

Structural damage continuous monitoring by using a data driven approach based on principal component analysis and cross-correlation analysis

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Abstract. Continuous monitoring for damage detection in structural assessment comprises implementation of low cost equipment and efficient algorithms. This work describes the stages involved in the design of a methodology with high feasibility to be used in continuous damage assessment. Specifically, an algorithm based on a data-driven approach by using principal component analysis and pre-processing acquired signals by means of cross-correlation functions, is discussed. A carbon steel pipe section and a laboratory tower were used as test structures in order to demonstrate the feasibility of the methodology to detect abrupt changes in the structural response when damages occur. Two types of damage cases are studied: crack and leak for each structure, respectively. Experimental results show that the methodology is promising in the continuous monitoring of real structures.

1. Introduction

“SHM is the integration of sensing and possibly also actuation devices to allow the loading and damaging conditions of a structure to be recorded, analysed, localized, and predicted in a way that non-destructive testing (NDT) becomes an integral part of the structure and a material” [1]. Thus, one of the main concerns in the field of condition monitoring is the implementation of systems with the capability to continuously evaluate the health of a structure. It is desirable that SHM system satisfy characteristics regarding to reliability, accuracy, robustness, and high sensitivity to presence of damage [2]. Additional requirements in order to achieve continuous and efficient SHM systems are related to hardware and software resource consumption when big data are recorded [3]. Therefore, the use of algorithms with low computational cost facilitates the implementation of diagnostic assessment approaches. In this sense, Principal Components Analysis (PCA) based methodology for structural damage detection becomes in a promising technique to be considered for online monitoring [4]. PCA is a mathematical tool widely used for feature extraction and pattern recognition that consists of well-defined matrix operations [5], which can be programmed by means of optimized procedures considering balanced memory/processor performance [6].



PCA in combination with piezo-diagnostics principle have been demonstrated be useful for structural health monitoring, with applicability for damage detection in aluminum plates, composite structures, aircraft sections and pipe work structures [7]. Damage detection is achieved by the use of PCA for obtaining a baseline of the pristine structure taking advantage of guided waves dispersion, which is statistically analyzed through squared prediction error indices. Thus, abnormal states are identified by means of scatter plots.

In this work, a data-driven approach for structural damage detection based on PCA technique is studied for online monitoring. The main contribution is focused on applying cross-correlation analysis as pre-processing technique. The performance of this approach is evaluated by analyzing data from two structures, a laboratory tower and a pipe section. The feasibility to detect cracks and leaks is demonstrated by processing online measurements.

2. Methods and Procedure for Damage Detection

The approach used in this work to detect structural damages is summarized in **Figure 1**. It consists of four main stages: Instrumentation system, Data pre-processing, statistical data-driven modelling and condition monitoring.

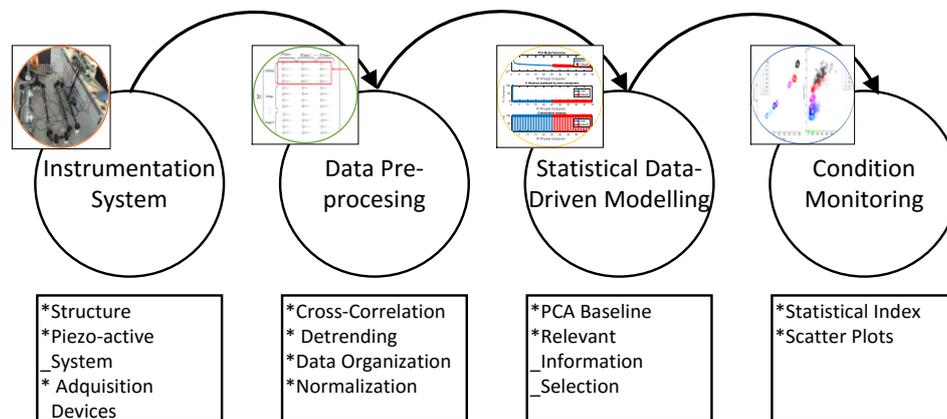


Figure 1. Damages detection methodology

2.1. Instrumentation System

In this work, the piezo-diagnostic principle is used as main approach for damage identification, which is based on analyzing guided waves propagation through the structure [8]. Guided waves are generated by means of piezo-electrical devices in order to find patterns with high sensitivity to structural damages. In this way, taking advantage of piezoelectric effect, information about the scattering, reflection, and mode conversion from elastic wave travelling caused by discontinuities is examined.

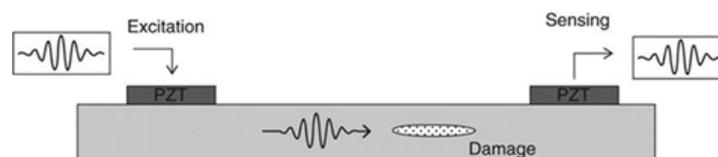


Figure 2. Piezo-diagnostic principle [8]

According to **Figure 2**, the instrumentation system belongs to a piezoelectric active scheme, where one of the PZT mounted on the surface structure operates as actuator, and the remaining PZT works as sensors in a pitch-catch mode. Other components of the instrumentation equipment consist of fine-tuning filters, high wide-band amplifiers and acquisition elements, among others.

2.2. Data pre-processing

The aim of data pre-processing stage is to minimize the presence of outliers and atypical data, as well as the application of methods intended for data cleansing and normalization. It also includes data organization in order to facilitate data fusion, which allows the implementation of statistical techniques. For this purpose, cross-correlation functions, *detrending* analysis, and *Group Scaling (GS)* procedure are applied.

Initially, linear trends are removed from piezo-electrical measurements due to artefacts noise and low frequency disturbances. Then cross-correlation is computed between actuation and sensing piezo-signals, with the objective to exclude common external noise signals, outliers filtering and as a tool for improving separation boundaries for damage conditions. A data matrix (X) is built using cross-correlated functions corresponding to each PZT sensors, and considering only measurements from pristine condition. Several repetitions from undamaged state are organized in this unfolded matrix as shown in Figure 3.

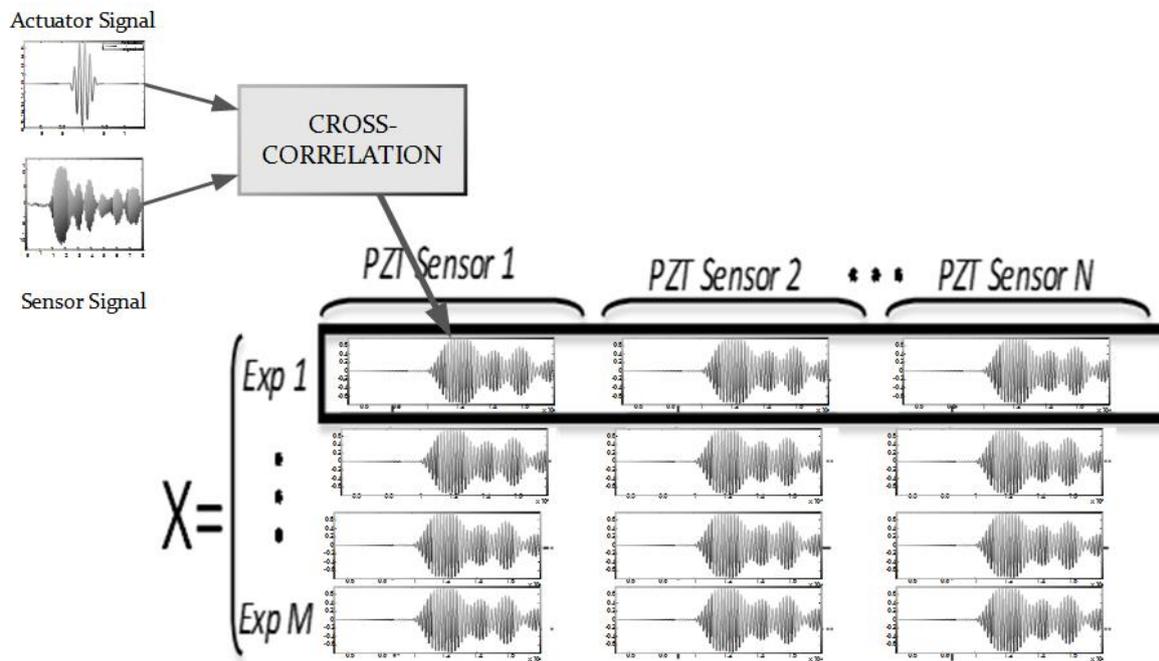


Figure 3. Undamaged cross-correlated baseline Matrix

The cross-correlation function between two signals $X(t)$ and $Y(t)$ is used to obtain elements in the undamaged cross-correlated baseline matrix, it is defined as:

$$R_{XY}(t, t + \tau) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N X_k(t) Y_k(t + \tau), \quad (1)$$

where N is the number of signal samples and τ is the lag time interval used to compute the cross-correlation function.

Finally, the undamaged cross-correlated baseline matrix is normalized by applying *Group Scaling (GS)* procedure to avoid scaling and bias issues. Normalization reduces the influence of different source of variability due to changes in environmental and operational conditions. In *Group Scaling* each data-point from the undamaged cross-correlated baseline matrix (X) is scaled by considering changes between sensors and the nature of data by estimating standard deviation for each block of piezo measurements [9]. The standardization of undamaged cross-correlated baseline matrix X is computed by using the mean of each time sample for every experiment and the standard deviation of each sensor sample vector, which result in the normalized data matrix \bar{X} :

$$\bar{x}_{ij} = \frac{x_{ij} - \hat{\mu}_j}{\hat{\sigma}_j}, \quad (2)$$

where $\hat{\sigma}_j$ is the standard deviation per piezo sensor and $\hat{\mu}_j$ is the mean value per column of undamaged cross-correlated baseline matrix X .

2.3. Statistical Data-Driven modelling

The baseline model is built by applying PCA to the standardized undamaged baseline matrix \bar{X} . Thus, cross-correlation functions from undamaged measurements are represented in the reduced space of principal components according to equation (3).

$$\bar{X} = TP^t + E = model + noise \quad (3)$$

The model in (3) belongs to a new reduced space of coordinates with minimal redundancy, based on the variance–covariance of the original data. T is the projection to the reduced space, P is a linear transformation matrix that relates the normalized data matrix \bar{X} in the new coordinates and denotes the principal components (eigenvectors). The noise E -matrix is the part of \bar{X} , which is not explained by the model and describes the residual variance neglected by the statistical model. The estimation of the baseline model involves the following steps [10]:

1. Compute the cross-correlation between actuating signal and measurements from PZT sensors when the structure operates in healthy condition.
2. Organize cross-correlation functions in the unfolded data matrix X as is shown in Figure 3.
3. Normalize the undamaged cross-correlated baseline matrix by using *Group Scaling* procedure, which produce mean values ($\hat{\mu}_j$), and standard deviations ($\hat{\sigma}_j$) from experiment repetitions in the nominal condition.
4. Compute the singular value decomposition of the standardized undamaged cross-correlated baseline matrix by applying PCA. Thus, the eigenvectors and eigenvalues are obtained.
5. Keep only the first r components in order to obtain a reduced representation for original variables. The variance for each new variable corresponds to their respective r eigenvalues.

As a result, the statistical baseline model corresponds to mean values ($\hat{\mu}_j$), standard deviations ($\hat{\sigma}_j$), and the r eigenvectors (P) and eigenvalues (λ).

2.4. Condition Monitoring

New PZT measurements representing the current structural state are compared with the baseline representation in order to identify structural condition, where differences between baseline model and current state are attributed to damage. Thus, the cross-correlation between actuation and sensing signals of these measurements are organized in a row vector and standardized by applying *Group Scaling* with the mean values and standard deviations of the undamaged cross-correlated baseline matrix ($\hat{\mu}_j, \hat{\sigma}_j$) with the help of eq. (2). This normalized row vector is projected onto the reduced space by using the statistical model (3). In order to compare the signature structure respect to undamaged condition two statistical indexes are computed: T-squared statistics (T^2) and squared prediction error (Q):

$$Q = \sum_j \left(e_j \right)^2 \quad (4)$$

$$T^2 = T^t \lambda^{-1} T \quad (5)$$

Where, e_j is the residual error for each j – th principal component used to reconstruct the trial experiment and λ (singular values) are the respective variances of the reduced-space.

The whole methodology can be summarized in two stages: Training and Monitoring. Figure 4 shows the concept of the system:

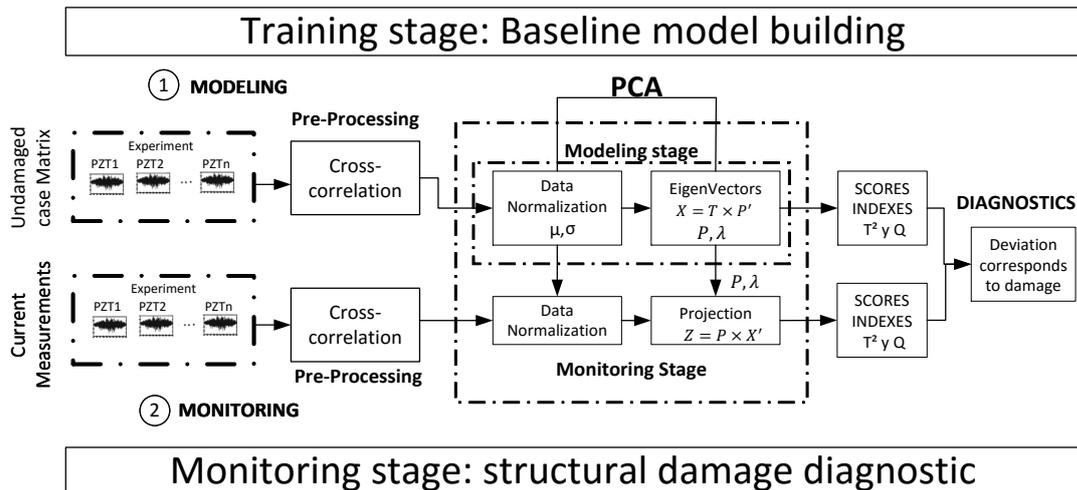


Figure 4: Two staged approach based on PCA for structural damage assessment.

3. Experimental Results

Experimental tests were conducted on two structural lab models in order to evaluate the capability of the methodology for continuous monitoring: A carbon steel pipe section and a laboratory tower. In both cases, the piezoelectric actuator device is excited with a periodic high frequency (~100 KHz) burst type signal in order to induce a guide wave. Each damage scenario includes 100-experiment repetitions during 1s of periodic excitation signal.

3.1. Carbon steel pipe section

The first specimen used as test structure is a carbon-steel pipe section of dimensions 100x 2.54 x0.3 cm (length, diameter, thickness). It was conditioned with piezoelectric devices in order to induce guided waves along the surface structure. Operational conditions are controlled through bridles, a valve, a manometer and a compressor. The air pressure is settled from a compressor in 80 psi at one of the ends. The test structure is depicted in Figure 5, where several sections can be identified. However, only measurements from the first section were considered in this study. In addition, bolts and other elements used to recreate leak damages are included in the nominal state of the structure and consequently in the statistical baseline model.

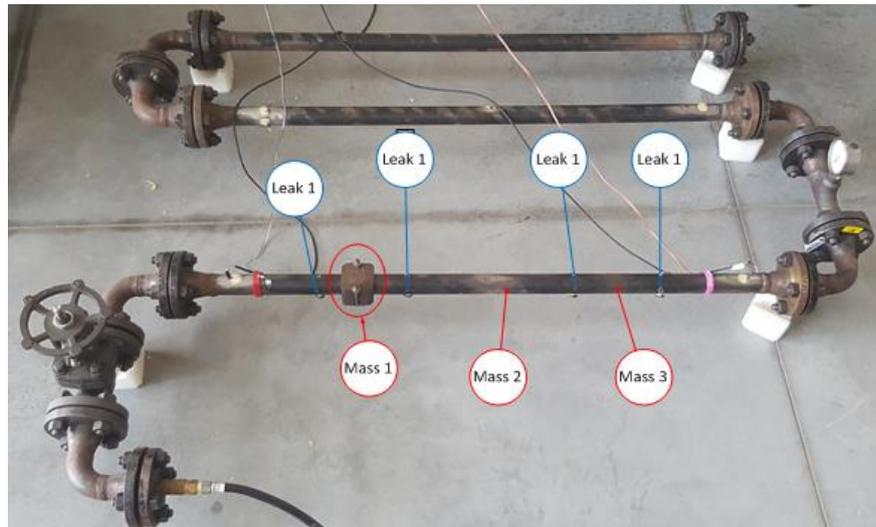


Figure 5. Pipeline experimental set-up

As illustrated in Figure 5, leaks were induced by a full opening of a hole between the PZT devices (Actuator-Sensor) and located at different points along the structure. These kinds of leaks are recreated by means of four $\frac{1}{4}$ -inch holes which were drilled along the pipe section wall. Thus adjustable screws were used to control the leak magnitude to be produced. Likewise, a special shaped accessory was added to the surface pipe section in order to simulate damage types corresponding to adding masses at different locations of the surface.

The T-squared and Q-statistical indices are depicted in Figure 6. The performance without cross-correlation is also presented in order to evaluate the influence of using cross-correlation analysis in the damage detection scheme.

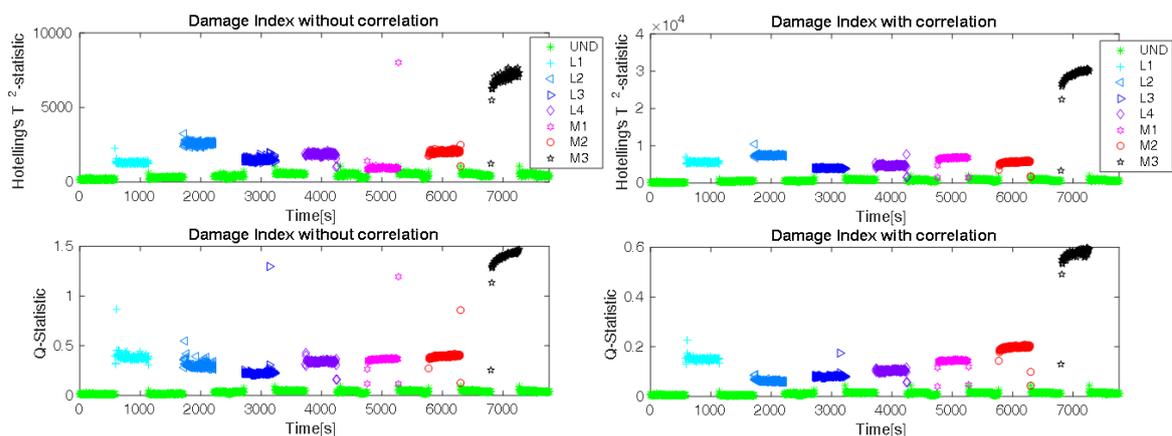


Figure 6. Statistical indexes for pipeline experiment. Left: without cross-correlation. Right: cross-correlated piezo-diagnostic approach

According to results in Figure 6, it can be observed that more dispersion appears without cross-correlation analysis. Also, the transient response when damage appears can be captured and it is possible to identify the time occurrence of damage, which facilitate decision making. Additionally, if correlation analysis is included in the damage detection approach, then some atypical data-cases are filtered. In order to emphasize the advantage of using cross-correlated functions, the Q Vs T^2 scattered plots are shown in Figure 7, where more clear boundaries between damage conditions can be observed when cross-correlation are included.

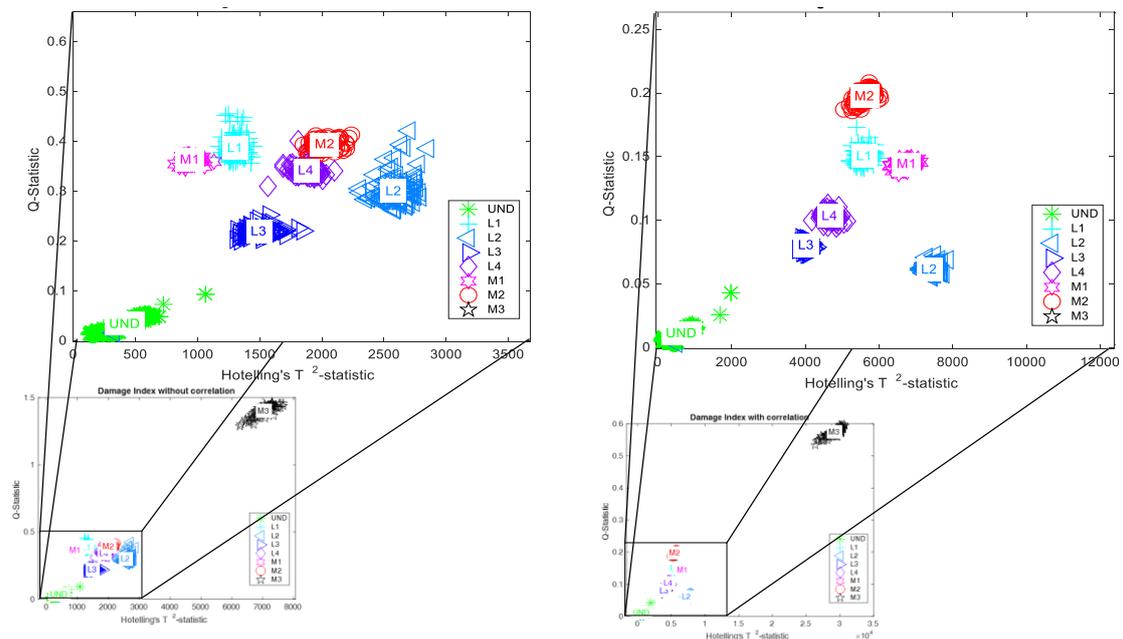


Figure 7. Q vs T^2 scatter plots for pipeline experiment. Left: without cross-correlation. Right: cross-correlated piezo-diagnostic approach

3.2. Laboratory tower

The second test structure is a tower model, representing a wind turbine model [11] (Figure 8). The structure (2.7 m high) is composed by three components (Figure 8a): jacket, tower and nacelle. Five PZT sensors were installed in the jacket (Figure 8a, red markers correspond to PZT devices) in order to record 50-experiment repetitions from guided wave structural responses produced by the PZT actuator using a sample time $T_s = 32.0$ [ns].

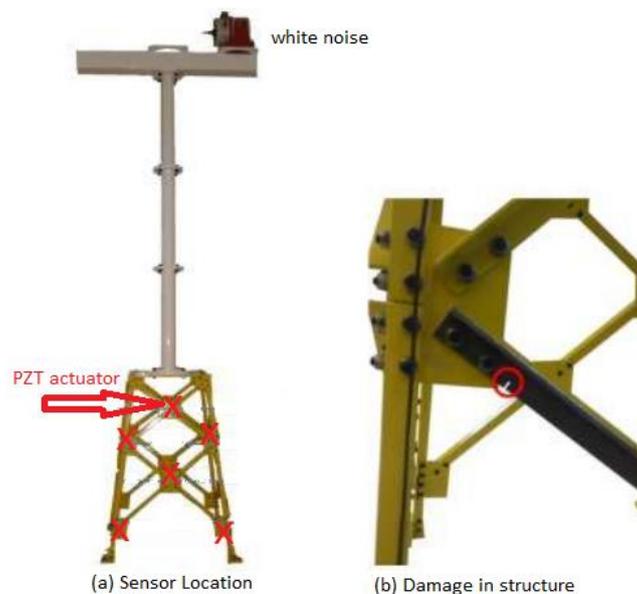


Figure 8. Laboratory tower structure.

Two kinds of damages were studied in the tower test bench. The first one corresponds to crack condition, which was induced by replacing one of the undamaged sections in the jacket with a 5-mm cracked section (Figure 8b). The second one consists of full/partial unbolted screws. **Figure 9** shows

the evolution for index values when damages are caused in the structure. The tag specification in Figure 9 corresponding to each damage is as follow: unbolt two screws in one section (D1), unbolt all screws in the section (D2), replacing cracked element (D3) and repetition of cracked damage (D4). All damages are generated in the same section.

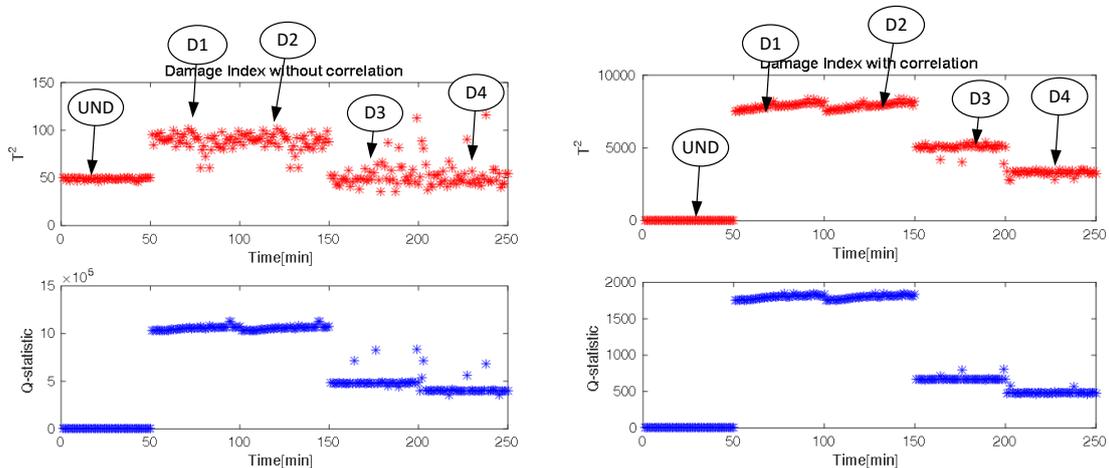


Figure 9: Statistical indexes for the Laboratory tower.

According to results in Figure 9, it can be distinguished the damage state from undamaged one (UND). However, the transient dynamics it is no clearly observable. It is possible establish meaning differences regarding to the undamaged state and a low dispersion for all experiments. Also, clear thresholds are identified between both damage types (unbolt and crack). Nevertheless, a local low linear trend is noted in the index values, which can be produced for sensor drifts.

4. Conclusion

The feasibility of using a data driven approach based on principal component analysis and cross-correlation analysis for monitoring cracks, leaks and mass aggregation in structures was experimentally validated in a pipe loop and in a laboratory tower. In this sense, the squared prediction error (Q-statistic) and T-squared indexes were proved to be suitable as damage index for continuous monitoring with good capability to differentiate unhealthy from undamaged structural conditions. It was demonstrated the applicability of using cross-correlation to reduce outlier data, minimization of damage type group dispersion and for obtaining better boundary separation damage classes. It is required future studies to include environmental and operational variations as well as methods to separate sensor faults such a bias and drift issues.

5. Acknowledgement

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