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Structural Health Monitoring of a long-span suspended bridge

Monitorização da Integridade Estrutural de uma ponte suspensa de grande vão

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Abstract

The increased importance of critical structures, such as large bridges or dams, as well as their growing age and actual demands has motivated the wide application of Structural Health Monitoring (SHM) to these type of structures. SHM can be defined as the development and application of damage identification strategies that should be run in real time to identify early damage before it impairs structural performance and safety. It must therefore rely on sensors permanently installed on site as well as on sensitive, robust and efficient analysis methods.

The present paper illustrates the application of SHM to the 25 de Abril Bridge, located in Lisbon, and describes not only the sensory system installed on site but also the pattern recognition techniques used to extract meaningful information from the data, process it and analyse it in real-time to define safety boundaries against which the data is compared to assess the existence of structural changes.

Resumo

A importância acrescida de estruturas críticas como grandes pontes ou barragens, assim como a sua idade crescente e as exigências que atualmente lhes são impostas motivam a aplicação da Monitorização da Integridade Estrutural (MIE) neste tipo de estruturas. MIE pode ser definida como o desenvolvimento e a aplicação de estratégias de identificação de dano que, ao ser aplicada em tempo real, permite identificar dano precoce antes que este possa afetar o desempenho e a segurança estruturais. Para tal, a MIE baseia-se na instalação permanente de sensores e em métodos de análise que sejam eficientes, robustos e sensíveis.

O presente artigo ilustra a aplicação da MIE na Ponte 25 de Abril, localizada em Lisboa, e descreve não só o sistema de sensores instalado mas também as técnicas de reconhecimentos de padrões usadas na extração de informação dos dados adquiridos, no seu processamento e análise em tempo real, de modo a definir limites de segurança, com os quais são comparados os dados adquiridos para determinar a existência de alterações estruturais.

Keywords: Suspended bridge / Structural Health Monitoring / Operational modal analysis / Regression / Statistical analysis

Palavras-chave: Ponte suspensa / Monitorização de Integridade Estrutural / / Análise modal operacional / Regressão / Análise estatística

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1 Introduction

The growing number of critical infrastructures exhibiting large socio-economic importance and growing age has been motivating owners to implement Structural Health Monitoring (SHM) systems and strategies to ensure permanent safety and aid in management. SHM can be defined as a discipline which aims at developing strategies to identify abnormal behaviour or structural changes, using measurements from sensors installed on a target structural system [1],[2],[3], as a way to continuously evaluate the structural health of critical infrastructures.

Detection of structural changes and abnormal behaviour has been considered in research and applied in practice following wither inverse or forward strategies. The latter consists of applying machine learning methods to the data acquired on site and afterwards testing new data based on the knowledge learned by these models [1], [4]. Its computational simplicity, automation capacity and fast development motivate its use in SHM applications in which permanent human input is difficult to allocate and where a continuous and permanent control of safety is needed [2], [5]. Contrarily, inverse methods, also named model updating, consist of defining numerical models whose responses fit those observed on site [6]. The fact that this type of problems does not usually have determinate solutions associated with their computational complexity makes them less adequate candidates for continuous automatic SHM.

Forward SHM strategies are generally described with the following four steps: (i) data acquisition, (ii) information extraction, (iii) structural response modelling and (iv) detection of structural changes [1], [7]. The first step is generally of an experimental nature and can be more or less extensively addressed, depending on the complexity of the structural system and of the behaviour to be monitored. The second and third are generally of a statistical or pattern recognition nature and are needed to remove disturbing effects thus increasing sensitiveness of detection and reducing the incidence of false detections. The fourth step is also of a statistical nature and aims at providing clear unambiguous information regarding the existence of changes monitored in the structural behaviour of the target structural system.

The present paper describes a generic SHM strategy that can be applied to any structural system, since it is not based on parametric or specific numerical models, and describes its application and validation in the suspended 25 de Abril Bridge, located in Lisbon, Portugal. After this brief introduction, section 2 describes the case study concerning the structural system, the SHM monitoring system and the data acquired in real-time. Sections 3 and 4 describe, respectively, the information extraction and response modelling procedures developed, while section 5 describes the automatic strategy for detecting structural changes. Section 6 draws the concluding remarks and achievements of the present work.

2 The study case – 25 de Abril Bridge

2.1 Structural system

The case study used in the present paper is the suspended 25 de Abril Bridge, located in the estuary of the Tejo River, and which connects the cities of Lisbon and Almada. This bridge has a total length of 2277.5 m, with three suspended spans: a central suspended span of 1012.9 m, two suspended lateral spans of 483.4 m each and tree non-suspended lateral not longer than 100 m (Figure 1 (b)). The North access is made through a prestressed concrete viaduct comprising 13 spans while the south span is made by a railway tunnel and road access.

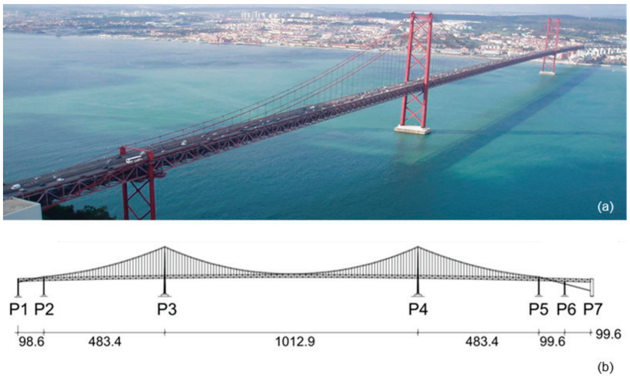

Figure 1 The 25 de Abril Bridge: (a) Global view, from left side and upstream. (b) Side view

The bridge deck is composed of a rigid beam, Figure 2, suspended by 1344 vertical hangers which, in turn, are suspended by 4 main cables, supported at piers P2 and P5 and at pylons P3 and P4, Figure 1(b). The cross-section of the deck's stiffening truss, shown in Figure 2 and Figure 3 (b), supports the road traffic at the upper chord level, with 6 roadway lanes, and the railway traffic on the lower chord, with 2 railway lines.

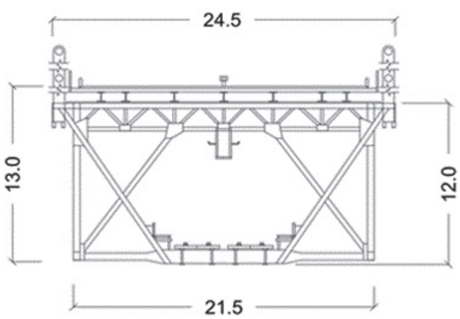

Figure 2 The 25 de Abril Bridge. Cross-section of the stiffening truss

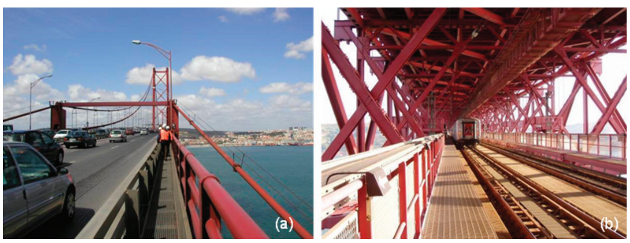

Figure 3 The 25 de Abril Bridge [8]. a) Road traffic view. b) Railway traffic view

All piers and pylons consist of steel trusses, being the single exception the P7, which was built as a concrete hollow section. The pylons P3 and P4 are 180 m high and, as happens for all piers, support the suspended truss at a height of 60 m, as it can be observed in Figure 4. The pylons P3 and P4 are supported by concrete foundations while P2, P5, P6 and P7, by piles. The abutment P1 and the cable's anchorage structures consist of concrete hollow elements, founded directly on the rock.

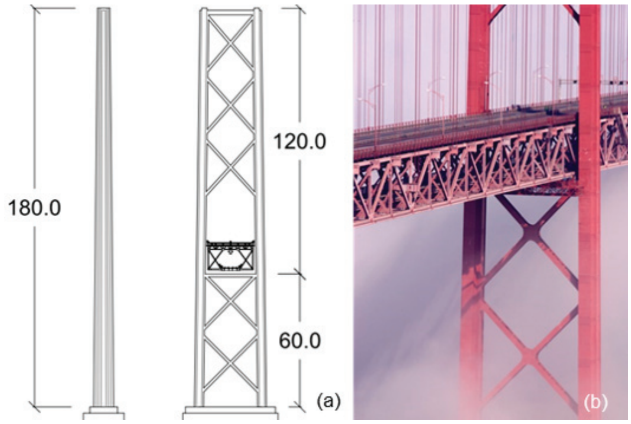

Figure 4 The 25 de Abril Bridge [8]. a) Lateral view of the pylons P3 and P4. b) View of pylon

2.2 Structural monitoring system

The monitoring system installed in the 25 de Abril Bridge comprises 8 types of sensors and allows acquiring the structural behaviour and the imposed actions, operational (traffic) and environmental (temperature and wind). In Figure 5, the schematic representation of the monitoring system is presented, including the sensors and the acquisitions, communication and processing units. The key areas for sensor locations are identified according to piers (P1 to P7), sections of the deck (66 S to 66 N, where "S" and "N" represent South and North respectively) and sections of the pylons.

The sensors are identified as "s.z", where "s" stands for the sensor identification and "z" for the key locations. All sensors can be observed in Figures 6 and 7.

The data is acquired at 500 samples per sensor per second, after which is filtered to a rate of 50 samples per second and decimated to distinct sample rates according to measurement type, as shown in Table 1.

Table 1 Factors of data decimation

Measure	Acceleration / Railway load	Stress / Rotation	Displacements	Temperature
Reading per seconds	100	10	5	1

The data acquisition system (Figure 5) is composed of 13 data concentrators which control 210 data loggers, all connected through RS485 on fibre optic cabling. Each of these concentrators, located

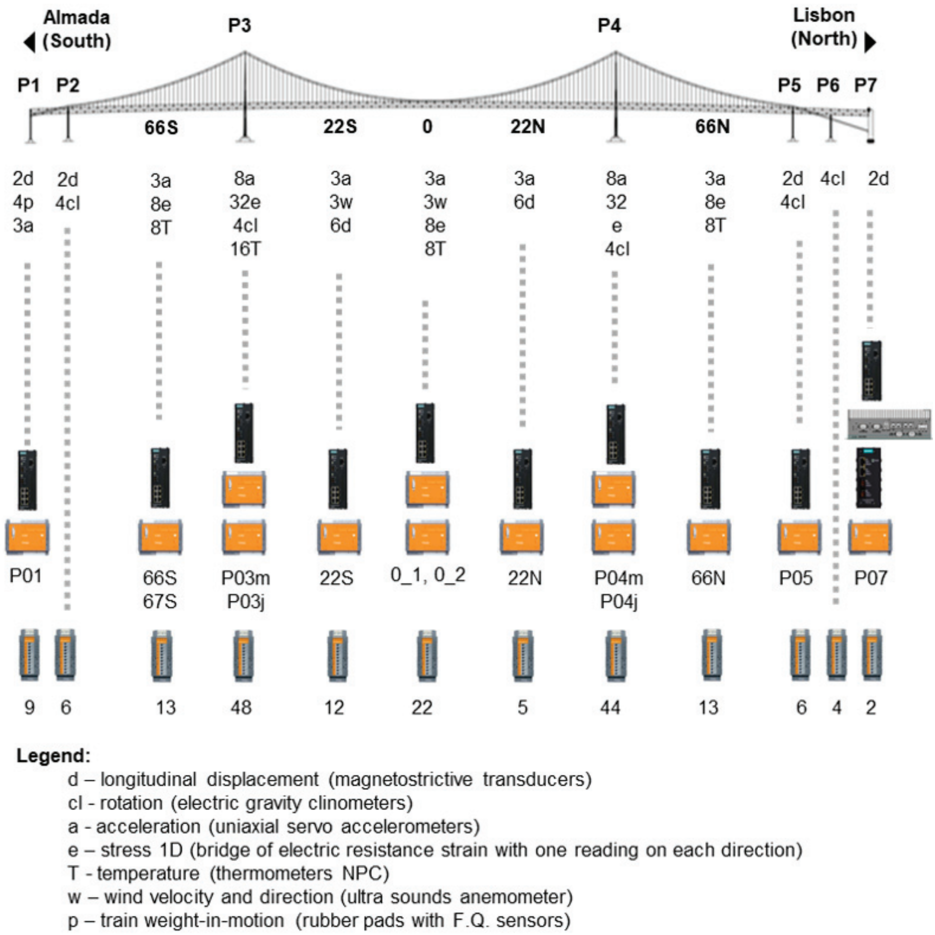

Figure 5 Schematic representation of monitoring system of the 25 de Abril bridge [8]

in the key areas of sensor location, are connected by an Ethernet network built also on fibre optic with ring geometry for redundancy. An industrial computer located also on site controls de acquisition from the concentrator network and establish the permanent link to LNEC's server, to ensure real-time availability and data processing.

The sensors installed on the deck's stiffening truss consist of (Figure 6): thermo compensated strain gages installed on the chord (identified as "e"), to measure the stress and overall force distribution, accelerometers (identified as "a"), to measure the natural frequencies and mode shapes, displacement transducers (identified as "d"), to capture the displacements between the bridges and the piers as well as those between road stringers and the transversal suspended frames, thermometers (identified as "T") installed on the locations of the strain gages. On the section over the abutment P1, four railway pads were installed under the rail, to allow detecting trains travelling over the bridge, and on sections 0 and 22S two triaxle ultra-sound anemometers were installed to allow estimating wind distribution applied on the bridge.

Concerning the sensors installed on the pylons (Figure 7), 6 sections (three on each pylons leg) comprise strain gages ("e") for stress measurement, tilt-meters (identified as "cl") are installed on the top section (D), to allow for the indirect control of the cable's cell displacements, and accelerometers ("a") are installed on the foundations and the upper instrumented sections (C and D).

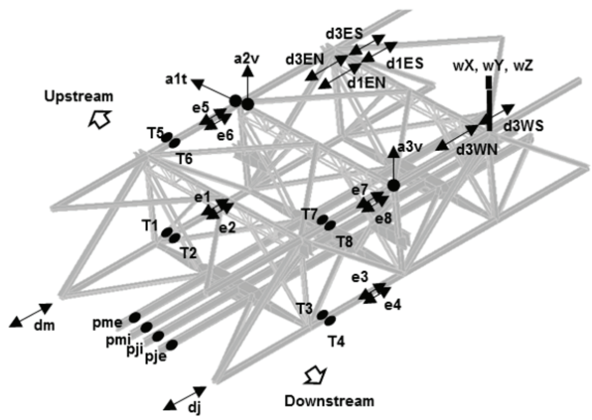

Figure 6 Identification and localization of the sensors [8]

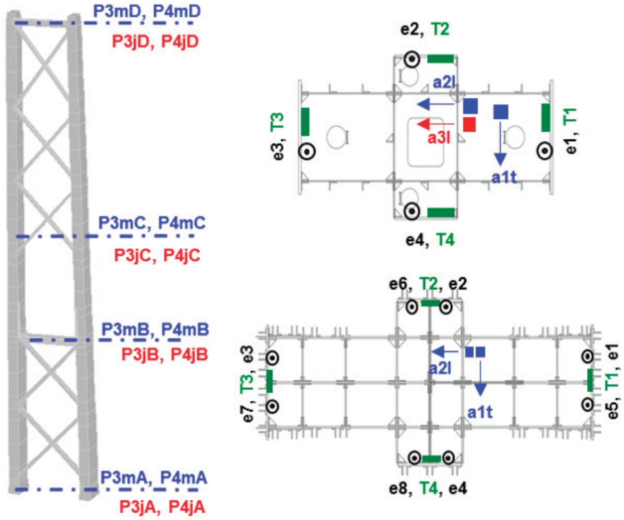

Figure 7 Identification and localization of the sensors in the pylons P3 and P4 sections [8]

2.3 The data

The data acquired continuously on the 25 de Abril Bridge is divided, for SHM purposes, into two subgroups: the imposed actions and the structural responses.

On the first group, temperature, wind speed, railway traffic and ground acceleration are continuously measured by thermometers, railway pads and accelerometers, respectively. Road traffic is indirectly estimated using the vibration levels captures by the accelerometers installed on the bridge deck. Examples of these quantities being monitored on the bridge are shown in Figure 8 for one day, where the temperature slow variation and the wind speed faster variability can be clearly identified in Figure 8 a, b, respectively, whereas in Figure 8 c, d, the higher density of train passages during the rush hours as well as the higher vibration levels during the day can also be easily observed.

The second group consists of the ensemble of structural responses characterizing the structural behaviour of the 25 de Abril Bridge, by resorting to magnetostrictive displacement transducers, to captures relative displacements on the deck and between the deck and piers/

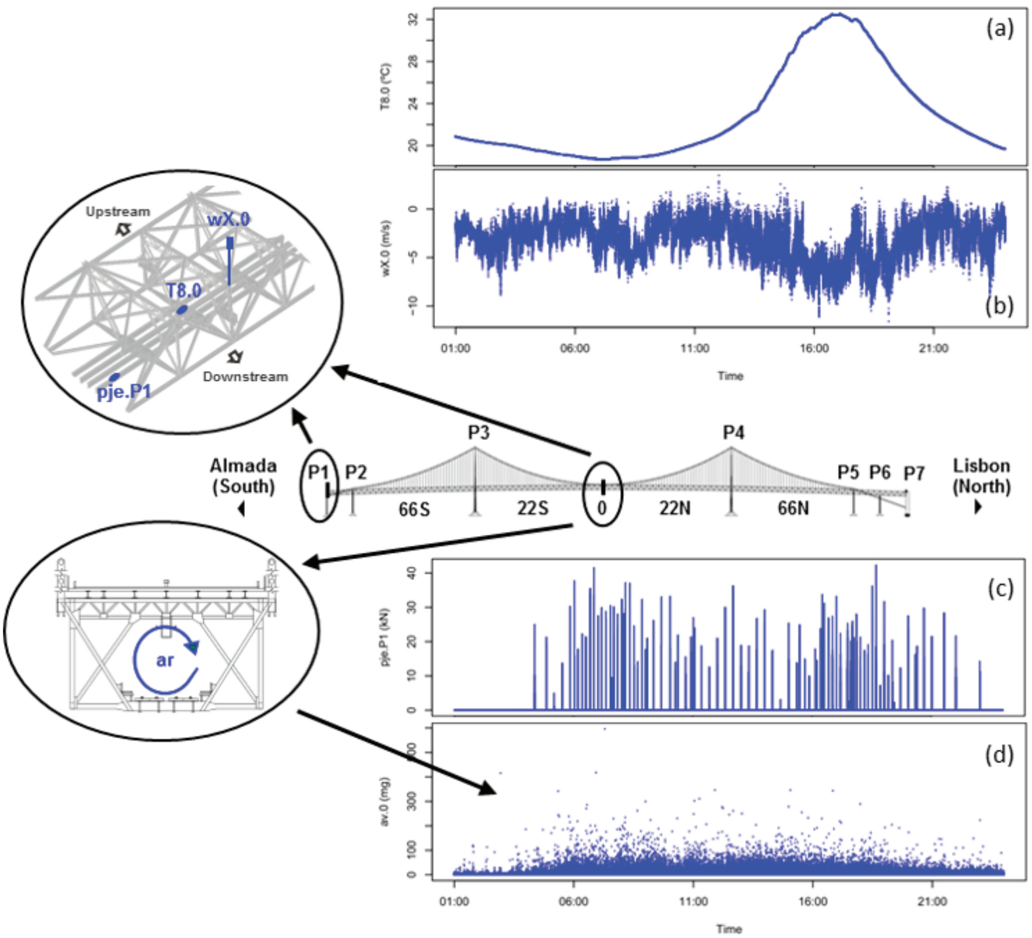

Figure 8 Time series of one example of each imposed action: (a) temperature, (b) wind speed, (c) railway traffic and (d) road vibration

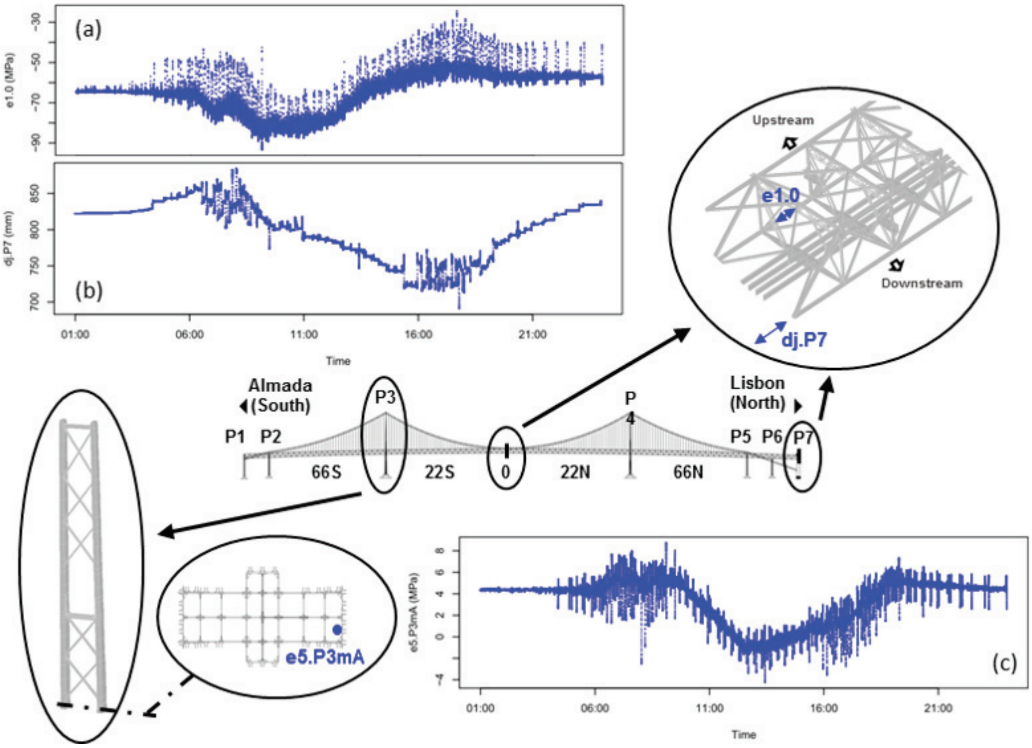

Figure 9 Time series of one example of each structural response: (a) stress on deck's chord, (b) displacement between deck and pier P7 and (c) stress at the bottom section of pylon P3

abutments, servo-pendulum tilt-meters, to measure rotations of the sections where cables are forced to change angles abruptly, force-balance accelerometers, for measuring low-to-high frequency vibrations and thermos-compensated strain gages for capturing stresses. Examples of these quantities acquired during the same daily period are shown in Figure 9, where the influence of temperature in the stresses and displacements can be clearly observed as a variation of trend while the effect of road and railway traffic can be observed as an increase in the time-series variability.

3 Information extraction

As happens in bridges and dams being monitored worldwide, the data continuously acquired on the 25 de Abril Bridge may, by itself, be too voluminous to be analysed or not as informative as required since it reflects numerous effects generated by simultaneous actions being imposed to the structure. As a consequence, SHM works generally report an important step which consists of information, or feature, extraction [1]-[3], [9], which allows obtaining, from the data acquired on site, vectors of compressed data (features) which contain all relevant information but are free of surplus effects.

Following the present state-of-the-art in SHM of bridges [3], [10]-[13], the information extraction strategy used for the SHM of the 25 de Abril Bridge is based on obtaining, from the time-series at certain predefined time-intervals: (i) statistical features that can be directly and precisely correlated with the actions imposed to the structure, and (ii) vibration information such as natural frequencies and their corresponding damping ratios and mode shapes.

The statistical features were obtained from all quantities measured on the bridge and consist of hourly maximum and minimum values, hourly medians and hourly quartiles (25 % and 75 %). The median values assume particular importance since they are expected to be free of traffic and other fast effect, thus reflecting only slow effects that can be analysed with higher precision, such as temperature. Examples of these are shown in Figure 10 for a period of one year, where the effect of annual temperature can be seamlessly observed in the overall trend while the effect of the daily temperature wave can also be observed in the important variability exhibited. The only exception to this remark consists of the wind speed (Figure 10 d), where some daily variability can be observed and where the annual trend only reflects itself in a small reduction of speed during the summer months.

Maximum and minimum hourly values are used to seamlessly characterize and analyse the effects of road and railway traffic on the 25 de Abril Bridge responses, based on the assumption that the transient effect generated by traffic consists of the difference between maximum/minimum and the median of the same hourly period [1]. These features are also important to characterize actions such as railway traffic, which is characterized using railway pads whose value only differs from zero when the train's bogies are on the corresponding sleeper, and maximum wind gust speed. Maximum and minimum stress values measured on one of the deck's chords at

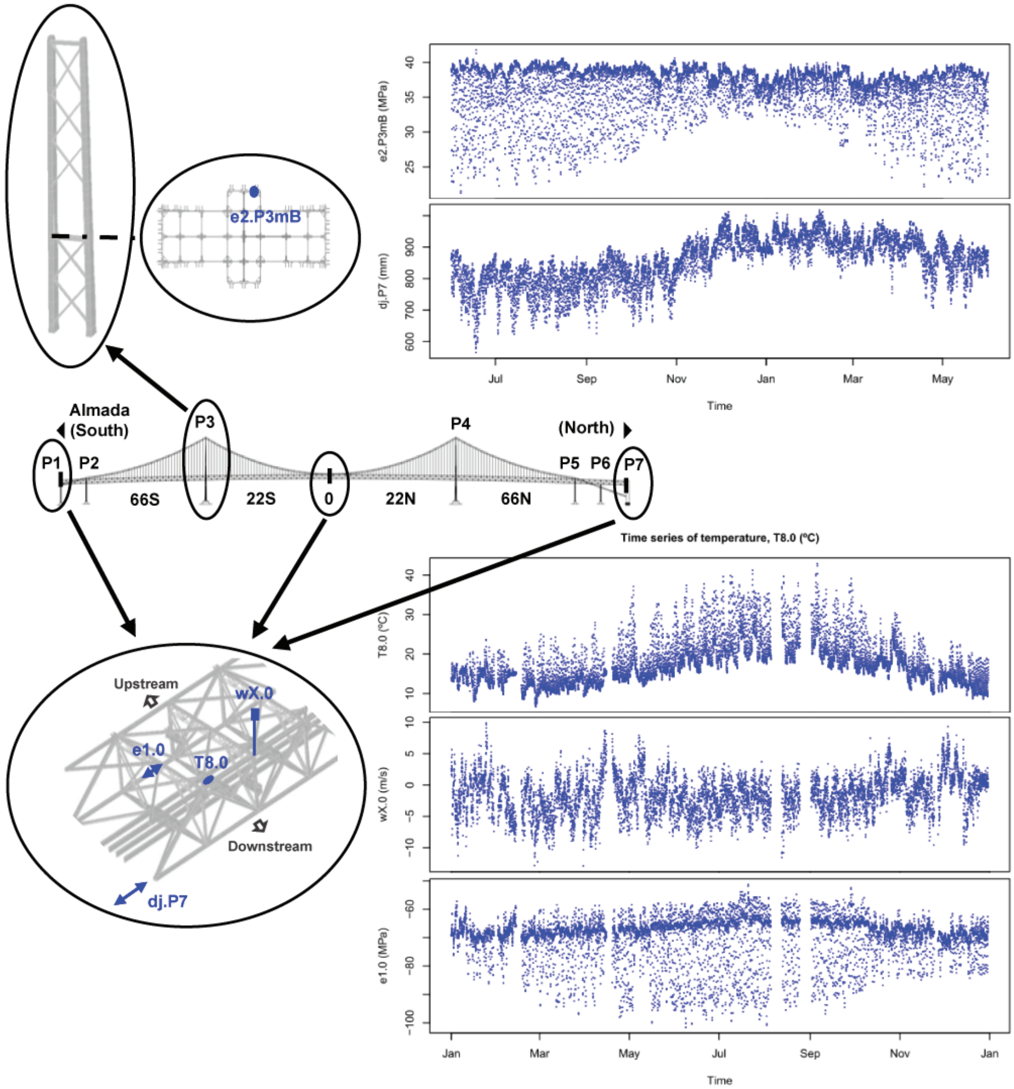

Figure 10 Examples of time median series of static-based information: (a) stress measured on the pylon, (b) displacement between the deck and pier P7, (c) temperature measured on the deck, (d) wind speed measured on the deck and (e) stress measured on the deck

mid span are shown to illustrate the hourly traffic effect, Figure 11, while the time-series of maximum values acquired on one of the railway pads during 4 months allows observing that the loads imposed by the type of traffic did not changed during that period.

The vibration-based information is obtained hourly from the time series of structural accelerations acquired on the 25 de Abril Bridge. These quantities assume particular importance since their changes are highly correlated with changes observed in the stiffness, especially for high order natural modes, which exhibit lower mass participation ratios. The procedure for obtaining vibration features associated with natural modes is preceded by filtering and the conversion, shown in Figure 13, from linear local accelerations to section-equivalent rotation, vertical and horizontal accelerations, and is detailed in [10], [11], [14], [15], for the 25 de Abril Bridge. It is based on applying the Stochastic Subspace Identification [16], [17] in its covariance version (SSI COV) method to the frequency domain under analysis and in analysing this method's output using a class of machine learning algorithms named cluster analysis [1], [5], [11], [18]. This method can be used to describe linear N-DOF (degree of freedom) of time invariant systems under white noise excitation, using the classical discrete state-space model:

$$x_{k+1} = Ax_k + w_k \quad (1)$$

$$y_k = Cx_k + v_k \quad (2)$$

where k identifies the instant, A the state matrix, C the output

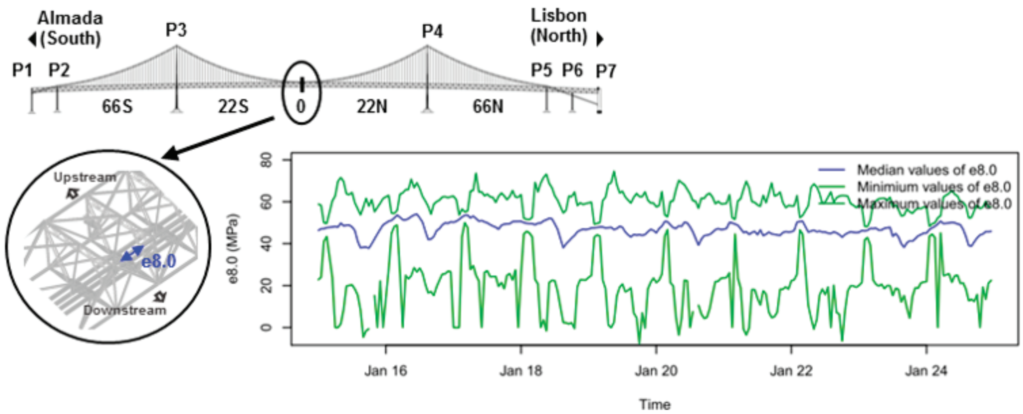

Figure 11 Time median, maximum and minimum series of e8.0

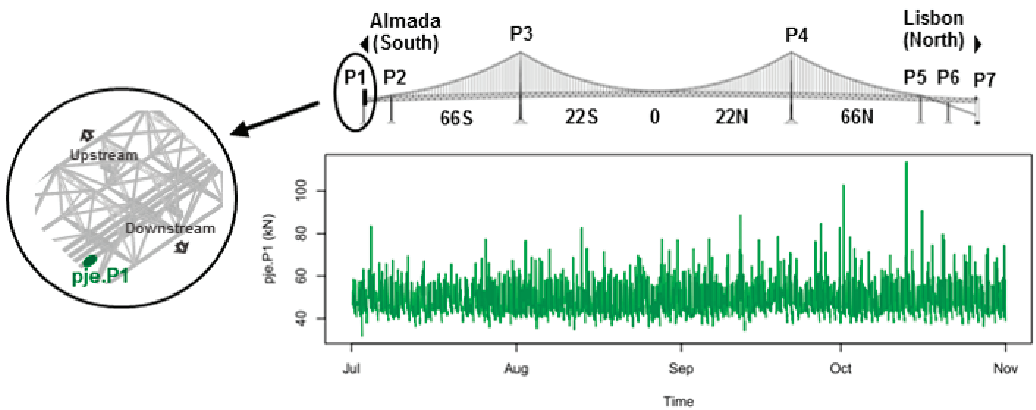

Figure 12 Examples of time maximum series of train weight-in-motion

matrix, x_k the state vector and y_k the measurements vector. The variables w_k and v_k are independent zero mean stochastic processes which represent unknown effects, noise, etc.

The SSI-COV relies on extracting singular values, S, from a Block Toeplitz matrix built using the system's output correlation matrix, evaluated for positive time lags varying from $1.\Delta t$ to $(2i-1).\Delta t$, where i is the SSI model order chosen,

$$T = U.S.V^T = \left[U_1\ U_2\right]\begin{bmatrix} S_1 & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} = U_1 \cdot S_1 \cdot V_1^T \tag{3}$$

and on obtaining the observability, O, and controllability, Γ, matrices, as follows,

$$O_i = U_1 \,.\, S_1^{1/2} \tag{4}$$

$$\Gamma_i = S_1^{1/2} \,.\, V_1^T \tag{5}$$

The state matrix A, is then obtained by solving a least-square problem on the first $n.(i-1)$ lines of O, using the Moore-Penrose pseudo-inverse,

$$A = O_i^{t0\blacksquare} \,.\, O_i^{b0} \tag{6}$$

where $\blacksquare$ represents the Moore-Penrose pseudo-inverse, O_i^{t0} the matrix that contains the first n.$(i-1)$ lines of O and O_i^{b0} the matrix that contains the last $n.(i-1)$ lines of O.The modal frequencies, the damping ratios and the mode shapes can be seamlessly extracted from matrix A by first obtaining its eigenvalues, μ_k, and the poles of the continuous-time model, λ_k,

$$\lambda_k = \frac{\ln(\mu_k)}{\Delta t} \tag{7}$$

The frequencies, f, damping ratios, d, and mode shapes, Φ_k, are then obtained as

$$f_k = \frac{Abs(\lambda_k)}{2\pi} \tag{8}$$

$$\xi_k = \frac{Re(\lambda_k)}{Abs(\lambda_k)} \tag{9}$$

$$\Phi_k = C_i \cdot U_i^A \tag{10}$$

where U_i^A are the eigenvectors of A for model order i.

The results obtained from applying the SSI-COV method to one hour of accelerations measured on the 25 de Abril Bridge are shown in Figure 14, where the SSI poles and the first singular value spectra are represented. By comparing the SSI poles, shown in blue colour, with the singular value spectra, shown in grey colour, it can be observed that perfectly vertical alignments of poles, with frequency values that repeat themselves throughout many SSI orders, are coincident with spectral peaks, and thus with the presence of natural mode shapes. Conversely, non-aligned sequences of poles, observed along the vertical axis, may not consist of natural modes but of spurious effects and have to be identified and not considered as natural modes. This aspect, along with the high density of natural modes observed in the domain 0 – 5 Hz, make automatic modal identification challenging, when compared to smaller and stiffer structural systems.

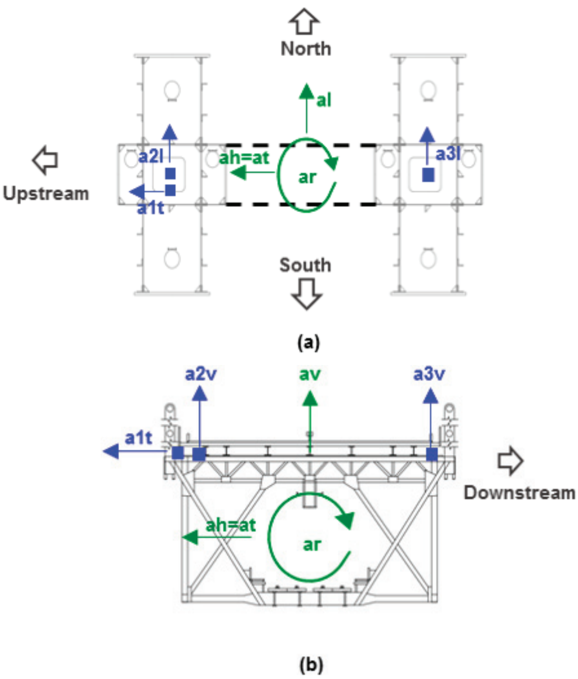

Figure 13 Schematic representation of the accelerations [8]

The challenging character of the automatic modal identification in the 25 de Abril Bridge has motivated the use of machine learning algorithms. Choice was made to use clustering methods, which are capable of classifying data objects belonging to a data set, without any prior information and by analysing only their distribution and density. The aim of a clustering algorithm is to minimize the dissimilarity between data objects (poles) assigned to the same subset (cluster) and, simultaneously, maximizing the dissimilarity between poles allocated to different subsets. Considering a given setup with K clusters, the overall within-subset dissimilarity $W(P_K)$, to be minimized, is defined as

$$W(P_k)=\frac{1}{2}\sum_{k=1}^{K}\sum_{c(i)=k}\sum_{c(j)=k}d_{ij} \tag{11}$$

where, $c(i)$ is a many-to-one allocation rule that assigns object i to cluster k, based on a dissimilarity measure d_{ij} defined between each pair of data objects i and j.

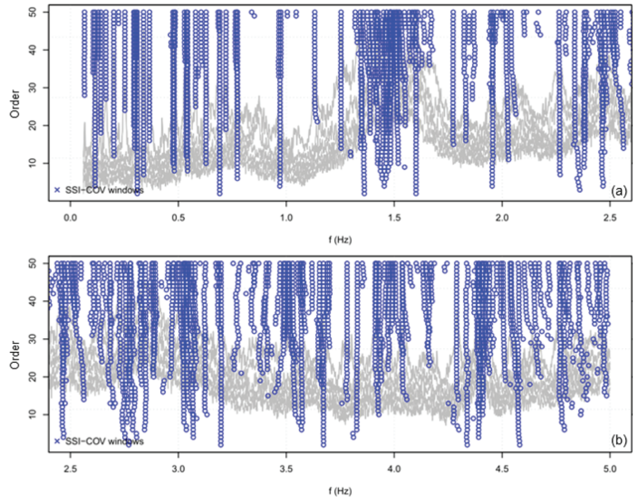

Figure 14 Poles estimated using the SSI-COV from the accelerations acquired during an hour period: stabilization diagram (frequency vs. order). a) Frequencies between 0 – 2.5 Hz. b) Frequencies between 2.5 – 5 Hz.

The most well-known and used clustering algorithms are iterative and based on greedy optimization [19]. These methods require that the number of subsets be defined beforehand along with their randomly located prototypes, taken herein as the centroids in the clustering space. Following this definition, each iteration starts by allocating the objects to the subsets according to the allocation rules which were defined as the assignment of each data object to the less dissimilar (closest) subset prototype. The second step of each iteration consists of redefining the prototypes (centroids) of the K clusters as their prototypes and assuming that each object belongs to the cluster whose prototype is closest. Since no number of clusters (or of natural modes) can be a priori, all possibilities ranging from 1 to 100 were considered and the one chosen as the best representative was that which allows obtaining the highest silhouette width, according to the procedure described in [1], [2], [5], [11].

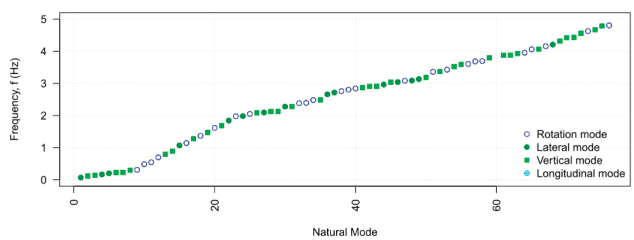

Figure 15 Frequency vs. natural modes

When applying the ensemble of SSI-COV and clustering, a set of natural modes is obtained, from which 76 (shown in Figure 15) successively identified and were included on a baseline mode set, upon which new identification are compared at each hour. Based on this procedure, a set of 76 time-series of frequencies, and the same number of damping ratios, is defined and analysed over time. One example of these time-series is shown in Figure 16 for the frequency of the first vertical natural mode.

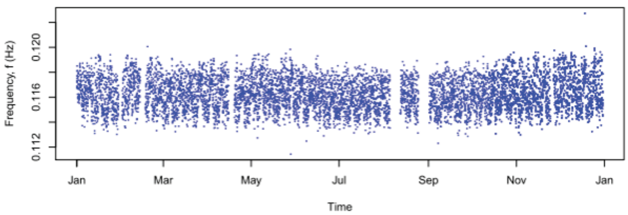

Figure 16 Time-series of the first vertical natural mode frequency

4 Structural response modelling

The analysis of the time-series of data acquired on site, shown in section 2, as well as those of information extraction from these, shown in section 3, allow observing, in an unambiguous manner, the influence of the actions applied to the structure. The effects generated by operational actions have been reported in the literature as having magnitude variations of one or more orders of magnitude than those generated by early damage [1], [13], [20]–[22] and therefore must be taken into account when in SHM systems and techniques. In the 25 de Abril Bridge, it can be readily observed, in Figure 9 or in Figure 11, that a single train crossing or a daily temperature cycle can generate changes of up to 40 MPa in the stiffening truss chords or 100 mm displacement in the bearing devices and joints.

To account for these variations in the damage detection and SHM strategies used for controlling the safety of the 25 de Abril Bridge choice was made to resort to linear and non-linear non-parametric statistical regression. The linear model is solved analytically while the non-linear model consists of a Multi-Layer Perceptron Neural Network with one hidden layer, due to its simplicity and capability of representing any continuous differentiable linear function [1], [7], [23], [24].

The linear model used consists of classical multivariate linear regression, as described and in [1]. This choice is based on the hypothesis that each imposed action to the structure generate one set of effects associated to one linear response due to the fact that the structure exhibits a linear elastic behaviour. Equation (12) describes the linear relationship between *d* actions measured in situ, $X_{n,q}$, and each structural response, Y_n, which is defined by a set of regressive coefficients U_q, which are obtained by minimizing the sum of the squared regression errors, a problem which exhibits a single solution that can be obtained analytically [1]. A graphical representation of this type of model is shown in Figure 17 a [1].

$$y_i = \sum_{j=1}^{q=d+1} x_{ij}u_j + re_i \Leftrightarrow Y_n = X_{n,q}\,U_q + RE_n \qquad (12)$$

Using this model along with the 8 temperatures measured on the stiffening truss in the central mid-span section of the bridge (shown in Figure 6) as well as the wind speed in the three directions measured at same location, all time-series of information obtained according to the methods described in the previous section were modelled. From each of these models, a time-series of estimates and the corresponding errors, which consist of information that is independent, with the effects generated by the actions used as input in the linear regression models. Due to their independency from the actions, this time-series of errors exhibits a smaller variability and is therefore the primary information analysed for real-time damage detection and structural safety control [1], [7], [18]. To ensure that no structural changes have occurred during the period under analysis, these time-series must exhibit no trend or important variations in time.

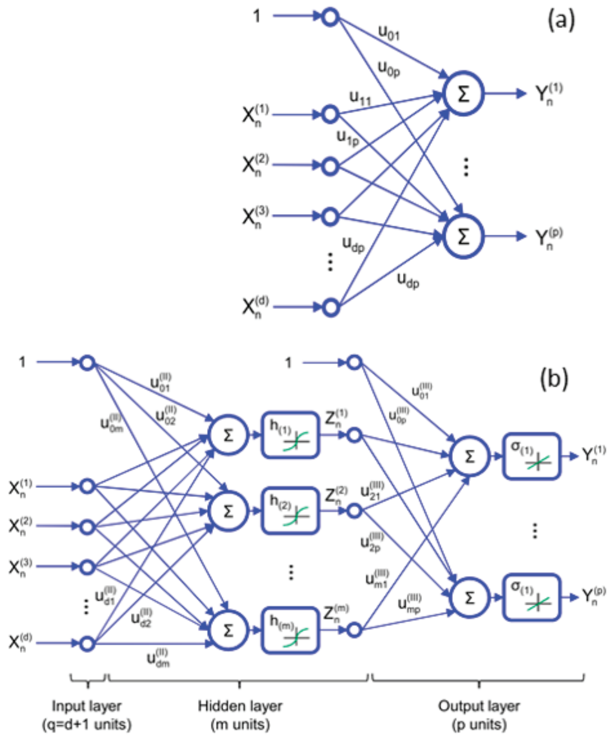

Figure 17 Graph representation of: (a) linear regression and (b) MLP neural network [1]

To illustrate the modelling and analysis described herein, the modelling errors of two time-series of stresses and displacements measured on the 25 de Abril Bridge, and shown in Figure 10 (e2.P3mB and dj.P7), are shown in Figure 18. These errors were obtained by training the linear regression models for a period of one year, shown in green colour in the figure, and in estimating subsequent periods, named as testing periods and shown in blue colour as example. This procedure is conducted continuously over time to assess if structural changes occur between the training and testing periods defined successively over time. The observation of the residuals errors obtained for the training and testing periods allows concluding that stress and displacement variations generated by effects other than temperature, wind and traffic (which were either removed in the procedure described in section 3 or used as input in the regression), exhibit standard deviation of 0.82 MPa and 7.8 mm. Any changes suffered by the structural system that may generates changes larger than these can therefore be detected.

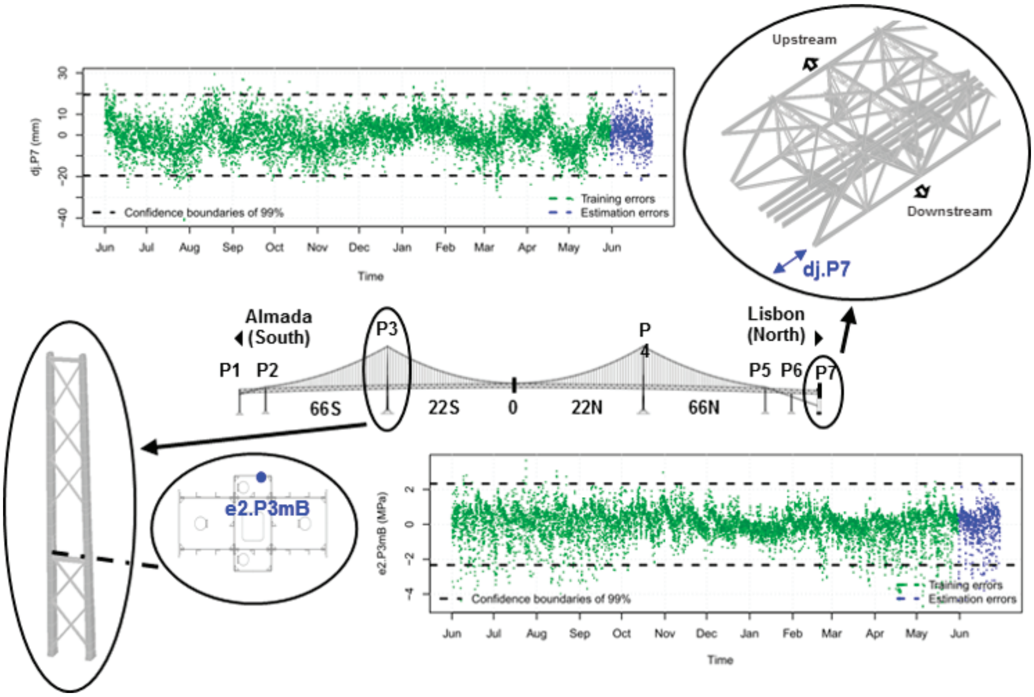

Figure 18 Linear regression applied to the time series of e2.P3mB and dj.P7 and respective bridge localization

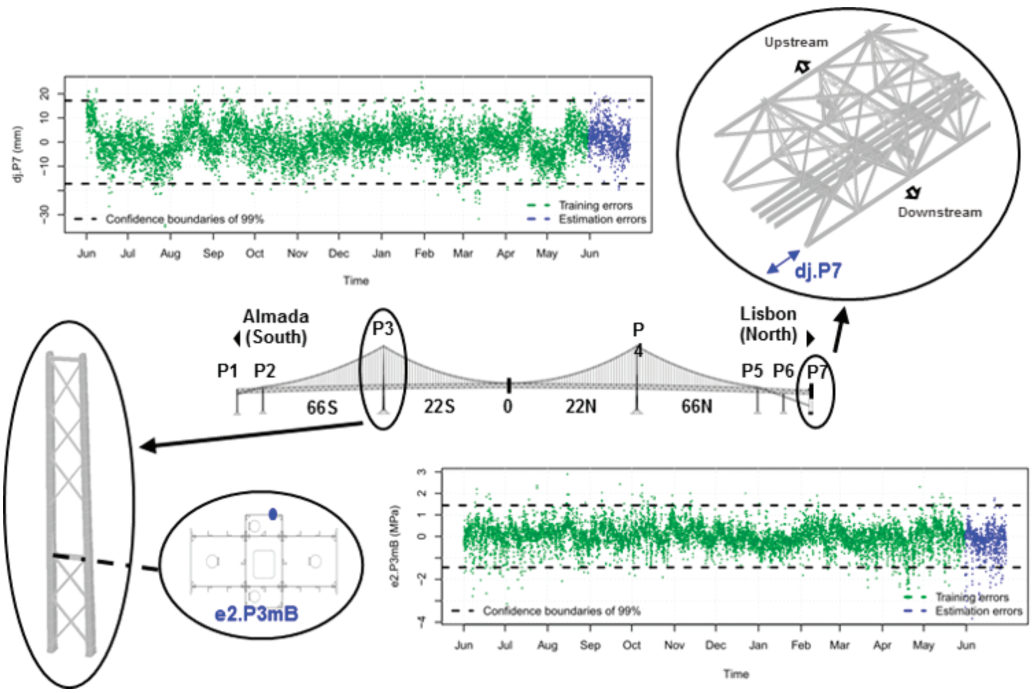

Figure 19 MPL neural networks applied to the time series of e2.P3mB and dj.P7 and respective bridge localization

The non-linear model based on multi-layer perceptron (MLP) neural networks [23] is applied as an alternative to the linear regression modelling. The most important advantage of this method consists of its non-parametric nature since it allows for nonlinear modelling without the need to explicitly define the mathematical functions between actions and responses [19]. The generic MLP model is shown in Figure 17 b and is described in Equation (13), where $u_{jk}^{(II)}$ and $u_{sv}^{(III)}$ represent the regression coefficients, which, as for the linear model, are obtained through the minimization of residual errors' sum-of-squares, h is a non-linear function chosen as the hyperbolic tangent [23], $\hat{y}_{iv}$ consist of the networks' estimates and re_{iv} the corresponding residual errors ($re_{iv} = y_{iv} - \hat{y}_{iv}$).

$$y_{iv} = \hat{y}_{iv} + re_{iv} = \sum_{i=1}^{m} h\left(\sum_{j=1}^{d} t_{ij}\, u_{jk}^{(II)}\right) u_{sv}^{(III)} + re_{iv}\,; \quad i = 1,\ldots,n;\ v = 1,\ldots,p \qquad (13)$$

In opposition to the definition of linear regression models, there is no analytical solution for obtaining the weights that define these neural networks and therefore iterative techniques must be adopted. The MLP iterative weight definition is therefore based on successive evaluations of the network in opposite directions: (i) from the inputs to the outputs to obtain the estimates associated with the set of weights present in the current iteration and (ii) from the outputs to the inputs by back-propagating the errors from the output layer to the first hidden layer. This iterative procedure is named back-propagation and relies on gradient descent for optimization, so as to converge faster to the global minimum of the error function, or to local minima which are close to the former. To avoid obtaining solutions corresponding to local minima associated with high errors, the iterative process should be repeated several times. Finally, when training neural networks for structural response modelling, care must be taken so as to avoid defining too complex and large networks [1], [23], [24] that may memorize all relations needed to generate null or near-null error sets, instead of learning the overall trends observed in the data. This process is named overfitting and is avoided herein by restricting the size of the network's hidden-layer and by stopping the network's training when errors start increasing for a validation data set, which is extracted from the training set. Concise descriptions and explanations of MLP neural networks and their use for SHM structural response modelling can be found in [1], [2], [7].

The procedure applied for linear regression modelling was repeated for the neural networks and the example time-series of corresponding errors are shown in Figure 19. Using this method, the standard deviations of the modelling errors obtained were significantly smaller than those obtained from linear modelling, 0.56 MP (0.82 MPa for linear modelling) and 6.67 mm (7.8 mm for linear modelling), with negligible time consumption.

5 Automatic detection of structural changes

As shown in the previous section, the analysis of the errors' time-series allows, by itself, the identification of structural changes with significant precision, especially bearing in mind the dimension of the 25 de Abril Bridge, the number of sensors installed, the margin of resistance of its materials and the magnitude of the actions imposed to this structural system. This identification can be made by seamlessly analysing the trend, the expected value and the variability of modelling errors. However, for the purpose of continuous SHM and damage identification, an automatic analysis procedure is needed.

In the present work, choice was made to use implement automatic damage identification using statistical hypothesis tests on the expected value of the modelling errors. This strategy allows defining a safety boundary composed of an upper and a lower confidence interval, defined herein with a confidence level of 99% and assuming that the errors series and deviations are described by Normal distribution. The confidence boundary's expression is shown in Equation (14),

$$\left[E[re] - N_{0.5} \times \frac{E[re - E[re]]}{\sqrt{n}}; E[re] + N_{99.5} \times \frac{E[re - E[re]]}{\sqrt{n}}\right] \qquad (14)$$

where $N_{0.5}$ and $N_{99.5}$ are the percentiles 0.5 % and 99.5 % of a Normal distribution with unit standard deviation and null average, n is the number of error values contained in the sample, $E[re]$ is the expected value of the training errors, estimated using the average, and $E[re - E[re]]$ is their variability, estimated using the standard deviation.

The automatic detection strategy described herein is applied daily to the entire set of information time-series, extracted in from the structural responses acquired on the 25 de Abril bridge, and allows controlling the variations in the structural response which are not explained by traffic, temperature and wind. This control is made by analysing the number of estimated values lying outside the safety boundary, per unit of time. This strategy is exemplified in Figure 18, for linear regression, and in Figure 19, for neural network regression. In these figures, the safety boundary is represented as dashed black lines, which are obtained from the training errors shown in green colour, for a training period of one year and an estimation/evaluation period of one month. These boundaries are then compared against the estimating errors, shown in blue colour, and those values which surpass the confidence boundaries are counted and retain for evaluation. Unusually high numbers of values surpassing the boundaries trigger alerts and alarms.

6 Concluding remarks

The present paper describes the structural monitoring system installed on the 25 de Abril Bridge and the SHM strategies applied at LNEC for controlling the safety of this critical infrastructure. The data acquired during one day on the bridge and the information extracted from this data during one year are to provide examples of the strategies and techniques use.

From the experience obtained in the monitoring of this large infrastructure, it was concluded that, to allow controlling the safety of the structure, global quantities representing the behaviour of the structure and of its major elements (deck, pylons, piers, cable and mechanical devices such as joints and bearings) should be measured, either directly and indirectly.

Regarding damage identification based on the analysis of the data acquired, it was concluded that real-time damage detection based on raw data can be highly prone to false detections due to the effects observed in this data, which are generated by operational and environmental actions such as traffic, wind and temperature. As a consequence, SHM strategies developed were based on robust information, filtered from fast effects and representing either the hourly static response, obtained to characterize the effects of slow actions such as temperatures and the maximum effects of traffic and wind, or the dynamic modal response measured also during 1-hour periods.

While the automatic extraction of static-based data proved straightforward based on statistics, the extraction of modal information proved challenging and was the subject of important research and development. It was concluded that time-domain methods such as the Stochastic Subspace Identification (SSI) performed better than those based on the frequency-domain since their output is easy to analyse automatically. It was also concluded that this automation can be effectively implemented using pattern recognition methods, from which clustering methods appear to be the most efficient and effective.

Regarding damage detection, it was concluded and exemplified that sensitiveness to structural changes and robustness to false detections can only be obtained through the modelling of the structural responses based on the values assumed by the actions. This modelling was made using linear regression and neural networks and their comparison allowed concluding that the latter is more effective and thus leads to more sensitive detection of structural changes.

Regarding the automation of the damage detection, it was concluded that considering the modelling errors as a Gaussian population, following a Normal distribution, and testing the location of their centre (expected value) with a confidence level of 99 %, allows obtaining safety boundaries which adjust correctly thus leading to sensitivity to monitored changes and robustness to false detections.

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