Time series analysis of tunnel underlining cracks based on temperature effects

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Abstract. Based on the crack width data monitored during the operation period of a tunnel in Dali, the development of the lining cracks in the tunnel was analyzed in terms of temperature changes. The crack widths were converted to the same condition at each temperature interval. The analysis found that the tunnel lining cracks and temperature changes will show a positive correlation trend, and converted to the same conditions under the temperature will show a linear relationship with the increase of time. Based on the appealing characteristics, the time series modeling method is used to establish a model of temperature and tunnel lining cracks, and the model is applied to make relevant predictions on the development of lining cracks in the short term. The results show that the model has a high accuracy.

Keywords: lining crack width; autocorrelation coefficient; residual analysis; partial correlation coefficient; time series

1 Introduction

Tunnel monitoring is an important measure to ensure the safety of tunnels during operation. It can provide a more timely response to changes in the surrounding rock and supporting structures during actual use which is widely used in tunnel monitoring. However, the change of time in the construction process of some small deterioration information will gradually appear and directly lead to the surface of the tunnel lining structure of the disease, such as tunnel cracks, water seepage, etc., which the tunnel lining cracks is the most common as the mastery of the development of the tunnel lining cracks for the tunnel lining cracks of the daily maintenance and repair is very important. A large number of experimental studies [1-8] have shown that temperature has a very great influence on the structural performance of concrete. In the monitoring of tunnels, the monitoring of temperature is essential, especially in the research process of tunnel lining cracks, which is a very important influence factor. Only the temperature of the tunnel lining cracks is mastered for the influence of the law to better grasp the whole structure of the tunnel development law to provide a reliable basis for the routine maintenance of tunnels and disease remediation. Research and experiments have shown

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that the establishment of time series and grey prediction models is very practical for tunnels and some other underground structures. Therefore, this paper adopts the time series approach for the study of lining cracks in tunnels.

2 Time series modeling

2.1 Characteristics of time series data

In layman's terms, time series analysis is the process of modeling the collected monitoring data which is used to predict future changes. For the data analysis of certain factors, regression equations are generally used to obtain the corresponding estimates. For some uncertain factors, the related time series models are autoregressive model AR, sliding average model MA and autoregressive sliding average model ARMA, which are for this type of data generally taking the method of model identification, model ordering, and parameter estimation. In view of the above data processing, this paper uses the ARIMA model. This ARIMA is based on the transformation of the ARMA model, ARMA model is for the t-period values for modeling, while ARIMA is for the t-period and t-d-periods between the difference in modeling, where d is a few orders of difference. ARIMA model is also based on the smooth time series or differentiation after the stabilization of the other. The previous several models can be regarded as some special form of ARIMA. ARIMA (p, d, q) is denoted. p is the autoregressive order, q is the moving average order and d is the time to become smooth when the number of differentials is made, which is the integrated word here.

The specific calculation steps are as follows:

$$x_t = \varphi_1 w_{t-1} + \varphi_2 w_{t-2} + \cdots + \varphi_p w_{t-p} + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q}$$

2.2 Analysis of crack width data for bridges

The data in this paper comes from the monitoring of cracks in a tunnel in Dali, which is 4021m long. After a long period of operation, it is now found that there are a large number of diseases inside the tunnel, the most important of which are cracks, which have been monitored for one year, and the data are recorded once a day for 6 hours. The above data can be analyzed to determine whether the temperature and crack width are closely related, as shown in Figure 1 for details.

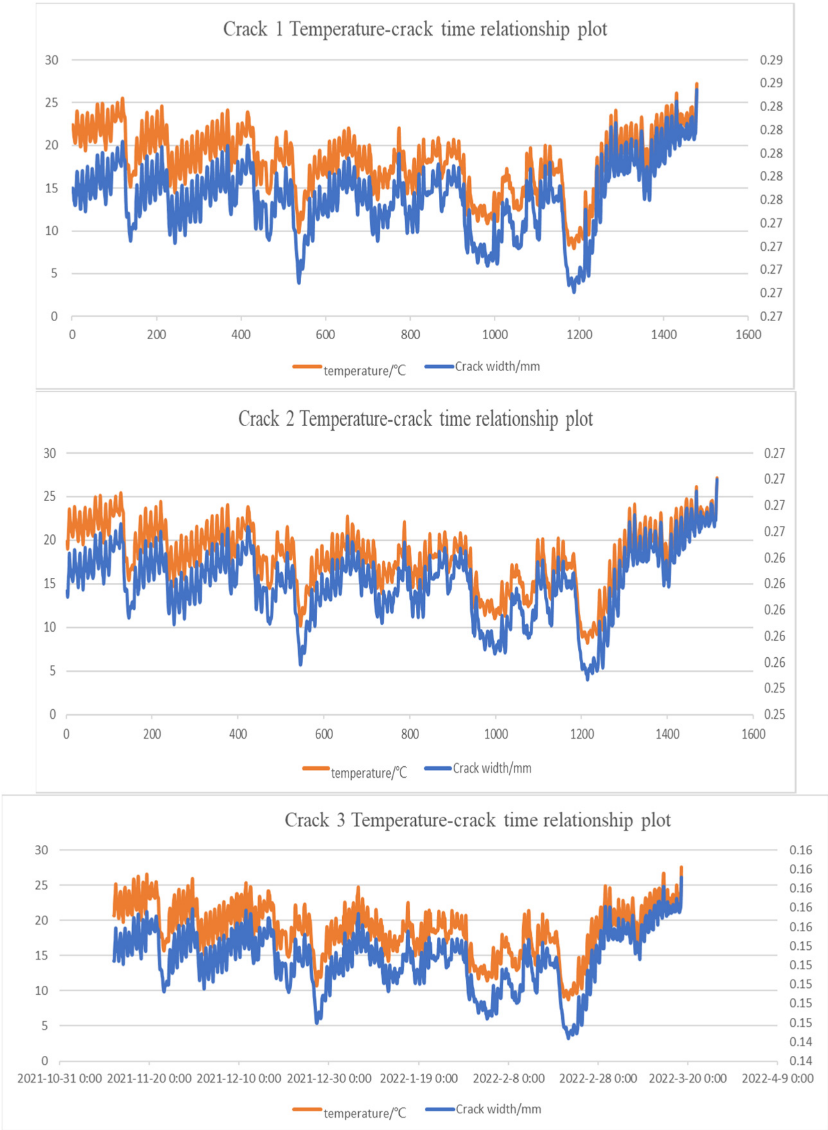

Fig. 1. Plot of crack width versus time

From the above figure, it can be seen that the crack width changes with time, the lower the temperature is, the smaller the corresponding crack width is, especially when the temperature is lower than 10 ℃, the crack width change is the largest. On the contrary, the higher the temperature is, the larger the change is. After 20 ℃, there is a significant increase in temperature. Through the monitoring data of the tunnel lining cracks and temperature, it was found that since the tunnel was in the operation stage, it was subject to less external interference, so the data collection and analysis concluded that the change in crack width was affected by the temperature.

2.3 Trend analysis of crack width at different temperatures

From the crack width with time and temperature changes, it can be seen that the tunnel lining cracks on the temperature will be with the temperature of the day ups and downs and affect the crack width changes to better analyze the temperature and the crack width of the law of change. It also will be the data for the following processing. The temperature for sorting takes every 0.1℃ as a temperature value.

Here we choose the data of crack 1. Through the appeal method for regression hair analysis, the relationship between the temperature and the width of the crack is generally consistent with the Gaussian (Gauss) function law, which is

$$f(t) = a*\exp(-((t_0-b)/c)^2) \quad (1)$$

where t is the temperature; a is the height of the spike of the curve, b is the coordinate of the center of the spike, c is called the standard variance, and a, b and c are coefficients to be determined. After multiple regression analysis, it can be seen that in the case of the initial length and width of the lining crack width of the tunnel is small, the amount of change in width is only related to temperature. It is shown in Figure 2.

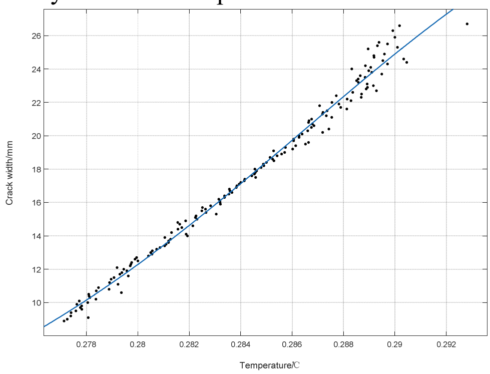

Fig. 2. Regression curve of temperature and crack width

The measured temperature can be used to estimate the crack width by using Equation (1). From the regression fitting curve, it can be seen that the temperature and crack width fit well, and the correlation between the two is as high as 0.9803. The law between the two and its conformity is the Gaussian (Gauss) function.

2.4 Time series analysis of time series plots, residual series and residuals

There are two ways to test the smoothness of the time series, one is the graphical test which makes a judgement based on the correlation characteristics of the time series plot and the autocorrelation function plot, and the other is the method of constructing the relevant statistics for hypothesis testing [9-10], as shown in Figures 3 and 4.

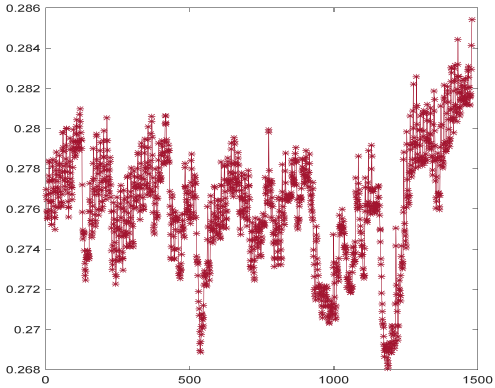

Fig. 3. Timing diagram of crack width

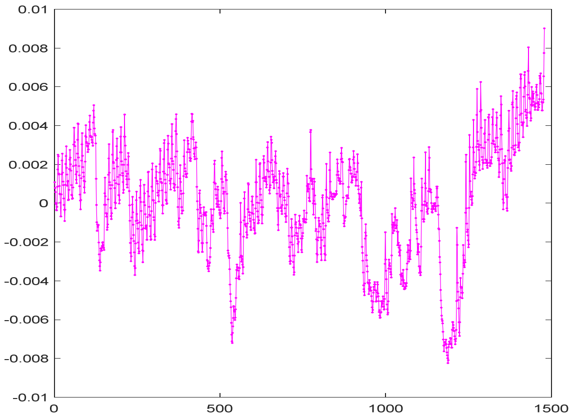

Fig. 4. Residual sequence data

The time series plot shows that the crack width always fluctuates randomly around 0.2760, and the range of fluctuation is bounded and there is no obvious trend or cycle, which can basically be regarded as a smooth sequence. However, to be on the safe side, we can further assist in the identification by using autocorrelation plots to analyse the residual autocorrelation coefficients [9-10]. Smooth series usually have short-term correlation. This property is described by the autocorrelation coefficient which is that as the delay period coefficient k increases, the autocorrelation coefficient ρk of the smooth series will quickly weaken to zero. Conversely the autocorrelation coefficient ρk of the non-smooth series is slower to weaken to zero, and this property is the criterion used in the judgment of the smoothness detection to build a combinatorial model, to carry out a fit. The overall residual autocorrelation function plot and residual variance plot [9-10] are shown in Figures 5 and 6 :

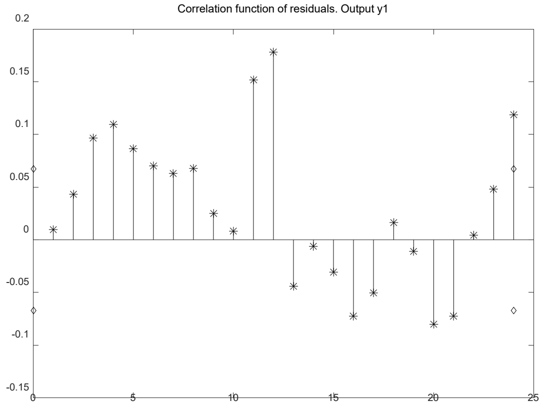

Fig. 5. Residual autocorrelation function after fitting the overall model

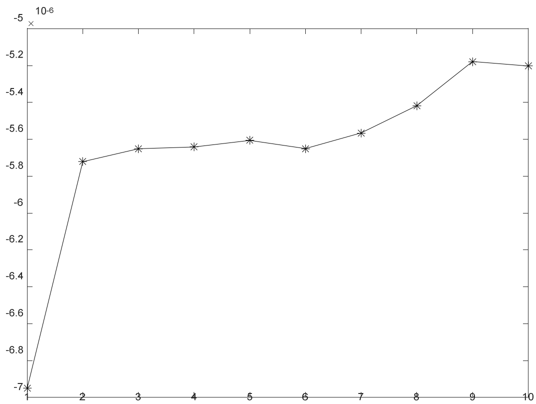

Fig. 6. Residual variance after fitting the overall model

The plot of the residual autocorrelation function shows that the autocorrelation coefficient of the series is always small and controlled within 0.2 times the standard deviation. It can be assumed that the series fluctuates around the zero axis from the beginning to the end, which is the autocorrelation characteristic that a smooth time series with a very high degree of stochasticity usually has.

2.5 Future prediction of crack width and error analysis

We used computer programming to perform simulations by using Gauss curves, the general form of which is:

$$y_i = y_{max} * \exp\left[-\frac{(x_i - x_{max})^2}{S}\right] \tag{2}$$

The parameters to be explained in Equation (2) are y_{max}, x_{max}, and S, which represent the physical meaning of the peak, peak position, and half-width information of the Gaussian curve. The physical meaning is the Gaussian curve's peak screwing, peak position, and half-width information.

By taking the natural logarithm of both sides of Equation (2), it is reduced to:

$$\ln y_i = \ln y_{max} - \frac{(x_i - x_{max})^2}{S} \tag{3}$$

$$\ln y_i = \left(\ln y_{max} - \frac{x_{max}^2}{S}\right) + \frac{2x_i x_{max}}{S} + \frac{X_i^2}{S} \tag{4}$$

$$\ln y_i = Z_i \qquad \ln y_{max} - \frac{x_{max}^2}{S} = b_0 \qquad \frac{2x_i x_{max}}{S} = b_i \qquad -\frac{1}{S} = b_2 \tag{5}$$

Then Equation (2) is substituted for the quadratic polynomial fitting parameter:

$$Z_i = b_0 + b_1 x + b_2 x_i^2 = (1, x_i, x_i^2) * (b_0, b_1, b_2)^T \tag{6}$$

which is shorthand for:

$$Z_{n*1} = X_{n*3} * B_{3*1} + E_{n*1} \tag{7}$$

Without considering the effect of the total measurement error E, the generalized least squares solution of the matrix B consisting of the fitting constants b_0, b_1, b_2 can be found according to the least squares principle as:

$$B = (X^T X)^{-1} X^T Z \tag{8}$$

According to Equation (4), the parameters S, x_{max} and y_{max} can be derived, obtaining the Gaussian function of Equation (2).

Since the crack width is greatly affected by temperature, it is unreasonable to unify the temperatures into the same regression equation, on this basis, the temperatures are divided into 2° respectively for the regression equation. b and c are taken as the parameter values of their overall temperature regression equations, i.e. b = 102, c = 204.9. The reference value of a is projected for regression analysis with a limit of 2°C. The value of a is obtained from the various data within 2°C respectively, and the average is taken as the value of a within that temperature. The average value of a was taken as the value of a within that temperature, as shown in Table 1 for the reference value of a at each temperature.

Table 1. Reference value of crack 1 a

Temperature (°C)	Reference values a
8-10	0.2202
10-12	0.2237
12-14	0.2260
14-16	0.2292
16-18	0.2324
18-20	0.2353

20-22	0.2379
22-24	0.2413
24-26	0.2448
26-	0.2495

Combining the reference values of a in Equations. (2), (4), (6) and Table 7 for the time series crack width, the prediction formula was calculated by using Equation 15 times thereafter and the actual values are compared in Figure 7.

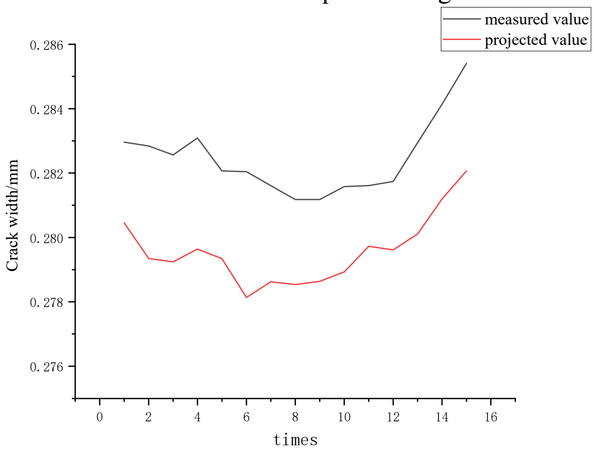

Fig. 7. Comparison of predicted and measured values

It can be seen from Figure 9 that its predicted data agree well with the actual measured data. The detailed results in terms of the actual error rate are shown in Table 2.

Table 2. Comparison table of predicted value and actual value

Predicted number of times	Predicted value (mm)	Measured value (mm)	Error rate (%)
1	0.280453	0.28296	0.89%
2	0.279346	0.28284	1.24%
3	0.279242	0.28256	1.17%
4	0.279642	0.28309	1.22%
5	0.278338	0.28207	1.32%
6	0.280138	0.28204	0.67%
7	0.279924	0.28161	0.60%
8	0.278534	0.28118	0.94%
9	0.278634	0.28118	0.91%
10	0.278931	0.28158	0.94%

The same analytical method was carried out for the remaining 2 cracks. The error rate between the measured values and the values predicted using the model was within 2% for both cracks.

3 Conclusion

Temperature is an important factor affecting the concrete structure. Under different temperature conditions, the lining crack width change rule of the tunnel is not the same. Through the actual monitoring data on the lining crack width of the tunnel, the following conclusions were made:

(1) Tunnel lining cracks own conditions such as lining force conditions, crack length, crack width, etc. The crack development of the driving force in the rest of the conditions must be the case of temperature on the development of cracks having a greater impact.

(2) In the short term, analyzing the trend of cracks in operational tunnels using time series gives more satisfactory results.

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