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Cointegration based modeling and anomaly detection approaches using monitoring data of a suspension bridge

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Abstract. For long-span bridges with a structural health monitoring (SHM) system, environmental temperature-driven responses are proved to be a main component in measurements. However, anomalous structural behavior may be hidden incomplicated recorded data. In order to receive reliable assessment of structural performance, it is important to study therelationship between temperature and monitoring data. This paper presents an application of the cointegration based methodology to detect anomalies that may be masked by temperature effects and then forecast the temperature-induced deflection (TID) of long-span suspension bridges. Firstly, temperature effects on girder deflection are analyzed with fieldmeasured data of a suspension bridge. Subsequently, the cointegration testing procedure is conducted. A threshold-based anomaly detection framework that eliminates the influence of environmental temperature is also proposed. The cointegrated residual series is extracted as the index to monitor anomaly events in bridges. Then, wavelet separation method is used to obtain TIDs from recorded data. Combining cointegration theory with autoregressive moving average (ARMA) model, TIDs for longspan bridges are modeled and forecasted. Finally, in-situ measurements of Xihoumen Bridge are adopted as an example to demonstrate the effectiveness of the cointegration based approach. In conclusion, the proposed method is practical for actual structures which ensures the efficient management and maintenance based on monitoring data.

Keywords: anomaly detection; cointegration; prediction; structural health monitoring; suspension bridge

1. Introduction

In past several decades, a large number of long-span suspension bridges have been widely constructed in the world for its excellent crossing capacity and beautiful appearance (Catbas *et al*. 2013, Xu 2018). It is one of the most important types of long-span bridges and supports vital arteries for national transportation systems (Wang *et al*. 2019a or g). These bridges are exposed to various risks during operational period, thus leading to increasing concerns regarding structural safety and service performance for management departments (Ye *et al*. 2018, Xu *et al*. 2019a). Nowadays, structural health monitoring (SHM) systems are gradually designed and installed in long-span bridges to trace their real-time status (Wan and Ni 2018, Zhang *et al*. 2020). Massive data that reflect bridge operational status are collected constantly by various smart sensors (Nguyen and Goulet 2018). However, deep mining for massive data to obtain useful information about bridge performance remains a great challenge in structural engineering (Posenato *et al*. 2010).

The existing studies prove that long-span bridges are highly sensitive to environmental temperature, and the temperature-induced responses may even mask expected information in SHM data (Chen *et al*. 2011, Yarnold and Moon 2015). Usually, cyclical temperature effects on a bridge are regarded as benign operational variations that need to be separated rather than abnormal changes. The existing thermal effects separate approaches can be generally classified into model-driven and data-driven (Lepidi and Gattulli 2012, Kromanis and Kripakaran 2017). For model-driven approaches, finite element (FE) models should be developed and updated to calculate structural responses and inherent characteristics (Cui *et al*. 2020). The main challenge for model-driven approaches is to build a reliable FE model that reflects actual situation of the bridge (Lepidi *et al*. 2007). To reduce the computational cost, Xu *et al*. (2019b) presented a practical multivariate linear-based method to separate thermal effects from bridges. Responses corresponding to each type of thermal actions were determined according to simulation results and recorded measurements. The data-driven approaches analyze directly on the measurements. In this respect, Ni *et al*. (2005) connected modal properties of bridges with temperature using SHM data and support vector machine technique. Zhu *et al*. (2018) presented a blind separation method to extract the temperature effects on bridge responses without any prior information of the loading conditions and models. A truss bridge test in laboratory was conducted to evaluate the separation method. Kromanis and Kripakaran (2014) developed a regression-based method to capture the relationships between temperature and structural response from distributed measurements recorded during a reference

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period. For long-span suspension bridges, temperature induced response is usually a fluctuation variation at specific low frequency. In view of such characteristics of measured bridge deflection, wavelet separation method is recommended as an effective way to eliminate temperature effects (Deng *et al*. 2018). Meanwhile, wavelet decomposition type and level should be specially determined and adjusted for a specific bridge (Xu *et al*. 2020a). The accuracy of these data-driven approaches relies much on rationality of the algorithm and precision of measurements.

In the structural anomaly detection field, the development of monitoring system promotes its progress to a certain extent. The initial method is to observe monitored dynamic parameters such as frequency to detect structural damage (Salawu 1997). Although the dynamic characteristics-based anomaly detection methods have been verified in theory, challenges still arise in practical applications when applied to sophisticated structures, including the influence of environmental variations (Nguyen *et al*. 2020, Xu *et al*. 2020b). Meanwhile, temperature effects are suggested to be distinguished with anomaly events (Peeters *et al*. 2001). In view of the limitations of traditional methods in practical applications, researchers have explored to utilize other indexes to conduct anomaly detection for long-span bridges in recent years. Meng *et al*. (2019) used the modal flexibility method to detect suspension bridge hangers. The method was demonstrated for several damage scenarios on a laboratory suspension bridge. Zhou *et al*. (2011) developed an improved auto-associative neural network with environment-tolerant capacity, the alarming threshold was also set based on the probability analysis of the novelty index. Ding *et al*. (2010) used wavelet packet analysis to extract energy spectrum from the measured dynamic responses, hence the warning parameters were provided. The usefulness of the approach was examined on an actual bridge with 236 days of monitoring data. As intelligent algorithm theory and monitoring systems have made great progress, various anomaly detection methods will be proposed (Ni *et al*. 2020).

On the other hand, there is still a strong demand for the efficient use of SHM data in the bridge performance (e.g., deflection, cable force and so forth) prediction models (Sun *et al*. 2019, Wang *et al*. 2019b). Modeling and prediction of temperature-induced responses for long-span bridges facilitate the bridge maintenance decision-making. Nowadays, some studies about performance prediction of bridge structures have been conducted based on monitoring information. Frangopol *et al*. (2008) presented a general approach for the development of performance functions based on monitored extreme data. All existing bridges in Wisconsin, USA, were used to test the proposed approach. Liu and Fan (2019) proposed a Bayesian-Fourier method for predicting periodic extreme responses of bridges, the monitoring periodic extreme stress data of a steel bridge were provided to illustrate the effectiveness of the proposed method. The time series analysis theory provides another way to utilize SHM data. For instance, the autoregressive moving average (ARMA) model have been built based on monitoring data to forecast bridge performance including deformation (Xin *et al*. 2018, Kaloop *et al*. 2019, Le and Nishio 2019). However, wider approaches are still needed to further improve the prediction accuracy be easier of computation.

Recently, cointegration theory, which is original from the field of econometrics, is proposed as a new approach to suppress the effects of environmental temperature in monitoring system. In applications of the cointegration theory for structural anomaly detection, the modal frequency is the most commonly used parameter to assess safety and detect damage of bridges (Comanducci *et al*. 2016, Liang *et al*. 2018). Huang *et al*. (2018) developed a cointegration based method to establish relationship between first several bridge frequencies, the change of structure states was then estimated by a recursive process. Based on the mathematical model of cointegration analysis, He *et al*. (2019) eliminated the environmental effect on structural frequency for a three-span concrete bridge model. Using cable force monitoring data from cable-stayed bridges, the cointegration based method has also shown a promising application in structural anomaly detection (Fan *et al*. 2020, Tomé *et al*. 2020). On the other hand, the combination of cointegration analysis and time series theory is expected to achieve prediction for temperature-induced deflection (TID). The cointegration-based method is rarely used to deal with structural deflection data in existing studies, whether in field of anomaly detection or prediction.

This paper presents an application of the cointegration based methodology to detect structural anomalies that may be masked by temperature effects and then forecast the TIDs of long-span suspension bridges. Firstly, temperature effects on girder deflection are analyzed with field-measured data. The correlation between environmental temperature and girder deflection in different locations are also studied. Subsequently, the cointegration procedure is conducted to test monitoring data series and extract cointegrated residual series as the detection index. A threshold-based bridge anomaly detection framework that eliminates the influence of environmental temperature is proposed. Anomaly events in bridges such as overload and stiffness attenuation can be monitored in this anomaly detection framework. Then, wavelet separation method is used to obtain TIDs from recorded data. Combining cointegration theory with autoregressive moving average (ARMA) model, TIDs for long-span bridges are modeled and forecasted. Finally, a case study is adopted as an example to demonstrate the effectiveness of the cointegration based approach by using the in-situ measurements from a suspension bridge.

2. Methodology

The general framework of the cointegration based methodology for anomaly detection and TID forecasting in this paper is shown in Fig. 1. The raw data from SHM systems should be preprocessed before further utilization, including de-noising, gross error check and missing data imputation. The data preprocessing procedure could refer to

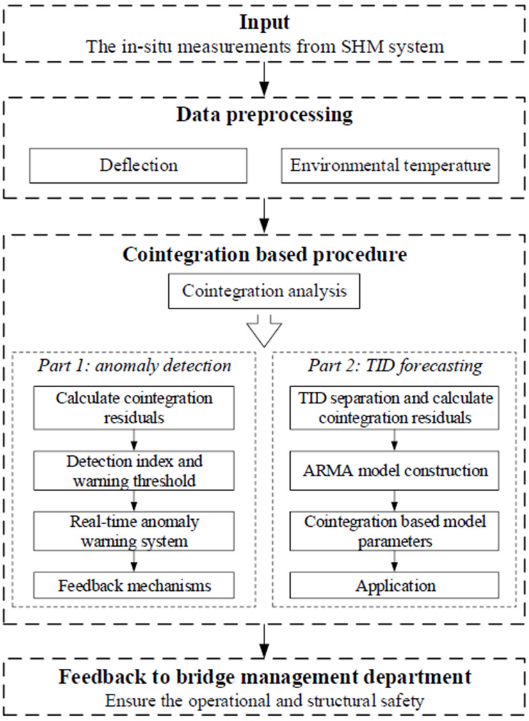


Fig. 1 Framework of the methodology

our previous work (Xu *et al.* 2019a). Environmental temperature and deflection measurements are then investigated to explore their characteristics and correlation. Meanwhile, temperature induced response separation is implemented for the following discussion. Subsequently, the cointegration procedure is conducted to test time series data. The cointegrated residual is extracted as an important index for next steps. Finally, applications of anomaly detection and modeling-forecasting are carried out, where the critical issues are: (i) determination of detection index and threshold; (ii) model parameters calculation and model assessment, respectively. In addition, to increase the effectiveness of anomaly detection in variable bridge operational conditions, the dynamic threshold is adopted in this study, which means to update the threshold periodically with the latest monitoring data. For a practical structure, it is suggested to annually update the threshold. Moreover, the non-stationary variables series will be linearly cointegrated in this paper, for there exists a linear combination of them that is stationary. It should also be admitted that common trends are nonlinearly related of other variables series in some situations (Zolna *et al.* 2016). If this is the case then the nonlinear cointegration theory is needed, which will be investigated in further research.

2.1 Cointegration method

The stationary linear combination of two or more nonstationary time series is defined as cointegration, which means that the time series can be represented to have a stable relationship known as a long-term equilibrium. Cointegration arises in economics, where for example money demand models, macroeconomic analysis, and fiscal policy research (Engle and Granger 1987, Dao and Staszewski 2013). Nowadays, cointegration has been applied successfully to address the challenge of environmental variation in structural monitoring (Worden *et al.* 2016, Shi *et al.* 2018). This section describes the concept and basic theory that is important for the application presented in the study.

Let $\{y_t\}$ denotes a response variable series while $\{x_t\}$ is the input variables series. One can say that $\{y_t\}$ is cointegrated with $\{x_t\}$ if there exists a (t+1)×1 vector $\beta = (\beta_0, \beta_1, \ldots, \beta_t)$ such that

$$y_t = \beta_0 + \sum_{i=1}^{t} \beta_i x_i + u_t \quad (1)$$

where $\beta = (\beta_0, \beta_1, \ldots, \beta_t)$ is called the cointegrating vector, u_t is the cointegrated regression residual. The regression residual series $\{u_t\}$ is stationary once there exists cointegration. In other words, the eventual aim of cointegration procedure is to identify the cointegrating vector to ensure the residual series stationary. It should be noted that the work presented in this study considers the action of creating the cointegrating residual series in following sections.

For a non-stationary variable series $\{y_t\}$, if it becomes stationary after d times difference operation, it is called integration of order d, which indicates there exists d unit root in series $\{y_t\}$, denoted as $\{y_t\} \sim I(d)$. Specially, when the variable series $\{y_t\}$ itself is stationary, it can be regarded as a particular case of 0 order integration, denoted as $\{y_t\} \sim I(0)$. The order of integration should be determined before cointegration procedure, for the cointegration based method can only be operated for non-stationary variable series with the same order of integration. If the target time series data are not under the same integration order, it can be considered that there is no cointegration relationship between them. Then the cointegration vectors β can be obtained in the process of cointegration test.

In respect of non-stationarity, various methods have been developed for non-stationary time series testing while the unit root test is the most proven one. It has been proofed that the time series will be non-stationary if exists a unit root (Cross *et al.* 2011). The Augmented Dickey-Fuller (ADF) procedure is used for unit root test in this study (Dickey and Fuller, 1979). For a time series model, which can be given as

$$\Delta y_i = \rho y_{i-1} + \sum_{j=1}^{r-1} b_j \Delta y_{i-j} + \varepsilon_i \quad (2)$$

where Δ is the difference operator with the definition of $\Delta y_{i-j} = y_{i-j} - y_{i-j-1}$, ρ is a coefficient of a real number, b_j is a coefficient of the model, ε_i is the Gaussian white noise independent normal random series with a mean value of 0 and a variance of σ^2, and r is the number of lags, which is expected to insure that ε_i becomes a white noise series. The number of lags can be selected based on information criteria (Dao *et al.* 2017).

The aim of the ADF procedure is to estimate the parameters in equation (2) and test the null hypothesis of $\rho = 0$. Then, the t-test statistic is carried out and be compared with critical values that constructed by Dickey and Fuller (1979). The test statistic t_ρ is conducted as following

$$t_\rho = \frac{\hat{\rho}}{\sigma_\rho} \tag{3}$$

where $\hat{\rho}$ is the least squares estimate of ρ and σ_ρ is the variance estimate. The result of the hypothesis test is obtained by comparing t_ρ with the critical value in the ADF statistic table. When the null hypothesis is accepted, time series $y_i \sim I(1)$. When the null hypothesis is rejected, ADF procedure is continued for each difference of y_i until the order for integration of y_i is ascertained.

When the non-stationarity order of variable series is determined, an attempt to create a stationary residual series through integrating variable series to the same order and meanwhile obtain the cointegration vectors β is made. Usually, the Johansen procedure and Engle-Granger (E-G) procedure are used as cointegration test methods. Considering two types of variables series (environmental temperature and deflection at a specific location) are related in this study, the E-G test with two steps is adopted to test the cointegration relationship (Shin, 1994). The cointegration vectors β can be simultaneously received from E-G procedure when variables series are proved cointegration.

Step 1: Estimation of the cointegration regression model

The cointegration regression equation is estimated as following

$$x_{1,t} = \beta_1 + \beta_2 x_{2,t} + \ldots\ldots + \beta_p x_{p,t} + u_t \tag{4}$$

where p is the number of variables, β_i is the regression coefficient of variables while u_t is the cointegration regression residual. To briefly illustrate the procedure, assuming that all the variables series are $I(1)$ non-stationary for instance, a stationary residual series can be obtained as

$$\hat{u}_t = x_{1,t} - \beta_1 - \beta_2 x_{2,t} - \ldots\ldots - \beta_p x_{p,t} \tag{5}$$

Once variables series are cointegrated, they will share a common stable trend and form a long-term equilibrium relationship. It is still workable for higher integration order.

Step 2: Unit root test in the residual process of cointegration regression

The unit root test for residual series $\hat{u}_t$ indicates the result of cointegration test for variables series, such that

$$\Delta\hat{u}_t = \alpha + \pi\hat{u}_{t-1} + \sum_{i=1}^{t} \gamma_i \Delta\hat{u}_{t-i} + \upsilon_t \tag{6}$$

where α is a constant term which can be omitted to improve estimation efficiency, π is the coefficient that represent unit root null, γ is the coefficient of the model corresponding to the cointegration equation and υ_t is the residual series of regression residual term. If the residual series $\hat{u}_t$ passes the unit root test and is confirmed to be stationary, the cointegration relationship exists between variables. Under the null of no cointegration, the estimated residual is $I(1)$ since that $x_{1,t} \sim I(1)$ and all parameters are 0. Thus, the coefficient π implies cointegration relationship (Osarumwense *et al*. 2017). The cointegration requirement is equal to

$$\begin{aligned} &H_0: \pi = 0 \quad \Rightarrow \text{No cointegration} \\ &H_a: \pi < 0 \quad \Rightarrow \text{Cointegration} \end{aligned} \tag{7}$$

2.2 Index extraction

Various indexes to indicate performance and detect anomaly for long-span suspension bridges based on long term monitoring data have been studied in recent years. Meanwhile, the modeling and forecasting process should also be established with specific variable time series. Based on the cointegration procedure, the stationary residual series $\hat{u}_t$ can be calculated through input variables series. Since the stationary cointegrated residual series $\hat{u}_t$ has potential for operational anomaly detection, it is extracted as an index that is independent of the environmental conditions. Both of two purposes can be achieved by this cointegration-based index. In the application of anomaly detection, the index (marked as $\hat{u}_{1t}$) is expected to be controlled between upper and lower intervals. The points above the intervals indicate anomaly occur in service period. When in the application of TID forecasting, the index (marked as $\hat{u}_{2t}$) will be used to develop the prediction model, different from using direct monitoring data.

Recently, several successful applications involve cointegration based index have been conducted in the field of structural monitoring, mechanics and industrial (Chen *et al*. 2009, Zhou *et al*. 2013, Zolna *et al*. 2016), the results showed the advantages of steady and sensitiveness to environmental variation.

2.3 Temperature-induced response separation

In view of its capability in processing instantaneous and nonstationary signals, as well as sufficient accuracy and calculation simplicity, the multi-resolution wavelet method based on distinguished frequency bandwidths can be used to separate ingredients in recorded measurements, (Taha *et al*. 2006, Xu *et al*. 2020a). The core idea of wavelet method is to use a finite length or fast decay wave to reconstruct signals. The continuous wavelet transform for a time-domain recorded signal $f(t)$ can be expressed as following

$$W_f^{\psi}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi\left(\frac{t-b}{a}\right) dt \tag{8}$$

where a and b are scaling shift parameters for wavelet function $\psi(t)$, respectively.

The multi-resolution wavelet method transforms the signals to approximation and detail coefficients that depict the frequency distribution in the time and space domains, as shown in Fig. 2. The Ai denotes i^{th} term of approximation while Di denotes i^{th} term of detail. The original monitoring deflection data can be separated to slow-varying ingredient and high frequency ingredient.

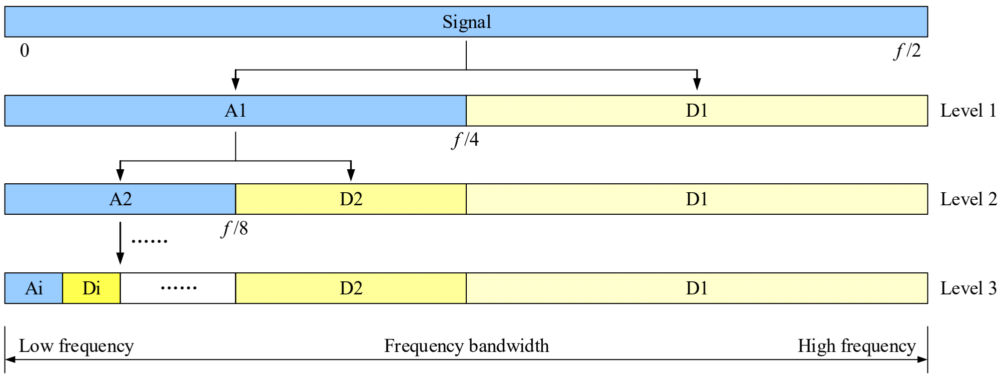


Fig. 2 Frequency distribution in multi-resolution wavelet method

2.4 ARMA model description

In this paper, the time-series model is established according to the analysis results. The time series models can be classified into two categories: stationary models, such as autoregressive model (AR), moving average model (MA), ARMA; or non-stationary models, such as ARIMA (Kaloop *et al*. 2019). In view of the residual series $\hat{u}_t$ obtained from cointegration procedure definitely is stationary, the ARMA(p, q) model is adopted. As a brief introduction, the model can be constructed as following

$$\begin{aligned}&(1-\varphi_1 B-\varphi_2 B^2-\cdots-\varphi_p B^p)u_t\\&=(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q)\varepsilon_t\end{aligned} \tag{9}$$

where u_t is t^{th} component of time-series process, φ_i (i = 1 – p) and θ_i (i = 1 – q) are coefficients of the autoregressive (AR) terms and the moving average (MA) terms, respectively, B is the lag-operator and ε_t is the white noise error term. Meanwhile, the orders p and q are defined to satisfy the given time-series data (Le and Nishio 2019). In this paper, the best model orders of AR and MA terms, p and q, are determined by using the Akaike Information Criterion (AIC). The computation of the AIC value is

$$AIC = 2k - 2\ln(L) \tag{10}$$

where L is the maximized value of the likelihood function of the model and k is the number of free parameters. The p and q are determined until the minimum AIC value is achieved, according its definition.

3. Case study

The Xihoumen Bridge in China is employed as an example to demonstrate the proposed cointegration based methodology for anomaly detection and TID forecasting. The in-situ measurements during two periods (July 1 to July 29, 2017 and October 1 to October 31, 2017) are selected for illustration.

3.1 The bridge and its monitoring system

The Xihoumen Bridge, which was opened to traffic on

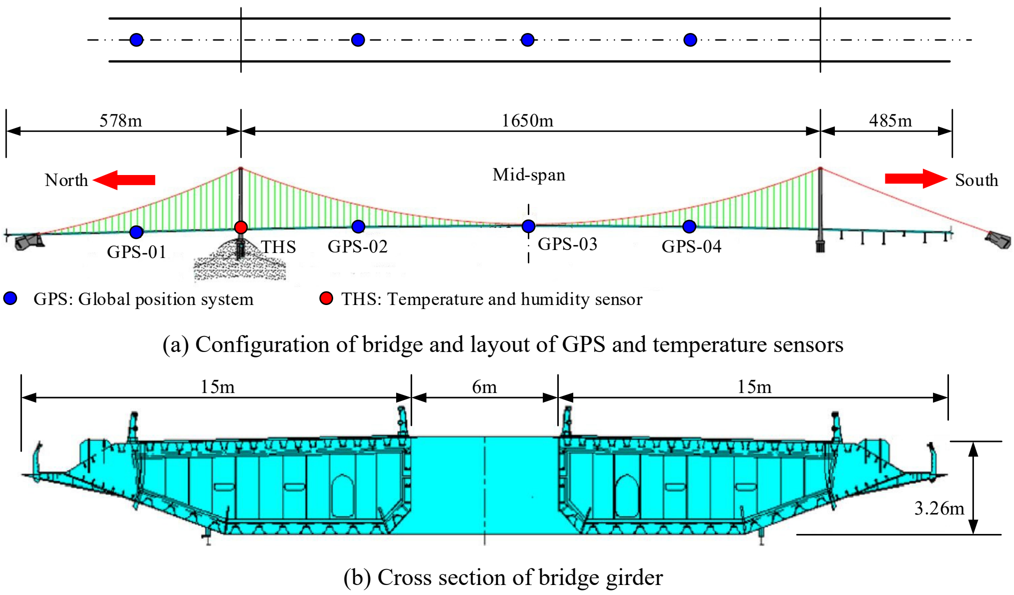


Fig. 3 Site plan and sensor layouts of the Xihoumen Bridge

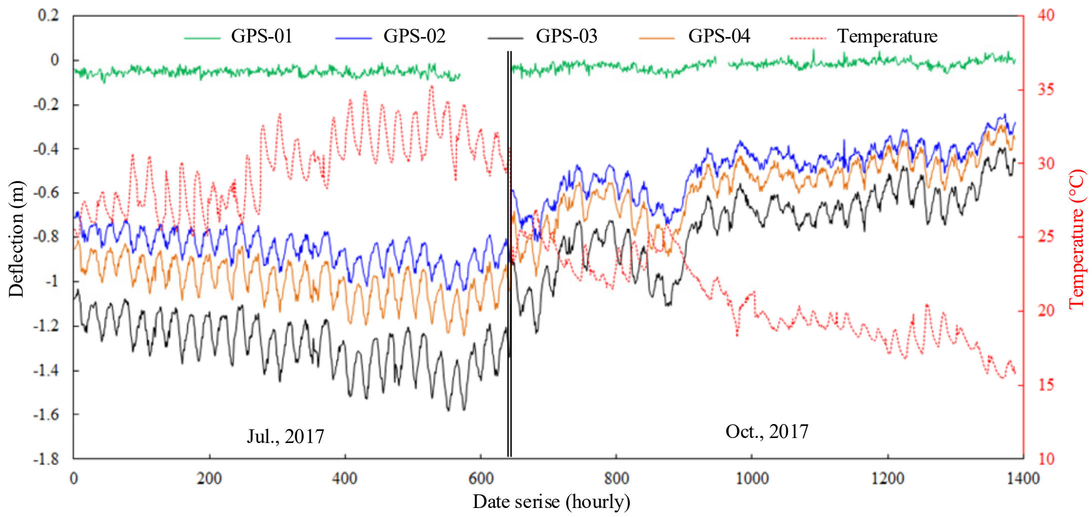


Fig. 4 Deflection and temperature measurement of the Xihoumen Bridge

December 25th 2009, forms an important transportation link connects Ningbo City and Zhoushan islands in Zhejiang Province, China. It is a sea crossing suspension bridge with a main span of 1650 m. The superstructure deck has a 3.26 m deep and 36 m wide orthotropic steel box girder that accommodates two lanes in each direction. The deck is supported by a total of 952 hangers and each hanging point installs 4 hangers.

With the aim of ensuring the operational and structural safety, a sophisticated long-term system was designed and installed on this long-span bridge to continually monitor its environmental indicators and structural health status after the bridge opened to traffic. The configuration and layout of some involved sensors are shown in Fig. 3. Girder deflections are measured by the global positioning system (GPS) and Trimble 5700-type receivers with an acquisition frequency of 10 Hz, the measuring point arrangement is shown in Fig. 3(a). The real-time dynamic measurements accuracy of GPS in vertical direction is ±20 mm + 1 ppm RMS which means the basic error of measurement is 20 mm, then the accuracy decreases by 1 mm for each 1 km between the measuring point and the base station. The alignment of the girder at bridge construction completion is defined as the baseline. The deflection is the vertical distance of the specific location from the baseline, where the positive values mean deform upward, while the negative indicate downward. Note that different from connected pipe system, the GPS data recorded from each measuring point are independent. In addition, ROTRONIC MP400H-type thermohygrometers are set near the bridge deck to monitor the environmental temperature and humidity, which have a resolution of ±0.3°C.

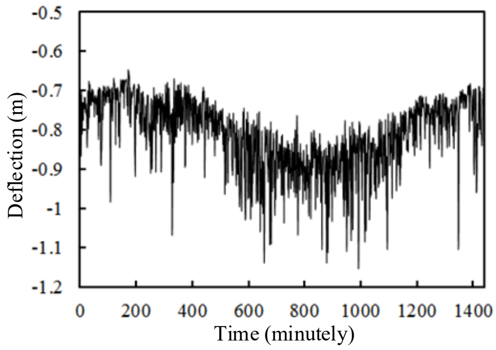
3.2 Processing monitoring data and feature extraction

To analyze the feature of monitoring data, the vertical deflection measurements (Z-direction data of GPS) extracted from four measure points (GPS-01 to GPS-04) during two periods (July and October, 2017, partial data are missing due to sensor faults) with corresponding environmental temperature are investigated in the target suspension bridge. Hourly monitoring data time histories are exhibited in Fig. 4.

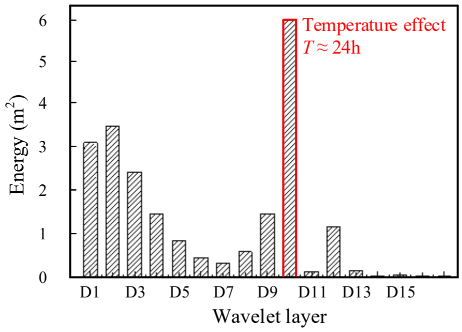
As shown in Fig. 4, the monitoring deflection data indicate significant daily periods. In July, the daily temperature difference is steady, deflection measurements are also changed slowly with temperature. But in October, similar to temperature variation trend, deflection measurements change day by day. In main span, the girder deformation is more notable at mid-span than at 1/4 span. But in 1/2 side-span, the girder deformation (GPS-01 data) is not significant. During the selected period, the average temperature falls from 35°C in July to 15°C in October. As the environmental temperature decreased, the main girder moved upward for 800mm approximately in the position of mid-span (GPS-03).

The deflection responses consist of two ingredients: slow-varying trend and dynamic ingredient. In this paper, the wavelet function Daube-chies 12 (termed as dbN, where N is the order of wavelet) is selected to separate thermal response from measurements based on the frequency bandwidth of signal decompositions (Xu *et al*. 2020b). One day deflections as shown in Fig. 5 are taken as instances to demonstrate the wavelet separation process. The energy spectrum of each layer shows the 10th detail layer (D10) subject to a period of approximate 24h contains the largest weights of energy, which indicate the daily thermal response lies on the 10th layer. The TID from wavelet separation is shown in Fig. 5(d).

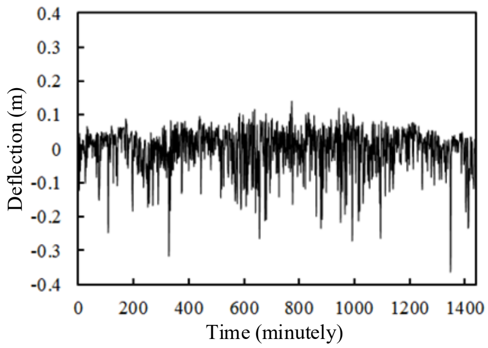
To comprehensively analyze the temperature effects on girder deflections of Xihoumen Suspension Bridge, the FE model based method is also used in this paper. The initial FE model for the Xihoumen Bridge was developed on the software platform MIDAS/CIVIL 2019 as shown in Fig. 6(a). Beam elements were used to simulate the girder, truss elements were used to simulate hangers, and cable elements were used to simulate the main cable. A total of 899 nodes and 896 elements (including 412 beam elements, 238 truss elements and 246 cable elements) were built up in the entire



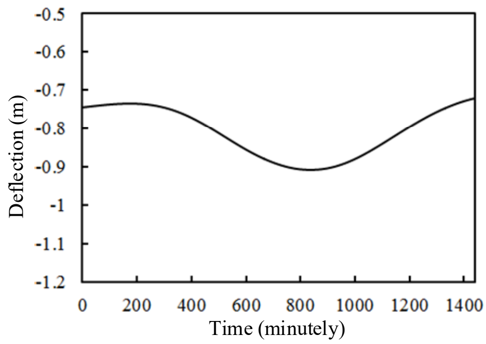
(a) Original data



(b) Energy spectrum of wavelet layers

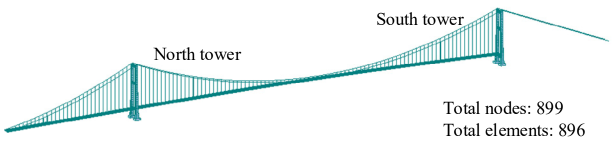


(c) Deflection without temperature effects

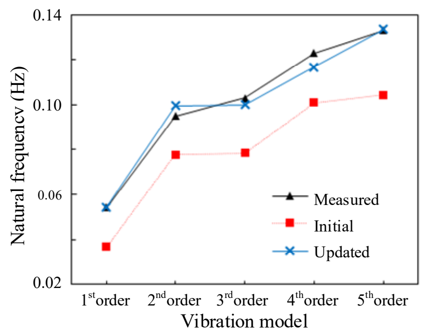


(d) Temperature induced deflection

Fig. 5 The sub-signal after wavelet separation



(a) MIDAS model with 3-D view



(b) Model validation result

Fig. 6 FE models of the Xihoumen Bridge

model. According to the field measurements from loading test, the model updating process was conducted to validate its responses in line with the actual ones. To brief, the model updating procedure will not be introduced herein. It is seen from Fig. 6(b) that frequencies calculated by the updated FE model agree much better with the field measurements than those calculated by the initial one.

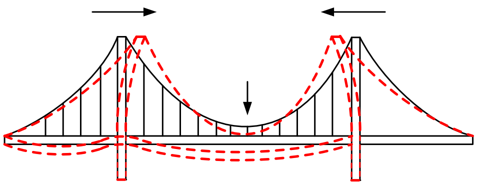
Although the wind, traffic and temperature gradient actions can cause structural deflection, the deformation of long-span suspension bridges during the normal service period is dominated by the environmental temperature variation (Deng *et al*. 2018, Zhou *et al*. 2020). All the field monitoring data and FE analysis results show that the girder moves upward with decreasing temperature while increasing temperature results in downward movement, as shown in Fig. 7.

The E-G procedure introduced in section 2.1 is used to test cointegration between field measurements. Specifically, each time E-G procedure needs to be performed for environmental temperature and deflections at a specific location (e.g., GPS-01). All deflection series collected from four GPS stations should be tested with environmental temperature, respectively. The results proof all the original deflections and TIDs are individually cointegrated with environmental temperature, hence the corresponding residual series $\hat{u}_t$.

3.3 Application to anomaly detection

The present section describes the application in anomaly detection of the proposed methodology to the datasets obtained from the monitoring system of the Xihoumen

(a) Original data (b) Energy spectrum of wavelet layers



(a) Under environmental temperature increase (b) Under environmental temperature decrease

Fig. 7 Global thermal deformation mode of Xihoumen Bridge

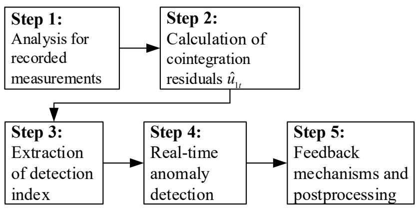


Fig. 8 Process of developed anomaly detection method

Bridge, as shown in Fig. 8. The detection index (cointegration residuals $\hat{u}_{1t}$) calculated from data series is depicted in Fig. 9. Thresholds for anomaly detection are specified as ±3σ (Shi *et al.* 2018).

As shown in Fig. 9, environmental temperature effects on girder deflection are eliminated by the proposed anomaly detection method. The values of detection index are significantly different in four positions, so that thresholds should be set respectively in GPS-01, GPS-02, GPS-03 and GPS-04. The values of detection index are in proportion to the measurements. The detection index drifts out of the threshold interval in several periods, which indicates some anomalous events may happen and should be noticed by bridge management departments. Moreover, the cointegrated signals in different positions vary with the consistent trends.

To further evaluate the anomaly detection ability of the proposed methodology, two scenarios involving the component damage of the main cables and overloading are numerically simulated (Tomé *et al.* 2018). Compared with deflections at other positions (e.g., 1/4L), mid-span deflection measurements (GPS-03) are more sensitive to actions, which can be commonly used to rate the short- and long-term behavior of long span bridges (Liu *et al.* 2015). For the sake of brevity, the girder deflections at mid-span in the period of July, 2017 are selected as the instance for illustration. The real data being acquired by the SHM system is superposed with the structural response due to

(a) GPS-01 (b) GPS-02

(c) GPS-03 (d) GPS-04

Fig. 9 Cointegrated signal of all deflection measurements for Xihoumen Bridge

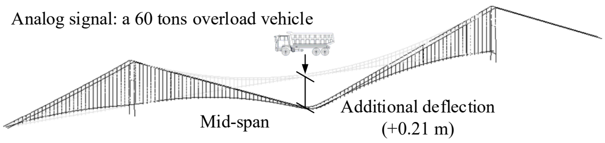


Fig. 10 Case 1: an overload vehicle passes through the bridge

anomalous events obtained via a previously validated finite element model of the bridge (Xu *et al*. 2020b). The two anomalous scenarios are

- Case 1: involving an overloaded vehicle with a weight of 60 tons in normal traffic flow at T_1 (14:00, July 6, 2017), which should be detected as an anomaly (seen Fig. 10).
- Case 2: damage introduction at T_2 (0:00, July 21, 2017), which is 40% of Young's modulus reduction in the main cable.

The anomaly detection results of Case 1 and Case 2 are shown in Fig. 11, which eliminate the influence of environmental temperature. For Case 1, as shown in Fig. 10, when a 60 tons overload vehicle crossed past the position of mid-span, the additional deflection is -0.21 m according to the FE analysis. The original GPS deflection measurement changes from -1.295 m to -1.505 m in that moment. Meanwhile, corresponding cointegrated signal shifts noticeably at Case 1 from -0.123 to -0.362, when it temporarily exceeds the lower threshold. However, this overloading can hardly be detected by traditional anomaly detection and warning system, since the influence of environmental temperature. Specifically, the recorded monitoring data during normal service period even exceed the overloading situation, which may lead to omission (such as 14:00~18:00, July 20, the maximum normal measurement reaches to the value of -1.529 m). Similarly, false alarm may also be raised in some conditions by traditional method. In addition, the sensitivity of the cointegration based method to detect structural changes is illustrated in Fig. 11, which shows cointegrated residuals computed from monitoring data. As for Case 2, along with the obtained results for the normal state is also presented the computed detection index for the same dataset corrupted with a simulated damage scenario in main cable. The

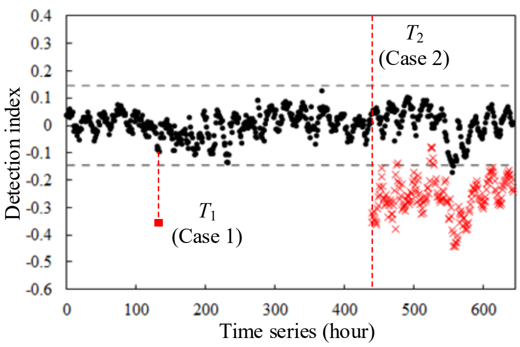


Fig. 11 Anomaly detection results for scenarios (black points correspond to the normal state and red points to the simulated abnormal scenario)

detection index drifts out of the threshold interval after Case 2, the anomalous operating state is successfully detected.

It can be concluded from above two cases that the cointegrated signal is capable of detecting the majority of anomalous events. Compared with the conventional anomaly detection system that based on direct measurements, the chosen cointegration based detection index is insensitive to environmental temperature but still sensitive to damage anomalous events. For an actual suspension bridge, once the anomaly detection system raises alarm, measures (e.g., vehicle track, special inspection) will be taken by bridge management department. In addition, it is also suggested to update the threshold synchronously with the latest monitoring data to ensure the effectiveness of the proposed anomaly detection method.

3.4 Application to TID forecasting

The procedure of the cointegration based application to TID forecasting is shown in Fig. 12. Without loss of generality, all the four GPS measuring points shown in Fig. 3(a) are chosen to illustrate the proposed forecasting approach.

Based on environmental temperature measurements and obtained TID, the cointegration procedure is conducted to calculate the cointegration residuals $\hat{u}_{2t}$. Then the cointegrated signal is modeled and forecasted by utilizing the ARMA model. Three components are involved in the ARMA model for TID: a trend component, a periodical component, and a regression component. The AIC method is used to identify the model orders, p and q, which requires the minimum AIC value. Taking the GPS-03 data (from July 1 to July 29) as an instance to illustrate the process. The AIC values with different order combinations was calculated, the heat map of calculation results is shown in Fig. 13. The minimum AIC is -3.46, corresponding to the situation of model orders p = 4 and q = 3. Hence the ARMA(4,3) model can be constructed.

The forecasting results of cointegration based method with suitable orders are shown in Figs. 14 to 17, the enlarged plots on the right represent the selected results within a certain day. One advantage of the proposed method is that it allows for probabilistic forecasts, providing massive information about the forecasts, such as mean square error and credibility interval. More specifically, the credibility interval represents the uncertainty of the target TID response. A 95% credibility interval is presented in this paper. The used data are divided into training period and

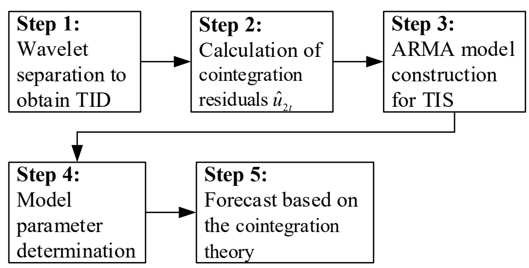


Fig. 12 Process of proposed TID prediction method

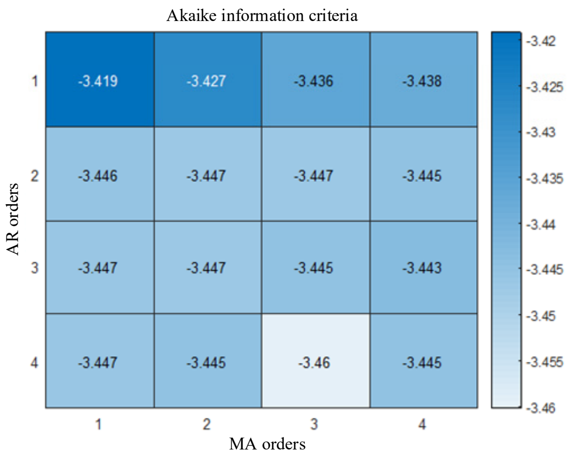


Fig. 13 The instance for calculated AIC value to select a suitable model order

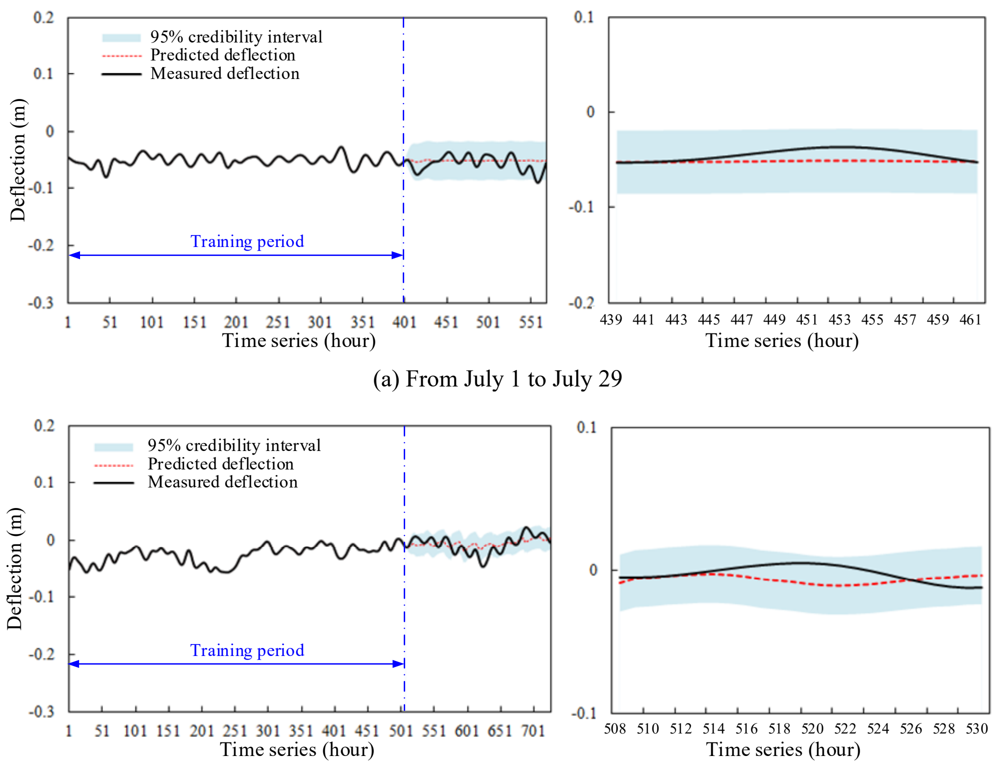
testing period, which account for 70% and 30% of the sample number, respectively.

As shown in Figs. 14 to 17, it can be concluded that the cointegration based method shows great accuracy using the historical data. The forecasting results demonstrate that most observations lie within the 95% credibility interval and the predictions closely match the observations. In the viewing of a certain day, the predicted deflection shows a significant characteristic of periodicity. Girder deflection usually reaches to the maximum value (absolute value) at 14:00 to 16:00. Although data from 4 measure points are different, similar variation trends are displayed. For the GPS-01 prediction, it can be seen from Fig. 14 that it is not as precise as other results but still within the 95% credibility interval. This is understandable, since the deflection measurements from GPS-01 are very small values (fluctuate from 0.02 m to -0.08 m) and show weaker regularity, thus the task model does not favorably take effect for data prediction. However, it does not need to worry about this situation much, because an SHM system usually embraces massive measure points in different important positions for a long-span suspension bridge. The prediction results of mid-span (namely GPS-03 in this paper) are usually more referenced for bridge management departments.

In order to evaluate the forecasting performance, the proposed cointegration based approach is compared with the back propagation neural network (BPNN) forecasting method. Similarly, the same data are used for training and the rest data for testing. When training the BPNN, an input-output system that takes the environmental temperature as input and the TID as output is established. The root mean squared error (RMSE) is used to compare the forecasting accuracy of models. To quantificationally measure the effectiveness of cointegration based method and BPNN method, RMSE can be presented as

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}\left(Y_n - \hat{Y}_n\right)^2}{N}} \tag{11}$$

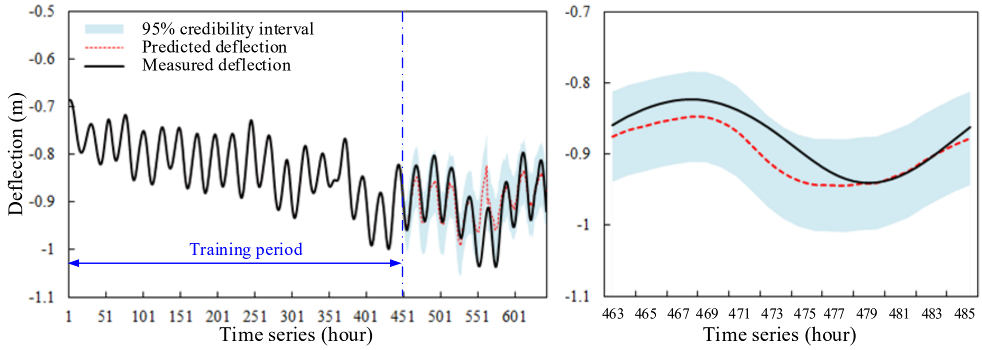
where N is the number of samples, Y_n is the TID and $\hat{Y}_n$ is the predicted value. According to RMSE criterion, the smaller the value of RMSE is, the more accurate the



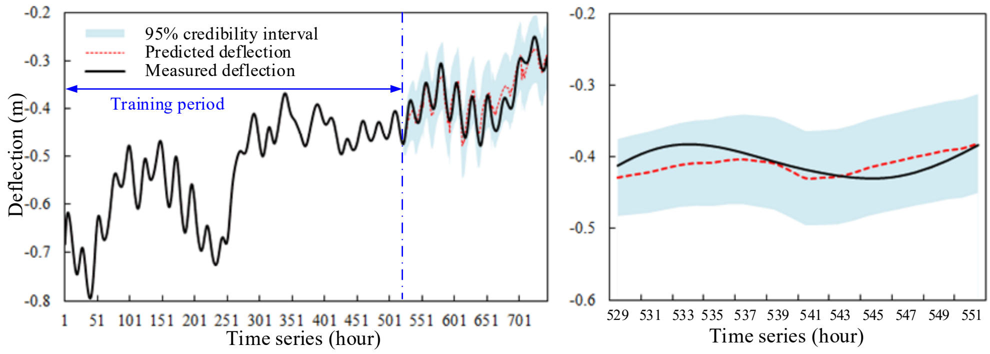
(a) From July 1 to July 29

(b) From October 1 to October 31

Fig. 14 Cointegration based forecasting results for GPS-01

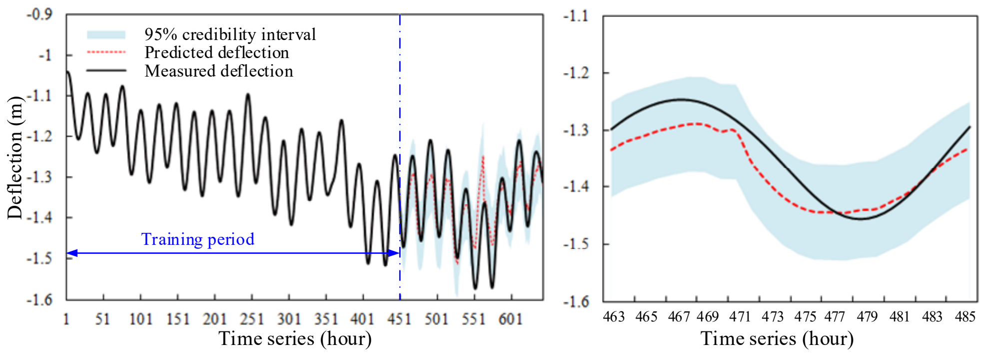


(a) From July 1 to July 29

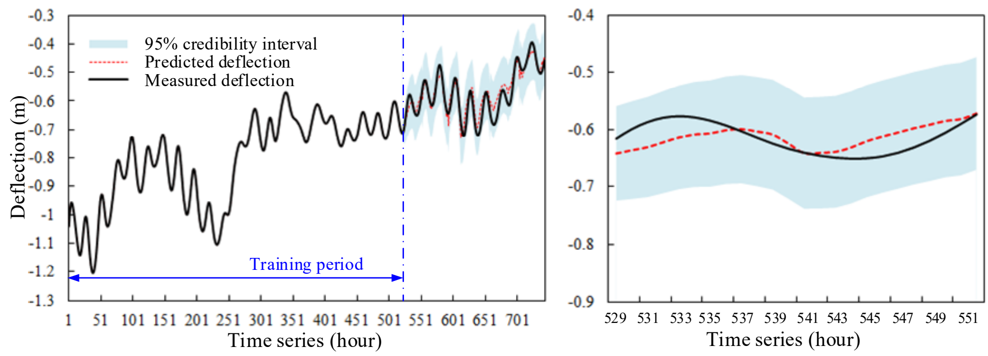


(b) From October 1 to October 31

Fig. 15 Cointegration based forecasting results for GPS-02

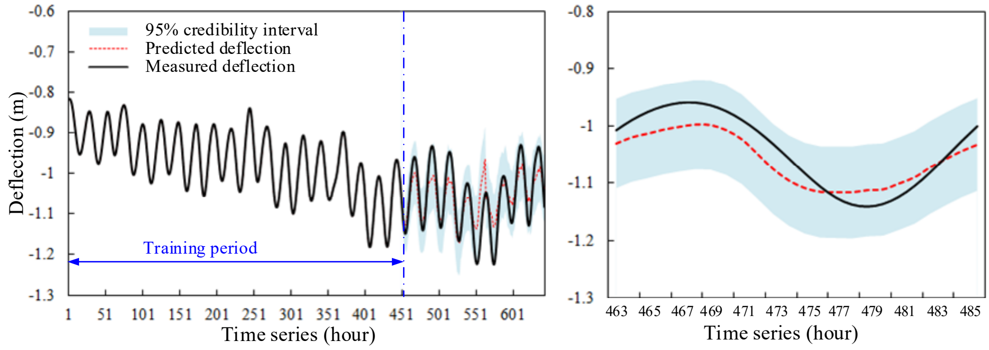


(a) From July 1 to July 29

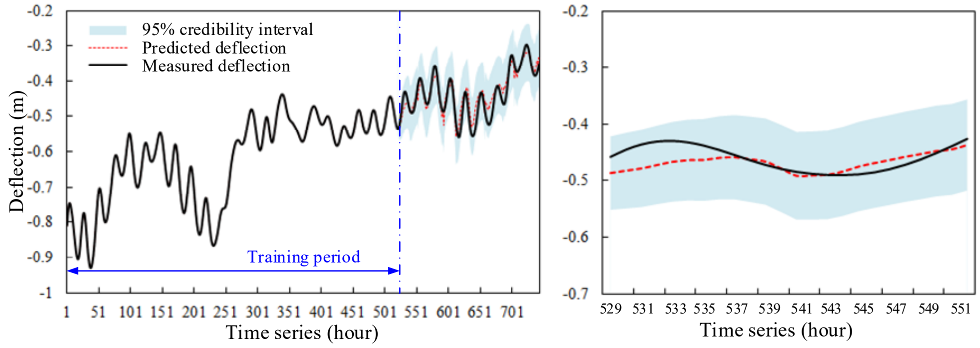


(b) From October 1 to October 31

Fig. 16 Cointegration based forecasting results for GPS-03



(a) From July 1 to July 29



(b) From October 1 to October 31

Fig. 17 Cointegration based forecasting results for GPS-04

Table 1 RMSE results of forecasting by the cointegration based and BPNN model

Position	Period	RMSE	
		Cointegration based method	BPNN
GPS-01	Jul.1 to Jul.29	0.013	0.031
	Oct.1 to Oct.31	0.013	0.032
GPS-02	Jul.1 to Jul.29	0.039	0.081
	Oct.1 to Oct.31	0.023	0.075
GPS-03	Jul.1 to Jul.29	0.055	0.074
	Oct.1 to Oct.31	0.029	0.066
GPS-04	Jul.1 to Jul.29	0.046	0.060
	Oct.1 to Oct.31	0.024	0.053

prediction results. The RMSE values of TID at different positions and periods are listed in Table 1.

The developed model combines the merits of the cointegration theory and ARMA model to well account for system uncertainty, thus mitigating forecasting errors. The calculated results in Table 1 show that in all situations, the RMSE values of cointegration based method are lower than BPNN method. The application to Xihoumen Suspension Bridge indicate that the proposed cointegration based method is able to not only model and forecast the TID with periodicity, but also obtain superior prediction accuracy compared with the BPNN method. This advantage can be explained by the fact that the proposed method considers the relationship between the current and historical output of TID as well as the relationship with environmental temperature.

Furthermore, in practical application to structures, too long forecasting period and the limitation of training data may lead to poor forecasting performance.

4. Conclusions

In this paper, a cointegration based methodology for anomaly detection and TID modeling-forecasting is proposed and applied to a suspension bridge. Firstly, the cointegration procedure is conducted with monitoring measurements and extracts cointegrated signals. An anomaly detection framework that eliminates the influence of environmental temperature is then proposed. Furthermore, the TID obtained from original data is modeled and forecasted. Finally, a case study is presented for illustration with the in-situ measurements from a long-span suspension bridge. The following conclusions can be drawn from this research:

- Considering the promising application of cointegration theory in structural response, a framework of the cointegration based methodology for anomaly detection and TID forecasting is proposed based on the field measurements from SHM system. Compared with conventional methods, the proposed method has advantages of simple in theory and efficient in calculation.

- The relationship between deflections and environmental temperature is analyzed for the Xihoumen Suspension Bridge. The vertical displacement of girder is a combined effect while environmental temperature contributes the most. When the environmental temperature increases, girder deflects downward. The cointegration between filed measurements is existent according to the E-G algorithm and corresponding cointegrated signals are extracted.
- The proposed cointegration based anomaly detection method is conducted based on monitoring data. The environmental temperature effects on girder deflection can be eliminated. The efficiency is also evaluated by two simulated scenarios. Compared to the traditional method, the results show that the cointegrated signal is insensitive to environmental temperature but still sensitive to anomalous events.
- The procedure of the cointegration based method combined with ARMA for TID modeling and forecasting is proposed and an application is given to investigate its performance. The forecasting results demonstrate that most observations lie within the 95% credibility interval and the predictions closely match the observations. Meanwhile, compared to commonly used BPNN, the proposed approach has a better predictive performance in terms of the measure criteria of RMSE for long-span suspension bridges.

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