Automated OMA through SSI-COV algorithm of a Warren truss railway bridge exploiting free decay response

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Abstract. The aging of bridges, coupled with increased traffic and the imperative for sustainable practices, has sparked a growing interest in Structural Health Monitoring (SHM). Modal parameters, recognized as key indicators of the structural performance of bridges and viaducts, possess the capability to unveil changes in their physical and mechanical properties resulting from damage occurrence. In this context, Automated Operational Modal Analysis (AOMA) emerges as a powerful tool for continuously identifying structural modal parameters and tracking their evolution over time. This paper proposes a robust method, based on Covariance-driven Stochastic Subspace Identification (SSI-COV) algorithm, designed for the continuous extraction of modal parameters from a Warren truss railway bridge. A permanent SHM system has been installed on the bridge, enabling the monitoring of environmental effects on the estimated modal parameters. The algorithm takes bridge free-decay responses following train passage as input, yielding promising results. These results are compared with the findings presented in a previous study that employed a peak-picking strategy.

Keywords: Operational Modal Analysis · Warren truss bridge · railway bridge · SSI-COV · free-decay.

1 Introduction

Transportation infrastructure is subject to aging and deterioration, while experiencing, nowadays, an increase in terms of daily traffic frequency and intensity [1, 2]. In this framework, a growing number of bridges and viaducts is reaching the limit of their service design lives [3]. However, due to budget constraints and sustainability targets [4], rebuilding all of them is not feasible. Consequently, the current scenario necessitates proactive measures to prevent sudden structural failures, aiming to extend the service lives of these bridges and viaducts. Infrastructure managers are actively seeking enhanced condition-based techniques capable of complementing visual inspections, which in some cases could exhibit limitations [5, 6]. Structural Health Monitoring (SHM), a powerful tool that has witnessed widespread adoption over the last two decades, plays a crucial role in supporting bridge condition monitoring alongside visual inspections. SHM can be defined as a continuous process for damage identification and evaluation, aiming to facilitate and optimize maintenance procedures for engineering infrastructures [7–10], among which it is possible to find bridges and viaducts. Direct bridge SHM systems rely on the deployment and installation of a mesh of sensors, with the goal to extract meaningful diagnostic information, by recording structural response resulting from the action of operational and environmental inputs. An established and effective set of damage-sensitive features is recognized in modal parameters, capable of reflecting the health condition of the structure and its changes due to damage occurrence. When dealing with Vibration-based SHM, Operational Modal Analysis (OMA) [11, 12] represents a popular tool to extract bridge modal parameters from structure dynamic response recorded in different positions. This paper presents an automated OMA procedure, based on an SSI-COV algorithm, applied to a sixteen-month dataset from a permanent monitoring system installed on a Warren truss bridge belonging to the Italian regional railway line. Employing the algorithm developed by Pasca et al. [13], it was possible to track frequencies, damping ratios and mode shapes behavior on a daily basis throughout the observed period. The outcomes, compared to the analogous outputs provided by the algorithm presented in [14], run in the same time interval and provide interesting insights in terms of modal parameters behavior against temperature for the structure under analysis. The paper is organized as follows: the next section will present the case study, consisting of the bridge under analysis and the employed sensors mesh. Subsequently, the SSI-COV algorithm will be briefly introduced along with its input parameters. Following that, results will be presented and discussed. Finally, conclusions will be drawn.

2 Case study

The subject of the present work is on a double-span Warren truss bridge (see Fig. 1), designed in 1946, and currently in service on the Italian railway line. The bridge configuration consists of two twin structures enabling train circulation in opposite directions. The spans, sustained by hinge supports at the entrance and sliders at the exit, are not directly connected, except for the track system and a discontinuity pier. The primary focus is on the 60.5 m main span (span A in Fig. 2).

A permanent monitoring system, equipped with resistance temperature detectors and velocimeters, captures the dynamic response of the structure through the latter (Fig. 2), and makes it possible, by the former, to analyze the effect played by temperature on modal parameters time trend.

Fig. 1. A view of the bridge object of study, on the left, and its twin structure, on the right.

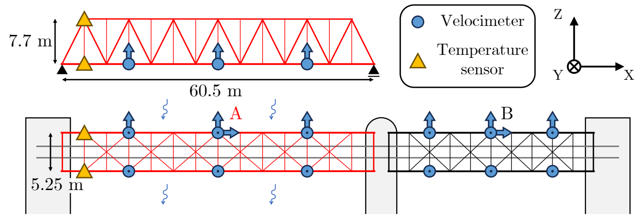

Fig. 2. Positioning of sensing devices (velocimeters and temperature sensors) along spans A and B.

In the present work, OMA employs signals collected from six velocimeters (whose recordings are converted into accelerations), symmetrically positioned on both sides of the bridge, along the lower chord members for ease of access and installation. The sensors are placed at mid-span and approximately at one-quarter and three-quarter of the length of the considered span. Upstream sensors measure in both lateral and vertical directions, while downstream sensors measure only in the vertical direction. Additionally, the mid-span sensor on the upstream chord also measures in the longitudinal direction, but it is disregarded in subsequent analyses due to its limited amplitude. The utilization of lateral and vertical channels allows for the estimation of lateral bending modes, vertical bending modes, and torsional modes, given the presence of sensors on both sides of the bridge. Finally, this sensor placement enables sufficiently accurate estimation of vibration modes up to the third order.

A dedicated acquisition system distinguishes between continuous and triggered acquisition. During the latter, the system stores data — with a sampling rate of 256 Hz — only during events in which the measured signal overcomes a predefined magnitude threshold, requiring pre-trigger and post-trigger duration settings. The post-trigger length, crucial for capturing the free decay response after train crossings, is set to 60 seconds in the present case. The presented analyses exploit a sixteen-month dataset of triggered signals, due to trains passages over the studied bridge.

This study selectively focuses on a subset of train passages occurring between 12 pm and 6 pm on a daily basis. This time window aligns with that used in [14], to enable a comparison of the results obtained. However, in this study, ten train passages during this time slot were utilized, characterized by the lowest possible thermal excursion, to minimize the variation in modal behaviors (during the same day).

As mentioned in the introduction, for each measuring channel, the SSI-COV algorithm does not take the entire triggered acceleration signal as input, but only its free-decay part. This approach enables proper extraction of modal parameters, which could be significantly hindered when considering train transits (forced motion).

3 SSI-COV algorithm

SSI-COV, which stands for covariance-driven stochastic subspace identification, belongs to the family of subspace identification methods [15]. It performs modal parameters identification through the application of a stochastic state-space model, defined as follows in its discrete form:

$$\begin{cases} x_{k+1} = Ax_k + w_k \\ y_k = Cx_k + v_k \end{cases} \tag{1}$$

where x_k is the state vector of the system evaluated at time instant t_k, while y_k is the output vector. The matrices A and C correspond to the state matrix and output matrix, respectively. Finally, w_k and v_k stand for the noise attributed to disturbances and modeling errors, as well as measurement noise [16, 17]. Modal parameters are extracted once the matrices A and C are estimated, and these parameters can then be represented on the stabilization diagram.

Two crucial input parameters must be defined before running the algorithm: the order of the model and the number of correlation points for covariance calculation. This operation is critical since there are no rules to determine their setting a priori. The model order, which is an unknown parameter for real civil and engineering structures [17], should be conservatively set, typically exceeding two times the expected number of vibration modes in the frequency range of interest. Then, attention must be put on the settings of the number of correlation points, which strongly influence the quality of the obtained stabilization diagram [16].

In this work, similarly to what was done by the authors in [17], the algorithm takes as input time histories of bridge free-decay responses collected synchronously at different measuring points (see Fig. 2) after train passage. This choice is based on the following consideration: free-decays can be treated as a response to an impulsive input, which, akin to white noise, excites the system across a theoretically infinite frequency range.

The algorithm employed in this work, developed by Pasca et al. [13], uses a maximum model order of 200, and the number of block rows for the Toeplitz matrix is set to 40. Evaluation of stable and spurious poles is based on three criteria imposed on frequencies, damping ratios, and mode shapes, as expressed in the following equations:

$$\frac{f_{p+1} - f_p}{f_p} < 1\% \tag{2}$$

$$\frac{\xi_{p+1} - \xi_p}{\xi_p} < 2\% \tag{3}$$

$$1 - MAC(\{\phi_{p+1}\}\{\phi_p\}) < 2\% \tag{4}$$

where f_p, ξ_p, and $\{\phi_p\}$ are respectively the frequency, damping ratio, and mode shape associated with a pole of the p-th order system. As mentioned earlier, the algorithm processes bridge free-decays following train transits, isolating the free-decay response from forced motion through an automated procedure that exploits fast and slow-moving time windows, as described in [14].

4 Results and comparison

The main natural frequencies of the bridge, obtained by running both the SSI-COV and peak-picking algorithms over a period ranging from April 2022 to August 2023, are shown in Fig. 3, plotted as a function of temperature. Blue points correspond to the outcomes of the peak-picking approach [14], while orange ones refer to the results of the SSI-COV algorithm. This figure provides a qualitative assessment of the differences between the two methods, in terms of estimated frequencies dispersion around the linear trend caused by the temperature variation over the sixteen-month observation period. To better quantify this variability, three statistical indicators are utilized, namely standard deviation (STD), median absolute deviation (MAD), and interquartile range (IQR), the last two widely recognized as robust measures of scale [18].

In Fig. 4, on the left, the ratios between dispersion indicators computed from the outcomes of the SSI-COV, and the analogous indicators provided by the peak-picking approach, are shown. The majority of bridge modes show a reduction in the dispersion of associated frequencies when transitioning from the approach used in [14] to the SSI-COV one. For most frequencies, the ratio is smaller than one across different statistical indicators.

However, the real focus is on the dispersion around the linear trend that characterizes the distribution of frequencies as a function of temperature. In other words, the variability of natural frequencies once the temperature effect is removed. To do so, a linear regression analysis can be performed between

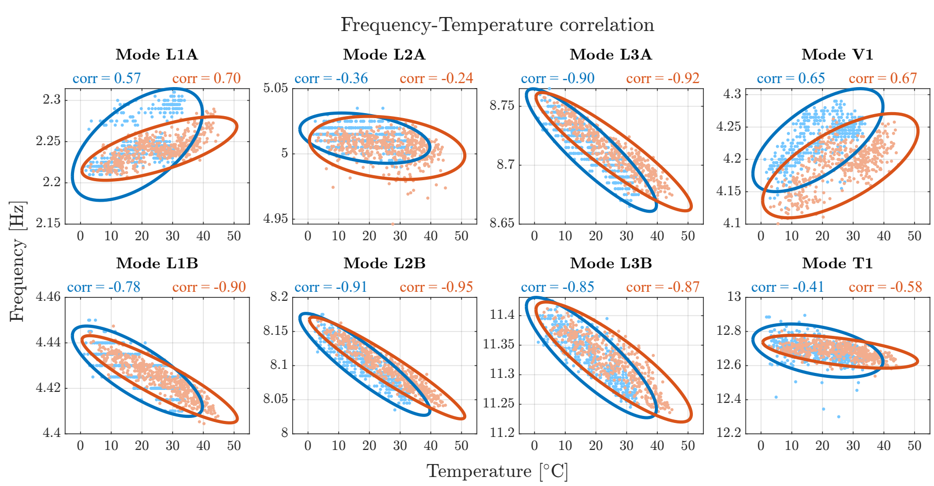

Fig. 3. Bridge natural frequencies plotted as a function of temperature, computed with SSI-COV methodology (orange) and peak-picking technique [14] (blue).

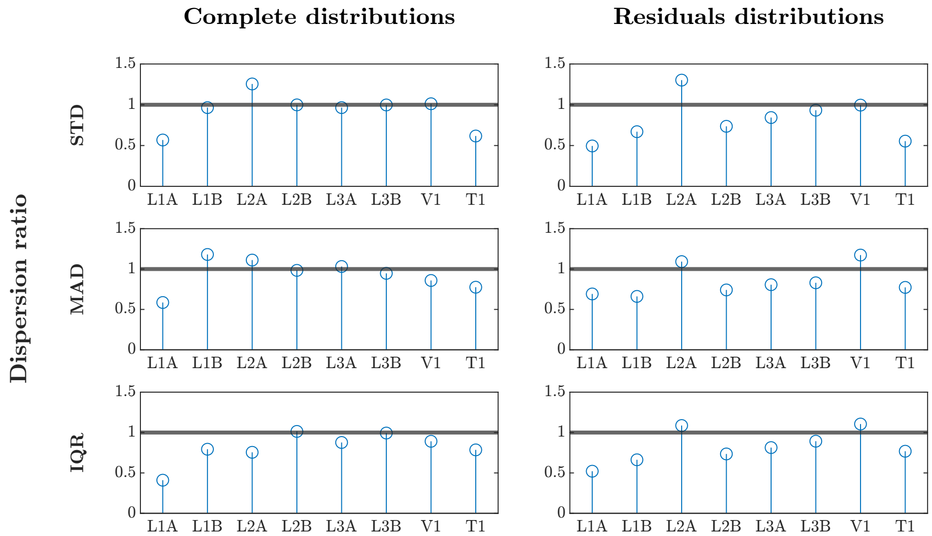

Fig. 4. Ratio between various dispersion indices (STD, MAD, and IQR) evaluated using the SSI-COV and peak-picking strategies, respectively. This ratio is determined for all analyzed natural frequencies of the bridge.

temperature and the estimated frequency for each vibration mode. The residual, denoted as e_i, is then evaluated using Equation 5, where f_i represents the raw frequency computed by the automated OMA procedure, and $\hat{f}_i$ is the predicted frequency for the i-th mode obtained through linear regression:

$$e_i = f_i - \hat{f}_i \tag{5}$$

This process is applied to both the outlined OMA methodologies, and the dispersion of residuals is subsequently assessed using the same dispersion parameters mentioned before (STD, MAD, and IQR). In Fig. 4, on the right, the ratios between dispersion indicators calculated from the residuals of the SSI-COV are presented, divided by those obtained from the peak-picking approach. The findings suggest that, with the SSI-COV methodology, the dispersion of residuals, for most of the modes, is generally smaller than using peak-picking. In fact, most of the stems decrease in height compared to the analogous on the left.

Fig. 5(a) illustrates the distribution of MAC parameters with a box plot representation. For each frequency, MAC over the year is calculated with respect to a reference mode shape that is computed in the first 30 days of acquisition. In particular, this reference mode shape is found with the following procedure:

- one estimation per day of the single mode shape is computed during the first 30 days;
- for each day, MAC is computed between the daily mode shape estimate and the ones from the remaining 29 days leading to a MAC symmetrical matrix

as follows:

$$[MAC] = \begin{bmatrix} MAC_{1,1} & MAC_{1,2} & \cdots & MAC_{1,30} \\ MAC_{2,1} & MAC_{2,2} & \cdots & MAC_{2,30} \\ \vdots & \vdots & \ddots & \vdots \\ MAC_{30,1} & MAC_{30,2} & \cdots & MAC_{30,30} \end{bmatrix} \tag{6}$$

– the sum over rows of the matrix is computed;
– the reference mode shape (for the 30-day period) is the one with the maximum value of the sum, that corresponds to the most similar compared to the remaining 29 mode shapes.

This approach effectively enables the tracking of mode shape evolution in time, in regard to an initial baseline. Fig. 5(a) reveals a low dispersion of MACs throughout the year for all lateral modes, and slightly greater dispersion for vertical and torsional modes.

Furthermore, with the SSI-COV approach, it is possible to overcome the impossibility of the peak-picking method in computing the damping ratio. In particular, in Fig. 5(b) the distribution of damping coefficients along the observed period is reported, for each frequency of interest. It is possible to observe that the mode shape featured by the highest dispersion is the vertical one, followed by the torsional and first lateral modes. Narrower populations are observed for the rest of the frequencies.

One last point to highlight is that, with the algorithm used in this study, both the trend of MACs and damping ratios do not show a noticeable correlation with temperature. Instead, they exhibit a random trend for all examined frequencies.

5 Conclusions

In this work, the authors investigate the performances of an SSI-COV algorithm in determining the modal parameters of the main span of a Warren truss

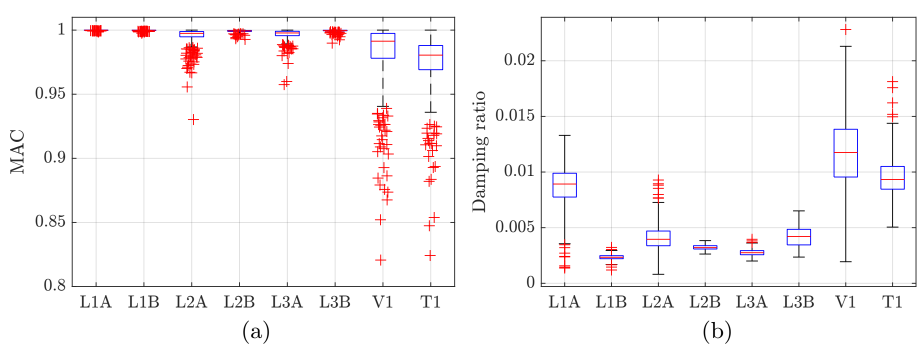

Fig. 5. Box plot representation of the MACs (a) damping ratios (b) distribution over the observed period, for each vibration mode.

railway bridge, exploiting free decay responses subsequent to train passage. The obtained results, regarding a sixteen-month dataset, are then compared with the outcomes of the algorithm proposed in [14]. Notably, the SSI-COV algorithm, in addition to providing estimates of modal frequencies, offers the capability to determine modal damping ratios — a feature not achievable with the methodology described in [14]. The SSI-COV algorithm proves to be highly effective, enabling the extraction of modal parameters within the targeted frequency range. Importantly, it achieves this with a reduced requirement for input data compared to the peak-picking-based methodology.

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