A large scale SHM system: a case study on pre-stressed bridge and cloud architecture

Gabriele Bertagnoli[1], Francescantonio Lucà[2], Marzia Malavisi[1], Diego Melpignano[3], Alfredo Cigada[2]

[1] Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, 10121 Torino, Italy

[2] Department of Mechanical Engineering, Politecnico di Milano, 20158 Milano, Italy

3 STMicroelectronics, 20864 Agrate Brianza, Italy

ABSTRACT

In recent decades, external prestressing is increasingly being used especially in motorway and railway bridge structures due to the substantial savings in terms of construction time and costs. In such systems, internal and external steel tendons work together with concrete elements to withstand external actions. This means that the deterioration or failure of these elements reduces structural safety in a meaningful way. Real time monitoring of prestressing tendons can provide useful information on the health of the bridge under service loads, detecting possible fatigue, corrosion and damage / deterioration processes. However, most of the currently used structural monitoring systems are rather expensive and time consuming to install.

Although many papers address high density sensing as the proper solution thanks to the “internet of things” tool, both for hardware and software, there are not so many applications in which this approach is really put into service.

This paper describes the application of MEMS accelerometers in a high performance and cost-effective SHM system for bridge structures. In particular, data from a real time monitoring system installed in a box section composite highway bridge are presented. The external tendons of this bridge have been instrumented with a total number of 88 triaxial accelerometers. Changes in the dynamic characteristics of the monitored elements have been analyzed by detecting the shift in tendons’ dynamic behavior. The main challenge was collecting a huge amount of data and find a way to properly process them, not requiring the operator’s direct action, unless the observed situation is out of the “normal” scenario. For this purpose, simple but easy-to-implement specific data processing algorithms have been tested in order to check the real feasibility of such a SHM system first, and then to analyze the collected sensor data and provide an efficient real time damage detection.

Keywords: SHM, Bridge, MEMS sensors, Prestressing tendons, Structural dynamics

INTRODUCTION

External prestressing is largely used in civil engineering and especially in bridges design to improve concrete performances by forcing the structure to be in a state of full compression through the use of multiwire steel tendons [1], [2]. As highlighted by some researches [3], [4], the damage or collapse of these elements could induce serious consequences for the integrity of the entire structure, which makes critically important the monitoring of tendons health condition. Thus, being able to assess the state of the tendons may grant higher safety levels for the users and a more efficient maintenance.

The research field that deals with the development of automatic strategies for damage detection is part of Structural Health Monitoring (SHM) [5]. Driven by the rapid development of more accurate and cost-efficient sensors, data acquisition systems and Internet of Things (IoT) architectures, an increasingly number of operating structures are being equipped with SHM systems [6]–[9], continuously getting data from the structures being monitored. Thus, the main challenge is extracting the useful information from a very big amount of data, synthesizing it in few indicators (or features) that could help assessing the integrity of a structure.

Considering the specific case of pre-stressed bridge monitoring, a large number of SHM methodologies and systems have been proposed by many researchers over the years. Several examples of SHM implementation can be found in [10]–[17]. Among the possible strategies, a lot of interest is being paid to the vibration-based methods: the basic idea is that if a change in the structural properties occurs, it affects the modal parameters of the structure (natural frequencies, mode shapes and damping ratios). Thus, monitoring the trend in time of the natural frequencies may represent an effective strategy able to highlight changing in the tension of the tendons, caused by fatigue, corrosion and deterioration processes [18], [19]. Some specific sensors also offer the chance of measuring different quantities like vibration and rotation at the same time: in this case the information merge (sensor fusion) can be quite useful to have a cross check helping to assess data reliability.

In this work, an application of SHM to a real operating bridge is described. The structure under examination, is being monitored 24 hours a day seven days a week since September 2017. Vibration signals are acquired by a network of 88 MEMS tri-axial accelerometers placed on the tendons; these are g-sensitive and this property can be also exploited to use them as clinometer. After a pre-processing, data are sent, stored, and processed in an IoT Cloud that allows real time access to data and their management in a simple though effective form. As a feasibility study, attention has not been paid to the algorithms (the choice has been for those easiest to implement, with the literature known limits [20]), rather to the network management and to the quality of data through the measurement chain, from the accelerometer performances to those of the network up to the cloud.

A database of the statistical features and the natural frequencies for every cable has been therefore continuously updated since the system was put in operation, representing an interesting case study in how the issues of big data management in a SHM perspective can be overcome through the integration of IoT technologies. The results related to the first eight months of operation are synthetically shown in this paper.

BRIDGE DESCRIPTION

The monitored structure is a highway concrete bridge located in Italy. The bridge, opened to traffic in 2006, is a composite box girder in which the concrete webs are replaced with corrugate steel plates to reduce the self-weight and simplify the construction. Mixed prestressing (internal/external) was used to strengthen the structure. Two abutments are supporting the bridge at the end points and five concrete piers clamped into the girder are holding up the 6 spans. The bridge is 580 m long and it is characterized by five equally spaced (120 m) hyperstatic spans and one isostatic span 43m long. The main girder has a cross-section height varying from 6.0 m (at the bearings) to 3.0 m (on the centerline of each span). The structural details of the bridge are shown in Figure 1.

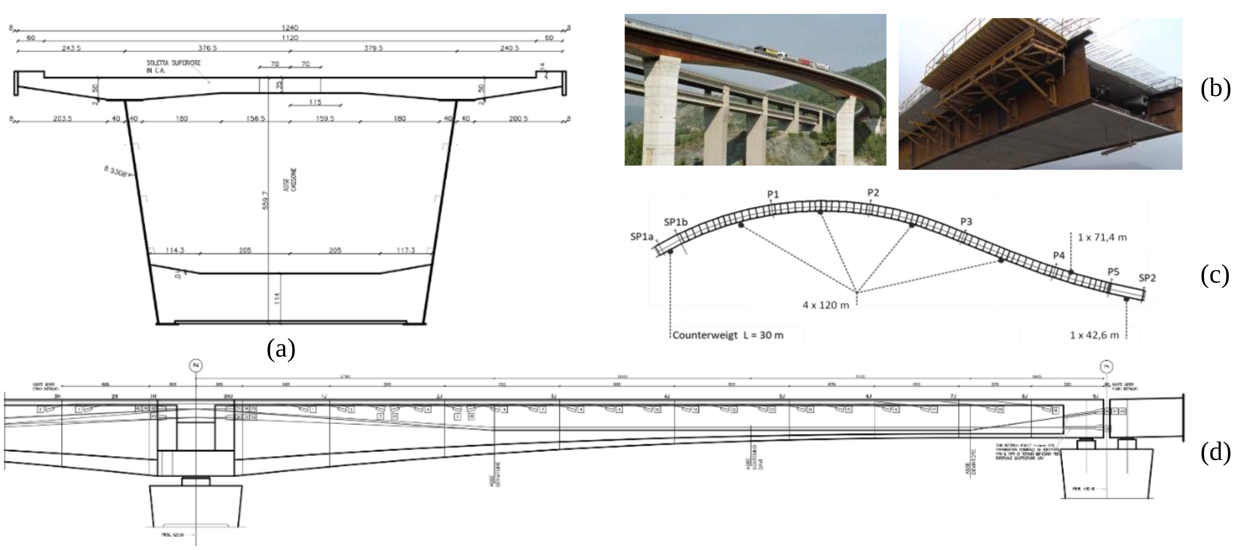


Figure 1. Structural drawings of the bridge. (a) Bridge cross-section; (b) bridge images after and during construction; (c) plan view of the highway bridge; (d) longitudinal section of a span.

The pre-stress of the structure is provided by means of bonded tendons arranged in the upper flanges of concrete slab and unbonded external tendons composed of 27 strands placed in the hollow section of the box girder.

The bridge was instrumented with a continuous monitoring system for the real-time detection of the tendon condition during the service life of the structure. The monitoring was instigated to check the behavior of external tendons after a failure of one tendon, probably due to an incorrect grout composition and in spite of checking the effects of the heavy daily traffic traveling on the bridge. Hence, in order to better understand the dynamic response of the bridge under operational conditions, external tendons were instrumented with 88 MEMS tri-axial accelerometers, 2 for each monitored tendon, between June and September 2017, the complete system being fully active since 20 September 2017.

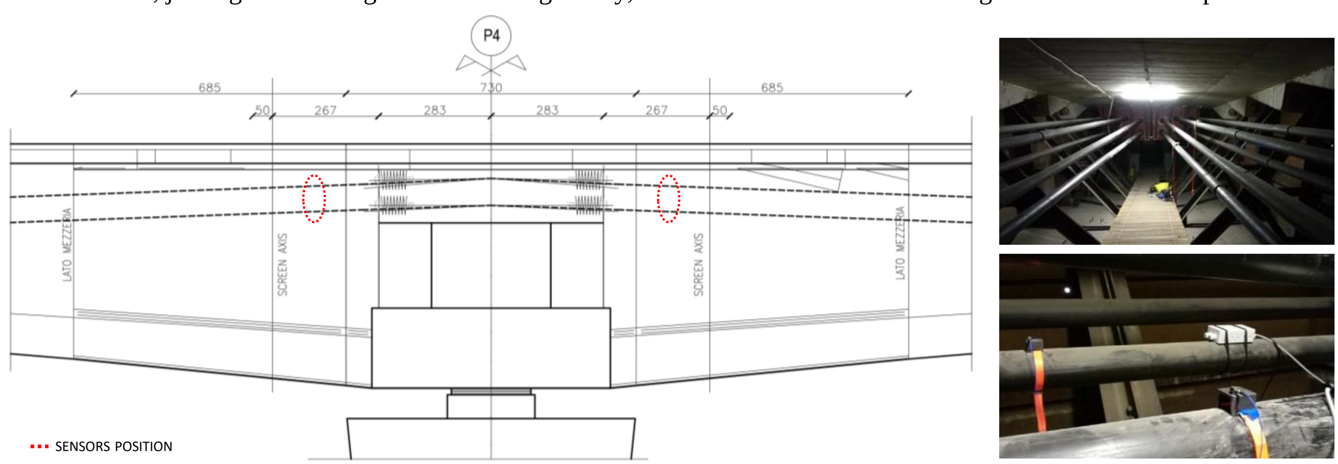
Each tri-axial MEMS accelerometer provides data in the 3 orthogonal directions (x, y, z); in this way it is possible to capture the bridge vibration and deformation under traffic excitations and to obtain some dynamic parameters. Environmental data, such as air temperature and humidity, have been collected in order to remove the effect of these parameters (especially temperature) in vibration measurements and trace measured data back to a constant value of temperature.

MONITORING SYSTEM

The accelerometers were mounted in 10 different cross-sections, close to the steel protection screens in the upper part of the prestressing cables, as shown in Figure 2.

A long lasting preliminary experimentation has allowed to assess that the accelerometer performances were fit for this kind of measurement, due to the high excitation especially produced by the heavy traffic travelling on the bridge day and night, with just a small reduction during the weekends. As MEMS accelerometers are g sensitive they can be used “twofold”, both as accelerometers and clinometers: the fusion of these information can help detecting any ongoing damage: this could turn into both a change in the cable dynamic performances or in its attitude. Then the main problems to be faced were then the maximum data streaming rate, a real bottleneck when working with accelerometers, then, in turn, the maximum allowable sampling rate per channel.

The sensor alone was “updated” to a sensor node, including a microcontroller providing data sampling and some elementary management, ready for any further “edge” computing strategy. In addition, the node encodes the sampled data into a CAN BUS driven network, joining and sending data to a local gateway, which also can offer some storage and calculation capabilities.



(a) (b)

Figure 2. Layout of the monitoring system. (a) Typical sensors position; (b) MEMS Accelerometers installed on the external steel tendons

The monitoring system is connected to the internet via a 5 GHz point-to-point Wi-Fi link between an access point located at one end of the bridge and an "Ubiquity Nano M5" station located at the P2 pier, halfway between the viaduct ends. An Ethernet cable connects the station to the two IoT gateways installed in the bridge: one for the right side and one for the left side. All the sensors are connected to these gateways, which, through the described path, send data to a specific cloud platform.

The 88 acceleration time series as well as temperature and humidity data are stored in a cloud monitoring infrastructure which allows access to data in real time. The maximum sampling rate allowed by the encoding procedure has been 100 Hz. To prevent from aliasing data are sampled at the sensor level at 25.6 kHz, then filtered and down sampled at the sensor node, to make the data streaming manageable by the network. Some preliminary tests have shown that the final allowed bandwidth, in the order of 40 Hz, can be considered enough to get any eventual damage detection.

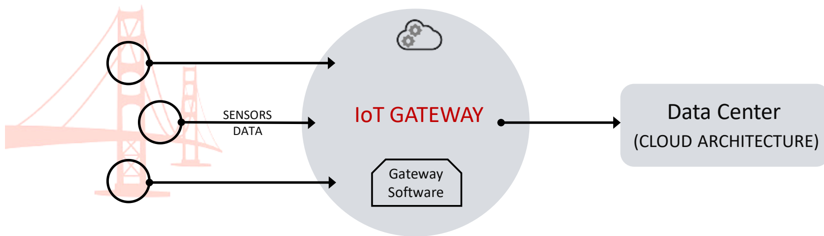


Figure 3. Gateway architectural overview

Before performing any modal identification analysis, sensors data are pre-processed in order to make the monitoring architecture more effective in terms of performance and network use. In particular, the IoT gateway performs the pre-processing of information before they're sent to the data center. The software installed on the device is indeed dedicated to collect data from sensors, pre-process that data, and sending the results to the cloud.

Pre-processing is especially aimed at filtering acceleration data, in order to detect unusual patterns that do not conform to the expected behavior (outliers) and to generate anomaly alert messages when needed. In particular, data for a selected time span are analyzed by calculating the average (AVG), root-mean-square (RMS) and minimum/maximum (MIN/MAX) values on interval-by-interval basis. The obtained interval statistics are then compared with preset thresholds.

Data from sensors are then sent, stored, and processed in a IoT Cloud platform. The main challenge was to elaborate a huge amount of data in the shortest time by using cloud resources at best. Taking advantage of the high parallelism (up to 1000 simultaneous executions), data composed by time series of length T seconds can be subdivided in m slot of T_W seconds such that the algorithm can elaborate a slice of data with low time and memory consumption.

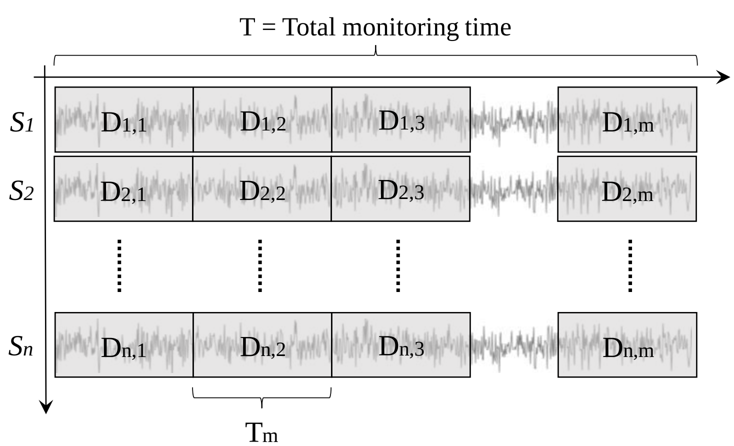


Figure 4. Time discretization. $S_1 \ldots S_n$ represent readings from the n sensors over a time length T. Each column corresponds to one of the m time slot of length T_W. This subdivision create a grid of n x m dataset slices $D_{i,j}$ where $i \in \{1, \ldots, n\}$ and $j \in \{1, \ldots, m\}$.

Although the parallelism provided by the IoT cloud is considerable, in order to save memory and time, the dataset is analyzed by a sequencing rule ordering the invocation of an action. Each performed action involves the steps of:

- download a dataset slice $D_{i,j}$ identified by some calculated input parameters;
- elaborate the dataset;
- upload elaboration results in a pre-determined location;

- invoke next action (with its input parameters) or terminate the sequence.

Figure 4 shows the time discretization scheme.

The static and dynamic parameter identification is thus performed for each interval time dataset slice $D_{i,j}$, lasting 30 minutes.

Even if some simple evaluations on the mean value, i.e. the actual cable position could be easily evaluated, the aim of this activity was to stress the system when dealing with a denser and intense data management, typical of dynamic analyses.

THE ADOPTED STRATEGY

Since the signals are of random nature, the power spectral density (PSD) of the acceleration signals represents the starting point for the analysis in the frequency domain. In order to improve the accuracy of the parameter identification, the best balance between noise reduction and a good frequency resolution has been obtained by means of some preliminary tests carried out with lab instrumentation, made up of low noise piezo accelerometers, a data acquisition board with 24 bit and a sampling frequency of 2048 Hz. These tests have allowed to get that first of all measurements on the pre-stressed tendon sheaths were meaningful in the description of the cable behavior, then some fine tuning has allowed to fix the best choices for a series of parameters: sub-records of 200 s and an overlap of 66% (Hanning window) have proven to be the best compromise between the need to average data for a better signal to noise ratio, at the same time preserving almost constant temperature and insolation conditions, affecting the dynamic parameters. An example of the shape of the PSD is shown in Figure 5, where it is in general possible to identify the peaks related to the modes of the considered tendon.

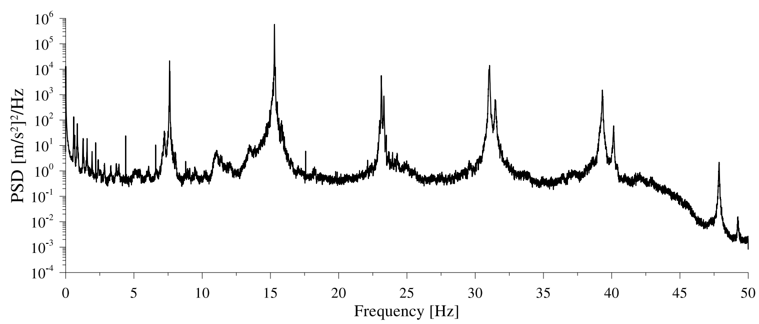


Figure 5. Power spectral density (PSD) of the signal measured by one of the 88 accelerometers installed on the bridge.

As this was a first approach, though being conscious about its limits [20]–[22], it has been decided to analyze damage in terms of natural frequency changes. Natural frequency changes have therefore been considered as the significant parameters to assess the damage of the pre-stressed cables: as stated attention was mainly paid to the possibility to apply this approach to a wide number of cables, exploiting the big amount of data both concerning the trend evolution of a single cable and a cross check among adjacent cables. In the case of cables injected with cement grout, only changes due to stiffness decrease are considered, since no mass losses are possible.

As well known the natural frequencies f_i for the cable vibration modes are derived as:

$$f_i = \frac{1}{2L_i}\sqrt{\frac{T_i}{m_i}}$$

where m_i, L_i and T_i are respectively the mass, length and axial force of the cable.

In the case of strand failure, the cross section of the tendon and consequently the corresponding axial force are reduced. As a consequence, a frequency shift should be observed.

Each frequency peak of the PSD can thus be used as a feature for damage detection. A peak identification algorithm has been developed in order to identify peaks in signal spectrum without prior knowledge on their number, shape or location. The variation of the frequency peaks over time has been then evaluated for each sensor. An experiment about a possible approach of edge computing has also been carried out by providing a synthesis over each considered window, including RMS, mean, max value and min value: this solution means a high data compression. As the traffic conditions over long time records are similar (at least considering working days), any trend in the RMS value can be considered a damage indicator, a change in the average is a change in the cable position, while this value, joined to the info from the max and min value are a sensor diagnostic indicator.

RESULTS AND DISCUSSION

This section summarizes the results obtained from the large-scale monitoring system installed on the pre-stressed concrete bridge described in the previous paragraphs. In particular, experimental results obtained under normal traffic operation are presented here. The traffic is mainly composed of passenger cars as well as small and heavy trucks.

Statistical identification of standard trends is essential for handling large amounts of data while detecting changes and deviations over the monitoring time. The process of trend recognition has been carried out in the time domain first, by using mean and standard deviation values. In particular, for each measured direction (x, y, z), the signal has been pre-processed by applying a high pass filter. Mean (μ) and standard deviation (σ) values have been then obtained from the filtered data. Standard deviation has been considered as a good indicator of the average vibration activity induced by traffic loads, wind and/or other external agents under standard or exceptional conditions. In addition, maximum and minimum values have been considered as relevant for detecting possible anomalous behaviors of the tendons.

Figure 6 shows the variation of the aforementioned parameters (mean, 5% fractile which corresponds to $\mu \pm 1.64\sigma$, maximum and minimum acceleration values) for the three measured directions (x, y, z) of a sample sensor, named "sensor A", calculated over a time period of 24 hours. A variable time window T_w of one minute has been considered for the evaluation of daily trends.

From Figure 6, it can be seen that the average acceleration value for the three directions is close to zero, resulting from an average of periodic and almost symmetrical oscillations of the cable to which the mean values has been subtracted.

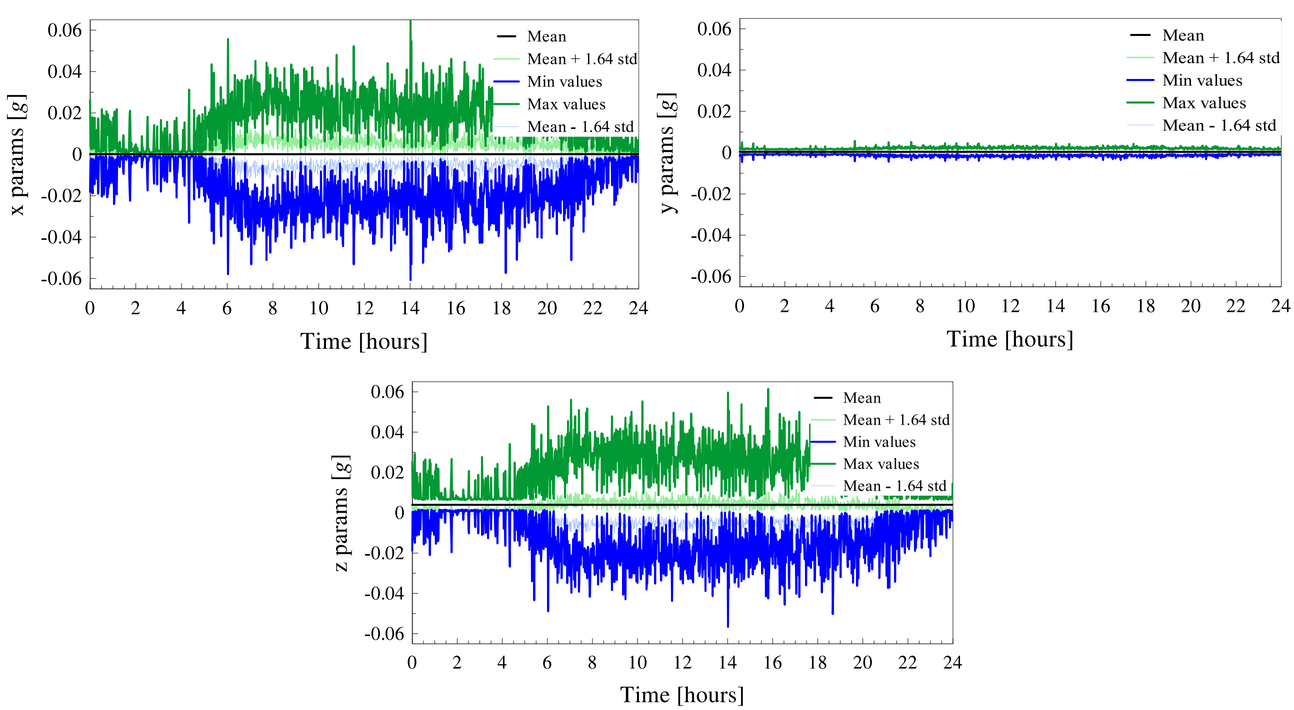


Figure 6. Daily trends calculated for the three monitored directions x, y, z – "sensor A"

The day-night cycle is clearly recognized: the maximum vibrations are mainly recorded during the day hours (from 6 a.m. to 10 p.m.) with an appreciable decrease at night (from 10 p.m. to 6 a.m.). This trend is also easily identifiable from the 5% fractile plot, which represents the 5% probability of the vibration data to exceed, in absolute terms, the $\mu \pm 1.64\sigma$ values.

Moreover, Figure 6 shows markedly that the x and z axes are the most excited ones, with respect to the y axis. This is indicative of an elliptical vibration of the cable in the x-z plane, which is orthogonal to the longitudinal development of the tendons. Y-direction has in fact reduced vibration levels (one order of magnitude smaller than x and z directions), meaning that it has a lower sensitivity with respect to traffic variations and environmental noise.

The trend of the vibration signals has been evaluated also over longer periods, for instance a month (a period suitable to appreciate the situation, longer periods make it more difficult to identify the situation). Figure 7 illustrates the variation of the considered parameters (mean, 5% fractile which corresponds to $\mu \pm 1.64\sigma$, maximum and minimum acceleration values), calculated over a time period of 2 months, for the x direction. A variable time window T_w of 30 minutes has been considered for the evaluation of monthly trends.

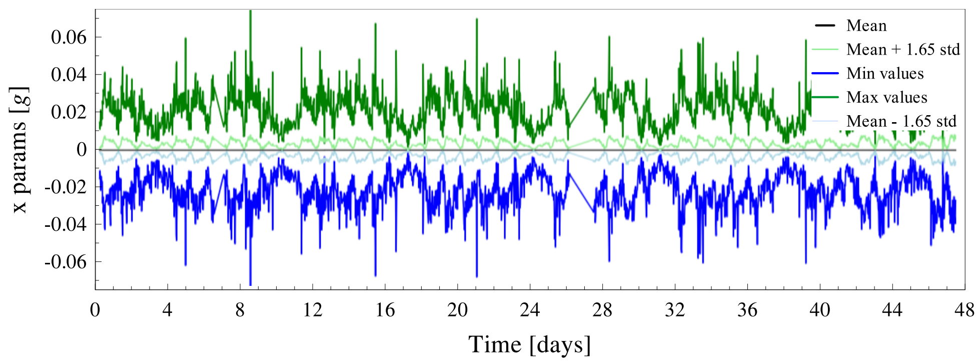
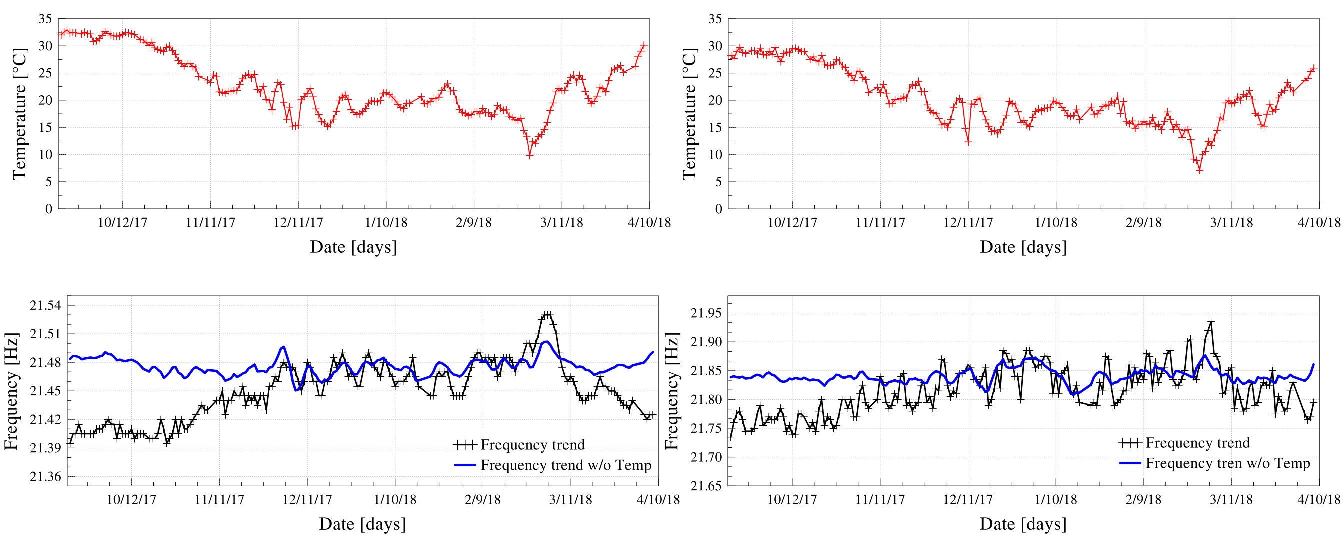


Figure 7. Monthly trend calculated for x direction – “sensor A”

Figure 7 displays the tendon vibration response under different traffic conditions. Indeed, a higher acceleration variation can be observed from Monday to Friday with a significant reduction in traffic during the weekend. The trends observed during the monitored period allowed for the definition of a benchmark of measurements corresponding to the standard behavior of pre-stressing tendons subject to traffic conditions or non-exceptional external loads.

Together with the time domain outputs, in order to perform damage detection, the identification of standard trends has been performed by carrying out also analyses in frequency domain, meaning a heavier load for the gateway/cloud system.



(a) (b)

Figure 8. Temperature and Frequency variation over time for two sample sensors. (a) Sensor A; (b) Sensor B

In particular, the variation of frequency peaks over the entire monitoring period has been obtained. Since damage detection is accomplished by comparing frequency values that are obtained at different times, it is essential to remove any environmental influences affecting the considered parameters. In fact, natural frequencies are strongly dependent from temperature changes. Figure 8 represents a time frequency plot with the corresponding temperature readings for two sample sensor, named sensor "A" and sensor "B". All the detected peaks are symbolized by small black crosses and are tracked over a 8 months period.

By comparing temperature and frequency trends, it is possible to observe that there is an explicit inverse correlation between them over the monitored period. Some noise on the peaks leads to the spread in the observed values, especially for sensor B. As this sometimes make it harder to identify the peak position, a smoothing procedure around the peaks has been carried out by means of a polynomial, to help keeping an automatic peak identification procedure. Anyway, for both sensors, frequency increases from September 2017 to February 2108, when temperature falls, and decreases from February 2018 to April 2018, when temperature starts rising. A standard regression analysis has been performed to assess the relationship between temperature and frequency evolution. The influence of temperature was therefore removed by the trend of frequency variation by applying the calculated regression coefficients.

The resulting trend, plotted in blue in Figure 8, is almost constant for the entire monitored period. Moreover, it could be noted that no particular anomalies in peaks evolution have been observed over time. All the frequencies are included in a small variation range, without values clearly outside the normal oscillations around a constant mean value.

CONCLUSION

This paper presents results from a permanent dynamic monitoring for the real-time assessment of the health of a structure. In particular, a widespread, innovative and minimally invasive monitoring system has been installed on a concrete highway bridge in Italy. The peculiarity of the system lies in being composed of low-cost sensors based mainly on MEMS technology, capable of monitoring various physical quantities, and connected to each other with different technologies for data transfer and sensor power supply. A IoT cloud architecture has been developed to process in short time a huge amount of data in order to synthesize with few parameters the most relevant information about the behavior of the structure. Time domain analysis have been carried out to highlight some significant standard trends in order to identify threshold values for the generation of alerts in case of anomalies. Then, frequency domain approach has been implemented for determining a frequency domain model of the structure to use for damage identification. In particular, power spectrum peaks have been extracted from sensor signals and variations in frequency values have been evaluated over the monitored period. A strong and evident inverse correlation with temperature was observed, whose effect was eliminated through a linear regression analysis.

REFERENCES

[1] J. Combault, “Long Span Concrete Bridges: Influence of construction techniques,” *Proc., IABSE Symp. Int. Assoc. Bridg. Struct. Eng. Zu¨rich, Switz.*, vol. Proc., IAB, 1991.

[2] A. Miyamoto, K. Tei, H. Nakamura, and J. W. Bull, “Behavior of Prestressed Beam Strengthened with External Tendons,” *J. Struct. Eng.*, vol. 126, no. 9, pp. 1033–1044, 2000.

[3] U. Starossek, “Progressive Collapse of Bridges - Aaspects of Analysis and Design,” *Int. Symp. Sea-Crossing Long-Span Bridg.*, pp. 1–22, 2006.

[4] R. J. Woodward, “Collapse of a Segmental Post-Tensioned Concrete Bridge,” 1985.

[5] C. R. Farrar and K. Worden, “An introduction to structural health monitoring,” *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 365, no. 1851, pp. 303–315, 2007.

[6] C. J. A. Tokognon, B. Gao, G. Y. Tian, and Y. Yan, “Structural Health Monitoring Framework Based on Internet of Things: A Survey,” *IEEE Internet Things J.*, vol. 7, no. 4, pp. 4–7, 2017.

[7] F. Lamonaca, P. F. Sciammarella, C. Scuro, D. L. Carni, and R. S. Olivito, “Internet of Things for Structural Health Monitoring,” *2018 Work. Metrol. Ind. 4.0 IoT*, pp. 95–100, 2018.

[8] C. Cremona, “Big data and structural health monitoring,” *IABSE Congr. Stock.*, no. October, 2016.

[9] H.-N. Li, L. Ren, Z.-G. Jia, T.-H. Yi, and D.-S. Li, “State-of-the-art in structural health monitoring of large and complex civil infrastructures,” *J. Civ. Struct. Heal. Monit.*, vol. 6, no. 1, pp. 3–16, Feb. 2016.

[10] I. N. Robertson, “Prediction of vertical deflections for a long-span prestressed concrete bridge structure,” *Eng. Struct.*, vol. 27, no. 12 SPEC. ISS., pp. 1820–1827, 2005.

[11] A. Nair and C. S. Cai, “Acoustic emission monitoring of bridges: Review and case studies,” *Eng. Struct.*, vol. 32, no. 6, pp. 1704–1714, 2010.

[12] J. R. Casas and P. J. S. Cruz, “Fiber Optic Sensors for Bridge Monitoring,” *J. Bridg. Eng.*, vol. 8, no. 6, pp. 362–373, 2003.

[13] J. Maeck and G. De Roeck, “Damage assessment using vibration analysis on the Z24-bridge,” *Mech. Syst. Signal Process.*, vol. 17, no. 1, pp. 133–142, 2003.

[14] S. Yuyama, K. Yokoyama, K. Niitani, M. Ohtsu, and T. Uomoto, “Detection and evaluation of failures in high-strength tendon of prestressed concrete bridges by acoustic emission,” *Constr. Build. Mater.*, vol. 21, no. 3, pp. 491–500, 2007.

[15] M. M. Reda Taha and J. Lucero, “Damage identification for structural health monitoring using fuzzy pattern recognition,” *Eng. Struct.*, vol. 27, no. 12 SPEC. ISS., pp. 1774–1783, 2005.

[16] G. T. Webb *et al.*, “Analysis of Structural Health Monitoring Data from Hammersmith Flyover,” *J. Bridg. Eng.*, vol. 19, no. 6, pp. 1–11, 2014.

[17] A. Cabboi, F. Magalhães, C. Gentile, and Á. Cunha, “Automated modal identification and tracking: Application to an iron arch bridge,” *Struct. Control Heal. Monit.*, vol. 24, no. 1, 2017.

[18] “Prestress Force Effect on Vibration Frequency of Concrete Bridges By M. Saiidi, l Member, ASCE, B. Douglas, 2 Member, ASCE, and S. Feng 3,” vol. 120, no. 7, pp. 2233–2241, 1994.

[19] J. Kim, Y. Ryu, and C. Yun, “Vibration-based method to detect prestress-loss in beam-type bridges,” *Smart Struct. Mater.*, vol. 5057, pp. 559–568, 2003.

[20] S. W. Doebling, C. R. Farrar, and M. B. Prime, “A summary review of vibration-based damage identification methods,” *Shock Vib. Dig.*, vol. 30, no. 2, pp. 91–105, 1998.

[21] W. Fan and P. Qiao, “Vibration-based damage identification methods: A review and comparative study,” *Struct. Heal. Monit.*, vol. 10, no. 1, pp. 83–111, 2011.

[22] C. R. Farrar, S. W. Doebling, and D. A. Nix, “Vibration-based structural damage identification,” *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 359, no. 1778, pp. 131–149, 2001.