A Robust End-To End Framework for Automated Modal Identification for Infrastructure Monitoring

A robust end-to end framework for automated modal identification for infrastructure monitoring.

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Abstract. The idea that the majority of bridges have reached the end of their service life has become widely accepted. The need for continuous monitoring of a large number of structures has become both a duty and a burden for administrations and operators. While technological advancements enable the acquisition of numerous structural parameters, effectively harnessing the vast amount of data generated is not a straightforward task. Therefore, an automated tool that can conduct end-to-end analysis with minimal effort and cost is crucial. The presented solution is applied to two different bridges, both in reinforced concrete and instrumented with tailored monitoring systems, from sensors to the cloud-based dashboard. Modal parameters such as vibration modes, modal shapes, and damping are determined using the OMA algorithm, specifically PolyMAX, in an automated process. The analysis are performed through robust software provided by Siemens, e.g. Test Lab. Finally, by enhancing the potential of the cloud for measurement data storage, the implementation of advanced data management tools is being considered as interesting emerging prospects.

Keywords: Structural Health Monitoring, bridge protection, automated Operational Mod-al Analysis, dynamic identification, PolyMAX.

1 Introduction

The construction of infrastructure assets in many western countries dates prior to 1980. Today, this infrastructure asset has exceeded its design life and due to the ageing and degradation phenomena to which the structures are subjected, safety could be compromised [1]. In order to understand the health and conservation status of these structures, Structural Health Monitoring (SHM) techniques can be very useful. Of the SHM techniques, the one historically most widely used and on which most monitoring systems focus is the dynamic identification techniques through Operational Modal Analysis (OMA) [2].

The application of OMA in the field of civil engineering is a well-known and fairly well-established discipline and is renowned in the literature [3], [4], [5]. Today, the main challenge is how to deal with the large amount of data available [6], [7]. In recent years, techniques for acquiring and storing monitoring data have advanced considerably, allowing a considerable amount of monitoring data from numerous facilities to be stored in the cloud and on dedicated dashboards. The challenge today is to be able to process this large amount of data in the most automated way, reducing the demand for human intervention [8].

This article aims to present the results obtained from the automation of a robust OMA software (Simens Test Lab) based on the PolyMAX algorithm [9], [10]. Specifically, in Section 2, the bridges investigated are described. The proposed framework is shown in Section 3. In particular, it allows to download data from the cloud and to analyze them in the most automated way in order to extract the modal parameters of interest for the structures analyzed (e.g. frequencies, damping ratio and modal shapes). The most interesting results for both applications are showcased in Section 4 to evaluate the evolution of these parameters over time in order to assess whether there are trends that can be correlated to structural degradation or only to changes in environmental boundary conditions [11]. Finally, in Section 5, conclusions are drawn, and future scopes are outlined.

2 Infrastructure description and monitoring system layout

In this section, a brief description of the two selected bridges is provided from a structural perspective and outline their respective monitoring systems **Fig. 1**. Each monitoring solution consists of dynamic transducers, data logger, grouped into several clusters with wired connections to a cloud platform for storing and processing synchronized data for subsequent analysis. The whole solution is designed, integrated, and delivered by Kistler, to assure a homogeneous measuring chain from sensor to data [12], [13].

The first case study is a reinforced concrete structure, built in the early 1900s, with two arched spans of 37.50 meters. The monitoring layout includes the installation of uniaxial and triaxial capacitive accelerometers. Mono-axial accelerometers are uniformly positioned on the two arches, while the triaxial accelerometers are installed in correspondence of the middle of the arches and in the central pillar. Additionally, a weather station is placed at the center of the bridge. In this case, due to the long service life of the structure, the purpose of the monitoring system is to evaluate the structural integrity, which could be potentially compromised due to the loads generated by the current traffic conditions for which it was not originally designed, as many other similar bridges. For this structure, data for OMA analysis are recorded and saved in the cloud twice a day: in a time window from 8:00 to 10:00 a.m. and in a time window from 7:00 to 8:00 p.m..

The second case study is a highway viaduct constructed in the late 1990s. It is a prestressed concrete continuous box-shaped deck supported by multiple piers. The bridge has spans of 100 meters between supports, resulting in a total length of 600 meters. **Fig. 1** illustrates the bridge's geometry, with monaxial accelerometers and triaxial accelerometers installed at specific locations. Monitoring of the bridge primarily utilizes uniaxial accelerometers, which capture data in the vertical direction. Among the six piers, only three are equipped with triaxial accelerometers. In addition to accelerometers, the monitoring system incorporates inclinometers, a weather station, and GPS devices to enable comprehensive data collection and analysis. The monitoring objectives for this bridge include analyzing the structural impact of junctions built after its construction and assessing the effects of heavy traffic loads associated with the construction site. For this structure, data for OMA analysis are recorded and saved in the cloud once a day: in a time window from 8:00 to 9:00 a.m..

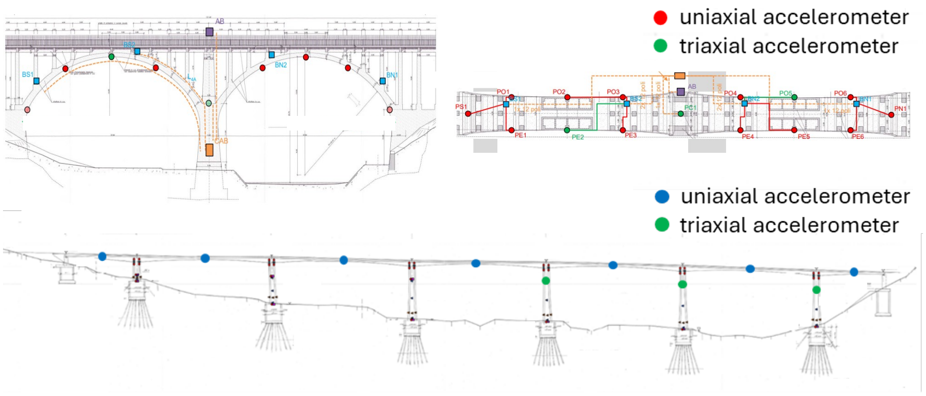


Fig. 1. Monitoring system scheme on the two structures.

3 Automated modal identification

Continuous monitoring provides a huge quantity of data, but the volume of records often exceeds what a user can handle in a timely manner, especially when different structures are being monitored at the same time. Here, the developed solution is presented, which can automatically download, process, and extract useful insights from OMA.

In **Fig. 2** the high-level software architecture is shown, showcasing the integration with Siemens Test Lab ® COM ports, which provided a specific library, developed in CLR and compatible with various programming languages such as C++, C#, and Visual Basic.

The solution consists of two main sections: the Configurator and the Run Manager. Initially, during the configuration, the key structural properties such as node positions, rotations, relationships, and mappings to sensor channels are defined. A single-line structural model or, more detailed, surface structure scheme combining different members could be adopted. A multi-component analysis allows for studying specific elements like joints and connections.

Next, accelerometer recordings from monitoring sensors can be imported and processed. This is where automation scripts excel compared to manual methods. OMA can be challenging due to the high computational effort involved in execution. Sensors are continuously recording data, and the pace must be maintained.

Additionally, each run consists of several steps, as listed below:

1. Import accelerometer data and select channels based on project configuration.
2. Normalize time series by removing the effects of gravity acceleration if present.
3. Cluster channels into execution groups, allowing the project to run OMA on different sets of sensors to assess specific structural sections or interdependencies.

For each execution group:

a. Compute auto-power and cross-power spectra, as well as their sum.
b. Automatically identify the optimal frequency band for PolyMAX.
c. Compute stabilization diagrams and select poles.
d. Extract and save the corresponding vibrational modes.
e. Validation of the OMA results.

To facilitate integration with different file formats and online cloud providers, the Data Loader plugin was developed to minimize the coupling between OMA analysis and data sources.

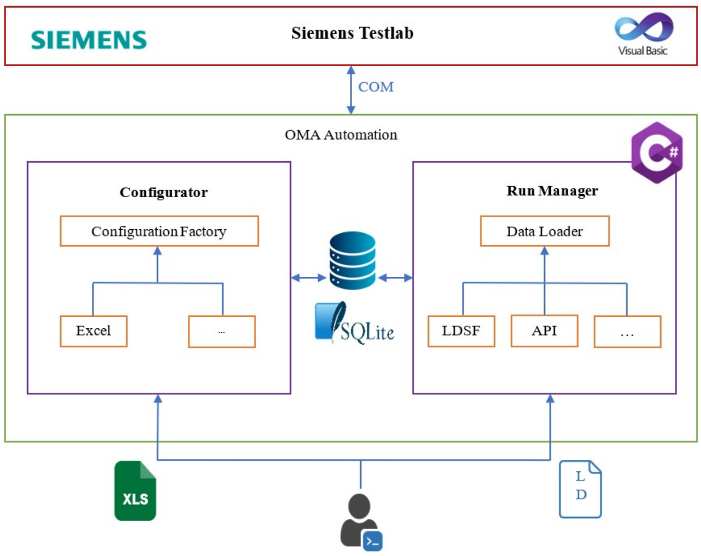
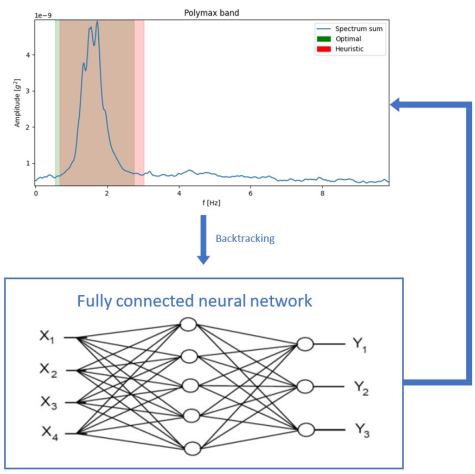


Fig. 2. Architecture of the automation algorithm.

The output of the entire process is highly relevant. Modal parameters such as natural frequency, damping, and modal shapes can be enriched with additional details for validation, such as stability rank. The availability of a wide range of execution results enables new applications, including predictive maintenance and modal trend tracking. This monitoring approach can help identify the initiation or progression of damage by associating well-known damage paths with the observed patterns. Determining the optimal frequency bands for PolyMAX is a nontrivial undertaking. Within this research domain, numerous metaheuristic algorithms exist for identifying these bands, some based on spectrum descent and others on energy analysis. To determine the most suitable approach, various validation methods utilizing L2 norm, F-score, and False Negative Penalty have been implemented [14]. Through this analysis, it was found that employing the Savitzky-Golay filter to smoothen the spectrum sum yields more robust results against noise. Specifically, the bands are deter-mined by locating adjacent local minima in the smoothed spectrum that surpass a threshold derived from its mean and standard deviation. In evaluating accelerometer data, this heuristic method has demonstrated remarkable efficacy in replacing human involvement in band selection. However, the performance on different datasets cannot be guaranteed without parameter tuning. To address this, machine learning proves to be a valuable tool for developing models that can generalize automatically to unseen data. Currently, a simple Convolutional Fully-Connected Neural Network, depicted in **Fig. 3**, is being developed. This network is fed with spectrum sums and autonomously predicts the most suitable bands. During the training, its results are iteratively compared with desiderata, obtaining the well-know Loss score. The internal weights of the network are then updated using the backtracking algorithm, derived from the application of the derivative chain rule on the Loss gradient. Finally, automation not only speeds up the analysis and ensures the integrity of outcomes but also enables a variety of new features, including real-time monitoring.



$\bar{x}$ = *spectrum sum*
$\bar{y}$ = *parameter*
f = *band selection method*
$\bar{b}$ = *expected bands*
$f(\bar{y}) = \bar{\bar{b}}$ = *selected bands*
$L\left(\bar{b}, \bar{\bar{b}}\right)$ = *Loss function*

Fig. 3. Algorithm for band selection.

4 Results

In this section, the results for the two structures under examination are reported. For both structures, there is approximately one year of data acquisition available. In this first phase, the results of an OMA analysis are reported every month. In order to assess the influence of environmental parameters (e.g., temperature) on the dynamic behavior of the structures and/or the presence of possible degradation phenomena that evolve over time.

The results are shown in **Fig. 4** for the highway viaduct and in **Fig. 5** for the arch bridge. With regard to frequencies, it can be seen that they are influenced to a very limited degree by environmental conditions (e.g. temperature), as shown in **Fig. 6**, at seasonal temperature changes, the frequency variation is few cent of Hz, this variation is practically marginal. The dynamics of reinforced concrete structures are very little affected by seasonal variations in ambient temperature, unlike steel structures [8]. Furthermore, no abnormal trends are present, indicating that no structural degradation is taking place. Damping exhibits a more unstable behavior with respect to frequencies, but this is a well-known phenomenon in the literature as the identification of damping is affected by several uncertainties [15], in any case, the variations remain moderate and do not indicate structural degradation phenomena. Finally, MAC values are always high (above 75%) indicating that modal shapes are almost always the same over time and this too is an indicator that no degradation phenomena are taking place.

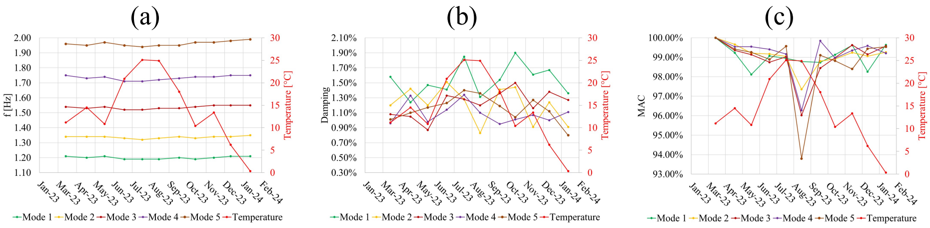


Fig. 4. Results for the dynamic identification of the highway viaduct with continuous beam. (a) Frequency, (b) Damping, (c) MAC.

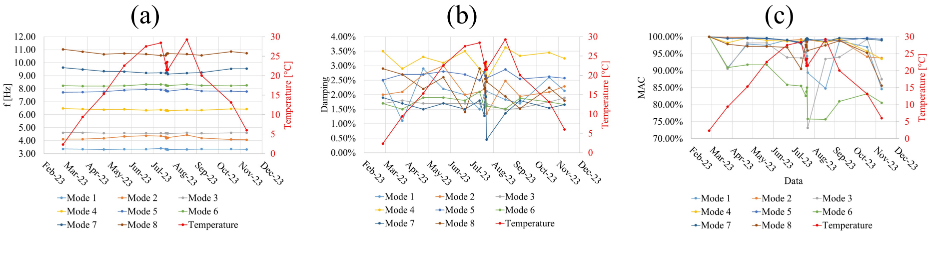


Fig. 5. Results for the dynamic identification of the arch bridge. (a) Frequency, (b) Damping, (c) MAC.

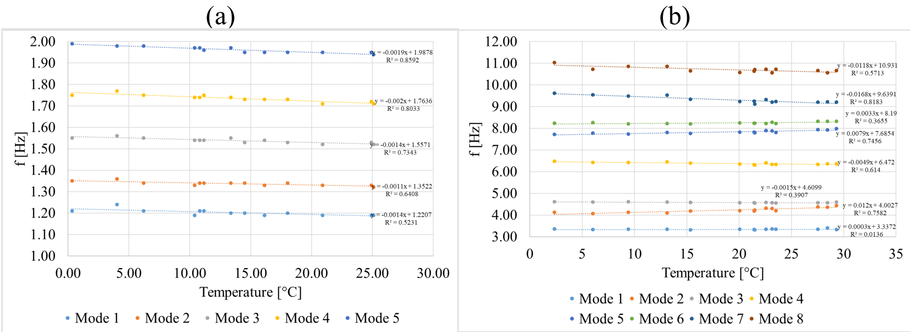


Fig. 6. Correlation between temperature and frequencies (a) Continuous-beam highway viaduct, (b) Arch bridge.

Between 20 and 25 July, the region where the arch bridge is located was affected by extreme weather events, which is why four consecutive days (24-27 July) were examined for July 2023. In particular, the most intense events occurred on 21 July and 24 July. The evening of 24 July was the last of the extreme weather events and the most intense. Therefore, in order to assess whether these events caused any damage to the instrumentation and/or the structure, an OMA analysis was performed for the acquisition of the morning of 24 July, and in order to robustly assess that the event on the evening of 24 July had no effect on the instrumentation and/or the structure, an OMA analysis was performed for the following three days. From the results it can be stated that the extreme weather events of July 2023 had no effect on the instrumentation and/or structure. With regard to the MAC of the arch bridge modes, it can be seen that Mode 6, Mode 3 and Mode 1 show considerable variability. These three modes are transverse or transverse modes with a torsional component; transverse modes in straight bridges are difficult to force (low signal-to-noise ratio), so the modal shape is strongly influenced by the type of forcing and its magnitude. In addition, these modes are strongly influenced by the central pillar, and the triaxial accelerometer on the central pillar exhibits sometimes anomalous sampling, but still reporting noncritical values. In conclusion, it can be said that the monitoring system for both structures is robust and that no evident structural degradation phenomena are visible during the monitoring period.

5 Conclusions

In conclusion, the developed solution for automated Operational Modal Analysis (OMA) offers significant advantages over manual methods. It streamlines the configuration process, handles the import and processing of accelerometer data, performs OMA analysis on different sets of sensors, and provides valuable in-sights such as mode characteristics, stability rank, and damage progression. The solution also incorporates machine learning techniques to optimize the frequency band selection for

PolyMAX analysis. With automation, the analysis becomes faster, more consistent, and opens up possibilities for real-time monitoring and predictive maintenance.

Furthermore, from the results obtained for the two structures analyzed, it can be said that the monitoring system is robust. The monitoring system was able to withstand extreme weather events for the arch bridge. For both structures, the modal parameters are very marginally affected by the environmental boundary conditions, thus temperature effects play a marginal role on their changes.

The work presented in this paper unveils several scenarios for future developments among the most relevant are the complete automation of some parts that to date still require user action and the definition of alerts and hazard messages when certain predetermined thresholds are exceeded.

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