Desarrollo de una metodología para la identificación automática, cuantificación y predicción de daños estructurales en puentes

Development of a methodology for the automatic identification, quantification and prediction of structural damages in bridges

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RESUMEN

No conocer cómo se produce el deterioro de una estructura influye en la eficiencia al realizar inversiones de mantenimiento, además de generar incertidumbre e inseguridad. Para ello, se ha desarrollado un algoritmo avanzado para el diagnóstico y pronóstico del daño estructural, donde una serie de nodos miden aceleraciones. Estas mediciones físicas se envían automáticamente a la nube y son tratadas por los diferentes módulos: identificación de daños, ubicación y caracterización de daños, pronóstico y vida útil restante del elemento.

ABSTRACT

Not knowing how deterioration of a structure occurs influences on the efficiency when carrying out the investment in maintenance, in addition to generating uncertainties and insecurity. For this, an advanced algorithm for the diagnosis and prognosis of structural damage has been developed, where a series of nodes measure accelerations. These measurements are automatically sent to the cloud and are treated by the different modules: damage identification, location and damage characterization. Forecast and remaining useful life of the element.

PALABRAS CLAVE: monitoreo, puentes, SHM, algoritmos, daño estructural, predicción
KEYWORDS: monitoring, bridges, SHM, Algorithms, Structural Damage, prediction

1. Introduction

Despite SHM systems are being used over the world, tragedies as Polcevera viaduct (Genoa,2018) collapse are not avoided. This fact is caused because the majority of SHM are focused on obtaining data that must be interpreted by a structural expert and it is difficult to evaluate such amount of data and also to prevent how deterioration will develop.

In order to solve this problem, an advanced algorithm for diagnosis and prognosis of structural damage has been developed. Our solution is composed by a series of nodes that measure different physical parameters. These physical measurements automatically are sent to the cloud and mathematically treated by the different integrated modules. The developed algorithms are composed by 4 modules: Damage identification, location and characterization of damage, prognosis, and remaining useful life of the element.

Bayesian networks are used to systematically integrate the sources of uncertainties and errors for each case after a sensibility analysis was performed to identify the contributions of these sources of uncertainty. This method allows to make a prognosis about the evolution of the behavior of the parameters

Finally, a prediction model will be developed based on maintenance decisions. To do this, an Artificial Neural Network (ANN) will be developed.

2. Background and motivation

In recent years some infrastructure managers have implemented infrastructure management systems (IMS). These IT tools are mainly used as a database where information on the state of deterioration of the different structures is stored. The objective pursued implementing IMSs is to have greater control over the infrastructure stock and thus prioritize the actions and the allocation of the overall budget.

The existence of this database been used to develop models of deterioration. Existing approaches to deterioration modeling depend primarily on statistical models. These statistical approaches use past observational data about how bridges have deteriorated over time to predict how other bridges will deteriorate. One of the biggest weaknesses of statistical approaches is the limited quantity of available data on which to base the statistical model. That is, millions of condition records without any maintenance interventions for a large number of bridge components at different condition states would be required in order to establish robust predictions. This affects the accuracy of the model, so the prediction data delivered by these statistical models should not be considered in any case a reliable prediction, but rather as a preliminary time line of bridge deterioration.

Structure deterioration process exhibits the complex phenomena of physical and chemical changes that occur in different bridge components. Existing mechanistic models of the underlying deterioration mechanisms (e.g. cracking by fatigue or corrosion individually, and also by its synergistically interaction, and others such as scouring) exist in the Literature.

In contrast to statistical models, mechanistic models consider the physical phenomena that cause deterioration and attempt to describe the evolution in bridge condition mathematically over time as a function of significant variables, such as material properties, environmental conditions and loading.

Although, these models have the ability to predict the deterioration with high accuracy and efficiency, none of the infrastructure owners incorporate them in their IMSs as it is difficult to consider the correct value of various variables affecting the deterioration process; some of them change continuously in time (e.g., traffic or the climatic conditions) and others are difficult to determine with certainty (e.g., how the characteristics of the material are evolving due to the aging). To consider this variability by means of finite element models would imply a process that would be impossible from a computational point of view.

The authors has managed to overcome all the limitations of current deterioration models through the development and validation of an innovative probabilistic algorithm for the prediction of damage evolution.

The successful development of this methodology has implied an intensive R&D process within the fields of fracture mechanics, fatigue-life analysis, and an approach to structural assessment that combines global structural models with local damage models to predict the evolution of damage.

A summary of what we are looking forwith our system and no other competitor can offer can be summarized as follows:

- **Prediction of growth of both visible and non-visible damages.**
- **Warning system based on predictions of overall structure stability over time**.
- Indication to the maintenance manager of **recommendations of the best moment to fix visible and non-visible damages** through prediction of its foreseeable evolution and its affection on the integrity of the structure.
- **Low cost and easy to install system that leads to maintenance cost saving of up to 62%**.

3. System operation

The system consists in the installation of accelerometers at maximum dynamic response points of the structure to perform the following diagnostic and prognosis modules:

Module 1. Damage Occurrence Identification module: thriugh the values registered by the accelerometers, this module filters and processes the data by means of the Fast Fourier Transform, resulting in the frequency spectrum of the structure, Modal parameters of the structure are extracted from this frequency spectrum. The variation between two frequency spectra recorded at different times for the same structure implies the existence of a visible-or non-visible damages.

Module 2. Location and Characterization of Damage module: if a structural damage has been identified by the first module, modal parameters extracted from the new spectrum are introduced in the finite element model of the structure initially elaborated and calibrated. By solving an Objective Function (Damage Equation), we determine how the stiffness matrix has varied with respect to the initial situation, expressing it through a reduction in the stiffness of each damaged element though the calculation of the Element Damage Index.

Module 3. Damage evolution prediction (prognosis) module: from the location and severity of the damage provided by the previous module, the new probabilistic algorithms for damage prognosis that have been developed and validated come into play. Time-variant predictions made by these probabilistic deterioration models take into account potential sources of uncertainty (physical variability and model uncertainty) and are based on mechanical stiffness degradation models (i.e., mathematical description of the underlying physical mechanisms of the deterioration process extensively described and validated in the Literature [1,2,3]). Data registered is integrated in a Bayesian inference framework to obtain increasingly accurate predictions.

Module 4. Remaining useful life and time to collapse prediction module: this module takes as input the values of the updated estimates carried out by the deterioration prediction module, and estimates the global stability using the updated finite element model of the structure, considering jointly all the identified deteriorations and their foreseen evolution. The results delivered by this module will be used by infrastructure managers to determine whether is the best time to carry out maintenance operations (predictive maintenance) or when the structure is at risk of collapse.

4. Damage Ocurrence Identification

The modal parameters of the structure (natural frequencies, modes of vibration and modal damping), are related its physical properties, so changes in the variable properties can cause variations in the dynamic response of the structure. For the knowledge of the dynamic properties of the structure, a technique known as Operational Modal Analysis [4] has been used, which allows their determination based on the response of the system sometimes in its service loads.

Structural Health Monitoring techniques, identify the presence, location and extent of damage from changes in the static and dynamic characteristics of the structure. These techniques can be implemented remotely and in real time reducing inspection costs and alert time. [5]

In Structural Health Monitoring techniques, it is necessary to start from a mathematical model, which must be validated through adjustment techniques [6].

Friswell et al. analyzed different problems encountered of a structure with damage to detect such damage. It is used structural models to calculate frequencies for different modes of vibration both for the undamaged state and for the different damage problems posed for the structure. With this data, it is calculated the frequency decrease in each mode and compared with the measured data. [7]

An ANN is performed for identifying dynamic properties. These systems are constituted by interconnected units for processing neuron calls [8]. The stiffness of the interconnections is defined by weights or weighting coefficients that are specific in the network training process [9].

To obtain these fundamental frequencies, commercial accelerometers were installed on different points from which records of accelerograms were obtained.

First, the records of the crude accelerations at a sampling frequency of 100 Hz were obtained.

Once the crude records have been obtained, a Low Pass filter is applied, eliminating in this way the frequency components below a cutoff frequency of 50 Hz, since the fundamental frequency modes of the bridge are below this value.

When the signal has been filtered, the value of the spectral power density is calculated, in this case it will be obtained in the frequency range of 0 to 50 Hz by the Nyquist theorem. [10].

Hereunder, the Power Spectrum Density (PSD) is obtained by applying the Welch method. After that, the decomposition in eigenvalues is carried out and the search for peaks in the frequency domain is carried out by using the Peak-Picking method [1].

This methodology has been validated on the following bridges:

(i)The <u>Seminario bridge</u> in Valparaíso Region (Chile) was calibrated based on the fundamental frequencies that mobilized the deck in vertical direction. In the records taken *in situ*, a lower than 0.5 Hz deviation was achieved from the numerical model predictions in first two bending modes.

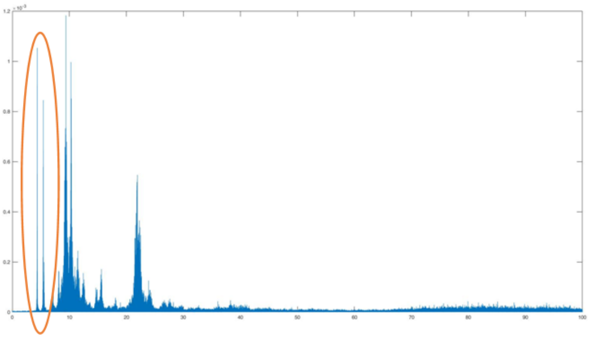
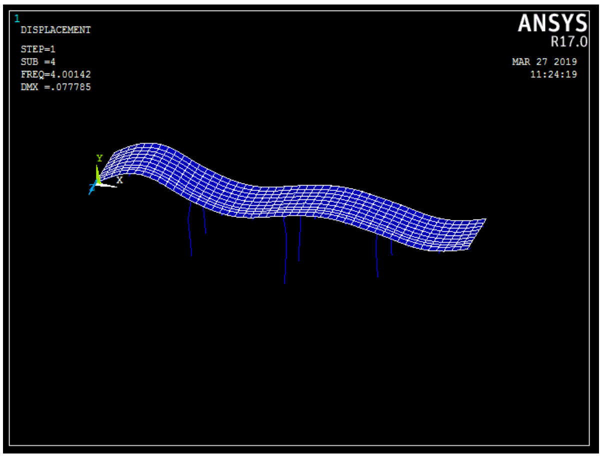


Figure 1.Identification of the first two fundamental frequencies. Source: Own elaboration.



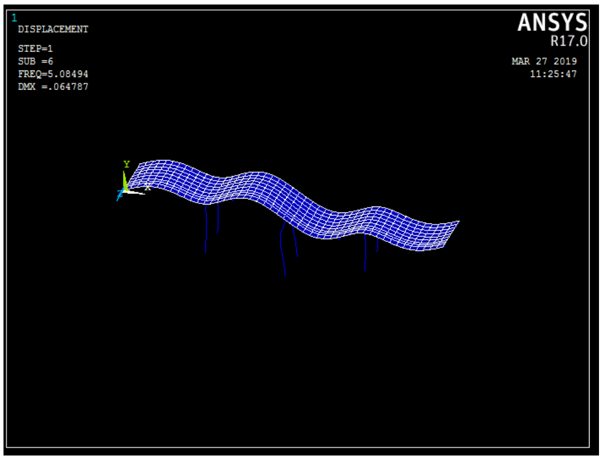


Figure 2. Modal response in Ansys. Source: Own elaboration.

(ii)Other example is <u>the Ulla viaduct</u> in Ourense (Spain). The stiffness of the foundation was also calibrated through real field measurements (transversal accelerations in piers). Once the model was calibrated, the first vibration modal frequency deviation was lower than 0.2 Hz.

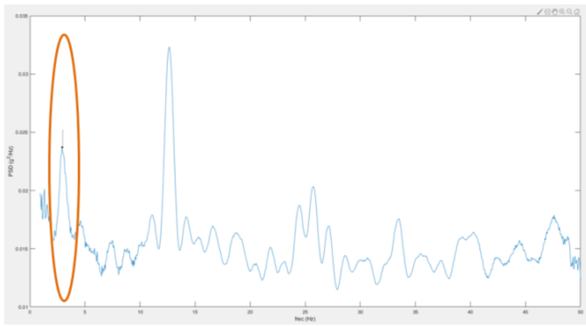


Figure 3. Identification of the first fundamental frequency. Source: Own elaboration.

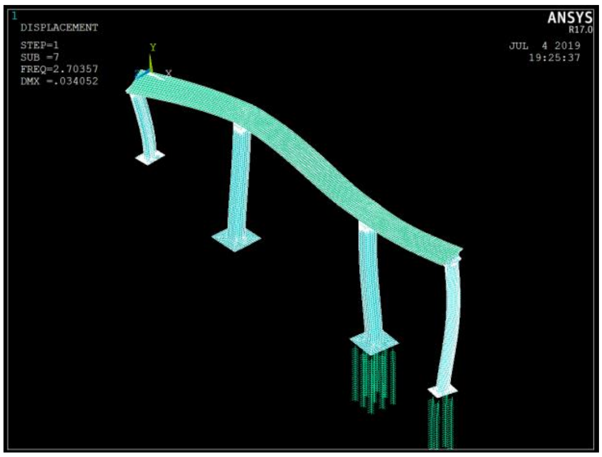


Figure 4. First modal shape. Modal response obtained in the numerical model. Source: Own elaboration.

Even though to date that no structural damage has occurred in any of the monitored structures, there is evidence that its identification is possible as well as its location using the Stubbs method [12]

A sample of this is the following example developed in [12], in which a gantry structure was built with a 1.5 m lintel and 0.7 m high pillars - The pillars and the lintel are HEB-100 standardized profiles, while X-saped is constituted by L-40.4

In the mentioned example, it can be seen as the damage identification was detected whit a variation of its frequencies. [12]

5. Location and Characterization of Damage

Once the occurrence of damage is identified, it is necessary to identify its location. Most damage detection methods are based on the correlation of damage with some changes in the properties of the structure such as frequency, vibration modes, flexibility coefficient, modal energy and stiffness. Some of the methods that work on this basis are considered in [13]:

The measurement of the natural frequency of a structure is essential to determine the good conditions of the structure. The simplest method is based on changing the natural frequency of a damaged structure compared to the structure without damage [14].

The change in the shape of the mode is used for being more sensitive as an indicator of damage and for being able to identify its location. Some cases of application can been observed in [15] and [16].

In this case, two algorithms have been applied to obtain the location and characterization of the damage.

5.1. Location Damage Algorithm

For the location of the damage, the Stubbs method will be used which is based on the location of a hypothetical defect occurring at the point where the parameter β_p reaches the maximum

$$\beta_p = \frac{\sum_{i=1}^{m} \mu_{ip}^{damage}}{\sum_{i=1}^{m} \mu_{ip}^{no\ damage}} = \frac{\sum_{i=1}^{m} \mu_{ip}^{d}}{\sum_{i=1}^{m} \mu_{ip}^{u}} = \qquad 1)$$

$$= \frac{\sum_{i=1}^{m} \frac{\int_a^b [\{\emptyset^d(x)\}_i'']^2 dx + \int_0^L [\{\emptyset^d(x)\}_i''}{\int_0^L [\{\emptyset^d(x)\}_i'']^2 dx}}{\sum_{i=1}^{m} \frac{\int_a^b [\{\emptyset^u(x)\}_i'']^2 dx + \int_0^L [\{\emptyset^u(x)\}_i''}{\int_0^L [\{\emptyset^u(x)\}_i'']^2 dx}}$$

Where m is the number of modes, i the mode and p the element.; Φ denotes the curvature of the modes, which is determined as the second derivative of these and the terms a and b are weight factors for each of the dynamic characteristics.

An example of its application is mentioned in [12], where the position error in the damage location is 0.76 %.

5.2. Element Damage Index.

If the relationship between the fundamental period of the structure and its current state is known, its damage rate can be calculated. For this, the expected damage index (ID) can be calculated using the normalized average damage status and can be interpreted as an average of the expected overall damage in the structure. [17]

$$\mathrm{ID} = \frac{1}{n} \sum_{i=0}^{n} iP(ds_i) \qquad 2)$$

Where n is the number of damage states considered and P (ds_i) is the probability that it will occur.

6. Damage evolution prediction (prognosis)

For damage evolution prediction, a Bayesian network was constructed to systematically integrate the sources of uncertainties and errors for each case after a sensibility analysis was performed to identify the contributions of these sources of uncertainty. From this, an uncertainty model (statistical distribution type) is created for each uncertain parameter that provides automatically the quantification and associated statistics (mean and standard deviation) of each parameter for each concrete structure considered.

This method is based on the idea of refining predictions from new evidence, so this method considers probability as a degree of uncertainty.

In this case, the Beta-Binomial model is used for the prediction of damages, which is based on the probability that one result (structure in perfect condition – α –) or another (need to maintain the structure – β –) will be met.

A random variable has a beta distribution of parameters α, β in [0, 1] (and is represented as X ∼ Be (α, β)), with α, β> 0 if its density function is:

$$f(x|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot x^{\alpha-1} \cdot (1-x)^{\beta-1} \qquad 3)$$

for 0 <x<1

The gamma function is defined as:

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx \qquad 4)$$

And its basic properties are

$$\Gamma(\alpha+1) = \alpha\Gamma(\alpha) \qquad 5)$$
$$\Gamma(n+1) = n!$$

for n ∈ N

The distribution moments are

$$\mu = \int_0^1 x \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1} dx = \qquad 6)$$
$$= \frac{\Gamma(\alpha+\beta)\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha)\Gamma(\beta)\Gamma(\alpha+\beta+1)}$$
$$\cdot \int_0^1 \frac{\Gamma(\alpha+\beta+1)}{\Gamma(\alpha+1)\Gamma(\beta)} x^{\alpha} \cdot (1-x)^{\beta-1} dx =$$
$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \frac{\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha+\beta+1)} \cdot 1 = \frac{\alpha}{\alpha+\beta}$$

Similary it is shown that:

$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \qquad 7)$$

When α < β the probability is concentrated to the left, and vice versa when α> β. The densities are more concentrated when the values of α and β are higher.

7. Prediction module

Heretofore, several algorithms have been developed that are capable of obtaining the fundamental frequency of the structure. Once obtained able to locate the position in which they are in the structure and characterize that damage by means of an Element Damage Index.

Once all these parameters have been obtained and the damage detected, we are able to make a prognosis of how the damage will evolve due to Bayesian networks.

Forthwith all this data collection, a predictive model will be developed based on maintenance decisions. To do this, a linear ANN will be developed, this network will be divided into the following layers:

- Layer 1: data entry layer **[B = (b_1, b_2, b_3,, b_4, …, b_n)]**, the fundamental frequency and location of the damage are introduced as imputs of the network in case there is damage.

- Layer 2: damage assessment layer **[C = (c1, c2, c3,, c4, …, cn)]**, in this layer the values of the damages obtained and located are weighted with their importance on the structure (a frequency value of 0.1 Hz is not the same that 1 Hz as well as the location in which it is).

- Layer 3: damage assessment layer **[D = (d_1, d_2, d_3,, d_4, …, d_n)]**, once the damages in this layer have been predicted and assessed, their evolution in the structure is evaluated.

- Layer 4: data output layer **[V = (V$_1$, V$_2$, V$_3$,, V$_4$, …, V$_n$)]**, in this layer the results of said assessment are obtained by providing an analysis for each frequency variation detected and detecting whether it is necessary to perform a preventive, predictive maintenance work or it is in perfect condition.

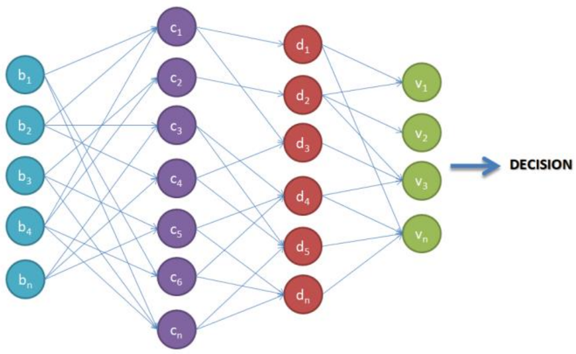


Figure 3. Artificial Neural Network scheme. Source: Own elaboration

8. Conclusions

In most cases, maintenance plans are still based on the results of traditional visual inspections. This visual inspections focus on appearance of cracking, spalling, excessive deflection of the bridge deck and local scour at bridge piers. The effectiveness of traditional visual inspections depends entirely on the skills and experience of the bridge inspector detecting faults and problems at an early stage, and on conveying accurate, consistent, and well-recorded information to the assessing engineer who has the responsibility for deciding on any action needed.

This system is a low cost and easy to install system capable of not only identifying (locating and quantifying) visible and non-visible structural damage in civil engineering structures but also predicts their evolution over time for making cost-effective maintenance, rehabilitation, and replacement decisions, and to ensure that safety, serviceability and functionality of the structure can be sustained over its designed service life.

For that purpose, a damage prediction system based on the following algorithms:

First, two algorithm have been developed, one for the location of the damage and another for the characterization of the damage. These algorithms are based on the Stubbs method and the element damage index.

The following algorithm is based on the probability that a phenomenon occurs or not, this algorithm is developed through the Bayesian method which allows to know the probability of deterioration of an element in the current state, due to the mean and the standard deviation of the records is constantly updated.

Finally, the last algorithm deals is the prediction of the structural state based on the decision-making process to carry out maintenance activities or not. This algorithm consists in a ANN network that is currently in training stage, which is intended to predict the state of the structure.

With all this, a comprehensive and real-time structural evaluation system is developed, which allows us to know the structural state, where an efficiently planning maintenance activities can extend the useful life of the structure.

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