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A full-scale case study of vibration-based structural health monitoring of bridges: prospects and open challenges

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Abstract

The implementation of Structural Health Monitoring (SHM) offers the prospect for sustainable and safe service-life extension of existing bridges, a large portion of which is approaching the end of their nominal life. Many SHM frameworks for civil infrastructure address timely damage detection and identification. However, the scarcity of case studies on real damaged bridges hinders the generalized application of SHM in practice. In this contribution, monitoring data from a four-day campaign on the Ponte-Moesa bridge, a three-span concrete box-girder bridge, is presented as a benchmark for data-driven damage diagnosis schemes. The monitoring data, covering accelerations from ambient and forced vibrations, contains the reference state after concluding the service life along with several gradually increasing damage states, including drilling holes and cutting reinforcement rebars and prestressed cables. The potential of damage-sensitive features to identify damage is presented and the uncertainties, resulting from the environmental and operational conditions and sensor malfunctioning, pertaining to robust damage detection are discussed. Drawing from real bridge monitoring data, a range of prospects and open challenges of vibration-based SHM for bridges are reviewed.

Keywords

Vibration Monitoring, Full-scale bridge application, Data-driven damage diagnostic, Controlled damage scenarios

1 Introduction

In addition to facing material ageing, as well as continuously evolving functional and operational requirements, existing civil infrastructure must comply with increasingly stern economic and environmental constraints. Leveraging continuous monitoring of structures allows for establishing actionable solutions for practical asset management, thus enabling a safer operation of existing infrastructure beyond the designed service life and the implementation of more efficient and sustainable life-cycle maintenance strategies. In particular, bridges represent key assets when it comes to vulnerability or operational resilience of road networks, therefore, the monitoring of their condition and performance allows proactive management of the assets and associated risks [1]. Continuous vibration measurements offer the most viable tool for global structural health monitoring, given the availability of affordable commercial sensors. Several approaches for structural health monitoring (SHM) of bridges with vibration data have been proposed [2-3], comprising purely data-driven [4-5] and model-based [6-10] techniques to monitor and diagnose damaged bridges. However, datasets from real bridges that contain both undamaged and damaged data, are limited to few case studies [11-14]. This lack of real-world applications presents a major obstacle when convincing bridge owners of the potential and benefits of vibration-based structural health monitoring [15].

Monitoring data stemming from controlled introduction of damage in real bridges fuels the development and validation of novel frameworks and methodologies, as was the case for the well-known Z-24 bridge [11, 16]. Therefore, in this contribution, a benchmark monitoring campaign of a typical Swiss pre-stressed concrete bridge, the Ponte Moesa Campagnola (PMC), is presented. Several controlled damage patterns were artificially introduced into the reinforced-concrete box-girder bridge after its decommissioning in 2019, such as drilling holes into the girders and cutting rebars and prestressed cables. Continuous vibration monitoring has produced datasets that comprise both, ambient and forced vibrations. Thus, the core dataset consists of vibration data from seven tri-axial accelerometers that can be used for real-world testing and validation of novel applications of vibration-based SHM.

The bridge and the testing campaign are described in Section 2. Identified challenges related to permanent vibration-based SHM that may be addressed with the Ponte-Moesa dataset are briefly discussed in Section 3, before preliminary data analysis and the potential of damage-sensitive features (DSFs) to detect and localize damage

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are shown in Section 4. Finally, practical lessons and possible improvements for future campaigns are briefly discussed in Section 5.

2 Benchmark data for vibration-based bridge monitoring

2.1 Bridge description

The PMC was a three-span bridge crossing the river Moesa between San Vittore and Roveredo in the canton of Ticino (Switzerland) and represented a part of the Swiss highway A13. The progressed degradation of the bridge led to its decommissioning and subsequent replacement with a new bypass, comprised of a 2.5 km-long tunnel and a new 106 m long bridge next to the studied structure. Consequently, the bridge has been demolished in 2020.

PMC was a 93.5 m long and 11.15 m wide pre-stressed concrete girder bridge (see Figure 1). The bridge was designed with a slightly curved longitudinal axis and skewed supports (see Figure 1a). The bridge cross-section consisted of a 1.5 m high and 5.7 m wide single cell concrete box-girder with a top slab cantilevering approximately 2.75 m towards both sides of the transverse direction. The girder was prestressed longitudinally by eight tendons, four in each web. The cables were of parabolic shapes and placed inside the webs and the tendons were anchored by anchor heads. According to the design documentation, each cable was prestressed up to 246.1 tons and released to 220 tons afterwards, while the nominal capacity of the anchor heads reached 260 tons. Massive reinforced-concrete crossbeams over the piers and the abutments transferred the vertical loads from the webs and slabs into the supports, via shear and transverse bending.

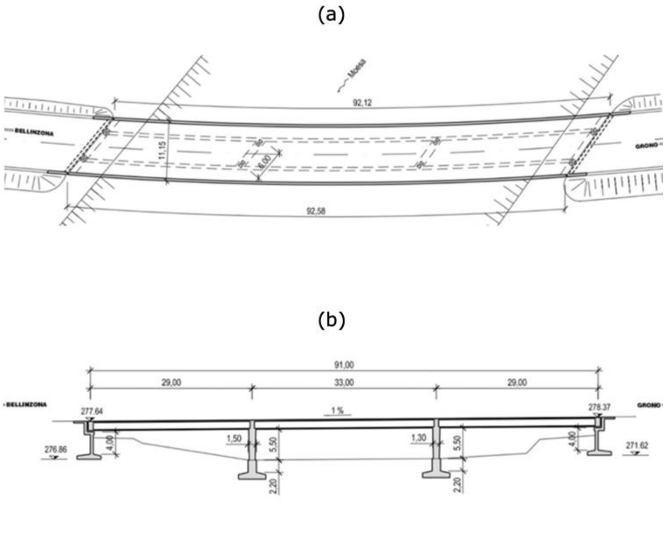

Figure 1 Documentation of the geometric characteristics of the bridge in top view (a) and elevation (b).

The bridge was supported by concrete-abutments at the riversides and concrete piers. The bridge-deck was connected to the abutments through two (probably friction) bearings. The intermediate supports consisted of concrete pillars, measuring approximately 5 m in height and width and 1.5 m in depth. The piers were founded on raft footings, embedded inside the riverbed to prevent scouring. The bridge deck was connected to the piers through bearings that were intended to offer primarily vertical support. Thus, the bridge deck was considered to function as a continuous beam with simple supports. However, the deteriorated state of the bearings, showing advanced corrosion, possibly compromised their decoupling performance (see Figure 2).

Figure 2 State of the bridge bearings before the start of the monitoring campaign.

2.2 Testing protocol

The 4-day long monitoring campaign was conducted in November 2019 and was focussed on continuous vibration monitoring. Namely, prior to its planned demolition in January 2020, several damage patterns were artificially introduced to the PMC and the dynamic response was recorded under ambient and forced excitation loadings. Seven high-sensitivity triaxial accelerometers (Syscom MR3000C) were deployed on the bridge for this purpose. Three of the seven sensors continuously measured at fixed reference positions (one per span). In order to provide a rich database for detailed modal identification and a testbed for various damage diagnostic metrics, the remaining 4 accelerometers were utilized as roving. The measurements were organized in a total of six measurement setups. The data acquisition system, composed by the sensors and cabled connections to a central unit, recorded at a sampling rate of 200 Hz with overall noise level below 10 $\mu g/\sqrt{Hz}$.

While the data was recorded continuously, the activities on the bridge were regularly halted for five minutes to ensure ambient conditions. In addition to ambient vibrations, a portable plate vibrator (see Figure 3) was used to generate forced vibration measurements that exceed ambient vibrations by an order of magnitude (see Figure 4). The vibrator was placed at two fixed positions, corresponding to the middle points of the central span and the east span, respectively. Additionally, roving excitation was done by moving the vibrator next to all sensors. While the amplitude and the frequency of the applied force could not be fully controlled, two different amplitude levels were applied, namely lower and higher amplitude. The two amplitudes of forced excitation resulted from increasing rotating frequency, which in turn increased the centrifugal force, leading to higher excitation amplitude.

Figure 3 A portable plate vibrator has been used to generate two different levels of forced vibrations: low-frequency excitation that produce low amplitudes of vibration and high-frequency excitation that lead to higher amplitudes of vibration.

2.3 Damage scenarios

Before the planned demolition of the bridge, three types of damage patterns were successively introduced in several positions of the bridge: exposure of rebars and tendons by removing the concrete cover (see Figure 5a); cutting of rebars (see Figure 5b) and one prestressed cable, and local reduction of the concrete web by drilling boreholes (see Figure 5c). These artificial damage scenarios have been progressively introduced and, thus, define a wide range of damage states from varying failure mechanisms.

After the introduction of each successive damage state, ambient vibrations, which comprise unknown vibration sources from the surrounding environment (wind, traffic, works in the vicinity of the bridge), and forced excitation, generated with the portable plate vibrator (see Figure 3), have been recorded to enable testing of vibration-based damage detection, localization, and quantification. A detailed log of the introduction of damage patterns and their location along and the measured damage state and sensor configuration are part of the dataset that will be made available to the scientific community in an open access platform as part of proceeding work.

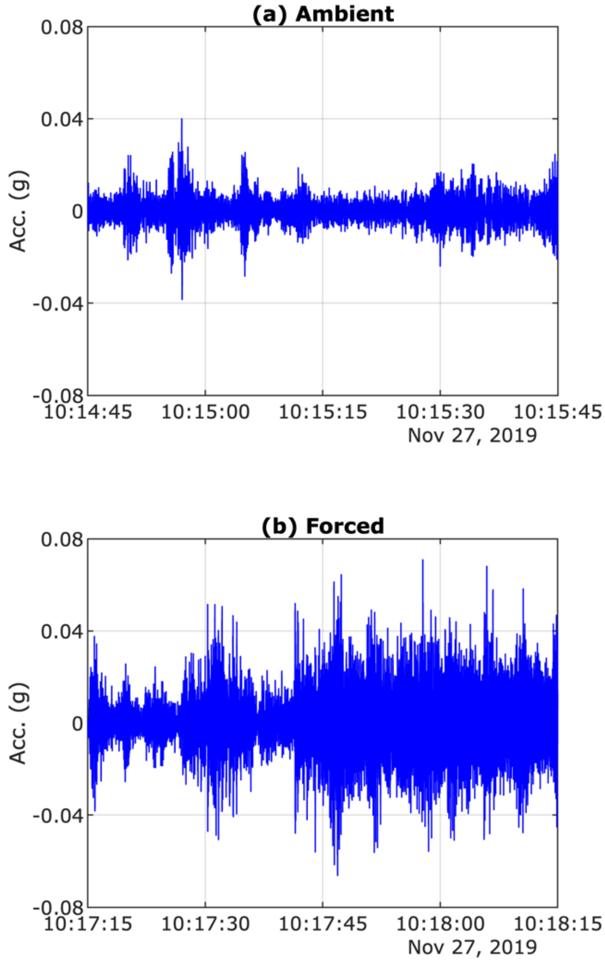

Figure 4 Example of acceleration recordings at mid-span of the bridge under ambient vibrations (a) and vibrations induced by the vibrator plate shown in Figure 3 (b).

3 Challenges of permanent vibration monitoring

Despite the manifold application of vibration monitoring and the large body of research in this direction, the application of global vibration-based indicators for the detection of local damage mechanisms, such as corrosion, cracks, and debonding, still requires further validation work [19], especially for complex structures with redundant load-bearing elements, such as civil infrastructure.

The introduction of local damage patterns and the contin-

Figure 5 Example of the three damage patterns: rebar exposure (a), rebar cutting (b), and concrete drilling (c).

uous measurement of the bridge with a discrete set of sensors offer a dataset that can be deployed to investigate the potential and robustness of vibration monitoring for the detection and localization of such damage mechanisms.

Environmental and operational conditions and lack of longevity of sensors are known challenges of continuous vibration-based SHM. These two challenges were also observed in the PMC dataset and are briefly reviewed in this section.

3.1 Environmental and operational conditions

The influence of environmental-and-operational conditions on the measured dynamic response and thus, DSFs that can be extracted from data, is oftentimes larger than the influence of damage itself. This behavior is also observed in the Ponte-Moesa dataset, as shown in Figure 6, where the scatter of one DSF over the course of one day (which includes excitation from forced vibrations, construction works on the bridge, and increased nearby traffic) is much higher than during the night.

A reduction in the scatter can be observed at midday, when construction activity on and around the bridge, as well as forced excitations with the vibrator plate, have been paused. Even during night-time, a slow evolution of the values of the DSF can be observed, which could be attributed to slowly evolving temperature changes. This scatter in DSFs may cover the influence of damage and undermine automated frameworks for data-driven damage diagnosis.

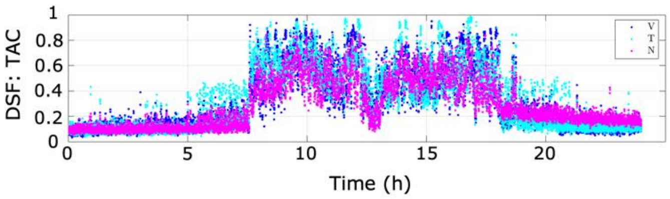

Figure 6 Influence of environmental-and-operational conditions on the value of a transmissibility-based DSF over a period of 24 hours. A large excitation-induced scatter can be observed.

Therefore, in Section 4 data windows during night-time or other similar operational conditions will be chosen with the goal of reducing the scatter arising from changes in excitation sources and other operational conditions. However, more sophisticated approaches, which incorporate influencing agents within robust models, exist [20] and the benchmark data of the Ponte-Moesa bridge could serve as a testbed for testing such frameworks on real-world bridge applications.

3.2 Sensor diagnosis

Long-term functionality and reliability of vibration sensors are key requirements to pave the way towards permanent monitoring applications on real infrastructure. However, many sensors have lifespans that are considerably shorter than the service life of bridges. Typically, sensors are not guaranteed beyond 8 or 10 years, especially in harsh environments, and thus, a robust sensor diagnosis framework is required to provide automated alerts, when sensor functionality is suspected to be compromised. To address this task, Martakis et al. [21] proposed a semi-supervised framework to identify a set of common types of sensor malfunctioning. While the framework had been trained and tested on data from a cable-stayed bridge, the formulation of the underlying data features is intended to be structure-agnostic.

Three data features that have been found to be particularly useful in distinguishing normal from abnormal operation of sensors [21], are tested with the data from the PMC bridge (see Figure 7): the root-mean-square (RMS) of the data; the highest bin count of the normalized data (when using 200 evenly spaced bins); and the standard deviation of the derived signal composed of short-term averages (calculated over one second) of the normalized signal, σ_{STA}.

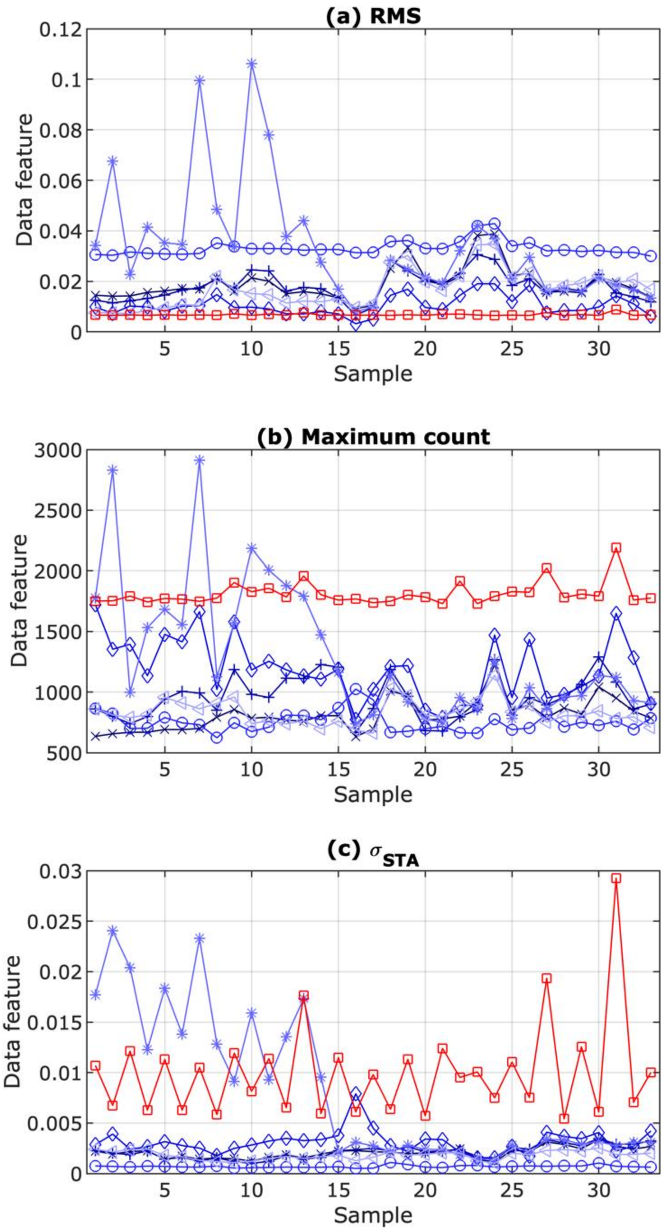

Figure 7 Comparison of three data features to diagnose the sensor health (a: root-mean square, b: maximum bin count, when splitting the signal into 200 bins, and c: standard deviation of short-time averages) derived from the seven acceleration sensors. These features may contribute to detect sensor malfunctioning, as the red values that correspond to a malfunctioning sensor can be visually separated from the blue lines.

The values of the three data features for 30 minutes of data stemming from all seven sensors are shown in Figure 7. The dataset contains one sensor that had been found to be malfunctioning a-posteriori and is highlighted in red in Figure 7. The highest-counted bin (Figure 7b) and the standard-deviation of short-time averages (Figure 7c) successfully separate normal from abnormal sensor behavior. The RMS (Figure 7a), on the other hand, plays an essential role to avoid false alarms for well-functioning sensors that may be perturbated by excitation sources in the near vicinity of the sensor. This shows the potential of the sensor diagnosis framework to be applied on permanently monitored pre-stressed box-girder bridges in the future. The dataset of the PMC may serve as a benchmark to validate automated sensor diagnosis frameworks.

4 Preliminary data analysis

To validate the influence of the introduced damage patterns on vibrational characteristics of the bridge, preliminary analyses have been conducted with the vibration data collected on the Ponte-Moesa bridge and are briefly introduced below.

Initial operational modal analysis in the undamaged reference state shows the presence of 8 stable modes under 10 Hz. The lowest global mode is found to be a horizontal (transversal) bending mode and has a frequency of 4.3 Hz. Despite the apparent simple geometry of the bridge, its modal shapes demonstrate significant complexity even in the low frequency range. Horizontal and torsional components govern the response, exposing the significant effect of the mild curvature along the longitudinal axis to the measured dynamic response. In terms of structural assessment, ignoring the three-dimensional effects in that case would lead to erroneous results.

Long-term vibration-based SHM often involves the definition of DSFs that encode presence of damage in the structural response from recorded time-history data. DSFs may take the form of traditional features, like modal frequencies and mode shapes, that provide a global indication of structural integrity or more refined features based on wavelet decomposition, transmissibility, and mode-shape curvatures.

4.1 Damage detection

Changes in transmissibility [17, 18] are one such feature that may reveal the presence of damage. The stiffness reduction provoked by damage in turn provokes a reduction in the frequency of peaks in the transmissibility. While the transmissibility depends on the general vibration modes and is thus a global indicator, it may also contain information about damage location in the substructure defined by the input–output sensor pair, for which transmissibility is defined [18]. The transmissibility, shown in Figure 8 for one sensor pair, tracks the evolution between three damage states (DS2: exposure of rebars in 2 positions; DS3: exposure of rebars in 3 positions; DS6: drilling of holes into the bridge girder in one position and cutting of prestressed cable). A clear shift in the peak of the transmissibility can be observed, which indicates increasingly severe damage.

For damage diagnostics of full-scale civil infrastructure, where uncertainty and variability are intrinsically stemming from measurements noise and environmental effects, the inclusion of a more robust probabilistic perspective is of crucial importance. For instance, when using the transmissibility assurance criterion (TAC) [18], defined in Eq. 1, the change in the transmissibility of a specific frequency range of interest can be evaluated in a more quantitative and robust manner.

$$TAC = 1 - \frac{|T^r(\boldsymbol{\omega_m})^T T^d(\boldsymbol{\omega_m})|^2}{|T^r(\boldsymbol{\omega_m})^T T^r(\boldsymbol{\omega_m})||T^d(\boldsymbol{\omega_m})^T T^d(\boldsymbol{\omega_m})|} \quad (1)$$

In Eq. 1, T^r and T^e refer to the reference and damaged transmissibility, respectively; $\boldsymbol{\omega_m}$ refers to the array of frequencies, for which the transmissibility is compared; $\cdot^T$ denotes the complex conjugate. Thus, the TAC provides an indicator of similarity between a reference and a damaged state, which is bounded between 0 (perfect collinearity) and 1, if the two transmissibility arrays are perpendicular. The structure of the TAC further makes it insensitive to the amplitude of shaking.

In Figure 9, the probability density functions (PDFs) of two-hour intervals of TAC values are presented. The TAC is evaluated for transmissibility functions that are derived on 30-second signal windows of a given sensor pair. In Figure 9, a clear separation can be observed between the PDF for signals that recorded during the nights of two consecutive days – before and after cutting the pre-stressed cables. This confirms the potential of transmissibility-based indicators to pick up structural damage, even if it is local.

When evaluating the TAC for multiple damage states (DSs), the evolution of damage and its severity can be observed (see Figure 10). This feature of tracking the evolution of the severity of damage over time is very valuable for continuous damage diagnosis. The presented results of the preliminary data analysis reveal the potential of vibration-based DSFs, in this case based on transmissibility, to uncover the presence and severity of structural damage in civil infrastructure.

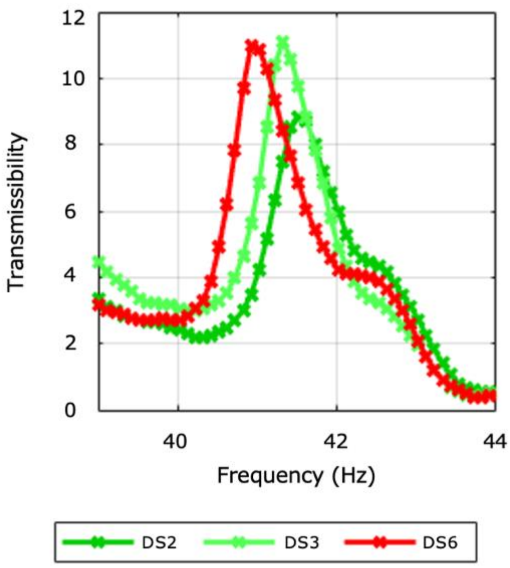

Figure 8 Example of damage-related drop of the frequency value, for which transmissibility peaks. Comparing three increasingly severe damage states (DS2, DS3, and DS6) shows that transmissibility-based damage indicators scale with the severity of damage.

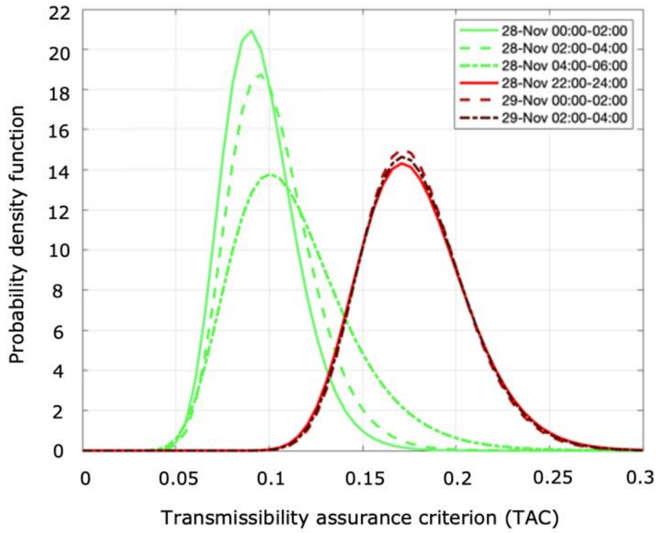

Figure 9 Example of acceleration recordings at mid-span of the bridge under ambient vibrations (a) and imposed by the vibrator plate around mid-span (b).

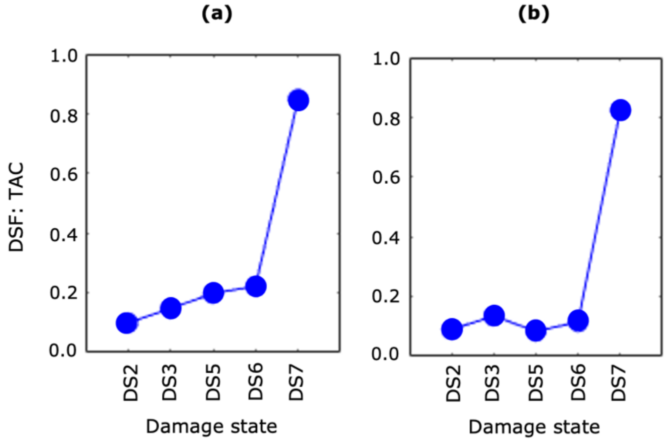

Figure 10 Evolution of TAC over increasingly severe damage states for two channel pairs involving fixed reference sensors 2 and 3.

4.2 Damage localization

In addition to uncovering presence and severity of damage, DSFs that provide information about the location of damage exist. One example of such a DSF is the change in the two-dimensional mode-shape curvature [22]. By fitting a spline to the vertical component of the mode shape of the first bending mode, the difference between the reference state and the ultimate damage state (DS7) is obtained and presented in Figure 11. While some scatter in the damage localization exists, this information is a valuable starting point for augmented inspection of the bridge as it successfully points towards the locations of damage on the bridge.

This result further confirms that the distribution of the seven vibration sensors is sensitive in view of the extraction of information regarding damage localization. Figure 11 contains a preliminary result of a single dataset, the full PMC dataset is attractive for further research as it contains information about different damage severities and locations.

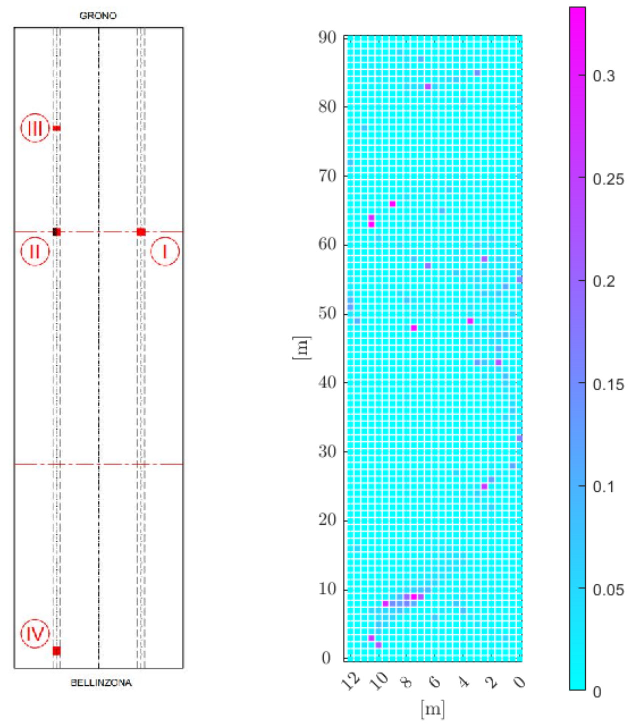

Figure 11 Location of artificial damage patterns (left) and damage localization based on changes in the two-dimensional mode-shape curvature (right). Despite some noise, information about the location of damage can be derived.

5 Lessons learned and future prospects

Monitoring real infrastructure and introducing controlled damage scenarios presents a unique opportunity. However, given the restricted timeline and the limited resources, certain aspects that are relevant to permanent monitoring installations have been neglected during this experimental campaign. Permanent monitoring installations in general and future similar experiments in particular should take into account the following points:

- The preliminary data analysis demonstrated that environmental/operational conditions and vibration amplitude influence the performance of employed DSF. In order to prevent false positives in data-driven strategies an appropriate training phase with varying levels of excitation and environmental conditions is necessary. Hence, previous long-term monitoring of the pristine structural state and potentially influential environmental quantities is recommended.
- Sensors and data acquisition components have shorter life spans, compared to the monitored structure. In view of permanent installations, sensor diagnostic routines should be integrated into the analysis, while regular maintenance / replacement of hardware components should be planned, in order to eliminate false alarms and monitoring downtimes. During the monitoring of the Ponte-Moesa bridge, one sensor was malfunctioning during large parts of the experimental testing. A near-real-time sensor diagnosis approach, such as described in Section 4.2, would reduce the time span of lost data during unique testing, such as the presented case of Ponte-Moesa.
- In the present case study, the evaluated damage scenarios correspond to relatively advanced states of structural degradation. Future work should resolve around the questions: what is the minimum damage

level that a monitoring system should be able to detect and what would be the necessary instrumentation to achieve this performance level? This will facilitate the cost-benefit analysis for permanent monitoring installations that are able to support decisions for efficient retrofit interventions.

6 Concluding remarks

The preliminary damage assessment of the PM bridge structure has demonstrated the promising potential and the additional value that permanent monitoring could add to ageing infrastructure. Although assessing the structural health based on sensor data consists nowadays a mature research domain, permanent monitoring has yet to be established in engineering practice. SHM can act as a supplement to the practice of scheduled inspection, supporting the timely, accurate and automated detection of damage. This in turn enables the support of decisions on optimal maintenance planning and ultimately the extension of the life span of existing infrastructures facilities. The exploitation of such data-driven condition assessment methods and their incorporation into maintenance planning is deemed as an eminent requirement towards materializing a sustainable and more resilient infrastructure footprint.

The testing and data-driven assessment of Ponte Moesa Compagnola has offered a unique opportunity to establish a SHM benchmark via monitoring of the structural response of a real highway bridge at controllably induced damage states of increasing severity. Accelerations of the bridge were permanently monitored during a period of four days, during which various artificial damage scenarios were introduced. Preliminary data analysis has shown the potential of vibration-based monitoring to detect and localize damage through derivation of appropriate features and indicators and led to identification of the following prospects for future research:

- Due to the various level and localization of introduced damages, employment of roving accelerometers and imposed variable forced vibrations, the dataset recorded during the Ponte-Moesa measuring campaign is an important testbed for damage detection, localization and quantification strategies.
- Accounting for environmental/operational conditions, as well as amplitude normalization schemes might be highly relevant for reaching robustness of extracted damage features.

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