Customised active monitoring system for structural control and maintenance optimisation

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Abstract

The paper illustrates the development and the application of an active monitoring system, and analyses the investigated dynamic behaviour of the structure where the system is applied. The system is installed on a 250 m suspended arch steel bridge that has been instrumented with sensors of different type. This work focuses on the employed methodologies and obtained results related to the dynamic monitoring of the bridge. The use of the Operational Modal Analysis techniques with data-driven stochastic subspace identification algorithms allows the extraction of the structural dynamic characteristics: natural frequencies, damping ratios, and mode shapes. These data are in overall accordance with those calculated through the computational model utilized by the active monitoring system. Besides, the definition of a range of scattering of modal parameters, under specific conditions, has been obtained. The bridge has very low vibration frequencies, below 1 Hz for all significant modes. The outcomes indicate that the estimation of dynamic characteristics and the corresponding accuracy is influenced by several factors, including the length of the accelerometric acquisitions and the followed specific procedures. The impact of environmental factors, with particular reference to the temperature, is examined. Compared to the damping ratio, the natural frequency shows higher estimation accuracy and marked sensitivity to the environmental factor. Consequently, in the selection of benchmark for damage detection, it should be taken into account that the two modal parameters have specific criticalities. Once that the modal parameter has been chosen, values outside the estimated uncertainty range can be considered as alarm triggers.

Keywords Structural health monitoring • Operational Modal Analysis • Environmental effects •Active monitoring

1 Introduction

Structural health monitoring of infrastructures is a process involving the development of strategies to identify possible damage. This process has the aim to ensure the safety and to shun grave waste of economic resources. The fundamental problem consists in detecting and locating the damage and its extension. In this way, the remaining service life of the structure is evaluated and it is possible to develop a plan to increase it through maintenance. SHM is of interest to various fields such as mechanical, aerospace, and civil engineering, and requires advanced research at multidisciplinary level (computational, acquisition and sensor hardware, signal processing and data analysis).

The structures, during their useful life, are subject to many phenomena including aging, corrosion, and fatigue that modify their initial characteristics. Bridges are among the infrastructures where this phenomenon is very evident. Increased traffic, exposure to corrosive agents, and freeze-thaw cycles over time are some of the motivations that make infrastructure bridges critical.

A systematic approach that checks the structural conditions for the implementation of *condition-based maintenance* is needed [1]. Laboratory testing on specimens and development of empirical models of deterioration are no longer sufficient [2]. In fact, laboratory testing is not fully reliable due to the change in scale and conditions, whereas the empirical models are not suitable for generalization. The opportunity to test the full structure [3] and to have a considerable quantity of data is essential for an effective approach. An SHM process can be considered consisting of four steps: operational evaluation, data acquisition, feature extraction, and statistical model development [1]. Starting from the definition of the problem, the choice of type and location of the sensors to acquire data is crucial. This enables to extract useful characteristics of the structure, namely sensitive to potential damage to be identified. Then, statistical models are required to intercept and quantify the damage. In most cases, 'unsupervised learning-algorithms' are used, because the available data do not cover damage cases.

In the literature, there are many examples of SHM processes through monitoring applied to bridges, that are adapted to specific needs. To give an example, for Tuas Second Link Bridge [4], SHM process has been based on the concept that the instability of the signal can be a proof of a structural state potentially damaged. The structural health has been investigated by the analysis of the parameters of an autoregressive model of the signal and by the observations of their fluctuations. Another example of damage research, through a pure analysis of the signal, has been conducted for the Pioneer Bridge [4]. In this case, peak displacements are utilized. Statistical models have been developed, before and after the implementation of a retrofitting project. Later, the validation of the interventions of reinforcement has been done.

Damage is often identified by changing of dynamic response and most commonly adopted techniques are output-only type. In addition to the signals own parameters, such as peak acceleration/displacement, what characterizes the evolution of the structural behaviour are the modal parameters: natural frequency, damping ratio and mode shape.

The Operational Modal Analysis (OMA) is among the most widely used dynamic identification techniques. OMA procedures are output-only techniques, because excitation is not known and is assimilated to white noise. In doing so, it operates in a stochastic context and avoids the use of instrumentation to excite the structure (e.g. vibrodyne and hydraulic actuators). Moreover, this type of dynamic test is quick and inexpensive. A further advantage of this type of analysis is the possibility not to interfere with the operation of the structure [5] and to consider actual loading conditions.

Conducting dynamic identification processes towards complete automation is the key to strengthen this strategy and making it truly effective for SHM purposes [6]. Several algorithms for identifying and tracking modal parameters have been developed, both in frequencies and in time domain.
One of the main drawbacks, often still present in these algorithms, is the necessity of an initial phase of calibration of specific parameters.

A study that shows many similarities with the case analysed in this paper is monitoring of the "Infante D. Henrique” bridge [7].

Beyond the used specific subspace technique, the analysis presented on this paper sheds light on many general aspects, allowing to highlight several considerations.
First, the importance of appropriate procedures for the choice of structural modes by means of stabilisation diagrams, which may include clustering methodologies (hierarchical or not).
Second, the lower suitability of damping ratio to be a criterion to distinguish vibration modes, compared to the other two modal parameters (natural frequency and mode shape). This is due to the high dispersion characterizing damping and to the fact that different modes may present the same damping ratio.
Finally, the need to link the modal parameters of a measurement with those of the previous one through criteria concerning natural frequencies and mode shapes.

The current paper presents an application of structural monitoring on a steel arch suspended bridge of long span. Accelerometric measurements are the input for a dynamic identification procedure. Analyses have allowed to observe variations in modal parameters and to establish their dispersion window. The following paragraphs will draw attention on how the estimation and the accuracy of the modal parameters are influenced, albeit in a different way, by some factors including the characteristics of the dynamic response acquired from the sensors (e.g. number of signal data points), the procedures followed to analyse the data and the environmental factors.

2 Description of the structure

The examined structure is a highway steel arch bridge in Italy. The bridge presents a single arch, with constant trapezoidal section, connected to the inferior way by vertical steel cables. It has a span of 250 m. The inferior way consists of a chain beam and a sequence of transverse cantilevers with a pitch of 8 m along the axis of the bridge. The chain beam has a hexagonal cross section and is supported by the arch through the aforementioned steel cables. Each cable consists of a different number of strands on the basis of its position along the structure longitudinal axis. The top part of the chain beam is placed at a higher level than the road level. This is to protect the cables from accidental damage by traffic on the carriageway. Indeed, the deck is composed by two carriageways and the total width of each way turns out to be approximatively 17 me considering the presence of the docks. Some illustrations of the bridge are reported in Figs. 1 and 2.

Fig.1 General view of the bridge

Fig.2 Transversal view during construction

3 Sensors network and active monitoring

The set of sensors and their locations, with reference to Fig. 3, is given below:

- D01 and D07, high resolution servoinclinometrs;
- D02, D04, D06, D08, D10, D12, steel surface temperature, 4 sensors per measuring point located on the four sides of the cross section (top, down, left, right);
- D04, D08, D10, D12, air temperature and humidity sensors;
- D03, D05, D09, D11, triaxial accelerometers;
- D08, D12, differential wind pressure transducers (probes are installed in between D08/D09 and D11/D12);
- D04 strain gauges at runway cantilevers;
- Each suspension cable is instrumented with a load cell.

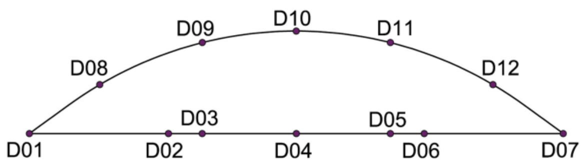

Fig.3 Position of the sensors in the structure

To give a standard mounting platform for the sensors so to guarantee a standard installation methodology to all positions, a mounting steel plate has been employed. The plate is differently populated by sensors, depending on the data acquisition point in the structure (Fig.4).

The sensor network is part of an elaborated and customized monitoring system for structural assessment and maintenance optimisation. This system has the ability to perform a real-time structural assessment in a fully automated way, highlighting potential crisis mechanisms. Because of this capability, the system has been labelled as “Active Monitoring System”. Although the details and the methodology of “Active Monitoring” are not the subject of the present work, the data acquisition and processing system is briefly described hereafter. More details can be found in [8].
The acquisition of sensor signals takes place at five data acquisition points, whose positions have been determined with the aim to minimize the length of sensor connection cables.
The analogic signals are digitised and conveyed to the data processing computer at a frequency of 5 Hz. Then, processed sensor data are converted into input quantities for a finite-element computational engine, that computes derived quantities. Afterwards, the coherence between acquired and calculated quantities is checked. The system sends warning signals if this verification is not met.

In this way, a continuous automated structural health assessment is possible, going beyond the limits of traditional monitoring. Finally, the signal warnings, issued by means of semaphores in an intuitive interface, allow to substantially reduce the advice of experts in the structural assessment process.

In the following paragraphs, a special focus will be placed on foundations, methodologies, and outcomes regarding the analysis of the dynamic behaviour of the structure. During the monitoring system tuning stage, this allowed to validate the computational model used by the Active Monitoring data processing software.

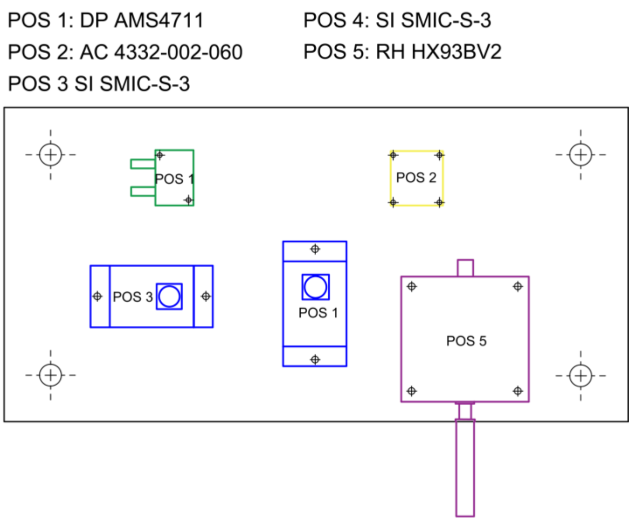

Fig.4 Sensor mounting plate for servoinclinometer, air temperature and humidity sensor, accelerometer and differential pressure transducer

4 Dynamic monitoring

An experimental output-only approach has been used with the purpose of extracting the dynamic behaviour of the bridge. The possibility to continuously monitor a facility for long time, starting from its construction and during its life, allows to obtain interesting information on the evolution of its characteristics in time [9]. It exploits, as often happens in the large civil structures, environmental excitement [10]. This approach is universally recognised as less expensive and not impacting on facility service than artificial excitation. The sensor number, degree of freedom, and location are depicted in Fig. 5.
Some recordings on the bridge deck and arch are shown in Fig. 6. Certain indices featuring the signals are also reported.

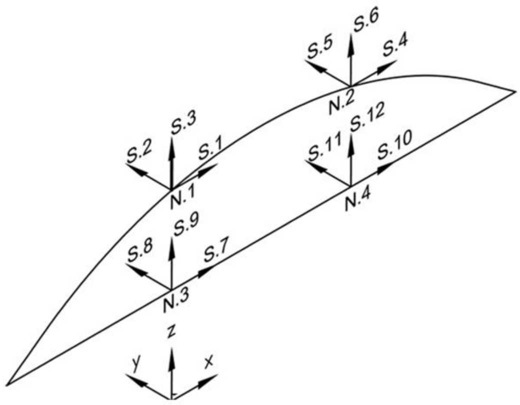

Fig.5 Numbered accelerometers and nodes application

Signal processing has been performed through the software ARTeMIS Modal [11]. ARTeMIS is a software able to implement different types of analyses, including OMA. Besides, it has been chosen for its processing speed and for the possibility to obtain results with a high degree of automation. In fact, to speed up the analyses, there is the opportunity to process the raw data of each measurement session with the same set of the features of a particular session called “Master Session”. Moreover, before processing the data, depending on the structure of measurements, some pre-treatment functions can be utilized. Among these stand out “detrend-function” (to remove average values and linear trends in the raw data), “decimation-function” (to reduce the frequency range to the one of interest), “projection channel-function” (to avoid redundant information) and ‘filtering functions’ (to select the range frequency of interest).
An example of processed signals and decomposition in singular values of spectral densities is displayed in the background of Fig. 7. Finally, this software provides the uncertainty of modal parameters estimation.

4.1 Data processing method: theoretical and applicative aspects

Examined datasets will afterwards be defined through the expression “measurement session” or more simply by the term “sessions” to highlights the serial nature of the provided records. To analyse the acquired data sets, the algorithm DD-SSI-UPCX (Data Driven-Stochastic Subspace Identification-Extended Unweighted Principal Component) [12,13,14] has been selected.

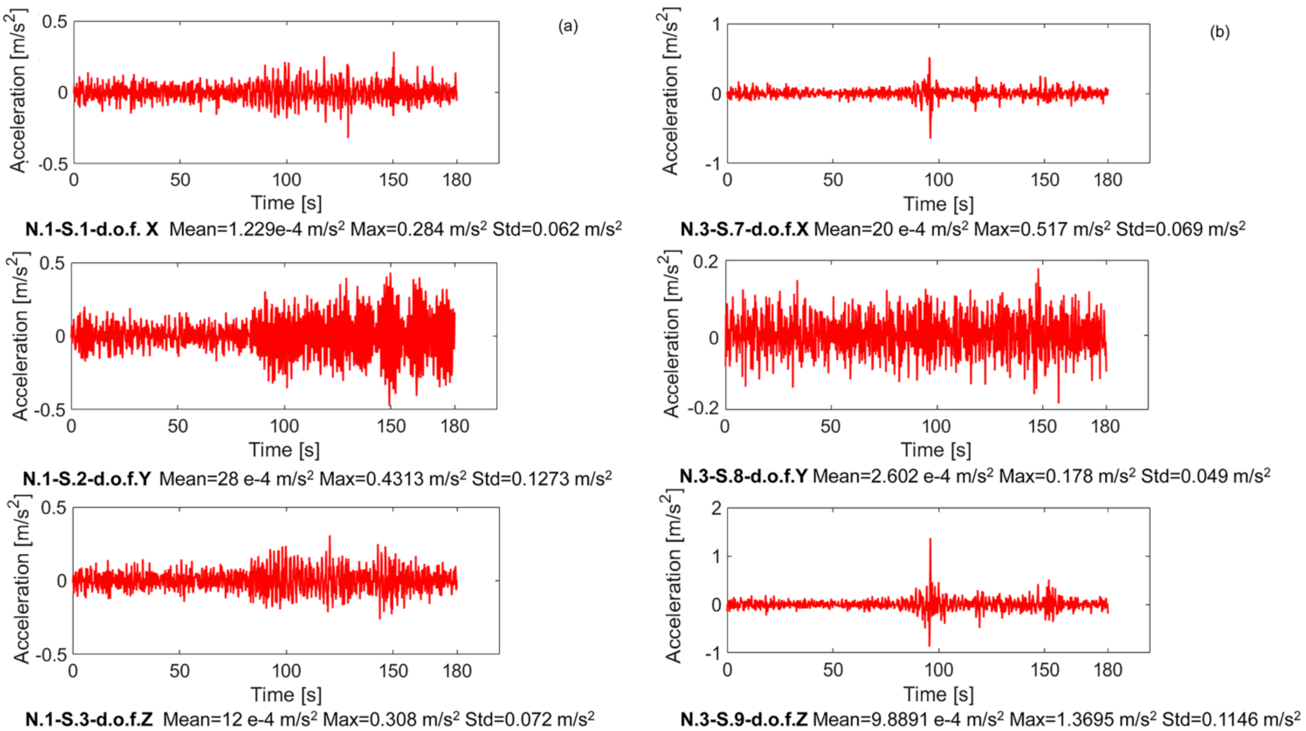

Fig.6 Some bridge recordings under environmental vibrations **a.** Sensors on the arch**; b.** Sensors on the beam

It uses a parametric model which fits the raw time series data.

This is the technique that, in the used software, also provides the advantage of estimating the uncertainties of modal parameters. Likewise, the reason for this pick lies in the reliability and robustness of this method. It is particularly effective for flexible structures with low natural frequencies and damping ratios and with closely spaced modes [15]. In this context, recent studies have been done to improve the quality of results in these cases [16].

Besides, it is used also when small data sets are available. Nevertheless, it should not be forgotten that, ideally, infinite measurements are needed to obtain an error-free estimate. In fact, in general, the assumptions on which SSI models are based are:

- Infinite amount of data
- Linear system
- White noise excitation

Another aspect to be considered is the number of row blocks in the output Hankel matrix; namely the sum of row blocks in the past output and future output partitions. Each row block contains a part of the total samples of the data set (e.g., j samples). The j samples inside of each row block are shifted by one time-step, equal to the sampling time, compared to those in the previous row block. The number of row blocks must be higher to capture lower frequencies, but this means sharp increase in computation time/effort and considerable use of memory [15,17-19].

At the same time, if this number is too high, there are negative effects on the accuracy, because spurious numerical modes will be produced [15].

In addition, the number of row blocks is linked with the maximum model order. Theoretically, the model order can be calculated by singular value decomposition of the projection matrix. In the case of noisy data, almost all values become non-zero singular values and the model order will be very high [15].

Consequently, the number of eigenvalues will be high and many of them will represent spurious modes. Therefore, the quality of the estimate may be lower if the model order is too high.

An option to improve quality of modal parameters estimation entails change of the key idea of the SSI method. An example is reference-based stochastic subspace identification [10] where the projection of the row space of the future outputs is no longer performed into the row space of the past outputs, but into the row space of the past reference outputs. It would be appropriate for the past reference output to be defined as those belonging to the "best sensors", namely those that are able to better capture motion. Candidates for this role should be the sensors fitted in the optimal positions, that are those where the largest modal accelerations are foreseen be present. In fact, data from sensors located at zeroes of the modal shapes or close to fixed boundaries worsen the identification results.

Choosing some sensors as reference and applying the projection of the row space of the future outputs on the past reference outputs, the calculation effort is smaller. A possible drawback of this approach is that there may be a loss in identification quality if all modes are not present in the outputs of the assumed reference channels. In Artemis, the pre-treatment function “project channel” allows the realization of this method and therefore, the comparison of outcomes with those obtained without the use of it.

In the software, the validation of the estimated modes is done using a tool that operates in the frequency domain. Structural modes are picked up through the stabilization diagram (Fig. 7). It presents the natural frequency in the horizontal axis (from zero to the Nyquist frequency) and the dimensions of determined state models in the vertical axis. The stabilisation diagram is a helpful tool to detect bias errors, including bias of the model caused by physical reasons and over-estimation of the system order, and bias of the modes resulting from under-estimation of the system order [7, 20]. Horizontal lines in yellow in Fig. 7 correspond to the singular values. The number of them indicates the number of eigenvalues present in the data. The choice of stable modes is done for each model order respecting some criteria, namely:

- Maximum deviation, for natural frequency and damping ratio, between a mode belonging to a model with an order *n* and the mode belonging to an order model *n*-1;
- Maximum deviation of modal assurance criterion (MAC) of mode shape vector between a mode belonging to a model with an order *n* and the mode belonging to an order model *n*-1;
- coefficient of variation (CV) for each natural frequency and damping ratio, namely the ratio between the standard deviation and the mean value.

The thresholds for these criteria are user-defined and depend on the problem at stake. There is a wide literature that highlights the usual used values for the thresholds related to those criteria [21]. The stabilization criteria used for the problem at hand are reported in Table 1. For the MAC maximum deviation, both for small and large data sets, a typical value has been used. The motivations behind the choice of the other limit values, depending on the length of examined dataset, are discussed in the following (see Sects. 5.1, 5.2).

In addition to these criteria, it is important to exclude the so-called “noise modes”. Noise can be caused by several factors including: inadequate number of measurements, low calculation accuracy, poor sensor accuracy, and inaccurate modelling. For this purpose, the modes with damping ratio greater than 5% (not physical) and less than to 0.1% (external periodic excitation) are removed. The estimation of final modal parameters shall be based on all stable modes.

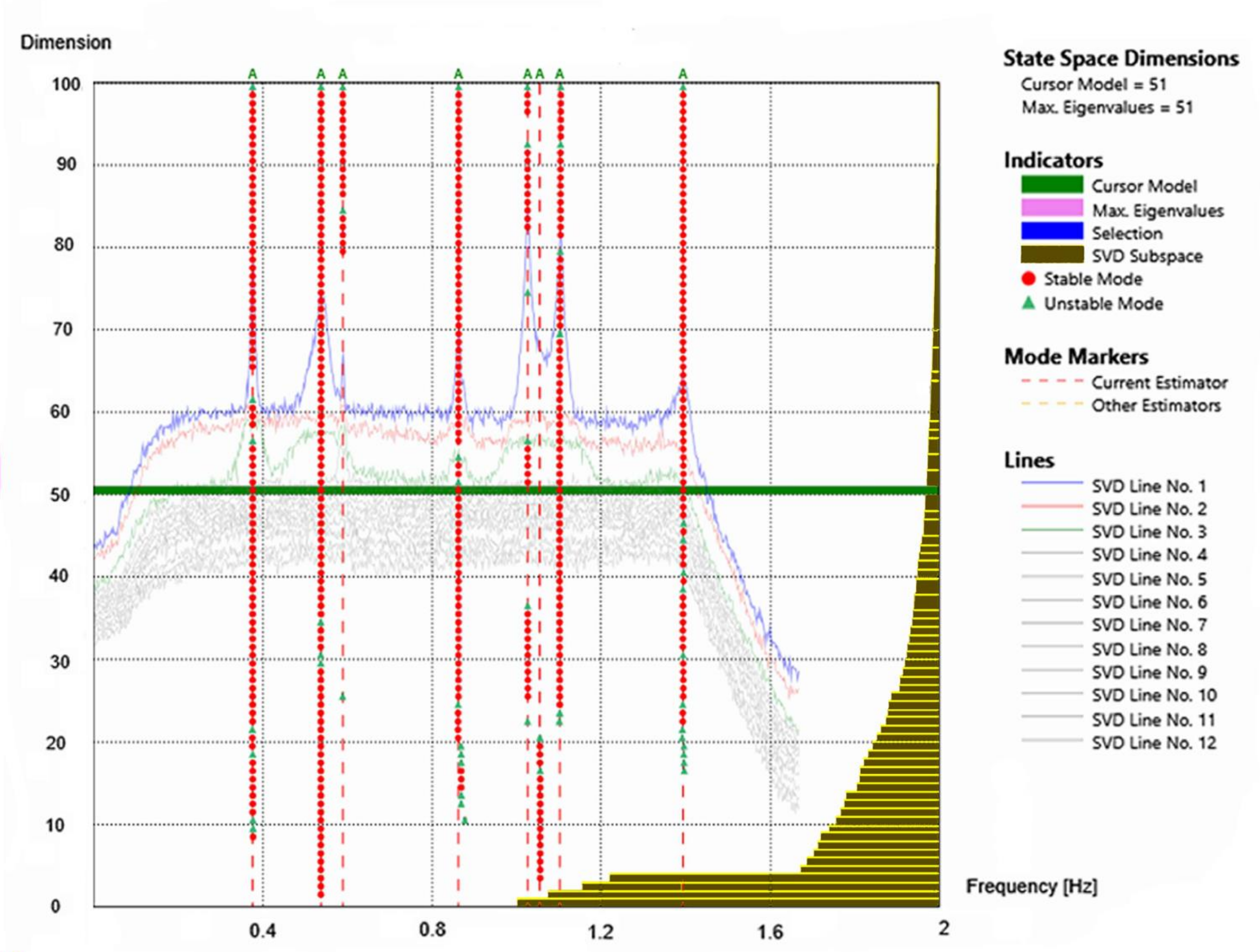

Fig.7 Stabilisation diagram

Table 1 *Stabilisation criteria*

Small Data Set			
Max Dev.	Frequency [Hz] 0.00375	Damping [%] 10	MAC 0.05
CV	Frequency 0.02	Damping 5	
Large Data Set			
Max Dev.	Frequency [Hz] 0.0002	Damping [%] 0.04	MAC 0.05
CV	Frequency 0.01	Damping 0.2	

The stable modes within the obtained 'alignments' represent the actual structural modes, where by the term 'alignment', in the context of the Stabilisation Diagram, we mean the vertical stripes in which are grouped the estimated modes that represent the same physical modes.
The stable modes contribute through their average value, with a different weight inversely proportional to their coefficient of variation, to determine the final estimate and the uncertainty of the parameters.

The results obtained by DD-SSI-UPCX method have been finally compared against those obtained through EFDD method (enhanced frequency-domain decomposition).
In this way, a benchmarking study between a methodology that operates in the time domain and a procedure that operates in the frequency domain [22] has been made.

4.1.1 Error estimation

The expected accuracy of the estimate is not the same for the three modal parameters of the structure. Errors affecting the damping ratio are systematically larger than those affecting natural frequency and mode shape. The causes of large error bounds in damping ratio estimation lie in his non-linear behaviour, in limits in estimators and in scarceness of measurements [15].
In stochastic subspace identification, the factors that mostly influence the accuracy of modal parameter are the number of data points in the records and the number of block rows. Other studies [15], through sensitivity analysis, have deepened this second aspect.
In this work, the first factor will be considered to bound the modal parameters uncertainty.

5 Natural frequency and damping ratio: range of scattering

Data collected unevenly over a period of about one and a half years are available. The sampling time used in the measurements is 0.15 s, resulting in sampling frequency equal to 6.66 Hz. The data recorded have been processed, with the SSI method, with the purpose to comprehend the range of dispersion of modal parameters. By means of the "Modal Parameter History Module" available in ARTeMIS, is possible to observe, in a historical view, the modal parameters of the structure as function of the measurement sessions. Two measurement sessions, namely two data sets, are selected as "Reference Sessions". The software is able to calculate, for the stable modes in these sessions, the mean values of modal parameters (Reference Modes). The stable modes in the Reference Sessions respect the following tolerances:

- Natural frequency may differ no more than 10% from the previous session;
- Maximum deviation between mode shape extracted by a measurement session and that derived from the previous, may be less than 0.2 in terms of MAC (minimum Modal Assurance Criterion 0.8).

Based on the reference modes, links/tracks in the graphical presentation of identification results are drawn. Those links allow an immediate visualisation of the modes evolution to changing sessions. In this way, it is also possible to draw immediate considerations. For example, a lack of link between adjoining sessions is a symptom of a modal parameters change.

5.1 Narrow viewing windows

The data acquisition system reads and stores accelerometric data in sets having a duration of 180 s. To analyse these single data sets, they have been preprocessed by the "function-detrend" filter only. It is useful to observe the results of the estimated first natural frequencies for the available data sets, Figure 8a. These give us a qualitative view of the values dispersion. In particular, it points out a max value around 0.382 Hz and a minimum value around 0.365 Hz. The range of variability of natural frequency is very small.

The same procedure has been followed for the first-mode damping ratio. The flow over time of the estimated damping ratios is shown in Fig. 8b. It shows a maximum value equal to 4.57% and a minimum value around 0.25%.

Figure 12 displays in a histogram in blue the results in terms of natural frequency and damping ratio. The first natural frequency has been fitted with normal distribution, whereas the first-mode damping ratio has been fitted with lognormal distribution. In the same figure, green curves are related to large viewing windows and are discussed in the next section. The values of the position and dispersion indices characterizing the two distributions are reported in Table 2 and in 3, respectively.

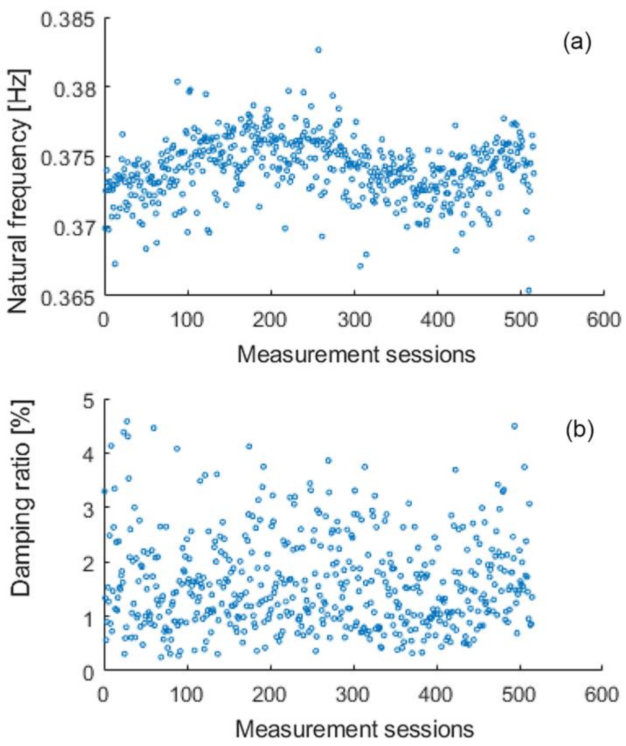

Fig.8 Estimated modal parameters **a.** First natural frequency **b.** First damping ratio

Table 2 *Indices of first natural frequency distribution (small data set)*

Position indexes	
mean	0.3742 [Hz]
median	0.3742 [Hz]
Dispersion indexes	
Range	0.0173 [Hz]
Variance	4.66 E-06 [Hz]
CV	5.77 E-3

Table *3 Indices of first damping ratio distribution (small data set)*

Position indexes	
mean	1.61 [%]
median	1.38 [%]
mode	1.01 [%]
Dispersion indexes	
Range	4.32 [%]
Variance	0.93 [%]

The subspace stochastic method shows a decent, but not very high capacity, in finding stable frequencies even with measuring sessions having few recordings.

On the other hand, it is much more difficult to make accurate estimates of damping ratio, which is jeopardized by a wide error (the coefficient of variation for the first mode is of order of 10^{-1}). Estimated modes in stabilization diagram present the highest value of their variation coefficient for damping ratio. Therefore, extremely high thresholds for CV and for maximum deviation of damping ratio (see Table 1) are established. Due to the unreliability of the damping ratio estimation, the creation of clusters on the basis of this parameter appears without sound meaning. The discrete quality of the frequency results along the model order led to use a CV equal to 0.02 and a maximum deviation equal to 0.00375 Hz (about 1% of the assumed first frequency). Consequently, the estimate of damping ratio, compared to natural frequency, is much poorer.

This is also visible from the frequency-damping diagram (Fig. 9), that shows the mean value of the first-mode damping ratio versus the mean value of the first natural frequency with confidence ellipsoid. It is apparent that the uncertainty of natural frequency estimation is very small, unlike that of damping ratio. Furthermore, there is no correlation between the damping ratio and frequency, since the ellipsoid appears to be vertical.

SSI-UPCX technique for these single data sets, despite the better behaviour of the natural frequencies, produces an estimation of the first-mode modal parameters for only part of the sessions (about 76%).

Concluding, the damping estimation is totally inaccurate with unrealistic scattering range and the first frequencies do not respect for about 24% of the measurement sessions the fixed criteria.

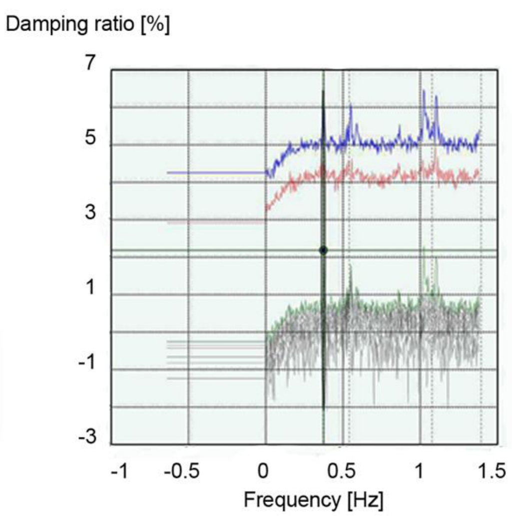

Fig.9 Frequency-damping ratio for the first mode

5.2 Large viewing windows

In this case, data sets are combined to form wider observation windows. Then, it is investigated how much the accuracy in the estimation of the modal parameters improves.

For this aim, monthly observation windows have been defined and the measurements recorded from May to December have been used to examine monthly changes. Measurements belonging to the same month have been grouped together and the estimates in terms of modal parameters (natural frequency, damping ratio, and mode shape) have been analysed.

The obtained first natural frequencies and damping ratios are reported in Fig. 10.

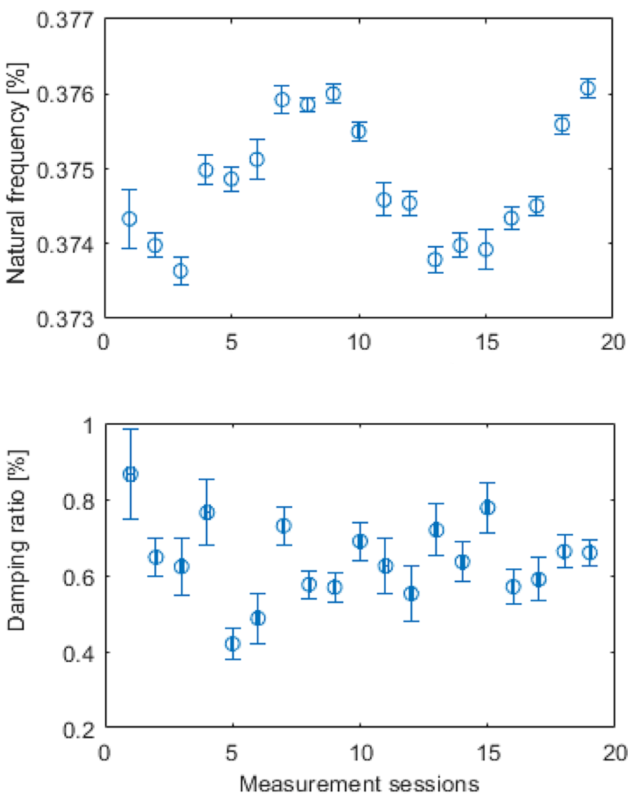

Fig.10 Estimated first natural frequency and damping ratio

With these data sets, it has been possible to set, also for damping ratios, a reasonable maximum coefficient of variation. In this case, the quality of the estimations along the model order renders meaningful the use of damping ratio as stabilisation criterion. Consequently, a low threshold for maximum deviation of damping ratio equal to about 5% of the expected value for the first mode has been used (see Table 1). On the other hand, due to the higher quality of the data, the limit values for frequencies are made more restrictive.

The uncertainty of parameters, in terms of coefficient of variation, decreases considerably for both parameters. In particular, for the first mode, the maximum coefficients of variation of the final estimates are around 10^{-4} for natural frequency and about 10% for the damping ratio. The frequency-damping ratio diagram (Fig. 11) for the first mode of a session is given to show the decrease in the confidence interval compared to the previous case, Fig. 9. This improvement allows gaining a much more accurate estimation and, therefore, more realistic determination of the damping ratio.

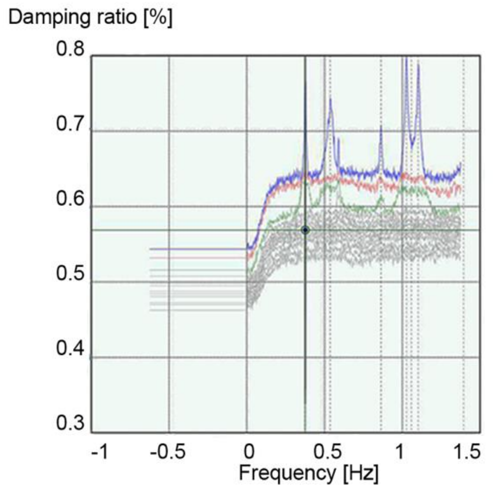

Fig.11 Frequency-damping of a session (February 2018) for the first mode

This confirms that it is necessary a minimum number of data points to obtain an estimate enough accurate. The use of short datasets implies large error in the modal parameters, as in other applications [23, 24]. In presence of structural frequencies less 1Hz and damping ratio less 1%, other studies [24] have established a minimum threshold of points per data set equal to 4000 points to achieve an accurate identification of both modal parameters. The results obtained so far confirm this. Data sets with low number of recordings (< 4000) indicate a response in terms of frequencies certainly better than damping but still insufficient. In fact, the sessions of measurement from which it is possible to extrapolate an estimate are equal to only one part of the totality of the measurement sessions. On the other hand, the values of damping ratio exhibit very high uncertainty.

Figure 12 depicts in blue and in green, the probability density function of modal parameters estimated for the first mode from narrow viewing windows and from large viewing windows, respectively. Table 4, 5 give the values of the position and dispersion indices portraying the distribution of the natural frequency and damping ratio for large viewing windows. By enlarging the observation window, the Gaussian distribution of natural frequencies narrows around the more frequent value, which is approximately invariant with respect to the length of the viewing window. This gives proof of correct parameters identification. On the other hand, the damping ratio distribution become almost symmetric and narrows around the more frequent value that is got smaller. In addition, if the frequency stabilization criteria are selected as more restrictive for datasets with few measurements, two observations can be made. The first is that the number of sessions from which an estimate of the parameters is extracted is naturally lower. The second is that there is a narrowing of the scattering range of the two modal parameters and a translation of the more frequent value of the two distributions towards the one shown for data set with many recordings. Smallest is the uncertainty accepted, more the two curves resemble each other. This is proof of correct identification.

Concluding, an elevate number of measurements points allows to obtain accurate estimate and a reduced range of scattering for both parameters.

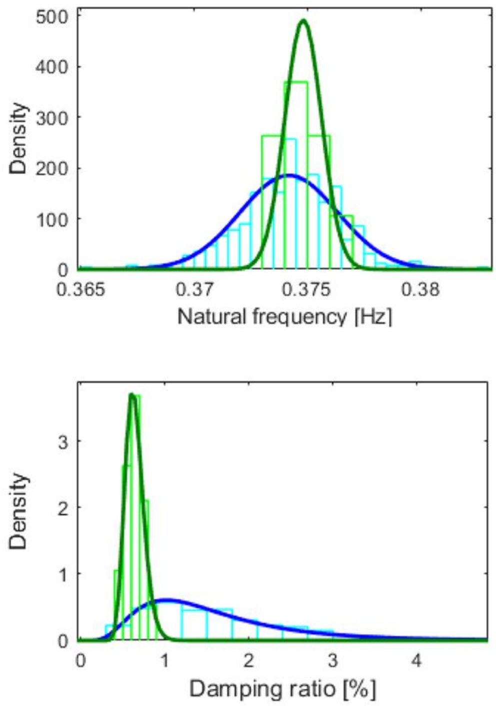

Fig.12 Normal distribution of the first natural frequency-lognormal distribution of the first damping ratio

Table 4 Indices of the first natural frequency distribution (large data set)

Position indexes	
mean	0.3748 [Hz]
median	0.3748[Hz]
Dispersion indexes	
Range	0.0024[Hz]
Variance	6.58E-7[Hz]
CV	2.16 E-3

Table 5 *Indices of the first damping ratio distribution (large data set)*

Position indexes	
mean	0.64 [%]
median	0.63 [%]
mode	0.61[%]
Dispersion indexes	
Range	0.44 [%]
Variance	0.01 [%]

As mentioned in Sect. 4.1, a way to improve the quality of modal parameters estimation is the reference-based stochastic subspace identification. This analysis can be activated in ARTeMIS through the pre-treatment function "project channel". Analysing short data sets, the obtained outcomes show a reduction of the amplitude of scattering range of both first mode modal parameters. Compared to results obtained without this technique, the amplitude of range is about 46% and 40% for first natural frequency and damping ratio, respectively. Nevertheless, the range of damping ratio still results wide and the uncertainty affecting each estimate in terms of CV seems to have a little decrease for natural frequency and an increase for damping ratio. Ultimately, the results obtained with this technique for narrow viewing window are not satisfactory. The same analysis, applied to large viewing windows, did not show significant benefits.

In conclusions, for an accurate estimate and reduced range of scattering, the use of a wide set of data has emerged as unavoidable. In this case, the minimum and the maximum value of range for first natural frequency is equal to 0.3736Hz and 0.3761 Hz, whereas for first mode damping ratio, it spans from 0.4204 to 0.8656%.

5.3 Validation

Validation of the results from SSI-UPCX method, for large data sets and first mode, has been performed by comparison to the findings derived from EFDD method.

Using the latter, the mode value of natural frequency distribution undergoes a slight increase, approximatively 0.1%. On the other hand, the mode value of the damping ratio distribution is affected by a decrease of about 6%. The dispersion around the mean value for the two methods is about the same both for natural frequency and damping ratio.

As regards mode shapes, the comparison between the outcomes obtained from the two methods has been accomplished by means of modal assurance criterion. This index is more than 90% in all cases. It is greater than 99% in 79% of cases, between 97% and 99% in 16% of cases, and less than 97% in 5% of cases. In conclusion, there is a positive validation of the results as the variations between the outcomes of the two methods are very low for all the three modal parameters.

6. Dependence of structural modal characteristics on operational and environmental factors

After noticing the variability of the results for the various measurement sessions, it is useful to investigate about the origin of this variability.

First, it is essential to realize if each single estimate has a high accuracy or not. If its uncertainty is too high, it must be deleted from the analysis. Second, as significant structural deterioration and/or degradation cannot be present, being the bridge just built and with no design issues, it is important to understand if the changes in modal parameters are due to environmental and/or operational factors.

While structural deterioration implies abnormal changes in dynamic behaviour, environmental factors (temperature, humidity, rain, and wind) mean normal changes of it [25]. For large civil structures, such as bridges, where the application of output-only analysis is widespread, the recognition and the consequent filtering of environmental effects are of paramount importance [26], especially for identification of closely spaced modes.

For steel structures like the one at hand, amongst environmental factors, temperature is the most influential. For this reason, the behaviour of modal parameters with respect to temperature has been investigated. Literature presents several case studies in which the temperature effects on bridges are discussed [27].

Despite the influence that the temperature has on materials and structural systems is well recognized, its accurate quantitative evaluation is very difficult, also in consideration of its uneven distribution in the bridge structure. Indeed, temperature and environmental factors can produce significant variations in the monitored features, i.e., of an order of magnitude equal or greater than damage.

Consequently, the development of physical models is often set aside and a black box system identification approach is used. Examples in this sense are: the use of SVM for the Ting Kau Bridge [28] and the application of ARX model for the Z24 bridge [25].

To do a truthful structural health identification, so avoid false condition assessment, it is useful to quantify the shifting of modal parameters driven by temperature fluctuations [29].

Among the three modal parameters, mode shapes are known to be those less sensitive to environmental changes and, for this reason, their behaviour with respect to temperature changes will not be inquired. Conversely, natural frequencies are the most sensitive [30].

6.1 Preliminary study: annual trend

A preliminary study to detect how temperature affects structural modes has been carried out analysing the annual trend. First, a temperature is associated to each accelerometric acquisition. The temperature at the time of the accelerometric measurements is determined from linear interpolation of the bridge surface temperatures measured by the system at intervals of 1 h. Second, the monthly average temperature of the measurements has been calculated. In Fig. 13a, the temperature at the time of accelerometric measurements (circles) and the average monthly temperature (diamonds) are depicted. The evaluated modal parameters of the first mode and the estimation errors for SSI-UPCX method are displayed in Fig. 13b, c. It is clear that there is an opposite trend of the first natural frequency with respect to the temperature. Consequently, the highest first natural frequencies have been found in the colder months and vice versa. In the present case, the observed maximum variation in the values of the first natural frequency is of the order of 0.6% and is much lower than the estimated variation (5-10%) for highway bridges of large span (100 m or longer) [29]. Indeed, this latter variation is often so high to overcome the changes caused by damages [31].

As regards the damping ratio, it is knotty to see a correlation with temperature, possibly because of its intrinsic more uncertain determination. In fact, the average-damping ratio shows an oscillating trend and, observing its error estimates, the results are basically superposed.

To compare the results between the two adopted analysis methods, in Fig. 13, the plot in green is relative to the results obtained with the EFDD method, while the

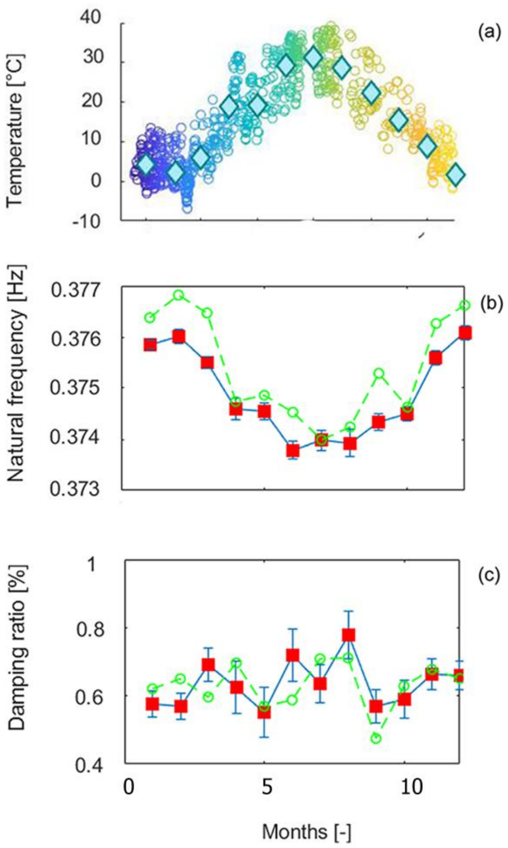

Fig.13 a. Temperature in time and average monthly temperature**. b, c.** Monthly modal parameters and estimation error for the first mode

blue graph has been obtained by DD-SSI-UPCX. With the EFDD method, the results are qualitatively similar to DD-SSI-UPCX method: the dependence of the first frequency on temperature is confirmed, while damping has a not clear relationship.

6.2 Study of structural behaviour for temperature range

From the first results on the connection between the vibrational first-mode frequency of the structure and temperature emerged in the previous Sect. 6.1, a more in-depth study has been carried out.

In particular, the behaviour of the first natural frequency and damping ratio for temperature ranges has been analysed by defining 23 temperature bands to examine the trend of the signals.

Each band has a span of about 3°C. Figure 14 shows two plots, the first in terms of natural frequency and the second in terms of damping ratio, versus the mean temperature of each bands and a linear weighted fit of the trend. To take into account the accuracy of the points, weights equal to the reciprocals of estimation variances have been used.

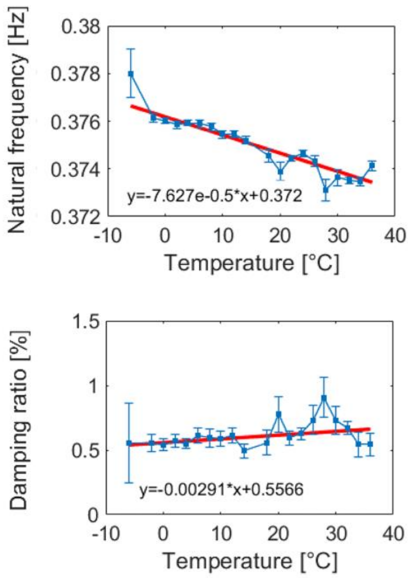

Fig.14 Trend of the first modal parameters for 23 ranges of temperature.

Table 6 and 7 synthesize the statistic indices that describe the linear fit. The indices SSE (sum squared error, which measures the total deviation of the actual values from the fit) and RMSE (root mean squared error or standard error, which is an estimate of the standard deviation of the random component in the data) are markedly smaller for the fit of first natural frequencies. Accordingly, the trend of first natural frequency can be

considered to be clearly descending as the temperature increases with a slope of 0.0762‰.
This effect seems to be more pronounced if the temperature is below the freezing point.

Table 6 *Indices of linear fit for the first natural frequency*

SSE	R-Square	Adj R-sq	RMSE
0.0107	0.8964	0.8907	0.0244

Table 7 *Indices of linear fit for the first damping ratio*

SSE	R-Square	Adj R-sq	RMSE
1.4026	0.1989	0.1544	0.2791

This kind of behaviour agrees with what has been reported on other studies [32-34]. On the other hand, the damping ratio behaviour cannot be considered effectively increasing, since the deviation from the linear trend line, remarked by the indices, is too high.

6.3 Determination of modes

The natural frequencies values range has a minimum of about 0.3 Hz and a maximum of about 3 Hz. However, the fundamental structural modes for the structure are grouped in the first half of this range. Through the Modal Assurance Criterion (MAC) it is possible to quantify the similarity between the various modal shapes [35]. A zoom on the natural frequencies of interest has been done. The MAC index highlights the fact that higher modes have a trickier mode shape as they show similarities to lower modes. By observing the tracks of modes (see Sect. 5) represented by red lines in Fig. 16, the similarity of some mode shapes corresponding to modes with different natural frequencies can be also inferenced. Indeed, these tracks/links display a cross trend among them.
In particular, for large data sets, the similarity between the fifth and sixth modes stands out, Fig. 15.

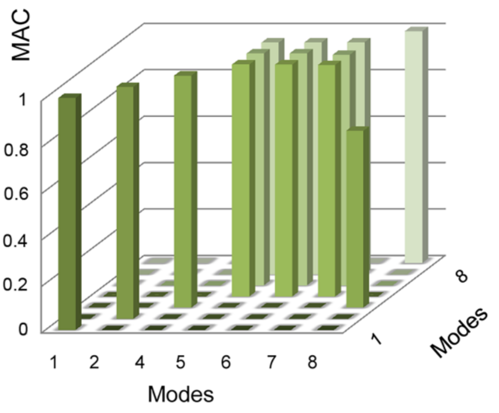

Fig.15 Modal Assurance criterion-MAC plot

This last corresponds to the second large data set in Fig.16 where the third mode is not present.
Another observation can be done by analysing the MAC graph of a session where the identification of the third mode is present (e.g., sixth session in Fig.16). In this case, the MAC index shows strong correspondences between this and the first mode.
In general, the components of mode shapes have a real and an imaginary part. Real values correspond to the proportional nature of the damping ratio. The complex part can be due to:

- Non-proportional damping
- Poor measurements or/and poor modal parameter estimation
- Uneven data

To understand which components of mode shape are real and which are imaginary, it is possible to refer to the complexity plot. This graph shows, in the complex plan, each components of the mode shape with a tip of a vector starting from zero. On the horizontal axis there is the real part of the component, while on the vertical one, there is the imaginary part. The complexity is described by the vertical component.
For large data sets, all modes, except for the third in an accentuated manner and the fourth and eighth in a moderate way, have a very low factor of complexity. Thus, most modes are almost completely real, confirming that they do not stem from numerical artefacts. For the natural frequencies of interest, a tracking of their evolution in function of the available sessions, with the natural frequency and the damping ratio of reference modes is reported in Fig. 16. The graph shows the modes that are part of the track (continuous red line) with fully visible dots. The dots in transparency, instead, are external to the track. The dashed blue line has been used a posteriori to simply highlight the dots of the third mode.
Finally, considering the not perfect synchronization of the accelerometer readings in the data acquisition system (estimated in max 10 ms), a check of the possible phase error effects has been made. Referring to the names of the nodes in Fig. 5, the obtained results have been compared by considering various combinations of the available channels.
The results carried out by using the channels on nodes in the list below have been analysed and compared with those obtained using all channels.
- N.1
- N.1 and N.2
- N.1 and N.4
- N.1 and N.3

From this analysis it emerges that mode 6 is captured only if all channels are used. The use of a part of the channels with respect to the whole of them implies an

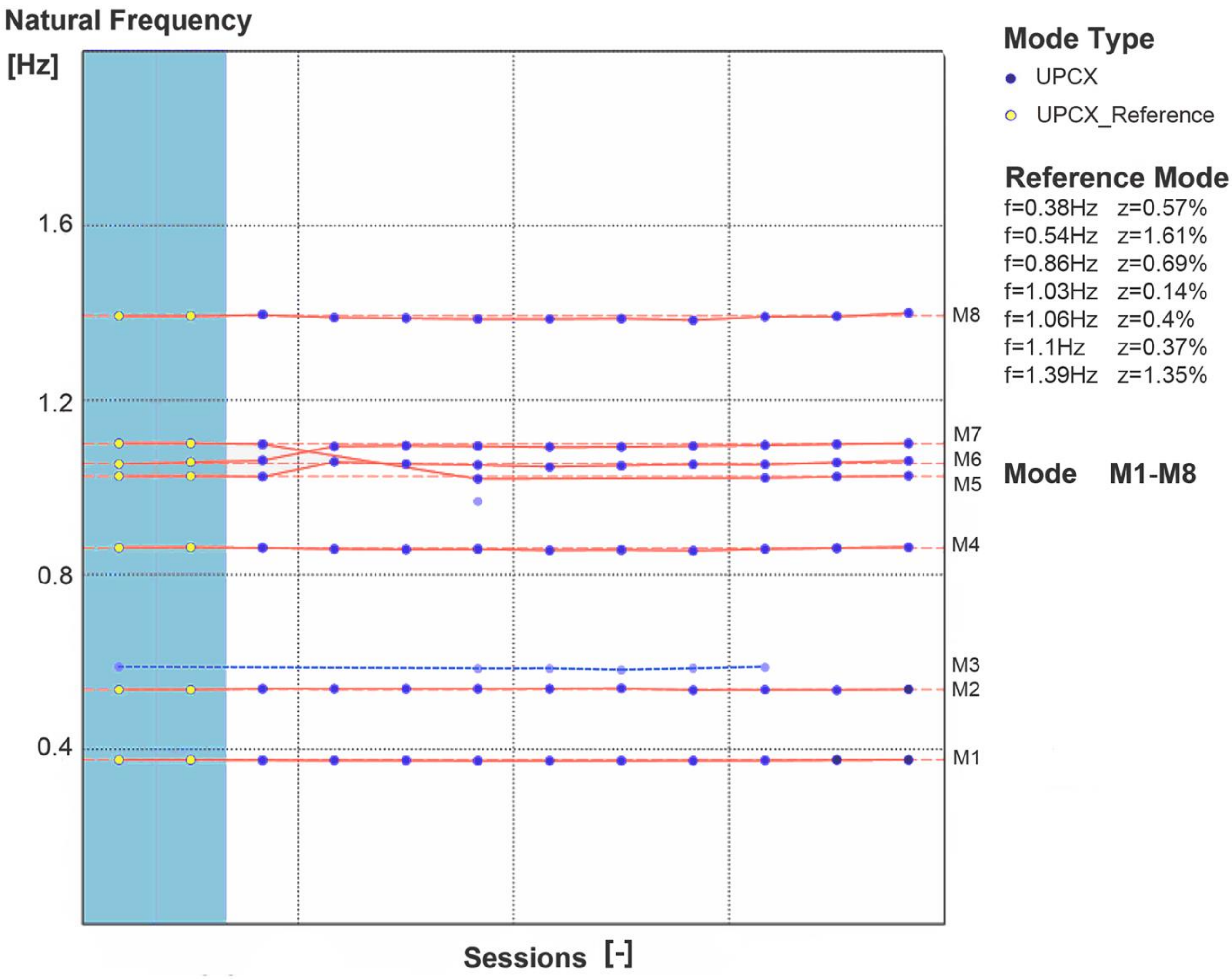

Fig.16 Natural frequency history (12 sessions belonging to the same year)

increase of the frequency of the first mode with a maximum relative variation equal to 1.77‰.

The absolute variation involves the fourth digit after comma. This order of magnitude is equal to the frequency uncertainty magnitude order in terms of standard deviation. More specifically, the ratio between the absolute variation and the standard deviation is, on average, equal to 3.

As regards the damping ratio of the first mode, the absolute variation involves the first digit after comma. The ratio between the absolute variation and the standard deviation (corresponding to the results of combination with all channels) is, on average, equal to 3.

Referring to the dispersion range of the first mode obtained for the 12 data set (Sect. 6.1, Fig.13b, c) using all channels, it is noted that:

- The maximum frequency reached using part of the channels slightly exceeds (fourth digit after comma) the maximum of this range.
- The minimum damping ratio reached using part of the channels is very close to the minimum of this range.

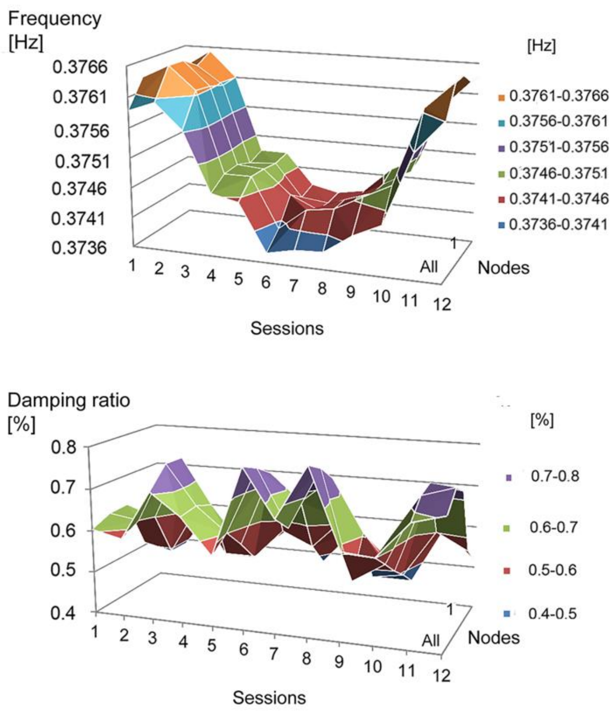

Fig.17 First natural frequency and damping ratio in function of measurement sessions and used channels

Concluding, the error due to non-perfect synchronisation can be considered negligible to correctly identify the vibration modes.
Figure 17 shows the trend of the first natural frequency and damping ratio with respect to the sessions and to the considered channel nodes previously listed.

The mode shapes for the modes found by ARTeMIS, except the third (due to its high complexity) and the sixth (present only with the use of all channels, showing strong similarity with the modal shape of the fifth mode and not corresponding to a marked peak of the singular value decomposition), are depicted in Fig. 18.

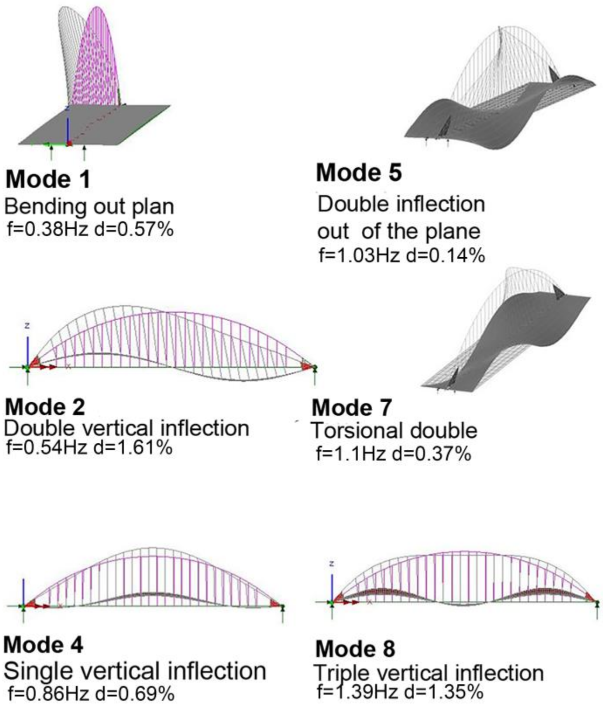

Fig.18 Vibration modes(Reference modal parameters from SSI-UPCX method)

Conclusions

This paper examines the dynamic data provided during the initial calibration period of a long-term monitoring system on a suspended arch steel bridge.
The work is focused on the vibrational characteristics that can be extrapolated from dynamic monitoring by employing ARTeMIS DD-SSI-UPCX method. For the sake of verification, a complementary approach using EFDD method has been employed as well, and the results coherence has been verified. The dynamic identification has been performed through the response of the structure in terms of accelerations (output-only techniques). The measurement sessions processing allowed estimating a modal parameter uncertainty window. Of course, this is closely related to the uncertainty of the modal parameter estimate for each session. Among the factors affecting the estimate stands out the length of the examined dataset in terms of number of records. The frequency estimation shows small errors, whereas the damping estimation is jeopardised by large errors. In particular, as reported by the literature, errors are larger for smaller datasets, confirming that, to obtain a narrow range of scattering, it is essential to have a significant number of points per observation.
Finally, the dependence from the temperature of the parameters of the first mode of vibration is analysed. The natural frequency shows a marked sensitivity with respect to the temperature. A downward trend of the natural frequency as the temperature increases has been found. A linear law seems to be able to describe this behaviour within the analysed temperature range. On the other hand, the damping ratio has no clear relationship with temperature.
The provided results can be useful to estimate the normal range of variation of identified modal parameters in the long term and with the action of environmental effects for a structure that is certainly unaffected by any damage, being the measurements taken when the bridge was just built. These windows of modal parameters variation can be useful when minimum structural damage detection capability is investigated.

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