A stochastic-based methodology for damage detection of bridges using stress data

Giulio Mariniello
Ph.D. Candidate, Dept. of Structures for Engineering and Architecture, University of Naples Federico II, Naples, Italy

Martina Scalvenzi
Post-doc Researcher, Dept. of Structures for Engineering and Architecture, University of Naples Federico II, Naples, Italy

Tommaso Pastore
Post-doc Researcher, Dept. of Structures for Engineering and Architecture, University of Naples Federico II, Naples, Italy

Daniele Losanno
Assistant Professor, Dept. of Structures for Engineering and Architecture, University of Naples Federico II, Naples, Italy

Fulvio Parisi
Associate Professor, Dept. of Structures for Engineering and Architecture, University of Naples Federico II, Naples, Italy

Domenico Asprone
Full Professor, Dept. of Structures for Engineering and Architecture, University of Naples – Federico II, Naples, Italy

ABSTRACT: Knowing the health state of bridges and viaducts in complex infrastructures enables the structural risk management and optimization of maintenance actions. Real-time data collection from infrastructures subject to traffic loads allows learning about their behavior and detecting anomalies. In this study, a probabilistic approach for damage detection of existing bridges is proposed. The methodology makes use of stress data sets, which can be provided by innovative sensors, to identify anomalies in the static response of bridges and viaducts. More specifically, the local stress data allows the definition of a reference stress distribution, which is strongly related to the state of the structure. When damage occurs, a redistribution of stresses is identifiable by analyzing the evolution of local stress data. The validation process involves performance analysis at the scales of the individual element and the whole structure. Traveling loads are simulated using a Monte Carlo method, while stresses are estimated using a numerical model. The validation of the proposed methodology analyzes the numerical model of an Italian reinforced concrete (RC) arch bridge with stiffening deck, evidencing excellent damage detection capabilities.

1. INTRODUCTION

Structural health monitoring is crucial to ensure safety and operation of infrastructures. The detection of anomalies in the early stage and optimization of maintenance schedules can prevent costly repairs and improve structural reliability. Many papers focused on the implementation of a real-time damage detection technique, able to identify damages in operative conditions. In recent years, there has been a growing interest in using probabilistic methods for damage detection in structural systems. These methods consider the uncertainty inherent in sensor measurements and traffic loads and can provide more accurate and reliable estimates of structural performance. Traditionally, exists two different types of SHM systems: dynamic systems, based on vibrational data, and static monitoring systems, that analyze rotations, displacements, stresses, and strains.

Studying dynamic measures, Gonen et al. (2022) proposed a hybrid structural health monitoring method for vibration-based damage detection of bridge structures based on the fusion of data from conventional accelerometers and computer vision-based measurements. The proposed method achieves satisfactory performance in detecting decreases in flexural stiffness of the bridge.

Al-Ghalib described a statistical approach for damage recognition using field measurements from real bridges. The proposed method, which combines principal component analysis (PCA) and linear discriminant analysis (LDA), outperforms PCA alone in classifying damage scenarios.

Nguyen et al. (2022) proposed a method for damage detection of bridge cables using the vibration signal coming from a sensor installed in a climbing robot. The proposed method can detect crack and local reduction in diameter in the cables. On the other hand, several papers proposed methodologies for the damage detection of bridges using static data.

One approach to this problem is the use of strain sensing with fiber Bragg grating (FBG) sensors. In the paper by Zhang et al. (2020), an output-only damage detection method for highway bridges under a moving vehicle is presented, which is based on the fractal dimension of strain responses measured by long-gauge FBG strain sensors. The method can detect bridge damage effectively and is not affected by vehicle parameters.

Another approach to bridge monitoring is the use of statistical analysis of operational strain response. In the paper by Azim and Gül (2020), a non-parametric damage detection method for truss railroad bridges is presented, which utilizes statistical analysis of bridge strain responses to operational train loading. The method can identify, locate, and relatively assess damage even under different operational conditions.

In the paper by Cao et al. (2022), a method for damage cross-detection between bridges monitored within one cluster is proposed. The method uses the difference ratio of projected strain monitoring data under time-varying environmental temperatures to establish a damage feature. The proposed method can detect damage in all bridges monitored within one cluster, even if the bridges have similar or identical structural characteristics.

Overall, these papers demonstrated the effectiveness of using strain sensing and statistical analysis for bridge monitoring. The methods presented in these papers can detect damage effectively, are not affected by vehicle or environmental parameters, and can be used for long-term monitoring without interrupting traffic.

On the other hand, FBG sensors require a costly measuring chain compared to other sensor types, and, in the case of existing structures, surface installation can result in limited accuracy. To overcome these limitations, recent studies developed of pressure sensors to evaluate stress distributions in structural elements (Guidetti et al., 2021). This sensing system was recently patented and considered in damage detection framework. Indeed, focusing on prestressed concrete (PC), Mariniello et al. (2021) proposed a novel methodology, named LA-ELM, which uses stress data to assess damage to the prestressing system of PC bridges.

In this work, the authors propose an anomaly detection approach for the structural health monitoring of bridges subjected to stochastic traveling loads. The methodology analyzes stress data, which can be estimated by low-cost sensors, to identify any pathologic behavior in the static response of bridges. The approach is validated analyzing the numerical model of an openspandrel arch bridge located on the Naples-Salerno highway (Southern Italy).

2. METHODOLOGY

Detecting and localizing bridge damage is a primary objective of infrastructural asset management. For a decision-maker, a proper assessment of the structural condition of a bridge portfolio allows the optimal planning of maintenance schedules to increase the safety of the bridges and their users. To this end, this work presents a novel approach to detecting and localizing structural damage to existing bridges using stress sensor data under stochastic traffic flow conditions.

The primary intuition behind this approach is that whenever structural damage affects the bridge, a change in the distribution of stresses happens. Accordingly, monitoring the evolution of the average stress distribution can evidence the presence of pathologic structural behavior. Therefore, this paper describes an anomaly detection approach that produces alerts whenever the stress distribution related to an arbitrary set of measurements deviates significantly from the expected behavior of the bridge.

2.1. Data Representation

As detailed above, the core of the proposed method is the comparison of different sets of stress time histories, related to distinct traffic configurations. To formally describe the method, the first step consists in the definition of the stress time history matrix $\mathbf{S}$. Given a generic traffic flow, $\mathbf{S}$ is defined as:

$$\mathbf{S} = (\mathbf{S}_{ti})_{\substack{t=1,\dots,T,\\ i\in I}}$$

where T is the length of the measured time window $[t_0, t_0 + T]$, t_0 is the starting time of the measurement, and I is the set of sensors. In particular, the generic (t, i) element is the value that the i-th sensor measured at the time stamp $t_0 + \ t$. Clearly, the actual values of the stress time history matrix depend on the specific traffic flow passing on the bridge deck in the time interval $[t_0, t_0 + T]$.

An arbitrary traffic flow can be expressed by defining the number, position, and types of the vehicles passing on the bridge. To specify a given traffic flow, the data representation scheme adopted in this work defines the matrix $\mathbf{T}$,

$$\mathbf{T} \ = \ (\mathbf{T}_{lt})_{\substack{l\in\mathcal{L},\\ t}}$$

with $\mathcal{L}$ being the set of traffic lanes of the bridge.

Thus, the element $\mathbf{T}(l, t)$ represents the size of the vehicle entering the l-th lane of the bridge at time t, with $\mathbf{T}(l, t) = 0$ if there are not vehicles approaching l at time t. To effectively tie the stress time history with the traffic flow matrix, these notations make use of the influence surfaces of each sensor measurement.

For each sensor $i \in I$, let $\mathbf{I}^i$ be its influence surface, i.e.,

$$\mathbf{I}^i \ = \ \left(\mathbf{I}^i_{lp}\right)_{\substack{l\in\mathcal{L}\\ p\in\mathcal{P}}} ,$$

with $\mathcal{P}$ being the set of possible positions on the deck. Specifically, $\mathbf{I}^i(l, p)$ represents the measurement of the i-th sensors due to the presence of a vehicle of a reference size in the traffic lane l at position p.

It is possible to observe that, $\forall\, i \in I$, $\mathbf{I}^i$ reflects the structural properties of the bridge, and it is invariant in standard conditions, but it is sensitive to structural damages that induces a different stress redistribution.

The combination of stress influence surfaces and the traffic flow matrices consents to define a stress time history for complex cases with several vehicles on the bridge. Indeed, let v the velocity of the traffic flow. Then, it is possible to define $p_0 = \ v \cdot \Delta t$ as the position of a vehicle entered at τ after a travelling time equal to Δt.

Let $[t_0, t_0 + T]$ be the time interval in which the stress values are measured. Then, an arbitrary traffic flow can be naturally decomposed by considering the different set of vehicles entering the deck of the bridge at time τ, such that, at least a portion of their passage happens in the time interval $[t_0, t_0 + T]$. According to this decomposition, the matrix $\mathbf{S}$ can be obtained by combination of the stresses obtained as τ varies.

Let $\mathbf{s}_\tau^i$ be the vector of stresses measured by the sensor i due to the passage of all vehicles the entering the deck at time. Since the measurement time window is $[t_0, t_0 + T]$, then $\forall\, i \in\, I$, the first component of these vectors, $\mathbf{s}_\tau^i(1)$, refers to the stress measurement recorded at time t_0, differently, the last component of s_τ^i refers to the measurement at $t_0 + T$.

In the following we show that s_τ^i can be obtained through the combination of $\mathbf{T}_\tau$ and IS^i, where $\mathbf{T}_\tau$ is the column vector of $\mathbf{T}$ related to the vehicles entering at time τ.

Within the proposed decomposition, three cases are possible (See fig. 1).

Case a) the vehicle enters at $\tau = t_0$, then:

$$s_\tau^i = \mathbf{T}_\tau \times \mathbf{I}^i.$$

Case b) $\tau < t_0$:

for $t = 1, \ldots, T,\quad s_\tau^i(t) =$

$$\begin{cases} (\mathbf{T}_\tau \times \mathbf{I}^i)(t_0 - \tau + t), & 1 \le t \le T - (t_0 - \tau) \\ 0, & t > T - (t_0 - \tau) \end{cases}$$

Case c) if $\tau > t_0$:

for $t = 1, \ldots, T,\quad s_\tau^i(t) =$

$$= \begin{cases} 0, & 1 \le t \le \tau - t_0 \\ (\mathbf{T}_\tau \times \mathbf{I}^i)(t - \tau + t_0), & \tau - t_0 < t \le T \end{cases}$$

Assembling the column vectors s_τ^i for all the sensors $i \in I$, we obtain the matrix s_τ, representing stresses measured by all the sensors, within the time window $[t_0, t_0 + T]$, for all the vehicles entering the bridge at time τ.

$$s_\tau = [s_\tau^1, s_\tau^2, \ldots, s_\tau^{|I|}]$$

Finally, the stress time history matrix $\mathbf{S}$ can be obtained as the sum of the matrices $\mathbf{s}_\tau$:

$$\mathbf{S} = \sum_{\tau=0}^{T} \mathbf{s}_\tau.$$

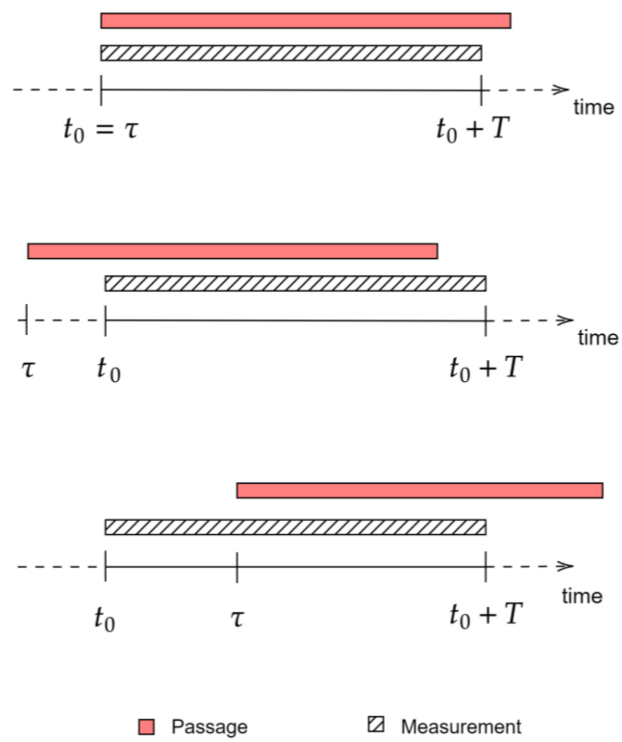


Figure 1: Relation between passage times and measurement window.

2.2. Derivation of Reference Stress Data

As described in the previous Section, the reference stress data can be collected either in a preliminary phase or numerically enhanced. According to the former approach, the structure is monitored in its healthy behavior, and the longer the time devoted to this phase, the richer and more significant the reference set will be.

Differently, in the latter approach, the preliminary phase relies on tests with controlled loads and only aims to achieve an empirical evaluation of the influence surface of each sensor. Then the stress matrices of the reference set are obtained by combining influence surfaces and traffic flow matrices, as detailed in Section 2.1.

According to this latter paradigm, a Monte Carlo simulation enhancing phase generates traffic flow matrices.

2.3. Monte Carlo Simulation

A stochastic simulation process can define arbitrary traffic flows through the random generation of **T** matrices. This simulation approach follows a three-steps procedure:

- **Step 1.** Uniform binary selection of the incoming vehicles.
- **Step 2.** Size extraction: for each non-zero element, this process randomly selects the vehicles' weights.
- **Step 3.** Adjusting phase: remove vehicles that don't guarantee vehicle length compatibility.

In Step 1, a random combination of 0 and 1 is extracted from a uniform distribution to populate the matrix **T**. The result of this step is to define the position of the vehicles. To differentiate the vehicles in size, Step 2 randomly extracts the size of each one of the vehicles introduced in Step 1. Since each weight is related to a length, the final Step 3 ensures that the vehicles do not occupy intersecting positions, thus ensuring the consistency of the traffic flow. Repeating this scheme as a Monte Carlo sampling process yields an extensive variety of traffic flow configurations.

2.4. Anomaly Detection Approach

The proposed framework leverages an anomaly detection algorithm to identify the presence of unexpected behavior. These anomalies indicate stress distributions on the deck that can be possibly related to a pathologic state of the structure.

The anomalies are expressed in terms of diversity from a set of stress measurements, taken as a reference. This reference set represents the behavior of the structure in its healthy state, under a wide variety of traffic flow combinations.

As detailed in the previous sections, a stress distribution measured for a specific traffic flow is represented through a matrix $\boldsymbol{S}$. Accordingly, within a time horizon of interest, the average behavior of the structure can be defined as the matrix $\overline{\boldsymbol{S}}$ that averages the matrices $\boldsymbol{S}$ for all the traffic flows happening within that time horizon. Consequently, it is possible to compare the behavior in two distinct periods by studying the differences in the relative average matrices. Notably, while the matrices $\boldsymbol{S}$ and $\overline{\boldsymbol{S}}$ depend on the traffic flows, if the periods are large enough, by the law of large numbers it is possible to observe that the average behaviors are mainly related to the structural properties of the bridge.

To compare two arbitrary averages matrices, $\overline{\boldsymbol{S}}$ and $\overline{\overline{\boldsymbol{S}}}$, this work considers a matrix resemblance function, as discussed by Sesma-Sara et al. (2018). Specifically, the resemblance Ψ of the normalized matrices is computed as:

$$\Psi(\overline{\boldsymbol{S}}, \overline{\overline{\boldsymbol{S}}}) = \prod_{i,j}\left(1 - \left(\bar{S}_{ij} - \bar{\bar{S}}_{ij}\right)^2\right).$$

If the $\overline{\boldsymbol{S}}$ and $\overline{\overline{\boldsymbol{S}}}$ are the same, then $\Psi = 1$, otherwise $0 \leq \Psi < 1$.

The anomaly detection algorithm divides the reference set in groups of measurements, for which average matrices are computed. For any two matrices of the reference set, the method computes the average similarity values, respect to all other average matrices of the set, thus yielding a distribution.

In presence of a new group of measurements, the average stress distribution is computed, and its average similarity value from the reference set is analyzed. If this average similarity value is significantly different from the values evidenced in the benchmark set, the algorithm outputs an alert.

3. CASE STUDY

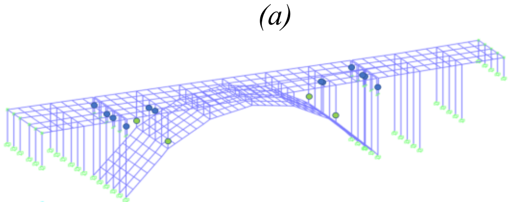
The proposed methodology was tested on the numerical model of an Italian reinforced concrete (RC) arch bridge with stiffening deck, which is called Canalone bridge and is located near Salerno, Southern Italy. The static scheme of the viaduct presents a central arch with two lateral frames for a total length of 120 m.

The arch of the bridge, shown in Figure 2(a), has a total span of 60 m distributed along 6 spans of the corresponding deck; each span, consists of RC piers with 6 columns of dimensions 50x40cm and 44x40cm for external piers and 50x30cm and 44x30cm for internal piers connected by a thin wall. The arch piers are framed into the RC deck girders at the top and transfer loads to the arch vault at their base. The arch transverse cross section has 6 stiffening arch-beams framing into the piers and connected by a thin vault.

The bridge deck, instead, consists of 6 longitudinal girders with dimensions 35x152cm for edge girders and 20x152cm for internal girders.

The structural model of the bridge was implemented in SAP2000 (Figure 2(b)) through frame elements only. For the sake of accuracy, the stiffness of longitudinal T-girders was updated and properly tuned to reduce the difference between dynamic properties estimated by field measurements through operational modal analysis (OMA) and the numerical modal properties. As shown in Figure 2 (b) a novel monitoring system was recently installed on the viaduct with a number of 16 stress sensors located in pillars.

(a)



(b)

Figure 2: (a) Case study structure, (b) structural model

For the healthy behavior of the bridge, a basic set of $\mathbf{I}^i$ matrices was generated using the moving load function to simulate the travelling vehicles on each one of the two lanes of the deck. The selected moving vehicle weighs 400 kN, and the loading patterns considers all the lanes of the bridge.

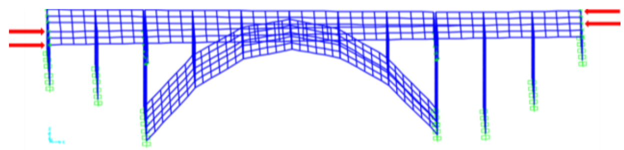


Figure 3: Moving loading patterns

The resulting axial forces and bending moments in the monitored elements were then processed for each sensor location and combined to yield a first set of stress measurements. As detailed in Section 2.2, these matrices were used in the generation of the reference dataset through a Monte Carlo simulation.

Given the length of average passing times and the sampling frequency of the sensors, the resulting stress matrices have dimensions of 16x116, indicating, respectively, the number of sensors and measurement timestamps, for each stress-recording session.

This set of stress matrices was divided into two subsets, a reference set (80% of the data) and a validation set (20% of the data).

Damages were introduced in the model through a local reduction of the stiffness of a single longitudinal girder. The data generation process considered local stiffness reductions of 30% and 60%. In the following, the two damage cases are labelled as LD-30 and LD-60.

The anomaly detection approach studied the differences of the damaged dataset when compared to the reference undamaged benchmark, to evidence the capability of the method in detecting pathologic behavior. Moreover, to analyze the sensitivity to false positives, also the validation set (exhibiting a healthy behavior) was compared to the reference set. The anomaly detection algorithm produced alerts whenever either the testing or validation data exceeded the thresholds $\mu + 3\sigma$ and $\mu - 3\sigma$ for any of the sensors, computed according to the mean value μ and the standard deviation σ.

Each stress distribution matrix is related to a measurement time window of approximately 11 seconds, while the average matrices, as defined in Section 2.4, represent the mean behavior of groups of 1000 stress distributions. Therefore, each average matrix refers to monitoring periods of approximately 3 hours.

Subsequently, examining new measurements, the algorithm leverages an anomaly-detection algorithm that computes a matrix resemblance function to evidence differences that deviate statistically from the expected behavior.

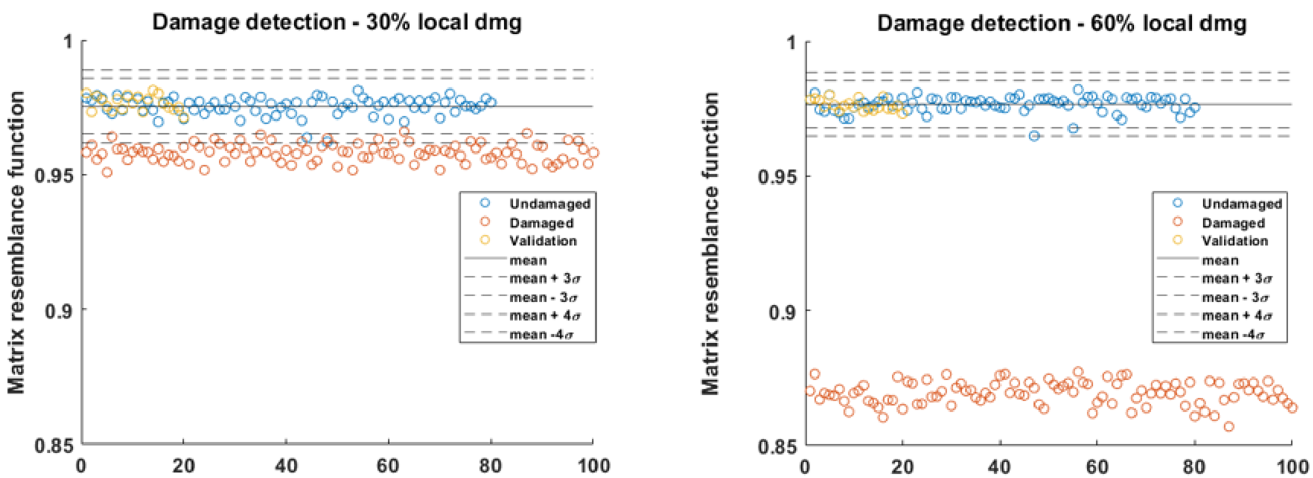


Figure 4: Results of the anomaly detection algorithm.

The results of the anomaly detection approach are represented in Figure 3. The alerts were correctly given (i.e. "true positives") in most of the damage cases: 97/100 for LD-30 and 100/100 LD-60. Instead, all the stress values of the validation set were correctly classified as "healthy state", evidencing the absence of false positives. While both LD-30 and LD-60 appear to be correctly separated from the undamaged samples, it is observed that the separation distance from the healthy state increases with the severity of the damage, as expected.

4. CONCLUSIONS

This paper presents a methodology for detecting local damage on bridges by analyzing stress data collected by innovative low-cost sensors.

The proposed approach uses influence surfaces and a three-steps monte Monte Carlo simulation process to enhance reference stress histories.

The method was numerically tested on a prototype model of a 120m arch bridge of the Naples-Salerno highway. The validation process analyzed the capabilities of the approach in detecting two distinct damage patterns, characterized by local stiffness reduction of 30% and 60%, respectively. The results highlighted that the algorithm correctly outputted alerts for both cases in almost the totality of the average matrix related to damages (197/200). In the validation, each average matrix refers to monitoring periods of 3 hours, thus implying that the proposed approach achieves reliable alerts with limited monitoring times. Notably, other advantages of the method are related to the possibility of constructing the reference stress data following two different approaches. Indeed, stress data can be obtained as either the combination of controlled testing and a Monte Carlo enhancing phase or by directly acquiring stress records from the structure subject to traffic. Lastly, this method makes it possible to evaluate the bridge under conditions of use without the need for closures or restrictions.

Further studies will have to investigate the effect of temperature on the performance of the method and identify the range of speeds for which the dynamic increase in stresses does not impact the accuracy of the prediction. Finally, a further validation step will analyze the performance to detect damages in real-world data.

ACKNOWLEDGEMENTS

The presented work has been partially supported by the project “DS2: Digital Smart Structures”, funded by INAIL (Italian Workers’ Compensation Authority), BRIC 2021, and the Programme STAR Plus (RESIST project “RobustnEss aSsessment and retrofItting of bridgeS to prevenT progressive collapse under multiple hazards”), of University of Naples Federico II and Compagnia di San Paolo.

REFERENCES

Al-Ghalib, A.A. (2022). “Structural damage detection of old ADA steel truss bridge using vibration data”. *Structural Control and Health Monitoring*, 29 (11).

Azim, M.R., Gül, M. (2019). “Damage detection of steel girder railway bridges utilizing operational vibration response”. *Structural Control and Health Monitoring*, 26 (11).

Fitzgerald, P.C., Malekjafarian, A., Bhowmik, B., Prendergast, L.J., Cahill, P., Kim, C.-W., Hazra, B., Pakrashi, V., Obrien, E.J. (2019). “Scour damage detection and structural health monitoring of a laboratory-scaled bridge using a vibration energy harvesting device”. *Sensors (Switzerland)*, 19 (11).

Gonen, S., Erduran, E. (2022). “A Hybrid Method for Vibration-Based Bridge Damage Detection”. *Remote Sensing*, 14 (23).

Guidetti, E., Gavarti, M. A., Caltabiano, D., & Bertagnoli, (Mar 2021) G. "Stress sensor for monitoring the health state of fabricated structures such as constructions, buildings, infrastructures and the like." *U.S. Patent No. 10,935,444*.

Jayasundara, N., Thambiratnam, D., Chan, T., Nguyen, A. (2019). “Vibration-based dual-criteria approach for damage detection in arch bridges”. *Structural Health Monitoring*, 18 (5-6), pp. 2004-2019.

Mariniello, G., Pastore, T., Asprone, D., & Cosenza, E. (2021). “Layout-aware extreme learning machine to detect tendon malfunctions in prestressed concrete bridges using stress data”. *Automation in Construction*, 132, 103976.

Martinez, D, Malekjafarian, A, OBrien, E. (2020). “Bridge health monitoring using deflection measurements under random traffic”. *Structural Control and Health Monitoring*.

Nguyen, K. V., Van Bach Pham, N., & Dao, T. T. (2022). “Damage detection of cables in cable-stayed bridges using vibration data measured from climbing robot”. *Advances in Structural Engineering*, 25(13), 2705-2721. pp. 2705-2721.

Sesma-Sara, M., De Miguel, L., Pagola, M., Burusco, A., Mesiar, R., & Bustince, H. (2018). “New measures for comparing matrices and their application to image processing”. *Applied Mathematical Modelling*, 61, 498-520.

Shang, Z., Sun, L., Xia, Y., Zhang, W. (2021). “Vibration-based damage detection for bridges by deep convolutional denoising autoencoder”. *Structural Health Monitoring*, 20 (4), pp. 1880-1903.

Chen, S. Z., Wu, G., & Feng, D. C. (2019). “Damage detection of highway bridges based on long-gauge strain response under stochastic traffic flow”. *Mechanical Systems and Signal Processing*, 127, 551-572.

Sun, S., Liang, L., Li, M., Li, X. (2018). “Vibration-based Damage Detection in Bridges via Machine Learning”. *KSCE Journal of Civil Engineering*, 22 (12), pp. 5123-5132.