of COD, the input of the model is temperature factor, stacking factor, wind pressure factor and time-effect factor which cause fracture change, Model output \( y \) is the COD. Sample sets are represented as \( Q = \{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\} \), where \( x_i \in \mathbb{R}^n \) are m-
dimensional column vectors for each factors, $y_l$ are measurements of COD, $l$ is the total number of samples.

LS-SVM transforms the non-linear fitting problem of input space into a linear fitting problem in high-dimensional feature space by mapping data sets from input space to high-dimensional feature space, that is:

$$y(x) = w^T \cdot \phi(x) + b$$

in which, $\phi(x)$—Nonlinear mapping function from input space to high dimensional characteristic space, $w$—Weight vector, $b$—Offset.

Combining the complexity of the function with the fitting error, Formula (9) can come down to the following optimization problems.

$$\begin{cases}
\text{min } J(w, b, \xi) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{l} \xi_i^2 \\
\text{s.t. } y_i = w^T \phi(x_i) + b + \xi_i, \quad i = 1, 2, \ldots, l
\end{cases}$$

in which, Super parameter $\gamma$—Regularized parameter, avoiding over-fitting; $\xi_i$—The Training Error of Sample Point $i$.

Establish the Lagrangian equation as follows:

$$L(w, b, \xi, a) = J(w, b, \xi) - \sum_{i=1}^{l} a_i \{ w^T \phi(x_i) + b - y_i + \xi_i \}$$

in which, $a_i \in R$ is Lagrangian Multiplier, According to the following optimum conditions:

$$\begin{align*}
\frac{\partial L}{\partial w} &= 0, \quad \frac{\partial L}{\partial b} = 0, \quad \frac{\partial L}{\partial \xi_i} = 0, \quad \frac{\partial L}{\partial a_i} = 0
\end{align*}$$

The following expressions can be obtained:

$$w = \sum_{i=1}^{l} a_i \phi(x_i), \quad \sum_{i=1}^{l} a_i = 0, a_i = \gamma \xi_i, \quad w^T \phi(x_i) + b + \xi_i - y_i = 0$$

Eliminate variables $w$ and $\xi$:

$$\begin{bmatrix} 0 & I^T \\ I & \Omega + \gamma I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}$$

in which, $y = [y_1, y_2, \cdots, y_l]^T$, $I = [1, 1, \cdots, 1]^T$, $a = [a_1, a_2, \cdots, a_l]^T$, $I$ is a unit matrix of $l \times l$, $\Omega$ is Kernel function matrix. Appling Mercer Conditions in Matrix $\Omega$:

$$\Omega_{ij} = y_i y_j \phi(x_i)^T \phi(x_j) = y_i y_j K(x_i, x_j)$$

The LS-SVM model of the COD is obtained as:

$$y(x) = \sum_{i=1}^{l} a_i K(x, x_i) + b$$

in which, $a_i, b$—Solutions of linear systems, $K(x, x_i)$—Kernel function. Symmetric functions
satisfying Mercer conditions can be used as kernel functions. The commonly used kernel functions are Polynomial functions, Radial basis functions and Sigmoid functions, where the radial basis functions have better statistical performance, and their expressions are as follows.

\[ K(x, x_i) = \exp(-\frac{||x-x_i||^2}{2\delta^2}), \delta > 0 \] (17)

By substituting formula (17) into formula (16), the LS-SVM regression function of COD can be obtained as follows:

\[ y(x) = \sum_{i=1}^{l} a_i \exp(-\frac{||x-x_i||^2}{2\delta^2}) + b \] (18)

The main parameters of the LS-SVM model for COD are regularization parameter \( \gamma \) and kernel parameter \( \delta \), which largely determine the learning and generalization ability of the LS-SVM model, and can be optimized by genetic algorithm [20].

### 3.3. Model evaluation

In order to understand the effectiveness of the model on the monitoring data of COD, it is necessary to evaluate the model. As to the accuracy of fitting and regression models, the commonly used evaluation indexes are complex correlation coefficient \( R \) and residual standard deviation \( S \) [1]. Thus, the calculation method could be described as follows.

\[ R = \sqrt{\frac{\sum_{i=1}^{l} (\delta_i' - \bar{\delta})^2}{\sum_{i=1}^{l} (\bar{\delta}_i - \bar{\delta})^2}} \quad S = \sqrt{\frac{\sum_{i=1}^{l} (\delta_i' - \bar{\delta}_i)^2}{f_\phi}} \] (19)

in which, \( \bar{\delta} \) —Average value of measured data for effect quantity; \( f_\phi \) —Degree of Freedom of the Sum of Residual Squares, \( f_\phi = l - m - 1 \); The rest of the symbols have the same meaning as before.

When evaluating the effect of the model, besides the accuracy of the model, the predictive extensibility of the model, which refers to the predictive ability of the model over a period of time in the future, is particularly important for building safety monitoring. Usually, absolute average percentage error \( MAPE \), mean square error \( MSE \) and average absolute error \( MAE \) are used to measure it, so the calculation method can be expressed as follows:

\[ MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right|, \quad MSE = \sqrt{\frac{\sum_{i=1}^{n} (A_i - F_i)^2}{n}}, \quad MAE = \frac{1}{n} \sum_{i=1}^{n} |A_i - F_i| \] (20)

in which, \( n \) is the number of samples tested; \( A_i \) is actual value, \( F_i \) is predicted value.

### 4. Case study

The high-piled wharf is located in Jiaojiang District, Taizhou City, Zhejiang Province. Its platform is 162.55 m long and 14 m wide, and main structural components are beams, longitudinal beams and slabs. The structural sketch is shown in figure 3.
Due to temperature change, wind load, wharf stacking load and other effects in the process of operation, there are corrosion diseases such as concrete cracking and steel bars exposure in each component of the wharf structure just as shown in figure 3. The deterioration grade of concrete in figure (3b) increases gradually in the order of A, B, C. In order to ensure safe operation of the wharf, relevant management departments repaired it in August 2015. Seam gauges were installed at longitudinal beams ZL15-2, ZL15-3, ZL15-4 and panel 15-4 during the repairing process, then the changes of COD in structure components were monitored from October 21st, 2015; and the frequency of monitoring was about once a week. In this paper, the measured points 5094 in the south side of the longitudinal beam ZL15-2 and 5098 in the south side of the longitudinal beam ZL15-3 are taken as examples, and the monitoring data series from October 21st, 2015 to May 26th, 2016 are used. The time-variation process lines of measured data and environmental variables are shown in figures 1 and 2. Finally, formulas (8a) and (16) are used to establish statistical models and LS-SVM models respectively. Their parameters are shown in tables 1 and 2, respectively. It should be noted that due to the short data series, the periodicity of temperature variation in figure 2(a) is not obvious.

| Measuring point | Parameter | $a$ ($10^4$) | $b$ ($10^3$) | $c$ ($10^3$) | $d_1$ ($10^2$) | $d_2$ | R    | S    |
|-----------------|-----------|--------------|--------------|--------------|----------------|------|------|------|
| 5094            | multiple regression | -2.45 | 1.34 | 1.37 | -1.37 | 0.04 | 0.92 | 0.01 |
|                 | stepwise regression | -55.4 | -1.36 |
| 5098            | multiple regression | -84.3 | 1.35 | -5.98 | -0.49 | 0.01 | 0.91 | 0.01 |
|                 | stepwise regression | -60.9 |

| Measuring point | $\gamma$ | $\delta$ | R    | S    | Measuring point | $\gamma$ | $\delta$ | R    | S    |
|-----------------|----------|----------|------|------|-----------------|----------|----------|------|------|
| 5094            | 10       | 4        | 0.94 | 0.009|
| 5098            | 12       | 3.6      | 0.95 | 0.01 |

Seen from tables 1 and 2, the complex correlation coefficients of both the statistical model and LS-SVM model are above 0.9, and the residual standard deviation is small. And compared with the statistical model, the accuracy of the LS-SVM model is higher. In order to further understand the relationship between COD and each component, and find out the main influencing factors of COD, the above stepwise regression model is used to separate the components. The time-variation process lines of measured values, fitting values and each component are shown in figure 4.

As can be seen from figure 4, the measured value and fitting value are close to each other for Measurement point 5094 and 5098. Temperature component is the main factor of COD at the two
measuring points, which verifies that the formation and expansion of cracks are very sensitive to temperature change. In addition, the time-effect component of COD at measuring point 5094 is shrinking gradually. The influence of wind load on COD is not obvious (the wind load factor is not selected into the stepwise regression equation), which is mainly influenced by the location of the two measuring points on the wharf platform. As for the reason why the wharf stacking load (whose factor has not entered the stepwise regression equation in this example) has no significant effect on COD of the two measuring points, and its influence rule on the COD needs to be further studied by collecting data and using long sequences.

![Figure 4](image_url)

**Figure 4** Process Lines of measured and fitted values and components of typical points. (a) Measurement point 5094 and (b) Measurement point 5098.

To verify the predictive extensibility of the model, stepwise regression model and LS-SVM model are used to predict the measurements in June 2016, and the measurement parameters in equation (20) are calculated. The results are shown in table 3.

**Table 3.** Prediction results of statistical model and LSSVM model.

| Sequence  | 5094 Measured value (mm) | Statistical model (stepwise regression) | LS-SVM model | Sequence  | 5098 Measured value (mm) | Statistical model (stepwise regression) | LS-SVM model |
|-----------|--------------------------|-----------------------------------------|--------------|-----------|--------------------------|-----------------------------------------|--------------|
| 2016/6/2  | 0.251                    | 0.264                                    | 0.265        | 2016/6/2  | 0.330                    | 0.343                                    | 0.349        |
| 2016/6/8  | 0.236                    | 0.258                                    | 0.261        | 2016/6/8  | 0.314                    | 0.337                                    | 0.317        |
| 2016/6/16 | 0.239                    | 0.258                                    | 0.243        | 2016/6/16 | 0.320                    | 0.336                                    | 0.275        |
| 2016/6/23 | 0.170                    | 0.220                                    | 0.178        | 2016/6/23 | 0.253                    | 0.297                                    | 0.268        |
| MAPE      | 12.9%                    | 5.64%                                    | MAPE         | 8.41%     | 6.68%                    | MAPE                                    | 8.41%        |
| MSE       | 0.029                    | 0.015                                    | MSE          | 0.027     | 0.026                    | MSE                                     | 0.027        |
| MAE       | 0.026                    | 0.013                                    | MAE          | 0.024     | 0.021                    | MAE                                     | 0.024        |

Table 3 shows that the statistical model and LS-SVM model have certain prediction ability. In terms of prediction effect, the LS-SVM model is better than the statistical model. This is mainly due to the stronger robustness of the LS-SVM model. It should be pointed out that due to limited data; this paper only forecasts the monitoring data for the next month.

5. Conclusion
According to the working characteristics of high-piled wharf, its crack opening displacement (COD) is studied in this paper. It is pointed out that the main influencing factors of COD are temperature, wind load, wharf load and time effect. The expressions of each influencing factor are given. Both the statistical model and the least squares support vector machine (LS-SVM) model are established for COD of high-piled wharf, and the evaluation method for the utility of model is discussed. The model
is applied to crack monitoring of a high-piled wharf in Zhejiang Province. The results show that the accuracy of the two models is high and the prediction ability is good, which shows that the selection of model factors is reasonable. In addition, LS-SVM model has more advantages than stepwise regression statistical model in dealing with non-linear problems, and its predictive extension is better than that of statistical model, which can be used for early warning of COD of high-piled wharf. Stepwise regression statistical model is recommended for separating each component. A preliminary study for monitoring and studying COD of high-piled wharf is proposed in this paper. However, cracking of high-piled wharf is a complex non-linear problem affected by many factors, in this paper, the effects of seawater erosion, creep of reinforced concrete and periodic wave pressure are considered and introduced into the COD model as "time component". Further research is needed on the completeness of factor selection and the efficiency of model establishment.

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