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ONLINE MONITORING OF THE DYNAMIC RESPONSE OF A STEEL RAILWAY BRIDGE

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Abstract: *A real-time data-centric engine has been developed to monitor the dynamic response of an instrumented steel railway bridge in the UK. Multiple sensing technologies were deployed into the asset since the construction stage ranging from fibre-optic cables and accelerometers to video cameras and environmental sensors. Firstly, a brief description of the bridge and the monitoring system is presented, paying particular attention to the network of accelerometers and their collected raw time-series. Secondly, the raw data collected in real-time, from train-induced dynamic response, is powering a set of structural health monitoring (SHM) algorithms that estimate dynamic properties such as natural frequencies, modal shapes and damping ratios. These estimations take advantage of the train-induced response of the bridge 60 to 70 times per day, on average, by passenger and freight trains, which allow us to see the free-vibration response immediately after the crossing of a train. Finally, we introduce further data-centric and hybrid-data analyses, currently under development, which are fed in part by the results presented in this paper.*

Introduction

Our ever-expanding transport networks are vital for the normal functioning of modern society, where infrastructure such as bridges and tunnels play a major role. In this context, research using structural monitoring aims to reduce the costs of inspection and maintenance, as well as to extend the operational life of aging infrastructure. Although the field of Structural Health Monitoring (SHM) has seen progress in recent years due to the development of new sensing technologies and the myriad of data these produce, there are many challenges that are imposed by the nature of the problem at stake. A first constraint is the fact every building or asset is different, limiting the portability of monitoring approaches across these, therefore demanding time-consuming bespoke solutions each time a new SHM option is explored. A second limitation is usually the lack of a baseline of the structural condition in new assets, where SHM solutions are rarely included at the design stage, and in particular, in existing structures which pre-date modern structural health monitoring approaches. A third limitation is that damage scenarios are not observable, for inducing damage to a real structure is not acceptable, hence these scenarios need to be recreated in computer-aided simulations, such as Finite Element (FE) models and Digital Twins (DT).

Vibration-based damage detection methodologies in civil engineering structures have concentrated historically on ambient vibration or static response (Brincker and Ventura, 2015). This is the case because of the complexity associated with providing significant levels of dynamic excitation to a large structure, by means of induced controlled forces (e.g., shaker tests, impact tests and pull-back tests). The premise of these techniques is that they can detect modal parameters of the structure, such as lower-order natural frequencies, mode shapes, and damping values, by recording the structural response in multiple key locations due to small-magnitude input loads (ambient noise with low energy). The rationale is that these modal parameters are damage-sensitive as they depend on structural characteristics such as stiffness whose reduction is usually deemed to result from damage. Nonetheless, early damage is frequently nonobservable as it is

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connected to small-scale and localised structural changes which affect higherorder natural frequencies, which are extremely difficult to measure reliably based on ambient vibrations.

Railway bridges are different. These are natural laboratories to study structural performance due to large and recurrent train-induced dynamic responses. The first unique condition is that large dynamic responses are induced several times per day (on average, 60 to 70 trains cross the Norton bridge), which heighten damage-sensitive structural features above those controlled by environmental conditions, such as temperature. A second characteristic is the repeated loading imposed by specific trains which results in a signature response of the bridge. A third condition is the myriad of measured structural responses that are accumulated due to the frequent passage of trains. All these distinctive features create conducive circumstances to use statistical data analyses and machine learning (ML) techniques, to detect early damage due to small structural changes and modal properties (Avci *et al.*, 2021; Meixedo *et al.*, 2022). The main obstacle to realising the potential of such novel techniques has been the lack of permanent and reliable deployment of sensors and remote data-acquisition systems, capable of monitoring continuously so that the influx of quality data is steady and guaranteed. Such obstacle no longer exists for the Norton Bridge.

This paper presents a first glimpse into an online modal identification engine for a large case study, namely a railway bridge that is well instrumented since its construction (Butler *et al.*, 2018; Lin *et al.*, 2019) and has been recently enhanced with a permanent real-time data acquisition system. This modal identification is crucial before any other complex analysis, as it helps to understand the natural dynamic properties and behaviour of the bridge; additionally, as expanded below, it makes use of the free-vibration stage immediately after a train crossing. Currently, a DT of this bridge is under development (Broo, Bravo-Haro and Schooling, 2022) and due to the robust monitoring system and quality of collected data, it has been used to showcase novel data-driven methods, such as StatFEM (Febrianto *et al.*, 2022). Further developments of this online modal identification engine to become part of the DT are presented, for the applications are vast, ranging from online early damage detection to online condition monitoring.

Norton Bridge

Bridge characteristics

This is a Network Rail E-type steel half-through railway bridge with a single skew span of 26.84 m which carries two rail lines on the West Coast Main Line near the city of Crewe in the United Kingdom. A photograph of the bridge is shown in Figure 1 (a). From the construction and instrumentation stages, the bridge is referred to as Intersection Bridge 5 (IB5) and is part of the critical infrastructure in the rail upgrade and redevelopment project known as the Stafford Area Improvements Programme. The bridge is equipped with multiple sensing technologies, some since the construction phase, such as fibre-optic-based strain and temperature Fibre Bragg Grating (FBG) sensors, installed along the flanges of the main steel girders and concrete deck. Recently, additional sets of sensors were installed, including four 3-axis high-end accelerometers deployed throughout the web of one of the main load-bearing steel girders: optical, humidity, and temperature sensors, as well as video cameras. The newly upgraded data acquisition system allows remote and wireless real-time monitoring of all existing sensors, producing a new synchronised batch of raw measurements immediately after each train passage. At the time of submitting this paper, the bridge DT had over 32,142 live trains fully recorded.

Instrumentation and datasets

For the modal identification engine under development, the accelerometers are the principal monitoring package utilised. These sensors are 4 EPSON M-A550AR2X sensors that measure in 3 axes with a detection range of $\pm 5g$, and they are installed across one of the main steel girders, at both ends and quarters from the ends respectively, shown in Figure 1 (c). The interested reader can find an exhaustive description of the rest of the sensing packages elsewhere, especially the dense network of fibre-optic sensors (Butler et al., 2018; Lin et al., 2019).

(a) (b) (c)

Figure 1. (a) Case study bridge. (b) Close-up of one of the accelerometers as installed in the steel girder. (c) Location of the four accelerometers across the girder using a 3D model from the DT.

For every live train recorded, a set of time-series is obtained and stored in SQL databases, which are part of the DT of the bridge. These time-series are synchronised across sensors so that postprocessing from multiple sensors of the same type or between sensing technologies (e.g. an accelerometer and a laser range sensor) is an easy task. Figure 2 shows a complete pool of the raw time-series collected by the 4 accelerometers, henceforth referred to as ACC1, ACC2, ACC3 and ACC4 according to the diagram shown in Figure 1 (c). These recordings correspond to a typical commuter train (London Midland Class 350 Desiro) in the 3 main axes, and therefore to a typical dynamic response of the bridge. A first observation is that larger accelerations are imposed on the bridge in the vertical (red plots) and transversal direction (green plots) with almost the same magnitude. This is explained by the skew of the bridge that couples the vertical and transversal response. Second, the magnitude of the maximum acceleration is relatively low and are of the order of 2.5% of g. Finally, the zero padding before and after the strong-motion is part of the data acquisition digitisation process and is consistent across live train recordings.

The train rolling stock crossing the bridge regularly are not only passenger trains, but freight trains and steam locomotives. Due do their nature, each one of these imposes a different forced dynamic response on the bridge, as shown in Figure 3 which presents periodograms - displaying the frequency content of the response signal over time (unlike the power spectral density function which only offers a static frequency composition). Passenger train travel faster across the bridge, with a speed limit of 160km/h, and therefore most of the energy is transferred to the bridge in a higher frequency range, between 70-80 Hz, as can be seen in panel (a). Conversely, freight trains usually cross at night to avoid delaying daytime passenger trains, reducing their speed to cross the bridge and producing a longer dynamic response at lower, steady frequencies, around 10-20 Hz. Steam locomotives are somehow a combination of the response of the previous two, for they are heavy and cross the bridge slowly, such as the one chosen in panel (c), which took over a minute to cross over the bridge, in opposition to passenger trains that take between 2 to 5 seconds. The dynamic state of the bridge once the train has crossed over (i.e., initial conditions before the free vibration until rest) is important for the preliminary modal identification results described in the next section.

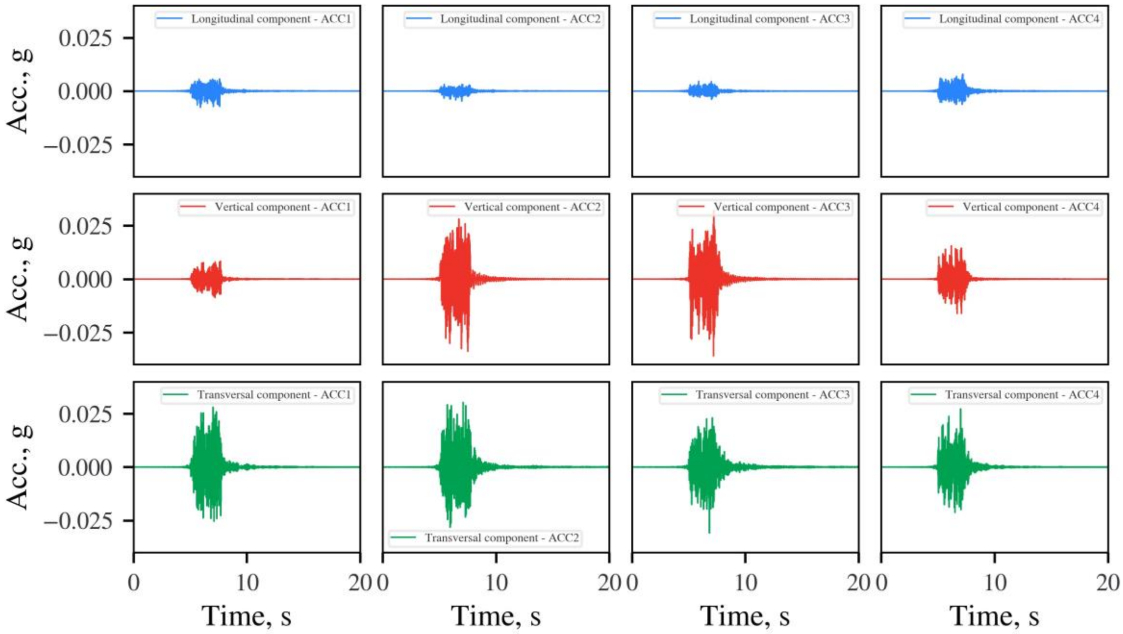
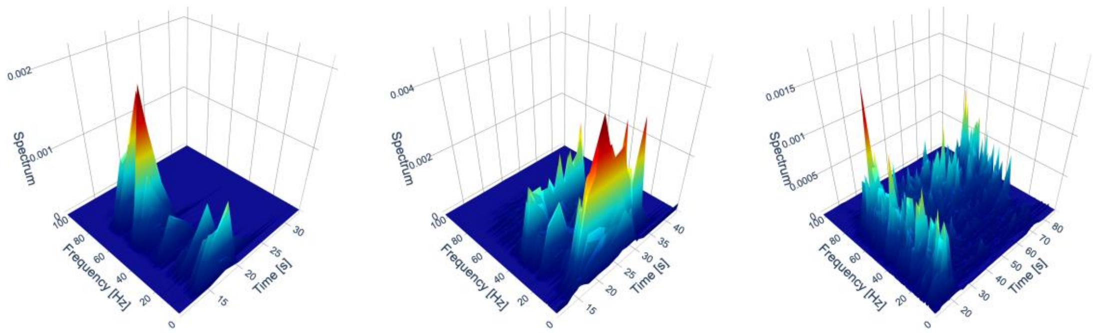


Figure 2. Structural dynamic response of bridge IB5. The full set of raw accelerometer data collected per live train. 4 accelerometers across the east main steel girders and their 3 components. These records correspond to a typical commuter train.



(a) Passenger train (b) Freight train (c) Steam locomotive

Figure 3. Periodograms for 3 archetypal train classes that frequently cross the bridge.

Results: Modal Identification

One of the most popular methods to perform modal identifications is OMA studies the modal properties of a structure under normal operating conditions or environment vibrations. Typically, in OMA applications, models such as autoregressive (AR) are used to enlarge a free-response of extremely small magnitude, a consequence of the small magnitude on the ambient vibration input signal, by using only sensor data such as acceleration or velocity across the structure, limiting its accuracy and scope. This contrasts with classical Experimental Modal Analysis (EMA) where the structure is subjected to controlled input loads (e.g., hydraulic shaker, drop weight and pull backs) and the response is used in the modal identification process. However, in railway bridges, substantial energy is transmitted to the structure due to train-loading input, creating a clearly measurable free response (i.e., the motion of a structure without any dynamic excitation) (Chopra, 2007) which can be seen as an operational pull-back. This is illustrated in Figure 4, which shows an archetypal structural response of Bridge IB5 in terms of vertical acceleration from one of the installed accelerometers closer to the midspan, where the free vibration (i.e., no external load) takes place right after the train has left the bridge (in yellow).

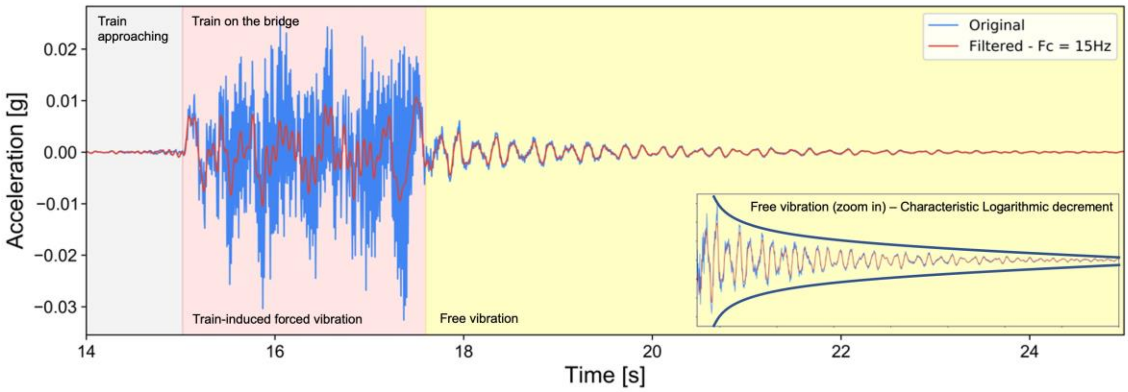
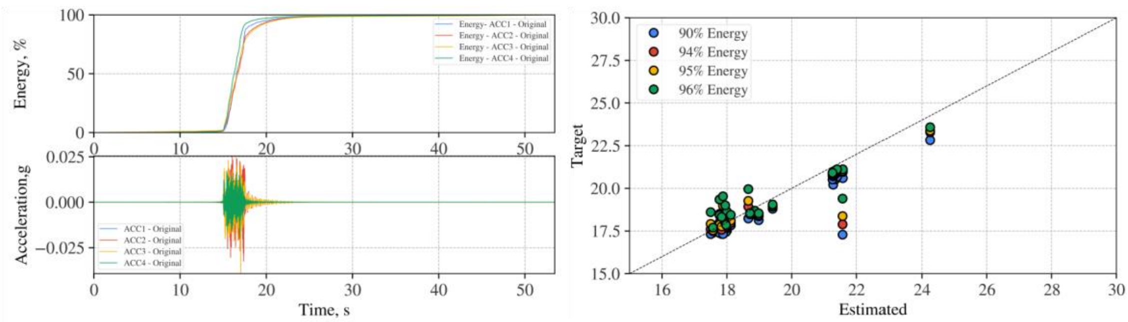


Figure 4. Main regions of a typical time-series of the structural dynamic response of the bridge. This corresponds to the vertical component of ACC2 placed at a quarter of the total length from the north end of the bridge. This commuter train was recorded on 2022-02-11- 16:01:21 PM.

The first step is to automatically isolate or clip the free vibration region of the time-series (yellow region). To do this, the exact time of train crossing is needed. In the existing monitoring system, this could be informed by other sensing technologies, since these are synchronised, including the video cameras and the laser range finders. However, it is preferred to perform this task autonomously using exclusively accelerometers data, so that the online modal identification process does not rely on the performance of other sensors (e.g., video cameras and laser range finders are less useful in the presence of rain, fog or snow). Focusing attention on the full timeseries of a live train in Figure 4, it is clear that the strong-motion (i.e., train crossing the bridge) is well demarcated by the magnitude of the acceleration. In other words, most of the energy of the time-series is concentrated during the train crossing. This is shown in Figure 5 (a) where the whole raw time-series recorded by the system for the vertical components of the four accelerometers are displayed vis-à-vis to the cumulative energy of the signal (Husid, 1969). It can be seen in the top panel of the left-hand side that when the train has crossed, and the freevibration commences, there is an inflection point in the cumulative energy curve around 90 to 96% of the total energy. To find this exact time, a range of corresponding percentages of total energies were estimated and compared to target values (i.e., time in seconds when the feevibration starts) that were obtained by visual inspection (i.e., hand-picking). These results are shown in Figure 5 (b) and the best fitting is achieved when using 96% of the total energy. It is important to mention that besides this validation, this threshold was confirmed when compared to the outputs from other sensing technologies, but not shown here.



(a) (b)

Figure 5. (a) Raw acceleration time-series of the vertical components for all 4 accelerometers and synchronised cumulative total energy of the corresponding signal. (b) Target versus estimated clipping time for the beginning of the free-vibration phase for different levels of total energy. This commuter train was recorded on 2022-02-11 – 16:01:21 PM.

The second step involves the estimation of the natural frequencies and their critical damping. The input data used to perform the analyses correspond to the clipped free-vibration section of the time-series described above. Initially, the peak identification of predominant frequencies of the power spectral density (PSD) is shown in Figure 6. These PSD responses were computed using at least 32 Hanning windows on the input signal. The results are based on ACC2 for the longitudinal, transversal and vertical components of 500 live train recordings respectively. The vertical motion component shown in Figure 6 (c) exhibits the most significant amplitude at a frequency of 5.1Hz, which is deemed to be the natural frequency of the first vertical vibration mode. This is consistent with preliminary results from a FEM of the bridge and the dynamic properties reported by the bridge designer. It's important to highlight the stiff condition of the bridge in spite of the 26.5m pan, controlled mostly by the large dimension of the main steel girders, resulting in turn in a fundamental period of vibration of 0.2s. The same predominant frequency can be observed in panel (a) with a smaller amplitude in the longitudinal direction, which is expected for the bridge is simply supported and therefore vertical and longitudinal motion can couple. A second important frequency seen across all three motion components is around 15Hz approximately, which is deemed to be the second vertical mode of vibration, but due to the skew of the bridge, this is also picked up by the transversal component. These are the two natural frequencies of vibration generally identified, with a high degree of confidence. Observe that the free vibration motion, hence the natural modes of vibration excited and involved in the response of the system until rest, depends on the amplitude and load distribution imposed by the crossing train (Chopra, 2007). Finally, Figure 7 shows the computation of the viscous elastic damping rate of the first vibration mode, using the bandwidth method (Tanaka *et al.*, 1969) for a larger dataset of 6,500 live train recordings. Similar results were obtained when using a variational mode decomposition approach (Dragomiretskiy and Zosso, 2013). It can be seen that the mean value of the observed damping ratio (ζ) is 1.25%, significantly below the common 2% assigned to steel structures. The dispersion observed in the computation of ζ is consistent with previous research that has estimated damping ratios experimentally, either using ambient vibrations or strongmotion inputs. Finally, similar damping values were obtained when using frequency-domain modal identification approaches, such as frequency-domain decomposition (Brincker and Ventura, 2015).

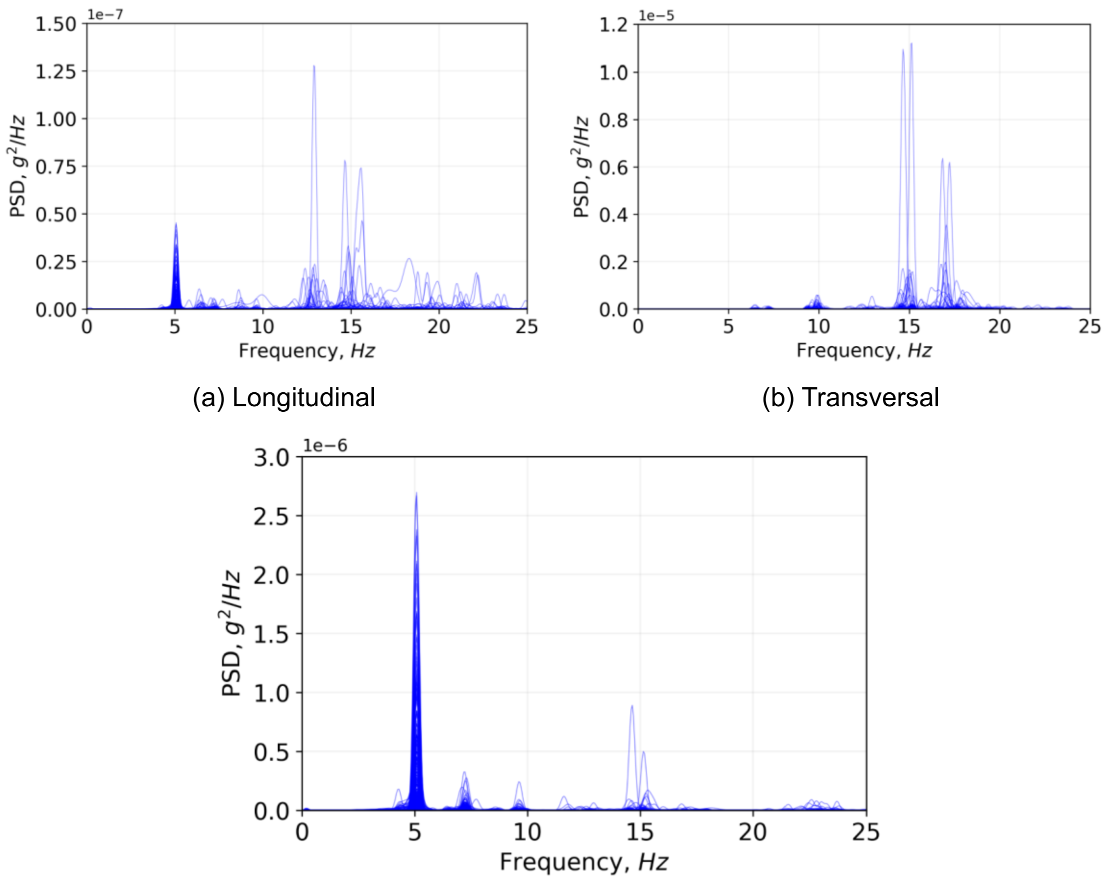


Figure 6. Power spectral density of the immediate post-train free-vibration of a 500 live trains dataset. Three components of ACC2 are shown.

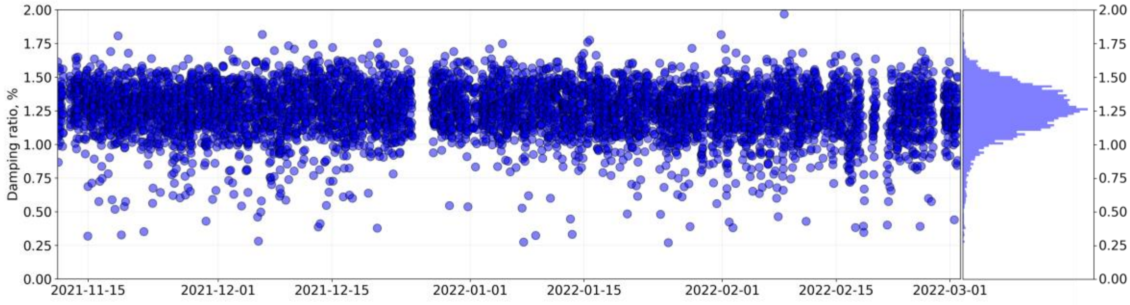


Figure 7. Damping ratio of the first vertical mode of vibration for a subset of 6,500 live trains over a time window of approximately three and half months.

The third step involves the identification of the mode shapes of the bridge, a task that was performed using different methods, exclusively for the two first natural modes in the vertical direction. Figure 8 shows the computed mode shapes using an AR model with moving average (ARMA) in the time-domain (Pi and Mickleborough, 1989; Huang, 2001), based on the freevibration following a typical commuter train. Similar mode shapes were obtained when using frequency domain algorithms for modal identification such as frequency domain decomposition (Brincker, Zhang and Andersen, 2001). Additionally, Figure 9 shows the equivalent vertical mode shapes but reported by the FE Model of the bridge developed in OpenSees (Mazzoni *et al.*, 2006). The details of this numerical model are not presented here for the sake of brevity, however, is worth mentioning that it has been previously calibrated with data collected by the accelerometers and fibre-optic sensors, thus, it reports results that closely match those of the monitoring system.

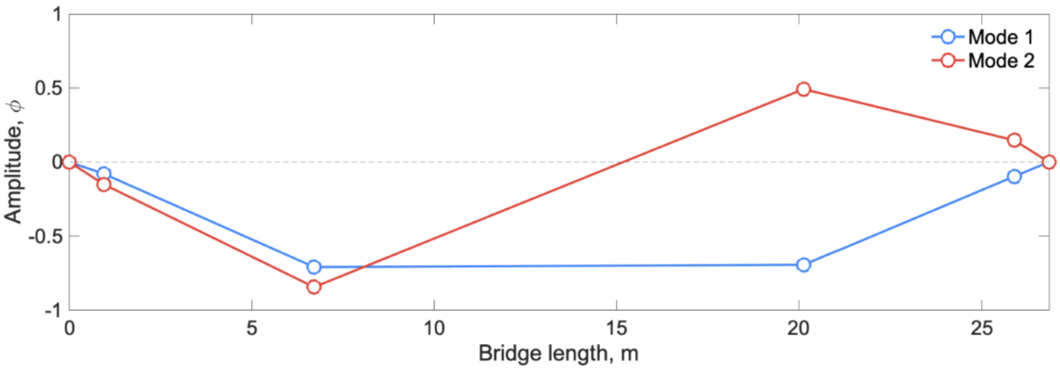
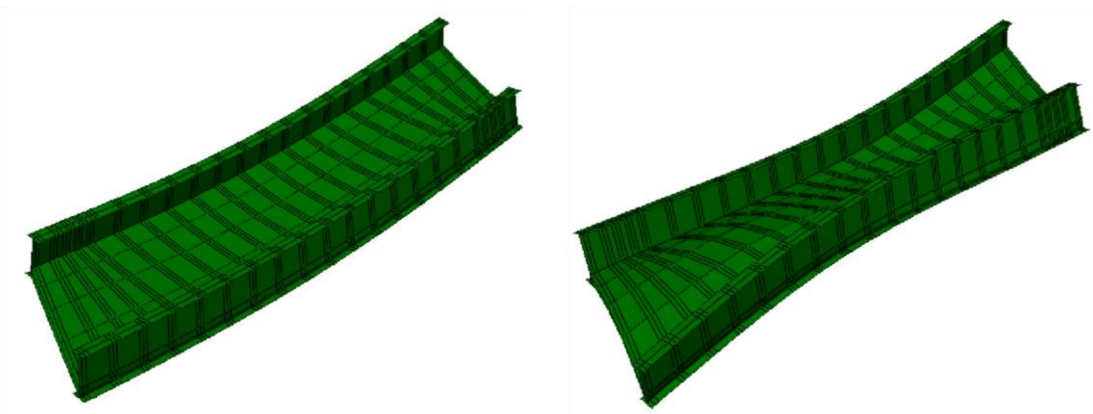


Figure 8. First two vertical mode shapes identified using time-domain ARMA method.



(a) First vertical mode shape $f_1 = 4.92s$ (b) Second vertical mode shape $f_2 = 7.32s$ *Figure 9. First two vertical mode shapes reported by the FEM.*

Further applications

Data-driven solutions

The online evaluation of the dynamic properties of the bridge, based on the analyses presented above, will be implemented as a standalone engine within the existing DT of the bridge. This engine will permanently store key metrics such as eigenvalues, eigenvectors, and damping ratios, along with features of the strong-motion of the acceleration time-series (i.e., train crossing the bridge), such as peak acceleration and Fourier amplitudes. In turn, this set of features will be used as input data for further analysis for the long-term monitoring of the Bridge. For instance, data like peak acceleration have shown to be a relevant feature for type of train classification, based on unsupervised clustering algorithms such as k-means.

Hybrid solutions

Collected data from the monitoring system will be fused with numerical data obtained from the calibrated FEM of the bridge. Firstly, a notable application will be an online version of the recently developed Statistical Finite Element Method (StatFEM) (Girolami *et al.*, 2021) whose first theoretical application has been on the Norton Bridge (Febrianto *et al.*, 2022), but limited to a single type of train, offline and using an alternative FE framework to OpenSees. Secondly, a bespoke version of an online unsupervised methodology for detecting structural changes based will be implemented. This framework, recently developed, takes advantage of the network of accelerometers to produce autoregressive models of the response of a given sensor using the response of another sensor. Subsequently, the autoregressive coefficients are used as features for a clustering process that allows to detection of structural changes, potentially including the stages of early damage.

Final remarks

The railway Norton Bridge in the UK is a unique research testbed due to the breadth of its online permanent monitoring system with multiple technologies. To this day, the bridge's structural response to more than 32,142 live trains has been recorded and stored in the existing DT of bridge. The first results of an online modal identification system, to be deployed within the DT were presented, largely based on analysing the free-vibration response window from the acceleration time-series. The frequency of first fundamental mode for the vertical component is clearly visible in the power spectral density of the free-vibration response, especially for the midspan accelerometers due to the higher amplitudes in the response. In contrast to higher modes that are not excited enough by the initial condition imposed by the train after crossing over the bridge. Such behaviour is common in relatively stiff systems, which is the case for the Norton Bridge, due to its structural composition and topology (experimental $T_1 = 0.2s$). These observations were consistent with a numerical FEM of the bridge developed in OpenSees. Likewise, the damping ratio of the first mode was computed over a large dataset of live trains, whose computed magnitude of 1.25% is lower than the 2% commonly used for this type of structures with principal steel structural elements. Finally, now that the dynamic behaviour of the bridge is better understood, further data-driven methodologies are being developed, and some details were presented at the end of this paper.

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