Structural monitoring: modal tracking with LoRaWAN wireless systems and automatic Cloud Algorithms

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Abstract. Every structure needs to be monitored throughout its useful life, to ensure an adequate level of safety and due to external events - both natural and not – that can disturb its state of equilibrium. Moving from these demands, in recent years, Move Solutions has implemented a structural monitoring system, static and dynamic, consisting of a variety of completely wireless sensors, operating with LoRaWAN technology, together with a special Cloud platform developed with the aim of facilitating the analysis and visualization of data by the operators in charge of the activities. The system is based on excellent sensor synchronization (500μs) through which a dataset conforming to OMA (Operational Modal Analysis) is obtained. From the accelerometric data, it is possible to extrapolate the daily frequencies and modal shapes using the FDD (Frequency Domain Decomposition) technique. For long-term monitoring, it is necessary to identify only structure modes of vibration among all those calculated by FDD; this is made possible by a multi-level clustering algorithm, designed by Move Solutions, that can differentiate useful vibrational modes from the "spurious" ones, which will be discarded. The following step is defined as Tracking, where the aim is to monitor the variations of the previously identified vibrational modes over time. The use of a wireless and fully automated monitoring system on the Cloud can give a big boost in simplifying the management of all infrastructures, cutting costs and digitizing processes.

Keywords: Structural Monitoring System, LoRAWAN Wireless Sensors, OMA, FDD, Automated Operational Modal Analysis

1 Introduction to the LoRaWAN monitoring system

Move Solutions is a company focused on electronics for telecommunications that designs LPWANs (Low Power Wide Area Networks) systems with LoRaWAN wireless communication for Structural Health Monitoring (SHM). Wireless monitoring plays an invaluable role in the construction, maintenance and especially in the security of infrastructure. By using the LoRaWAN communication protocol it is possible to communicate over large areas (over 10 km in optimal situations). This communication protocol is characterized by low transmission power and power consumption, which makes it perfect for transmitting raw data with devices that do not have large power reserves.

Thanks to these features, LoRaWAN wireless communication is perfect for Internet of Things (IoT) applications where many devices need to be spread over large areas.

1.1 System Architecture

Move Solutions SHM system is based on three main elements as shown in Figure 2: a LoRaWAN wireless sensor network, a LoRaWAN/Cellular communication gateway and a management and control platform.
The wireless sensor system automatically transmits the data measured by the sensors to the gateway which in turn forwards all data received via 4G or LTE to the online platform. The transmitted data can be viewed on the Move Cloud Platform, which allows users to remotely access information about their structure and check the status of the devices. The platform is designed with algorithms that process the data, converting them into useful information to help users understand the state of the structure in the short and long term.
The advantages of having a wireless monitoring system are many. Firstly, the installation is quick and easy: sensors start collecting data as soon as the gateway is powered. Secondly, thanks to the LoRaWAN communication protocol and the gateway on site, sensors can automatically send the information collected to the Cloud Platform, even if they are spread out over an area of thousands of meters. Lastly, since the system is modular, when the project needs to evolve it is possible to easily add, move and remove sensors from the system.

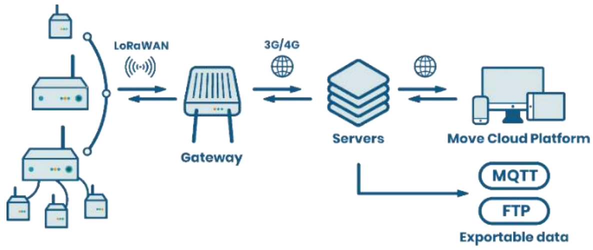


Fig 1: System operation

1.2 Types of sensors

Move Solutions monitoring system includes a variety of unique wireless sensors for both structural dynamic and static analysis for every kind of structures.
The following dynamic devices are currently unique on the market.

- The *Deck* device is a dynamic displacement sensor patented by Move technology. It is the only sensor on the market that measures the monoaxial oscillations of the structure by providing dynamic displacement values (range 0.7 - 20 Hz) with an accuracy of 0.01 mm. It constantly samples at 100 Hz and, when a threshold is exceeded, it transmits 30-second data packets (10 previous + 20 after the exceedance). Starting from velocity acquired by a geophone technology, the sensor produces a displacement value because of an analog integration chain. The device is also integrated with a temperature sensor for correlations. It is commonly used on all structures where dynamic displacement is relevant, such as bridge decks, and it is useful to detect traumatic events and to understand if and how the stress reaction of the structure varies over time.

- The *SHM Accelerometer* is a wireless sensor designed to measure the triaxial acceleration of the installation point, which is essential to obtain vibration frequencies and carry out a modal study of the structure. What makes it unique on the market is the ability to be wirelessly synchronized to other accelerometers, with an accuracy of ±500 μs. In fact, inaccurate synchronization between sensors can lead to important errors in estimating modal parameters, especially on modal shapes [1]. The sensors have a user-configurable sampling rate (40, 80, 160, 320 or 640 Hz). The sensitivity of the instruments allows this kind of measurement to be carried out even in situations with absence of vibrations, where only environmental noise occurs. This device has a temperature sensor too, used for correlations with accelerometric readings.

2 Modal analysis with SHM accelerometers

2.1 Data acquisition

Since the purpose of the paper is to talk about OMA, we will focus on data acquired from SHM accelerometer which is a sensor specifically designed for modal analysis. In the case of LoRaWAN wireless systems there are limitations in terms of the amount of data that can be sent due to duty cycle constraints as strictly imposed by ETSI regulations [2],[3]. From a theoretical point of view, the more data that are acquired the better the modal analysis will be. However, in implementing a real system that is automatic and scalable it can become very onerous to process and store a continuous flow of information. Furthermore, on structures with a multi-decade life cycle and on which we want to perform medium to long-term analyses, it may be an acceptable trade-off to reduce the number of daily data in favor of a cheaper and leaner system. In addition, the system proposed by Move Solutions also consists of other sensors that can meet the "complementary" need to detect sudden and macroscopic damage caused by extraordinary events such as landslides, earthquakes, or fractures in a short time.
Without additional arrangements, the data that can be sent with LoRaWAN complying with ETSI regulation would not be sufficient to perform OMA. To increase the amount of sendable data to a level sufficient for our purpose, i.e., to perform OMA comparable in quality and reliability to that performed with a wired system, the following strategies were implemented:

- *Data Compression*: sensors often record acquisitions of ambient white noise that have reduced amplitude dynamics; this allows the use of a lossless bitwise compression algorithm that can result in up to 50% compression under ideal conditions.
- *Duty Cycle Increase*: LoRaWAN protocol uses a pure ALOHA technique as Carrier-sense multiple access (CSMA) strategy and, according to the ETSI EN 300 220, this allows an average of 36 seconds of radio transmission per hour on each channel. This ALOHA technique, while very simple, is poor in terms

of occupancy of the 8 available radio channels. To maximize the transmission efficiency of the system and relax the duty cycle restrictions to an average of 100s of radio transmission, we adopted an LBT AFA approach i.e., Listen Before Talk with Adaptive Frequency Agility like the one described in [4]: each end-node of the network before sending data makes sure that the radio channel is free. If the channel is busy, it switches channel otherwise it transmits.

Thanks to these two improvements, sensors can capture and send one event per hour, up to a maximum of 80 minutes per day to meet the constraints on duty cycle; that time is enough for the correct identification of the modal parameters of the structure even in the case of free environmental oscillations.

2.2 OMA and FDD

OMA (Operational Modal Analysis) is one of the most important methodologies used in structural monitoring. Its biggest advantage is that it can be used during the usual dynamic operation of the structure without the need for a controlled test environment with certain load conditions. This type of technique is also called output-only modal analysis because it is processed only based on the response of the system following an uncontrolled and unknown input such as the environmental and operational forcing of the structure (wind, traffic, microtremors and so on) [5]. The most important requirement for a correct OMA is that the structure is excited by white noise: this condition is always met in the case of free environmental oscillations. However, it may not be the case when the structure is stressed by particularly intense forces such as heavy traffic, the passage of a train or an earthquake.
One of the best-known techniques in the OMA field is the FDD (Frequency Domain Decomposition) [6]: it is a nonparametric algorithm that operates in the frequency domain that, starting from a singular value decomposition (SVD) of the power spectral density matrix (PSD), determines the frequencies and modal shapes of the structure. If we have a single dominant mode at a certain ω_k pulsation, the frequency response of the structure can be expressed as follows:

$$G_{YY}(\omega) = \lambda_1 \underline{u_1}\ \underline{u_1} \qquad \omega \rightarrow \omega_k \qquad (1)$$

The first singular eigenvector and the first singular eigenvalue correspond respectively to an estimate of the modal shape and the power spectral density of the k-th mode.
Over the following sections of this article, it is described the functioning of Move Solutions automatic monitoring system based on the FDD algorithm.

3 New Automated - OMA algorithm based on FDD

3.1 Daily data processing

The daily data processing automatically takes place on the Cloud, with the following steps:

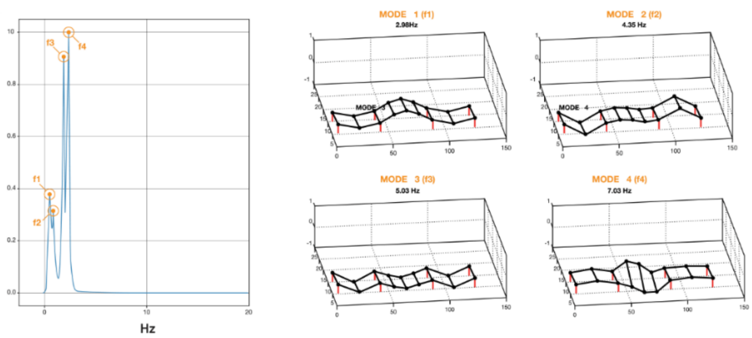
1. *Pre-processing:* before being processed, the accelerations are filtered with a bandpass rate [0.004, 0.4] *f_s Hz where f_s is the sampling frequency to purify

the signal from any noisy components that are not needed. All the events with too intense acceleration peaks, caused by external agents that would risk altering the modal characterization, are also eliminated.

2. *Data stationarizing and PSD matrix creation:* during long-term monitoring the algorithm is launched once a day on all acquisitions obtained by the sensors in the last 24 hours. To be sure that white noise enters the system, a data stationarizing operation is carried out to reduce the effect of light forces that were not discarded by the previous control [7]. The following step is the calculation of the PSD matrix of the events recorded through the Welch method with Hanning windows of length 2^{11} overlapped with each other by 50%, applied to FFT (Fast Fourier Transform) of the signal length $M = 2^{15}$.

3. *SVD:* from the previous step there is, for each frequency, a square PSD matrix (N x N) where N is the number of sensors; to this tensor it is applied the decomposition to singular values from which a product of three matrices $U \Lambda U^H$ is obtained, which in turn have a dependence on the frequency. At this point we identify the first eigenvalue Λ_1 (vector 1 x M/2) of Λ and the first eigenvector U_1 (matrix N x M/2) of U which are respectively the daily estimate of the Frequency Response Function (FRF) of the structure and its modal shapes..

4. *Identification of the Peaks:* once the estimated FRF of the structure has been calculated, an automatic search is made for the peaks of greater intensity to identify the daily modal frequencies. Then, we associate the k-th modal vector of the matrix U_1 to the k-th value in frequency, thus obtaining a frequency-modal shape pair. Figure 2 report an example of a possible results obtained from the daily processing of data with the procedure described above.



2a 2b

Fig 2: Modal frequencies (2a) and modal shapes (2b) extrapolated from the estimated FRF.

3.2 Classification of structural modes and initialization of traces

SHM is one of the fields where the digital revolution has brought greater benefits. New automated data processing techniques have led to both accelerated extrapolation of modal results and simplified interpretation by engineers. This is where the so-called AOMA (Automated Operational Modal Analysis) comes from: the ability to do OMA fully automatically.

Many approaches have been developed to ensure correct automatic identification of vibrational modes starting from the outputs produced by the SSI-COV method.
The most widely used approach is hierarchical clustering based on a similarity measure between frequency and modal shape estimation. Several variations of this strategy have been proposed in [8-12]: in some cases, a single distance check is performed and must be satisfied to proceed with the aggregation of two physical vibrational modes, in others they use multi self-adaptive and self-trained association distances based on the collected data. More complex multi-stage clustering algorithms are also proposed: they start with the elimination of spurious modes and then go on to aggregate vibrational modes with the subsequent removal of outliers from each identified cluster.
Starting from the analysis of the state of the art, Move Solutions designed an automatic multi-level clustering algorithm that can recognize vibrational modes between all the frequency-shape pairs found by daily processing of FDD. Once the structural modes have been classified and outliers removed, traces are initialized (the term 'traces' is used to highlight the temporal evolution of the structural modes during the monitoring period): the latter will help to identify any damage and structural anomalies that may occur over time. Multi-level clustering is launched on all frequency-shape pairs after 14 days from the start of monitoring and it works in the following way (the initialization period can be varied according to the case study and the duration of monitoring):

1. *DBSCAN on modal frequencies and shapes*: the first level of clustering is used to remove obvious outliers in both the frequency and shape domains.
2. *Clustering based on frequency and MAC distances*: after removing the first outliers, a Monte Carlo simulation starts running N times a hierarchical clustering algorithm based on frequency and MAC distances [10]; it associates two points in the same cluster when these three conditions are met simultaneously:

   - $df_i < dMAX\_F_k$ where $df_i = \left|\frac{f_k - f_i}{f_k}\right|$
   - $dMAC_i < dMAX\_MAC_k$ where
     $$dMAC_i = 1 - MAC_i\ , \quad MAC_i = \frac{|\phi_i^T\,\overline{\phi_k}|}{(\phi_i^T\phi_i)(\overline{\phi_k}\ \overline{\phi_k^T})} \qquad (2)$$
   - $d_i < dMAX_k$ where $d_i = df_i + dMAC_i$

   f_k and ϕ_k are the frequency and average shape of cluster k, respectively, while $dMAX\_F_k$, $dMAX\_MAC_k$ and $dMAX_k$ are the thresholds used to associate the i-th point to the k-th cluster. Initially, these thresholds are set at the values 0.008, 0.012 and 0.02, respectively, until the cluster has at least 4 points within it, after which the thresholds become self-adaptive and are calculated according to:

   - $dMAX_{F_k} = \sqrt{med(|df_k - med(df_k)|)}$
   - $dMAX_{MAC_k} = \sqrt{med(|dMAC_k - med(dMAC_k)|\,)} \qquad (3)$
   - $dMAX_k = \sqrt{med(|d_k - med(d_k)|)}$

df_k , $dMAC_k$ and d_k are the distances between points belonging to the cluster k and its centroid.
Thresholds have very small starting values so that initially only points that are very similar to each other are aggregated.

3. *Elimination of the most dispersed points and initialization of the traces*: once the first two steps have been completed, the obtained clusters are associated to the vibrational modes that are monitored over time. Before doing that, any internal outliers within each cluster are eliminated and all those clusters that have less than 6 points are discarded.

3.3 Tracking of structural modes

After identifying the vibrational modes to be monitored, we proceed with Tracking: the data is processed daily as described in section 3.1 and associated with one of the tracks or the group of outliers. The association takes place only when these three conditions are met simultaneously [10]:

- $df_i < dTRACE\_F_k$ where $df_i = |\overline{f_{traces,k}} - f_i|$
- $dMAC_i < dTRACE\_MAC_k$ where

$$dMAC_i = 1 - MAC_i \, , \quad MAC_i = \frac{|\phi_i^T \cdot \overline{\Phi_{traces-k}}|^2}{(\phi_i^T \cdot \phi_i)\cdot(\overline{\phi_{traces-k}^T} \cdot \overline{\Phi_{traces-k}})} \qquad (4)$$

- $d_i < dTRACE_k$ where $d_i = df_i + dMAC_i$

$\overline{f_{traces-k}}$ e $\overline{\phi_{traces-k}}$ are the frequency and average shape of trace k while $dTRACE\_F_k$, $dTRACE\_MAC_k$ and $dTRACE_k$ are the thresholds used to associate the i-th point to the k-th trace. These thresholds are self-adaptive and are calculated as follows:

- $dTRACE_{F_k} = \sqrt{std(df_k)}\,\left(1 + \frac{1}{\log h}\right)$
- $dTRACE_{MAC_k} = \sqrt{std(dMAC_k)}\,\left(1 + \frac{1}{\log h}\right) \qquad (5)$
- $dTRACE_k = dTRACE_{F_k} + dTRACE_{MAC_k}$

df_k , $dMAC_k$ and d_k are the distances between points belonging to the trace k-th and its centroid while h is the number of points of that trace.
Because of the strong variability of high frequencies with respect to environmental factors, especially temperature, a correction factor must be introduced for traces that contain at least one point above 15 Hz. This term is calculated as

$$b = \left(1 + \frac{\overline{f_{traces-k}}}{100}\right)^2 \qquad (6)$$

3.4 Case study

A dynamic monitoring system made of a network of 17 sensors was applied on a road bridge with a metal structure. It was a single-span bridge with a span of 25 meters with a mixed section steel concrete deck formed by 9 main beams. The accelerometers were placed in a line of three on the edge beams. In the central beam, five sensors were installed as shown in the Figure 3. The purpose of the monitoring was to dynamically characterize the structure in its main frequencies and modal shapes.

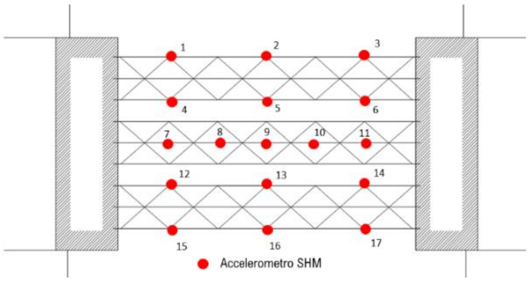


Fig 3: Sensor arrangement on bridge deck

We applied the above-mentioned algorithm to this case study: after the 14-day initialization period, the algorithm identifies vibrational modes and initializes the traces associated with them. Next, the vibrational mode tracking phase begins, which has a duration of just over a year from the start of monitoring. The temporal evolution of modal frequencies during the tracking period is shown in Figure 4 while in Figure 5 the corresponding average modal shapes. In Table 1 the statistical information of the traces in the figure is summarized.

Table 1: Modal frequency traces information after one year of tracking

Trace	f_{avg} [Hz]	σ_f [Hz]
1	8.4345	0.201
2	11.2818	0.176
3	13.4040	0.477
4	14.8847	0.419
5	17.3112	0.604
6	18.0740	0.378

Fig 4: Modal frequencies during the first year of monitoring

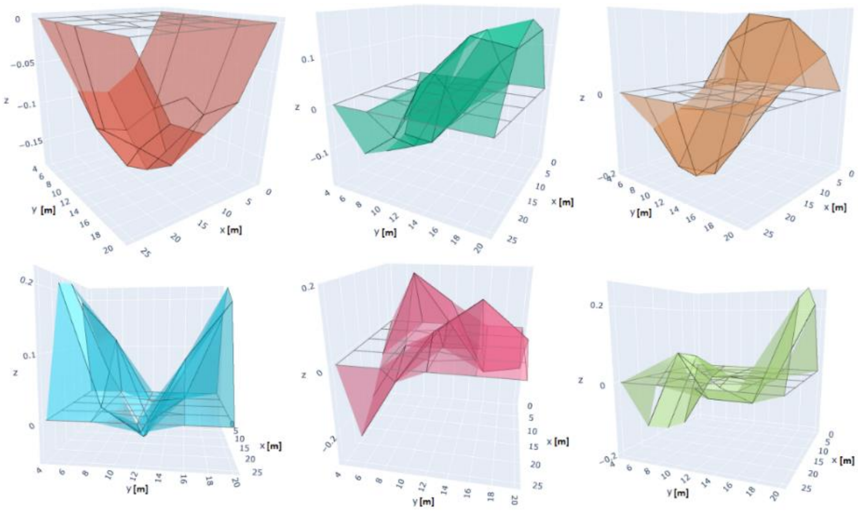


Fig 5: Average modal shape for each trace

4 Conclusions and future developments

The purpose of this paper is to present a new wireless monitoring system based on LoRaWAN technology combined with a fully automatic and integrated Cloud-based data processing algorithm capable of doing modal analysis. The results shown in this article have been fully validated through the main commercial software used for structural analysis. Our system wants to support the operators in charge of monitoring to identify any damage or deterioration of the structure. Moreover, the process of system identification paves the way for a future implementation of damage detection algorithms. Such algorithms [13],[14] aim to find suspicious variations of frequencies and/or mode shapes to assess damage both in time and location. Damage detection algorithms are usually extremely effective if applied after purifying the modal parameters of the structure from environmental effects such as temperature, humidity, and traffic. The process of removing environmental effects from frequency traces has been studied in [15], [16] and it will be soon implemented for the Move Solutions Platform. Among the different damage detection algorithms, some are based on multivariate statistical methods [15],[17] while other involve Machine Learning/ Deep Learning techniques [18]. Cases from both groups will be considered in the near future to embed a damage detection feature in the automatic pipeline.

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