Damage detection through continuous monitoring of the response of a cable-stayed bridge to temperature variations

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ABSTRACT

In this study, the possibility of early detection of structural damage through the analysis of the measured structural response of a cable-stayed bridge to daily and seasonal temperature variations is evaluated. A continuous monitoring system has been installed in the Corgo Bridge, here selected as a case-study, which is acquiring data without significant interruptions for about a year. The structural monitoring system is described and the software being used to access remotely and in real-time the measured data is presented.

KEYWORDS: Structural health monitoring, data management, damage detection, bridges.

1. Introduction

Structural health monitoring (SHM) technologies can be defined as a tool to ensure the safety, serviceability, durability, and sustainability of structures by employing long-term real-time monitoring [1] with the aim of assisting and informing operators about the structures condition under gradual or sudden changes to their state [2]. The use of SHM technologies is envisaged as a way to rationalize the maintenance procedures of important bridges, allowing a continuous follow-up of the structural condition and complementing the visual inspections with quantitative information. SHM arises as a potential solution for damage detection before it becomes critical. Its main goal should not be the replacement of the traditional inspection techniques, but the optimization of the inspection and management processes with modern and smart tools [3].

In the last decades several bridges have been provided with structural monitoring systems all over the world [1, 4]. However, notwithstanding the large efforts placed on the development of SHM technologies, it has been argued that in only a few cases SHM systems have clearly demonstrated their value to operators and owners [5, 6]. In fact, these systems often include a large number of sensors and generate big amounts of data which in many circumstances is of difficult interpretation and of low usability by the bridge owners/operators [2, 5, 7-9]. The implementation of automatic and real-time data processing algorithms in order to bring the big amounts of data down to a human and useful scale is often pointed out as a key step for increasing the value of SHM.

The case presented in this paper is a cable-stayed bridge, the Corgo Bridge, recently opened to traffic and in which a permanent monitoring system has been installed [10] and is acquiring continuous data. The bridge and the structural monitoring system, as well as the software being used to access remotely and in real-time the measured data are presented. The ability of detecting damage using the structural response to thermal loads is evaluated applying Multilinear Regression Analysis (MLR) and Principal Component Analysis (PCA) for removing the environmental effects of the structural response. At this stage, simulated datasets were adopted so that at least one year of data can be used in order to remove the environmental effects from the structural response of the bridge in the undamaged state. Finally, several damage scenarios are simulated involving stiffness losses of the stay-cables and it is shown that the adopted methodology, jointly with the installed monitoring system, is able to provide early detection of small damages.

2. Corgo Bridge

The Corgo Bridge (Figure 1) is a prestressed concrete box-girder bridge with a total length of 2790m, divided into three continuous sub-viaducts: the West Sub-Viaduct (WSV), the Central Sub-Viaduct (CSV) and the East Sub-Viaduct (ESV) with length of, respectively, 855m, 768m and 1167m. The West and East Sub-Viaducts are continuous frame bridges with the majority of the spans being 60m long. The Central Sub-Viaduct is a cable-stayed bridge with a 300m long central span balanced by 126m long adjacent spans and two continuous end spans with 48m and 60m on each side (see Figure 2). The suspension system consists of one single central plane with four symmetric semi-fans of 22 stay-cables each.

The deck holds two carriageways with two traffic lanes each and is constituted by a unicellular box-girder of constant height (3.5m) with overhangs supported by prefabricated concrete struts spaced at regular intervals of 3m, see Figure 1 (b). The pylons receiving the vertical loads from the stay cables are monolithically connected to the deck and have a total height of about 193m. The piers, with heights varying between 18m and 113m, are connected to the deck using pot bearings which are either fixed in both longitudinal and transversal directions, or only transversely fixed. Further information about the Corgo Bridge can be found in Barata [11].

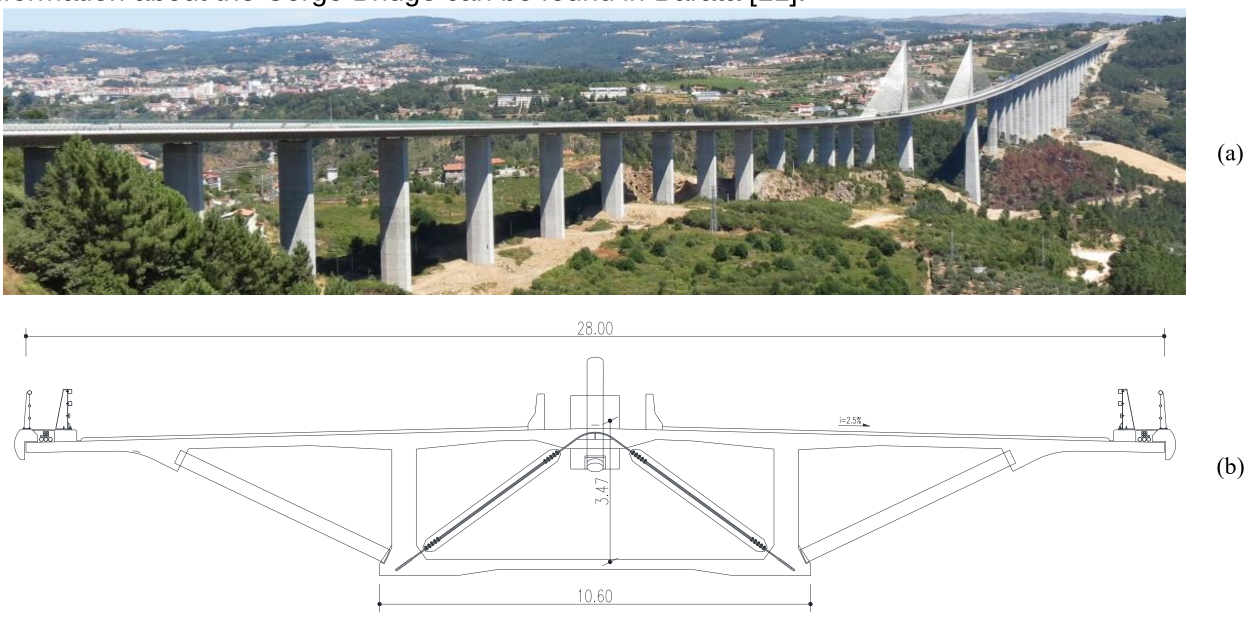


Figure 1. Corgo Bridge: (a) general view, (b) cross-section of the CSV.

3. Structural monitoring system

3.1. Description of the implemented system

A comprehensive structural monitoring system was implemented in the Corgo Bridge, with a particular focus on the Central Sub-Viaduct. The schematic layout is shown in Figure 2. The system contemplates the measurement of bearing displacements, span deflections, rotations, cable forces, average concrete strains, strains in the steel diagonals, ambient and concrete temperatures, ambient and concrete humidity and durability indicators. For the measurement of these magnitudes both fibre-optic sensors (span deflections, steel and concrete strains of the Central Sub-Viaduct and concrete temperatures of the Central Sub-Viaduct) and electric sensors (relative bearing displacements, rotations, cable forces, concrete strains of the East Sub-Viaduct, temperature, humidity and durability indicators) were used [12].

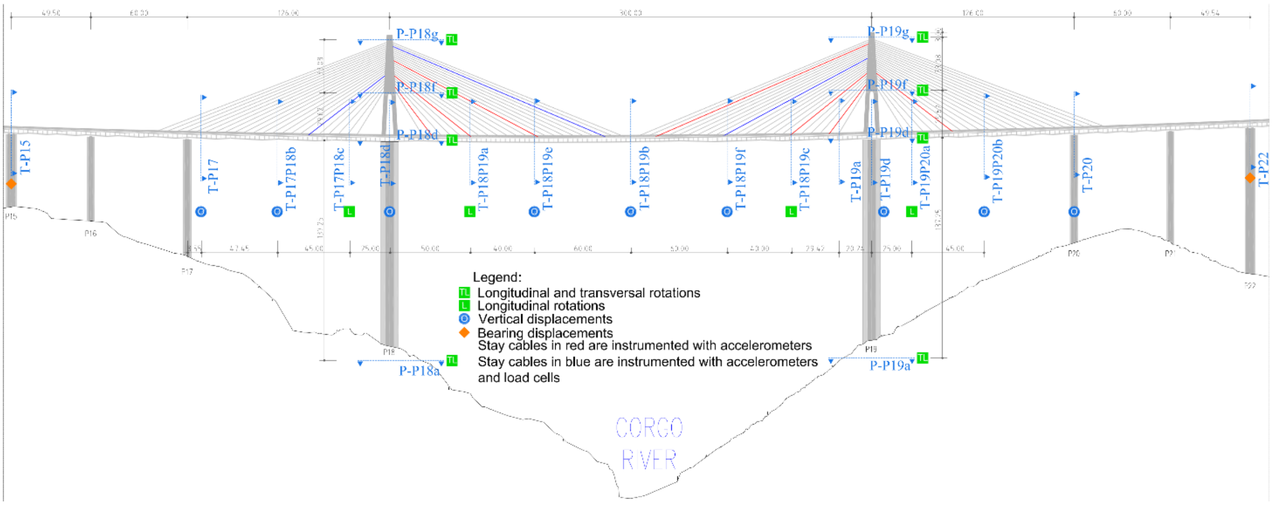


Figure 2. Side elevation of the Central Sub-Viaduct with the location of the monitored sections.

The structural monitoring system was designed for tracking both the construction process and the in-service operational cycle. During the different construction phases, the behaviour of the structure was monitored and evaluated to validate both the numerical model adopted in the structural design and the implemented construction process. At the end of the construction, the monitoring system was put in full operation to evaluate the response of the structure in service, over the following years. Further details about the implemented structural monitoring system may be found in Félix *et al.* [10] and Tomé *et al.* [13]. To this date, the electric sensors are operating without significant interruptions for more than two years while those of the optical system are operating continuously for almost a year.

3.2. SHMmensus – a web-based software tool for structural heath monitoring

For entities responsible for infrastructures management and conservation, rather than the collection of isolated measurements coming from monitoring systems, it is essential to have access to indicators able to effectively and expeditiously reflect the actual state of the structure. In this regard, it is also very important that this information is updated and provided in due time. Only in this way an updated diagnosis can be made and a proactive conservation strategy can be devised, allowing the appropriate measures to be taken.

In this context, a web-based software tool, the SHMmensus platform (*www.newmensus.pt*), was designed and developed for the examination and management of the monitoring results. The developed tool enables the observation and analysis of the measured parameters in order to detect, in real time, modifications of the structural response patterns which might be an indication of damage progression. In a comprehensive way, this tool seeks to integrate, in a centralized access, the structural health monitoring results of a set of structures. Figure 3 depicts the layout of the monitoring system for acquisition, processing, storage and remote display the results. The sensor network is connected to data acquisition devices that read all the transducers at a pre-set sampling rate. Periodically, the recorded results are remotely sent to an external server where the monitoring data is imported, converted, processed and stored in a specific data base.

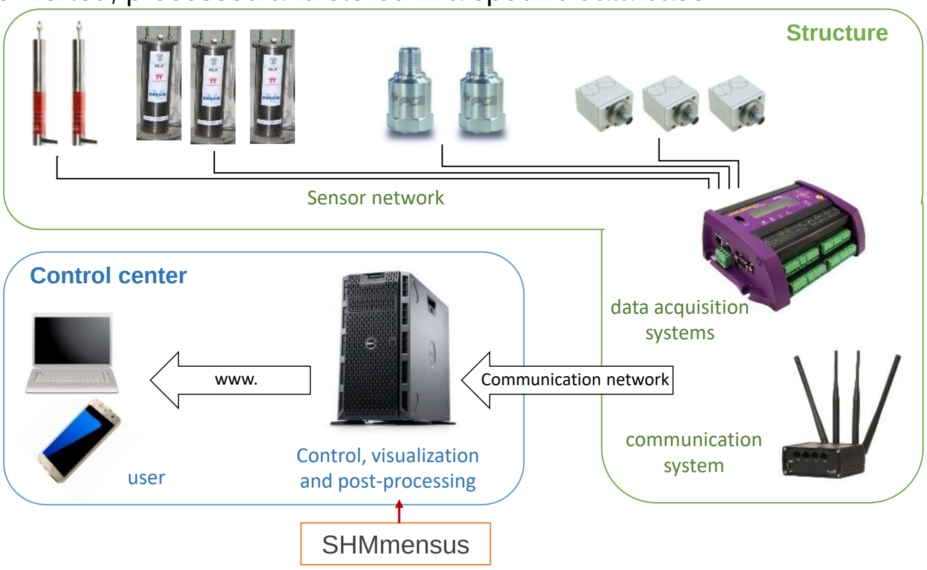
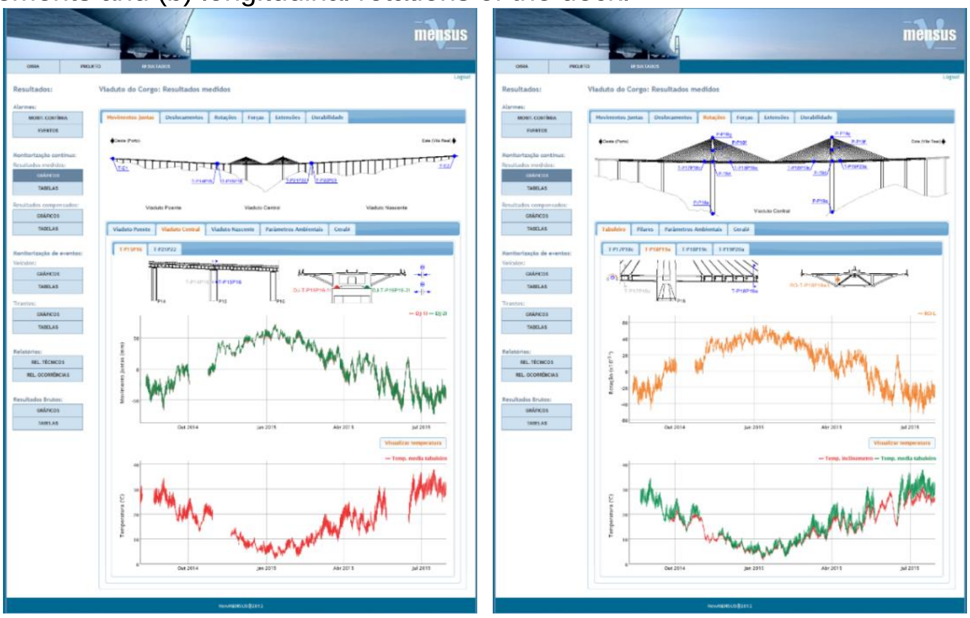


Figure 3. Scheme of the implemented monitoring system.

The results can be assessed and visualized (by authorized users) through an interactive web application, in the form of tables, charts or pictograms. Representative results provided by the SHM system during the operational phase of the Corgo Bridge are shown in Figure 4 namely, (a) relative joint displacements and (b) longitudinal rotations of the deck.



(a) (b)

Figure 4. SHMmensus web interface for real time display of the results: (a) relative joint displacements and (b) longitudinal rotations of the deck

SHMmensus tool also includes algorithms and additional indicators that aim to increase the level of available information. In this sense, the treatment of results to eliminate the operational and environmental structural effects, and summary tables with alert limit states are included in the SHMmensus platform. For each of the observed physical quantities, yellow and red thresholds are established regarding permissible deviations from the reference behaviour of the structure (Figure 5). Moreover, alarm messages are automatically sent to the entities involved if any of the threshold is reached. The yellow limit is expected to correspond to a small deviation from the reference structure condition. Once reached, the structure response has to be followed with closer attention and criticism. The red limit might indicate significant modifications in the structure.

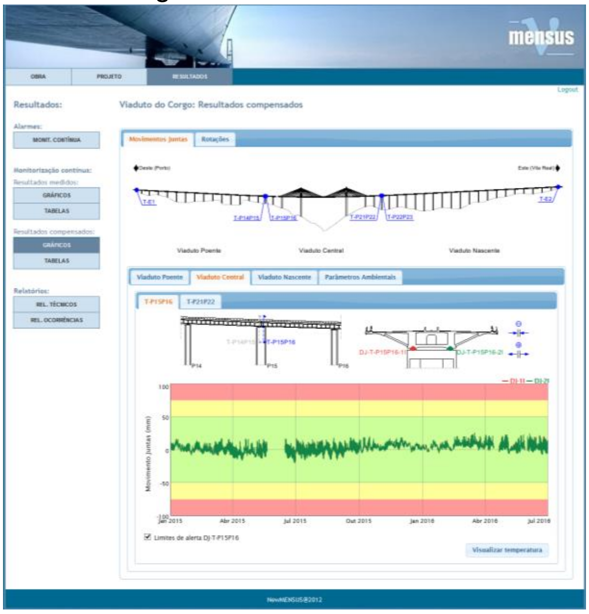


Figure 5. SHMmensus web interface for real time display of the results and threshold values.

4. Removing the environmental effects and novelty detection

With the aim of removing the environmental effects and detect the presence of damage, two well-established multivariate statistical tools used on the scope of SHM were sequentially applied, following the methodology proposed by Magalhães *et al.* [14]. First, a multiple linear regression (MLR) model, where the structural responses are the dependent variables and the concrete temperatures are the independent variables, is fitted using the first year of data. Therefore, the principal component analysis (PCA) is used to remove the environmental effects not explained by the regression model. Finally, the identification of damage is done using the Hotelling T^2 control chart. Since the first year of continuous data is still being acquired, simulated data was used to test the ability for removing the environmental effects and novelty detection of the used multivariate techniques. Details about the simulated datasets can be found in Tomé *et al.* [15].

4.1. Theoretical background

4.1.1. Multiple linear regression (MLR)

The linear regression analysis is probably the simplest multivariate statistical tool to relate the observed environmental and/or operational factors with the observed structural responses and/or features. This statistical tool can be used to predict one or more responses (dependent variables) from a collection of predictors (usually called as predictor, regressor or independent variables) and to assess the influence of the predictors on the dependent variables [16]. The multilinear regression model is expressed by [16]:

$$\mathbf{Y} = \mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{MLR} \tag{1}$$

where $\mathbf{Y}$ is a *n*-by-*m* matrix of the dependent variables, being *n* the number of observations and *m* the number of dependent variables, $\mathbf{Z}$ is a *n*-by-(*r*+1) matrix with the corresponding *n* values of *r* selected predictor variables, $\boldsymbol{\beta}$ is a (*r*+1)-by-*m* matrix with the parameters to be determined that weight the contribution of each predictor variable, and $\boldsymbol{\varepsilon}_{MLR}$ is a *n*-by-*m* matrix with the random error of the MLR model. The estimates of the model parameters $(\hat{\boldsymbol{\beta}})$ are usually obtained through the least squares method, being given by:

$$\hat{\boldsymbol{\beta}} = (\mathbf{Z}^T\mathbf{Z})^{-1}\mathbf{Z}^T\mathbf{Y} \tag{2}$$

Therefore, the obtained model can be used to obtain predictions of the dependent variables $(\hat{\mathbf{Y}})$, being the error of the forecasts the difference between $\mathbf{Y}$ and $\hat{\mathbf{Y}}$. Within the scope of SHM, the multilinear regression model should ideally be constructed using data of an entire year [14].

4.1.2. Principal component analysis (PCA)

Principal Component Analysis can be defined as a statistical tool for explaining the variance-covariance structure of a set of variables through linear combinations of these variables [16] and it has been extensively used in the scope of SHM, namely for the recognition of patterns in the data, data cleansing and data compression [17, 18]. The fact that PCA is a latent-variable method, that is, it is a method that is able to remove the environmental effects using only the structural responses, without any knowledge about the input, is usually pointed out as its most attractive feature[19-21].

Considering a *n-by-m* matrix $\mathbf{Y}$ with the original variables, where *m* is the number of sensors or/and features and *n* is the number of observations in time, a transformation to another set of *m* variables $\mathbf{Z}$, the principal component scores, can be made by:

$$\mathbf{Z} = \mathbf{Y} \cdot \mathbf{T} \tag{3}$$

Where $\mathbf{T}$ is the transformation matrix, an *m*-by-*m* orthonormal matrix that applies a rotation to the original coordinate system [14]. The covariance matrix of the original variables in the training period, $\boldsymbol{\Sigma}$, is related to the covariance matrix of the principal component scores, $\boldsymbol{\Lambda}$, by the following equation,

$$\boldsymbol{\Sigma} = \mathbf{T} \cdot \boldsymbol{\Lambda} \cdot \mathbf{T}^T \tag{4}$$

being the $\mathbf{T}$ and $\boldsymbol{\Lambda}$ matrixes obtained by the singular value decomposition of the covariance matrix $\boldsymbol{\Sigma}$ of the original variables. The columns of $\mathbf{T}$ are the singular vectors and the diagonal matrix $\boldsymbol{\Lambda}$ contains the singular values of the matrix $\boldsymbol{\Sigma}$ in descending order. The singular values stored in $\boldsymbol{\Lambda}$ are the variances of the components of $\mathbf{Z}$. Moreover, the matrix $\boldsymbol{\Lambda}$ can be split into a matrix with the first *p* singular values and in a matrix with the remaining *m-p* singular values, which are not relevant to explain the variability of $\mathbf{Y}$.

After the choice of *p*, the first *p* components of the matrix $\mathbf{Z}$ can be calculated using equation (3) and a transformation matrix $\hat{\mathbf{T}}$ built with the first *p* columns of $\mathbf{T}$. Those first *p* components can be re-mapped to the original space [14, 20] using the following equation:

$$\hat{\mathbf{Y}} = \mathbf{Z} \cdot \hat{\mathbf{T}}^T = \mathbf{Y} \cdot \hat{\mathbf{T}} \cdot \hat{\mathbf{T}}^T \tag{5}$$

being then the residual error matrix estimated from:

$$\boldsymbol{\varepsilon}_{PCA} = \mathbf{Y} - \hat{\mathbf{Y}} \quad (6)$$

The residual error matrix $\boldsymbol{\varepsilon}_{PCA}$ is expected to be insensitive to the effects modelled by the PCA and can be used to detect damage. However, it should be borne in mind that this approach assumes that the environmental factors have a linear or a weakly non-linear effect on the structural responses [20]. Once again, to account for a large range of variation, with the aim of removing environmental effects from the monitored structural responses, the covariance matrix to witch the singular value decomposition is applied should be estimated from an entire year of data. Finally, this tool can be used alone to remove the environmental factors on the structure response [20] or it can be used to remove the environmental factors not explained by the regression model [14].

4.1.3. Hotelling T^2 control chart

After removing the environmental factors from the measured structural response, a control chart can be used to track the existence of abnormal values, which can be related to the presence of damage. The so called control limits define the accepted process variability. If an observation exceeds those control limits, the observation is said to be an out-of-control observation. In context of SHM, this out-of-control observation may be associated with the presence of damage in the structure.

In order to have only one control-chart instead of having one for each variable/sensor, the multivariate Hotelling T^2 control chart was adopted, being the T^2-statistic calculated from the following expression:

$$\mathbf{T}^2 = r(\bar{\mathbf{x}} - \bar{\bar{\mathbf{x}}})^T \mathbf{S}^{-1} (\bar{\mathbf{x}} - \bar{\bar{\mathbf{x}}}) \quad (7)$$

where r is the number of observations considered (window size), $\bar{\mathbf{x}}$ is the average of the observations inside the window, $\bar{\bar{\mathbf{x}}}$ is the process average when it is in control and $\mathbf{S}$ is the process covariance matrix, also estimated in the reference period. The lower control limit is zero and the upper control limit (UCL) is obtained from:

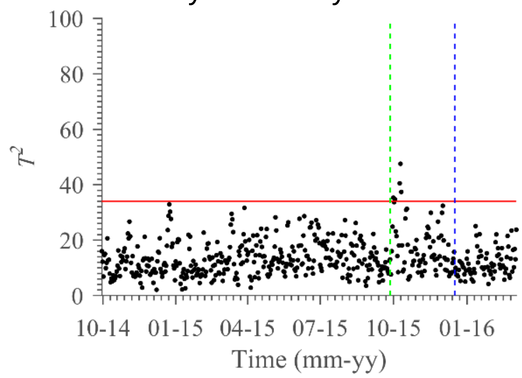
$$UCL = \frac{m(s+1)(r-1)}{s \cdot r - s - m + 1} F_{m,\, s \cdot r - s - m + 1}(\alpha) \quad (8)$$

where $F_{m,\, s \cdot r - s - m + 1}(\alpha)$ is the α percentage point of the F distribution with m and $s \cdot r - s - m + 1$ degrees of freedom, being m the number of sensors and/or features and s the number of subgroups (or windows) collected during the reference period. This statistic, as all the multivariate control charts, has the advantage of condensing all sensors responses into a scalar indicator, working in the context of SHM as a damage indicator. However, after an abnormal behaviour is flagged, it is not possible to know which sensor(s) are responsible for that behaviour.

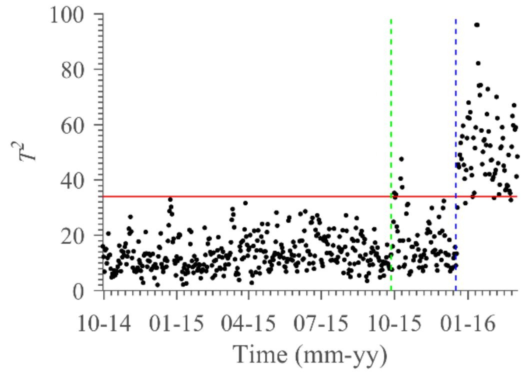
4.2. Results

The stay-cables are the most crucial elements of the cable-stayed bridges since the cable forces are the best indicators of the internal force distribution as well as the alignments of the cable-supported structures. Therefore, in order to test the ability of the multivariate techniques previously presented for removing the environmental effects and detecting damage, several damage scenarios involving the reduction of the stiffness of eight stay-cables were analysed. For the sake of clarity, only the scenario corresponding to a stiffness reduction of 1.5% in stay-cable T19L17 is presented here, corresponding to the failure of one strand.

Fifteen sensors were chosen from the monitoring system of the bridge for inclusion in the MLR and PCA models: five vertical displacements of the girder and ten cable forces. In order to make the present study more realistic, noise was added to the (simulated) structural responses. The noise of the vertical displacements was assumed to follow a normal distribution with null mean and a standard deviation of 0.10mm, which is in accordance with the observed noise on site and with the level of noise reported previously in a similar deflection measuring system [22]. For the noise in the cable forces, a normal distribution with null mean and a standard deviation of 10kN was assumed, which is also in accordance with the observed noise on site. The temperature series were rounded to the second decimal case and standardised. In order to account for the yearly variation of the environmental action, the first year (from October 2014 to October 2015) of the simulated data was used to establish the multivariate models. The remainder data (from November 2015 to February 2016) were used to validate the fitted models, evaluate the quality of the forecasts of the models and evaluate the ability for novelty detection.



(a)



(b)

Figure 6. T2 control chart using MLR-PCA (daily values): (a) undamaged; (b) damaged (stiffness reduction of 1.5% of the stay-cable T19L17). The green dashed vertical line corresponds to the end of the reference period and the blue vertical line corresponds to the time instant of introduction of damage. Window size: three days.

Considering the available temperature sensors and the contribution of the different elements of the bridge in the deflections and force variations in the stay-cables, the following variables were chosen as predictor variables of the fitted MLR models: stay-cable temperature $(T_{stay-cable})$; average of the concrete temperature sensors of a girder cross-section $(T_{u,sensors}^{Girder})$; average of the concrete temperature sensors of a cross-section of a pier $(T_{u,sensors}^{Pier})$. $T_{stay-cable}$, $T_{u,sensors}^{Girder}$ and $T_{u,sensors}^{Pier}$ are expected to be, respectively, representative of the temperature of the stay-cables, of the uniform temperature component of the girder and of the uniform temperature component of the pylon and piers. The residuals of the adjusted MLR models are then used to construct the PCA model, being the residuals standardised in order not to bias the model due to the different scale of the considered variables. For the construction of the PCA model, the first four components were chosen. These are the components that have eigenvalues higher than one and correspond to a cumulative percentage of total variation of 64.0%. A window size of three days was chosen for the calculation of the T^2 – statistic since it is the smallest window size where after the introduction of damage the large majority of the points are above the UCL. The UCL was established using the equation (8) with $\alpha = 0.99$. This high value for α was adopted in order to minimize the probability of false positives since the simulated damage scenarios are very small and do not affect the safety of the bridge. Although there are some false positives outside the training period, when damage is present it is clearly flagged after having been introduced since there is an unequivocal shift in the mean value of the T^2-statistic, being the majority of the points above the defined UCL.

5. Conclusions

In the present work the structural monitoring system in the Corgo Bridge and the developed software for data management and examination in real-time (the SHMmensus) were presented. The SHMmensus not only allows the collection and organization of the monitoring results of different kinds of sensors and acquisition systems, but also the easy access and interpretation of the current state of the structure by non-specialists in SHM, providing useful information for the bridge management.

The ability to detect small damages in the suspension system of the Corgo Bridge using data-driven techniques applied to the structural response of the bridge to the temperature variations was also evaluated in this work. Only a subset of sensors of the installed monitoring system was considered. Damages on the stay-cables were simulated, which consisted on the stiffness reduction of 1.5% of eight stay-cables, corresponding to the failure of one prestressing strand. The ability to detect small damages in the suspension system of the Corgo Bridge using the installed structural monitoring system and the adopted techniques was demonstrated.

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