Damage identification in railway bridges using a novel nonlinear time series analysis methodology with sensor clustering

Pedro Oliveira[1[0000-0003-4117-267X]], Xu Min[1[0000-0002-1063-6198]],
Andreia Meixedo[2[0000-0001-8327-1452]] and Rui Calçada[2[0000-0002-2375-7685]].

[1] National Laboratory of Civil Engineering, Lisbon 1700-066, Portugal
[2] Faculty of Engineering of the University of Porto 4200-465, Porto
pmoliveira@lnec.pt

Abstract. Vibration-based methods for damage detection have been widely used, particularly those relying on ambient excitations. These methods are based on the principle that changes in a structure's physical properties, such as mass, stiffness, and damping, will lead to changes in its vibration characteristics.
A promising area of research focuses on utilizing operational loads, such as vehicular traffic, instead of ambient excitations. Dynamic responses generated by operational loads, such as trains, induce higher levels of vibration compared to those caused by temperature variations or ambient vibrations. The consistent and repeatable nature of this load can also reduce the time required for training predictive models. Furthermore, as vehicles cross the bridge from end to end, structural damage, even if localized, will generate anomalies in the dynamic responses, which may be detectable by sensors installed in the structure. With a higher signal-to-noise ratio, this approach enables more efficient and cost-effective monitoring systems.
This paper presents a data-driven approach for identifying damage in railway bridges based on train-induced dynamic responses. In this methodology, nonlinear autoregressive models with exogenous inputs (NARX) are developed for different sensor clusters, using the structure's free response after train excitations. The damage index is defined based on the prediction errors of each NARX.
The effectiveness of the proposed methodology is validated using real acceleration data from a long-span steel-concrete composite bowstring arch railway bridge. Changes in the longitudinal stiffness of the bearing devices were identified through acceleration data recorded during the passage of Alfa Pendular trains.

Keywords: Railway Bridge, Damage Detection, Experimental Data, NARX, Free Response.

1 Introduction

Over the last two centuries, huge investments have been made in infrastructures such as bridges, buildings, railways, dams, and airports to support the development of society and the economy. During their lifetime, factors such as material aging and harsh environmental conditions can lead to damage or even failure. The deterioration of critical infrastructure can have various economic and social impacts. In this context, Structural Health Monitoring (SHM) plays a crucial role in assessing structural conditions and ensuring reliability and safety [1, 2].

SHM involves the continuous observation of the structure by collecting periodically measurements, to obtain accurate and real-time information concerning structural condition and performance. Damage identification is a fundamental part of SHM and has been extensively studied to address three key objectives: determining the existence of damage, locating the damage and assessing the severity of the damage [3].

The SHM of bridges presents unique challenges due to the diversity of structures, materials, loads, and environmental conditions. Among the available methods, vibration-based damage detection techniques are the most widely employed in real-world applications, particularly those relying on ambient vibration [4, 5]. Vibration-based damage detection methods can be broadly categorised into three groups: model-based (e.g., natural frequencies and mode shapes), frequency-based (e.g., frequency response functions), and time-series-based approaches.

Significant research efforts have been dedicated to the development and application of time-series-based methods. In these approaches, dynamic responses such as acceleration, velocity, and displacement of the structure are fitted into time-series models. Damage detection is then performed by extracting damage-sensitive features from model coefficients [6] or residual errors [7, 8].

Recently, there has been increased interest in developing vibration-based damage detection techniques that rely on operational response such as vehicular traffic, rather than ambient vibrations [8, 9]. The measurement pattern recorded by a sensor during the passage of a vehicle over a bridge serves as signature of the structural response, offering values insights into the system behaviour. Compared to traditional vibration-based methods relying on ambient loads, moving load-based approaches present several advantages: higher structural vibrations, high signal-to-noise ratio, and require fewer sensors. Additionally, vehicles traverse all sections of a bridge, including damaged areas, which result in anomalies in the structural response.

Despite the significant potential of structural time-series methods that rely on operational responses to achieve the localization in the damage identification process, critical gaps remain. Specifically, there is a lack of effective implementations for bridges that enable online and continuous damage identification. Most existing methods are applied to simple structures, numerical models [2, 10] or experimental models [11]. Furthermore, the nonlinear behaviour of train-induced dynamic responses is often misjudged, and the environmental and operational influence on structural responses is frequently underestimated or inadequately addressed.

Considering this limitation, this study explores the combination of sensor clustering with a nonlinear time series model to identify the presence of a damage based on train-induced dynamic responses. The proposed methodology employs nonlinear autoregressive models with exogenous inputs (NARX) for different sensor clusters, using the structure's free response after train excitations.

The effectiveness of the proposed approach is validated using real train-induced acceleration data collected from a long-span steel-concrete composite bowstring arch railway bridge. Changes in the longitudinal stiffness of the bridge's bearing devices were successfully detected using this approach.

2 Methodology

The use of real data from train-induced responses represents a significant innovation in the field of SHM. Experimental data enhance the accuracy of the damage identification process and improve the applicability of the methodology to real-world scenarios, providing valuable insights and practical advancements. By incorporating real data, the approach overcomes uncertainties often associated with theoretical models, such as track irregularity profiles and wheel defects (e.g., wheel flats and polygonization), which are critical for realistic assessments.

The proposed damage detection framework is an output-only, data-driven approach relying exclusively on measured acceleration responses. This method does not require prior information about physical structural properties, wheel defects, or track irregularities, making it versatile and practical for diverse applications.

The methodology involves four key steps: sensor clustering, time-series modelling, damage-sensitive feature extraction, and outlier analysis.

2.1 Sensor clustering

The concept of sensor clustering, introduced by Gul and Catbas [12], enhances the ability and reduces the complexity of time-series approaches for damage identification. In this approach, the sensor’s network is considered as multiple system rather than a single system. Each system, or cluster, consists of a group of sensors, with one sensor designated as the reference sensor, and the others classified as neighbour sensors (Fig. 1). This clustering strategy simplifies the processing of time-series data by focusing on localized areas of the structure, improving the efficiency and precision of damage detection and localization processes.

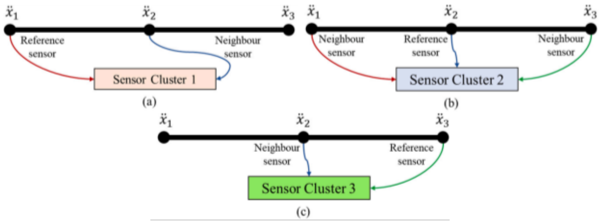

Fig. 1. Sensor clustering concept [7].

2.2 Time-series modelling

After clustering the sensor network, free-response acceleration data from the base-line condition were utilized to develop separate time-series models for each sensor cluster. The response of each reference sensor is predicted using inputs from the neighbouring sensors. In this study a NARX is employed to predict each reference sensor based on the response of the neighbouring sensor. Given the discrete-time nature of the data, a NARX model can be defined for a multi-input, single-output system as:

$$y = f[x(t)] \tag{1}$$

with $x(t)$ a vector defined by:

$$x(t) = \left[y(t-n_y), \dots, y(t-1), u^1(t-n_u), \dots, u^1(t-1), u^1(t), \dots, u^M(t - n_u), \dots, u^M(t-1), u^M(t)\right] \tag{2}$$

where $y(t)$ represents the output (reference sensor response) at time step t, f is the nonlinear function representing the multi-input, single-output system, $u^1(t), \dots, u^M(t)$ are the inputs (responses measured at the neighbouring sensors), the n_u and n_y the input and output orders, repectivily, and M is the number of neighbouring sensors employed.

For systems with more complex nonlinear behaviour, neural networks are often preferred due to their flexibility in capturing complex patterns and relationships. Herein, the nonlinear function f is approximated by a single hidden layer neural network.

A critical parameter in these machine learning algorithms are the model orders (n_u and n_y), which refers to the number of past outputs and inputs used in the model. According to the embedding theorem, model orders need to be sufficiently large to provide an adequate representation of the input data. When there is no prior knowledge about the underlying process, traditional statistical tests can be used to determine the appropriate model order, such as the Akaike Information Criterion (AIC) [13].

2.3 Damage sensitive feature extraction

After constructing the NARX neural networks for all sensor clusters under baseline condition, the trained networks are used to predict the response of the same sensor cluster using signals from the current unknown state. The difference between the measured responses and the prediction is then used to extract damage sensitive features.

Considering that prediction errors follow a normal distribution, in case of novelty behaviour the probability density function will be more spread, and the peak value of probability density function (PDF) is much smaller [7]. For this reason, a damage index can be formulated by:

$$DI = \frac{\sigma(e)}{f_{max}(e)} \tag{3}$$

where $\sigma(e)$ is standard deviation of the prediction error, and $f_{max}(e)$ is the maximum value of the PDF calculated of errors. Then the DI of a sensor is affected not only by a nearby damage but also by the damages at distant locations.

2.4 Outlier analysis

The main idea of outlier analysis is to determine the discordancy measures of the data and compare it with a threshold. The discordancy of a candidate outlier is some measure that can be compared against the corresponding objective criterion and allows the outlier to be judged as statistically likely or unlikely to have come from the assumed generating model [14].

For SHM applications, the discordancy should be evaluated with respect to a model constructed from a normal condition of the system of interest [14]. One of the most common to multivariate data is the Mahalanobis Squared Distance (MSD) measure [15]. MSD is a n-dimension generalisation of the Euclidean distance, normalised through the covariance matrix and is given by:

$$D_\zeta^2 = (\{x\}_\zeta - \{\bar{x}\})^T \cdot [\Sigma]^{-1} \cdot \left(\{x\}_\zeta - \{\bar{x}\}\right) \tag{4}$$

where $\{x\}_\zeta$ is the potential outlier, $\{\bar{x}\}$ is the mean of the normal condition features and $[\Sigma]$ is the normal condition feature covariance matrix. In the literature, it is generally assumed that multivariate data are normally distributed, so that the MSD can be approximated by a chi-square distribution in n-dimensional space [16]. Under this hypothesis, the Mahalanobis distance (MD) can be approximated by a normal (or Gaussian) distribution and threshold for outlier detection can be estimated as the percentile of the features collected by the system under normal conditions [15, 16]. Zhou et al. [17] define that typical confidence level is stated typically between 0.001 (99.9%) and 0.050 (95%).

3 The case of Study

3.1 Structural system description

The main railway bridge over the Sado River with three continuous spans of 160 m is part of a longer structure with 2,7 km that includes two approach viaducts. It is a multiple bowstring arch bridge (Fig. 2a), with a steel-concrete trapezoidal composite deck, continuous over the support sections at the intermediate piers, axially suspended from a single plane of hangers [18].

The steel box girder of the deck is 2.60 m height and has a width ranging from 5.65 m to 7.75 m between the webs, with three steel flanges supporting the concrete slab (Fig. 2b). The concrete slab has a maximum thickness of 0.43 m and a total width of 15.82 m. The steel arches have a variable hexagonal cross-section, with the width increasing from 1.49 m to 3.20 m and the high decreasing from 2.40 m to 1.80 m towards the top.

The bridge deck is supported on four tubular reinforced concrete piers with a hexagonal cross-section. At the top of each pier there are two spherical and multi-directional steel sliding bearing devices, except on pier P1 fixed in both directions by means of a steel bar.

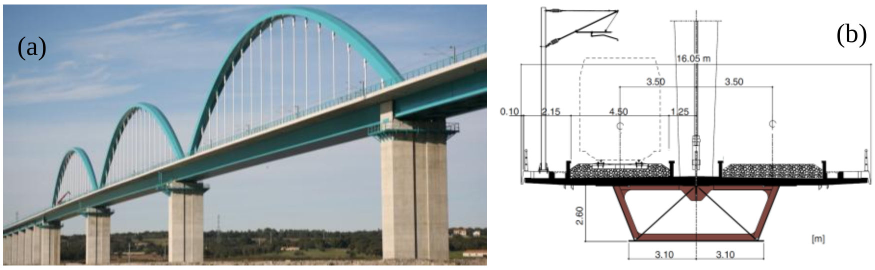

Fig. 2. Main railway bridge over the Sado River: (a) general overview; (b) deck cross section.

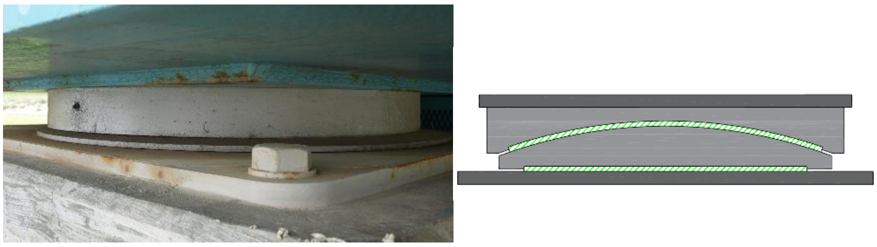

Fig. 3. Bearing devices of railway bridge over the Sado River.

3.2 Structural health monitoring system description

The monitoring system encompasses the measurement of accelerations, strains, rotations, vertical and horizontal displacements, temperature, and relative humidity at different sections of the deck, arches, and piers, as shown in Fig. 4.

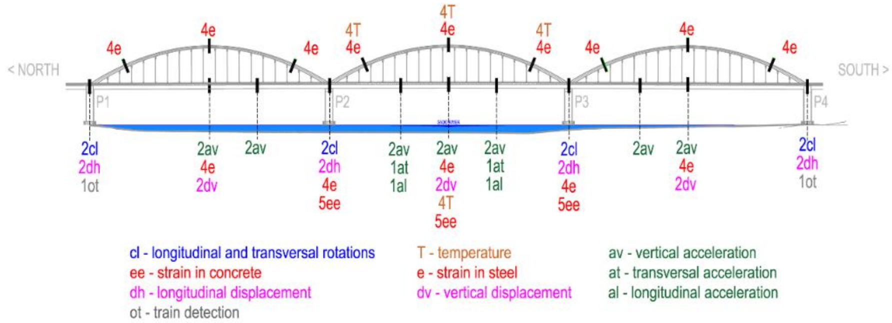

Fig. 4. General overview of monitoring system of railway bridge over the Sado River.

The accelerations are measured through uniaxial and triaxial servo-type accelerometers and the presence of the trains over the bridge is identified by two photoelectric sensors at each end of the bridge.

The acquisition of acceleration data is handled continuously at a rate of 500 Hz. The data acquired is filtered with low pass of 50 Hz and then decimated to 100 Hz.

3.3 Procedure and results

The methodology proposed in this study was applied to the case study bridge to detect a modification in the longitudinal stiffness of the bearing devices at pier P2, which caused a change in the natural frequency of the first three vertical modes, as exemplified in Fig. 5. To reduce complexity, only acceleration data from train AP number 186, which crossed the bridge heading north at speeds between 210 km/h and 220 km/h, were considered in this work. For the analysis, 80 train passages were used as the baseline, 89 were used for the damage case, and 32 were used for validation. The data were acquired between 2022 and 2024.

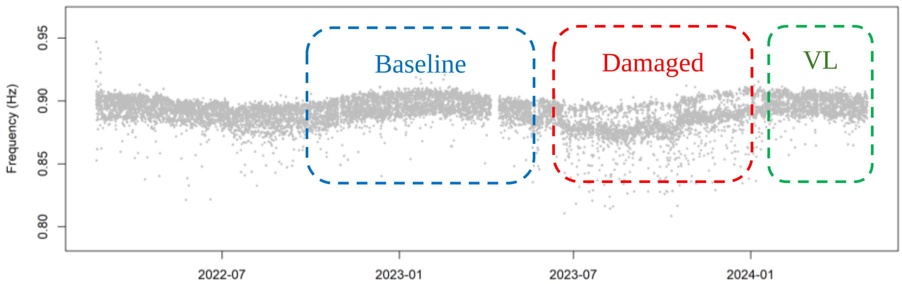

Fig. 5. Time series of the frequencies of the 1st vertical mode.

Following the sensor clustering concept, the time-series responses from 14 vertical accelerometers were considered, hence forming 14 clusters as exemplified in Fig. 6. In this analysis, only vertical acceleration was considered.

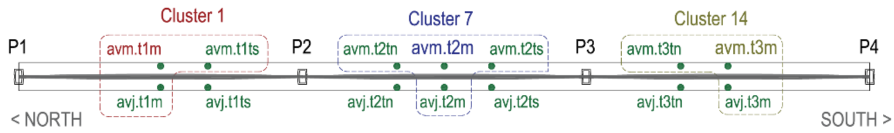

Fig. 6. Sensor clustering concept applied to the railway bridge over Sado river.

Fourteen NARX models using feedforward neural networks (FFNNs) with a single hidden layer and sigmoidal activation functions were constructed, with one network assigned to each sensor cluster. Prior to network training, the free acceleration response of each sensor was normalized. The model order of the NARX networks was determined under the baseline condition using the AIC, and the results indicated that the optimal model order is 8.

The NARX FFNNs were trained using the Levenberg–Marquardt algorithm as the learning function. In this experimental study, the number of neurons was set equal to 32 $(M \cdot (n_u + 1) + n_y)$ to ensure an adequate representation capability while maintaining a controlled network size to avoid overfitting. To reduce computation time, a weight decay parameter of 5×10^{-4} was applied. The acquired acceleration data were filtered using an 8^{th}-order low-pass digital filter with a cut-off frequency of 10 Hz.

For each sensor cluster, the associated NARX neural network is used to approximate the response measured by the reference sensor. Fig. 7 shows a comparison of NARX neural network prediction and measured response at accelerometer *avj.t2m*, for both cases. From this figure, it is evident that the predicted response closely matches the measured data, demonstrating that the trained NARX neural network effectively predicts and represents the undamaged structural response with high precision.

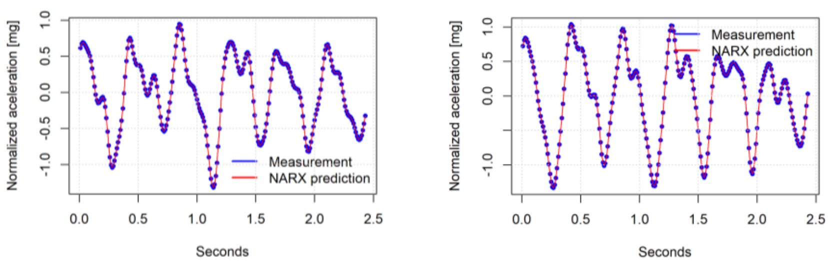

Fig. 7. Comparison of the predicted response at *avj.t2m*: (a) undamaged and (b) damaged.

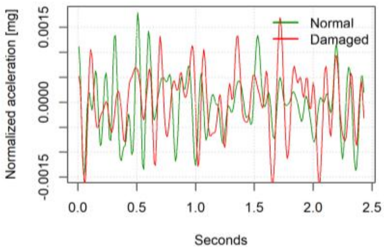

Fig. 8. Comparison of the residual errors at accelerometer *avj.t2m.*

The data from the damage case was fed into the trained NARX FFNN for response prediction. Subsequently, the DI, as described in Section 2.3, was computed from the residual errors. A Global Damage Index (GDI) was computed by fusing the damage-sensitive features (DI) from all sensor clusters using the MSD approach (Fig. 9). To establish a reliable threshold was set at a 99% confidence boundary.

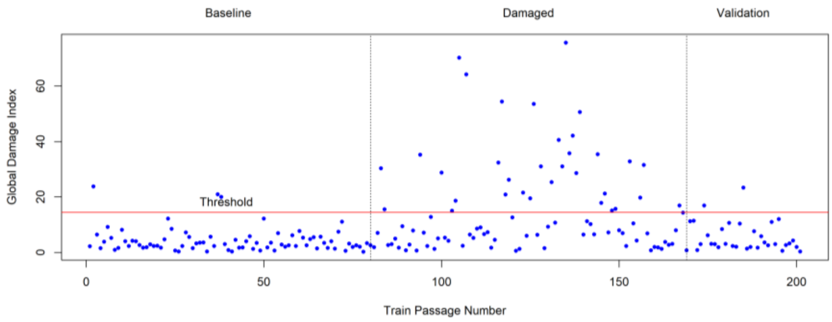

Fig. 9. Global Damage index.

Although the NARX FFNN trained for damaged data response prediction appears to show a good fit (Fig. 7), the GDI was able to highlight the difference between damaged and undamaged data, as shows Fig. 9. This approach ensures that any significant deviations in the GDI beyond the threshold are indicative of potential structural damage, minimizing false positives while maintaining high sensitivity to actual changes.

In both conditions, points above the threshold, classified as damaged, and points below the threshold, classified as normal, can be observed. However, in the damage condition, the number of points exceeding the threshold is higher, and their deviation from the threshold is more pronounced. Despite the presence of damage, some points continue to be classified as normal. This behaviour is also evident in the time series of frequencies (Fig. 5), where certain data points remain within the normal range despite the structural modifications.

4 Conclusions

This study proposed a novel methodology for damage identification in railway bridges using nonlinear time series analysis and sensor clustering, validated with real experimental data. The results demonstrated that the NARX neural networks effectively captured the dynamic response of the bridge and achieved high accuracy in modelling its behaviour under baseline conditions. The methodology successfully identified changes in the longitudinal stiffness of the bearing devices at pier P2, reliably distinguishing between different conditions through the DI derived from prediction errors.

The sensor clustering strategy proved to be an efficient approach for damage detection, reducing computational complexity while maintaining high precision by grouping sensors and using reference sensors within each cluster. Additionally, the fusion of damage-sensitive features from multiple sensor clusters into a GDI provided a robust and comprehensive assessment of the structural condition.

The practical applicability of the proposed methodology was demonstrated using real acceleration data collected from a long-span steel-concrete composite bowstring arch railway bridge over the Sado River. The use of train-induced dynamic responses validated the approach as a reliable and cost-effective solution for structural health monitoring in complex bridge systems.

Regarding future research, once damage is detected, a subsequent step involves studying the correlation between different accelerometers to pinpoint the location of the damage. Additionally, tests will be conducted using different velocity ranges to further evaluate the robustness and sensitivity to varying operational conditions.

Acknowledgements

The authors would like to express their gratitude to Infraestruturas de Portugal, S.A. for the support provided through the contract signed with LNEC for the monitoring of main railway bridge over the Sado River, which enabled the development of this study and its publication.

References

1. Farrar CR, Worden K (2012) Structural Health Monitoring: A Machine Learning Perspective. Wiley.
2. Sun Z, Nagayama T, Su D, Fujino Y (2016) A Damage Detection Algorithm Utilizing Dynamic Displacement of Bridge under Moving Vehicle. Shock and Vibration 2016.
3. Santos JP (2014) Smart Structural Health Monitoring Techniques for Novelty Identification in Civil Engineering Structures. Phd thesis, University of Lisbon.
4. Figueiredo E, Santos A (2018) Machine Learning Algorithms for Damage Detection. World Scientific Publishing Co. Pte Ltd.

5. Farrar CR, Worden K (2010) An Introduction to Structural Health Monitoring. In: Draemaeker A, Worden K (eds) New Trends in Vibration Based Structural Health Monitoring. Springer Vienna, Vienna, pp 1–17
6. Meixedo A, Santos J, Ribeiro D, et al (2022) Online unsupervised detection of structural changes using train–induced dynamic responses. Mechanical Systems and Signal Processing 165:108268.
7. Umar S, Vafaei M, C. Alih S (2021) Sensor clustering-based approach for structural damage identification under ambient vibration. Automation in Construction 121:103433.
8. Azim MR, Gül M (2019) Damage detection of steel girder railway bridges utilizing operational vibration response. Structural Control and Health Monitoring 26:1–22.
9. Roveri N, Carcaterra A (2012) Damage detection in structures under traveling loads by Hilbert–Huang transform. Mechanical Systems and Signal Processing 28:128–144.
10. Laory I, Trinh TN, Posenato D, Smith IFC (2013) Combined model-free data-interpretation methodologies for damage detection during continuous monitoring of structures. Journal of Computing in Civil Engineering 27:657–666.
11. An Y, Ou J (2012) Experimental and numerical studies on damage localization of simply supported beams based on curvature difference probability method of waveform fractal dimension. Journal of Intelligent Material Systems and Structures 23:415–426. https://doi.org/10.1177/1045389X11434172
12. Gul M, Catbas FN (2011) Structural health monitoring and damage assessment using a novel time series analysis methodology with sensor clustering. J Sound Vib 330:1196–1210.
13. Tsung-Nan Lin, Giles CL, Horne BG, Sun-Yuan Kung (1997) A delay damage model selection algorithm for NARX neural networks. IEEE Transactions on Signal Processing 45:2719–2730. https://doi.org/10.1109/78.650098
14. Sohn H, Oh CK (2008) Statistical Pattern Recognition. In: Encyclopedia of Structural Health Monitoring. John Wiley & Sons, Ltd, Chichester, UK
15. Worden K, Manson G, Fieller NRJ (2000) Damage detection using Outlier Analysis. Journal of Sound and Vibration 229:647–667.
16. Datteo A, Busca G, Quattromani G, Cigada A (2018) On the use of AR mod-els for SHM: A global sensitivity and uncertainty analysis framework. Reliability Engineering & System Safety 170:99–115.
17. Zhou HF, Ni YQ, Ko JM (2011) Structural damage alarming using auto-associative neural network technique: Exploration of environment-tolerant capacity and setup of alarming threshold. Mechanical Systems and Signal Processing 25:1508–1526.
18. Reis A, Cremer JM, Lothaire A, Lopes N (2010) The steel design for the new railway bridge over the River Sado in Portugal. Steel Construction 3:201–211.