# Chapter 8
# Multi-Bridge Indirect Structural Health Monitoring: Leveraging Big Data and Drive-By Crowdsensing Techniques

**Jiangyu Zeng, Qipei Mei, and Mustafa Gül**

**Abstract** This paper presents a novel structural health monitoring (SHM) methodology that analyzes in-vehicle data from vehicle-bridge interaction (VBI) signals across multiple bridges to detect damage in individual structures. Unlike traditional SHM methods that monitor each bridge independently, the proposed approach compares the dynamic responses across a network of bridges using vehicle-collected data. By analyzing changes in correlation coefficients between these bridges, our method improves the accuracy of damage detection while reducing the likelihood of missed detections. Numerical simulations demonstrate the effectiveness of the method for both single-span and multi-span bridges. This scalable approach offers a significant advancement in SHM systems, particularly suited for smart cities where large-scale, cost-effective monitoring is essential.

**Keywords** Structural Health Monitoring (SHM) · Bridge Network Monitoring · Multi-Bridge Damage Detection · Drive-By Monitoring · Smart Cities · Scalable Infrastructure Monitoring

## Introduction

Structural health monitoring (SHM) is essential for maintaining bridge safety and serviceability, particularly as aging infrastructure necessitates proactive interventions to prevent failures [1]. Traditional SHM methods, which rely on fixed sensors installed on bridges, face limitations such as high costs, logistical challenges, and scalability issues, especially in large bridge networks [2–4]. Recent advancements, such as drive-by monitoring techniques, utilize vehicle data to infer bridge health, eliminating the need for permanent sensors and offering more flexible, cost-effective solutions for infrastructure monitoring [5–10]. These methods, however, often focus on individual bridges, limiting their effectiveness when applied to networks of bridges within smart cities [11].

The key innovation of this paper is the use of in-vehicle data from multiple bridges to determine the structural health of a single bridge. By comparing the correlation between dynamic responses across a network of bridges, this signal-level SHM approach leverages the collective information from other bridges to improve damage detection accuracy. This simultaneous monitoring of multiple bridges offers a significant improvement over traditional methods that evaluate each bridge independently. This concept is inspired by the work of Catbas *et al.* [12], Malekzadeh *et al.* [13], and Riasat Azim and Gül [14], who demonstrated a similar approach by tracking correlation coefficients and vibration data to monitor structural health in various types of bridges. The method, validated through numerical simulations, shows strong potential for large-scale SHM in urban environments, making it particularly well-suited for smart city applications.

Jiangyu Zeng
PhD Student, Department of Civil & Environmental Engineering, University of Alberta, Canada
e-mail: jiangyu1@ualberta.ca

Qipei Mei
Assistant Professor, Department of Civil & Environmental Engineering, University of Alberta, Canada
e-mail: qipei.mei@ualberta.ca

Mustafa Gül
Professor, Department of Civil & Environmental Engineering, University of Alberta, Canada
Corresponding author
e-mail: mustafa.gul@ualberta.ca



Brian Damiano et al. (eds.), *Structural Health Monitoring & Machine Learning, Vol. 12*, Conference Proceedings of the Society for Experimental Mechanics Series, https://doi.org/10.13052/97887-438-0157-3_8

## Numerical Simulations

This study employs numerical simulations to collect vehicle vertical acceleration signals as vehicles traverse bridges under various conditions. The data collection focuses on both the baseline and damaged states of bridges, with the dynamic interaction between vehicles and bridges simulated using an iterative decoupled Vehicle-Bridge Interaction (VBI) model.

In the baseline case, vertical vibration signals were recorded as twelve distinct vehicles, modeled using a one-axle moving spring-mass system, traversed the bridges. These vehicles varied in mass, spring constant, and speed, with combinations of three masses, two spring constants, and two speeds to represent different vehicle types. Each vehicle made 20 passes over each bridge, generating a total of 240 signals per bridge. The bridges used in these simulations shared identical properties except for their lengths. Bridges Bridge-1-SS through Bridge-10-SS were single-span bridges, while bridges Bridge-11-TS through Bridge-20-TS were two-span bridges with an additional support located at mid-span.

A validation case, identical to the baseline, was included to ensure consistency and reliability in the monitoring process. The validation state served as a baseline comparison against future damaged scenarios, ensuring that the monitoring system can differentiate between normal and damaged conditions accurately.

To simulate structural damage, a reduction in stiffness was introduced. Specifically, a 30% stiffness reduction was applied to the mid-span region of the bridges, affecting 1/4 of the total bridge length. This damage was designed to reflect realistic structural deterioration and assess the method's ability to detect such changes. As in the baseline and validation cases, each vehicle crossed the damaged bridges 20 times, generating 240 signals for each damaged bridge. The study focuses on two representative bridges: Bridge-4-SS (Single-Span) and Bridge-17-TS (Two-Span), chosen to assess the method's performance across different structural types. .

During all simulations, the vertical acceleration signals of the vehicles were collected. To mimic real-world conditions, 10% artificial noise was added to these signals. To enhance the clarity of the signals, a Gaussian low-pass filter was applied to suppress high-frequency noise while preserving the key signal components related to the bridge's structural response.

## Analysis

This section presents the analysis of the structural health monitoring process using the signal-level approach, focusing on direct comparisons of the vehicle acceleration signals collected from multiple bridges. The goal of this method is to identify structural damage by analyzing changes in the correlation coefficients between the signals from different bridges over time.

### *Signal-Level comparison and correlation coefficient calculation*

The analysis begins with preprocessing the vehicle acceleration signals. The original time-domain signals collected from vehicles crossing the bridges are transformed into the frequency domain and resampled to focus on the 0-20 Hz range[6]. This frequency range is chosen because it encompasses the typical fundamental frequencies of bridges. In our study, the highest first-mode frequency among all the bridges is 5.7 Hz, and the highest second-mode frequency is 8.5 Hz. Both of these frequencies occur on the shortest two-span bridge, ensuring that no critical information is lost by focusing on the 0-20 Hz range.

Following the preprocessing, the Correlation Coefficient (CC) Matrix is constructed. For a system of $m$ bridges, indexed by $i = 1, 2, \ldots, m$, the Correlation Coefficient Matrix $CC[i, j]$ is computed to quantify the correlation between the vehicle acceleration signals of Bridge $i$ and Bridge $j$.

$$CC[i,j] = \frac{1}{P \times Q} \sum_{p=1}^{P} \sum_{q=1}^{Q} R(S_p^i, S_q^j) \tag{1}$$

In this equation, $S_p^i$ represents the resampled frequency-domain signal from the $p$-th run on Bridge $i$, and $S_q^j$ denotes the resampled frequency-domain signal from the $q$-th run on Bridge $j$. The terms $P$ and $Q$ refer to the total numbers of vehicle runs on Bridges $i$ and $j$, respectively. The function $R(S_p^i, S_q^j$ denotes the Pearson correlation coefficient between the signals $S_p^i$ and $S_q^j$.

The vehicles entering each bridge are entirely random, meaning that no specific sequence or order of vehicles is assumed across the bridges. This randomness is important to consider in the correlation analysis, as it reflects realistic traffic conditions and ensures that the method can handle different vehicle combinations over time.

This average pooling technique provides a robust summary of the correlations between the structural responses of the bridges. The focus of our method is not on the absolute correlation values, but rather on how these correlations change when structural damage occurs. These changes help detect potential structural discrepancies.

### *System-wide cross-comparison and separation factor calculation*

Following the construction of the Correlation Coefficient Matrix, the next step is to assess the changes in correlation coefficients between the baseline, validation, and unknown states of the bridges. This is achieved through the calculation of Percentage Difference Matrices (PDMs) between the correlation coefficients in these states. For every pair of bridges $i$ and $j$, the Percentage Difference $\Delta CC[i,j]$ is calculated as follows:

$$\Delta CC_{\text{state}}[i,j] = \frac{CC_{\text{state}}[i,j] - CC_{\text{baseline}}[i,j]}{CC_{\text{baseline}}[i,j]} \times 100\%, \quad \text{where } i \neq j \tag{2}$$

Here, "state" refers to either the validation or unknown state, depending on the context. For the diagonal elements ($i = j$), which represent the correlation between a bridge and itself, the percentage difference is defined as:

$$\Delta CC_{\text{state}}[i,i] = 0 \tag{3}$$

These diagonal elements are zero since the correlation between the same bridge in different states does not change. The PDMs constructed using these percentage differences enable visualization of the changes in correlation values between the baseline and the unknown or validation states, helping to identify potential damage in any of the bridges.

### *Relative damage index and threshold calculation*

To quantify the extent of structural damage, the Relative Damage Index (RDI) is computed for each bridge, which measures the change in its correlation coefficients relative to the rest of the system. The RDI is derived from the Separation Factor (SF), which quantifies how distinctly a bridge's response deviates from others in the system. The SF for each bridge $i$ is calculated as:

$$SF_i = \frac{\sum_{k=1}^{m} \Delta CC[i,k] + \sum_{k=1,k\neq i}^{m} \Delta CC[k,i]}{\sum_{h=1}^{m}\sum_{k=1}^{m} \Delta CC[h,k]} \tag{4}$$

Next, the RDI for the unknown state is computed as:

$$RDI_i = \frac{e^{SF_{i,\text{unknown}}} - 1}{e^{SF_{i,\text{baseline}}} - 1} \tag{5}$$

The Threshold Relative Damage Index (TRDI) is calculated similarly but based on the validation state, replacing the unknown state in the equation above. The TRDI sets a threshold for identifying damage and accounts for environmental and operational variations.

Finally, the RDI is compared against the TRDI. If the RDI exceeds the TRDI, the bridge is considered damaged; otherwise, it remains classified as undamaged. This method provides a robust and scalable approach to detecting damage across a network of bridges by analyzing changes in correlation values over time.

## Results and Discussions

This section presents the outcomes of the signal-level comparison approach applied to two damaged bridge cases: Bridge-4-SS (single-span) and Bridge-17-TS (two-span). We demonstrate the method's effectiveness in identifying structural damage by comparing the PDMs and RDI for both cases.

### *Percentage difference matrices*

The PDMs illustrate the changes in correlation coefficients between pairs of bridges, revealing how the structural responses deviate from the baseline state. Figures 1 and 2 display the PDMs for Bridge-4-SS and Bridge-17-TS under damaged conditions, each having experienced a 30% stiffness reduction at mid-span.

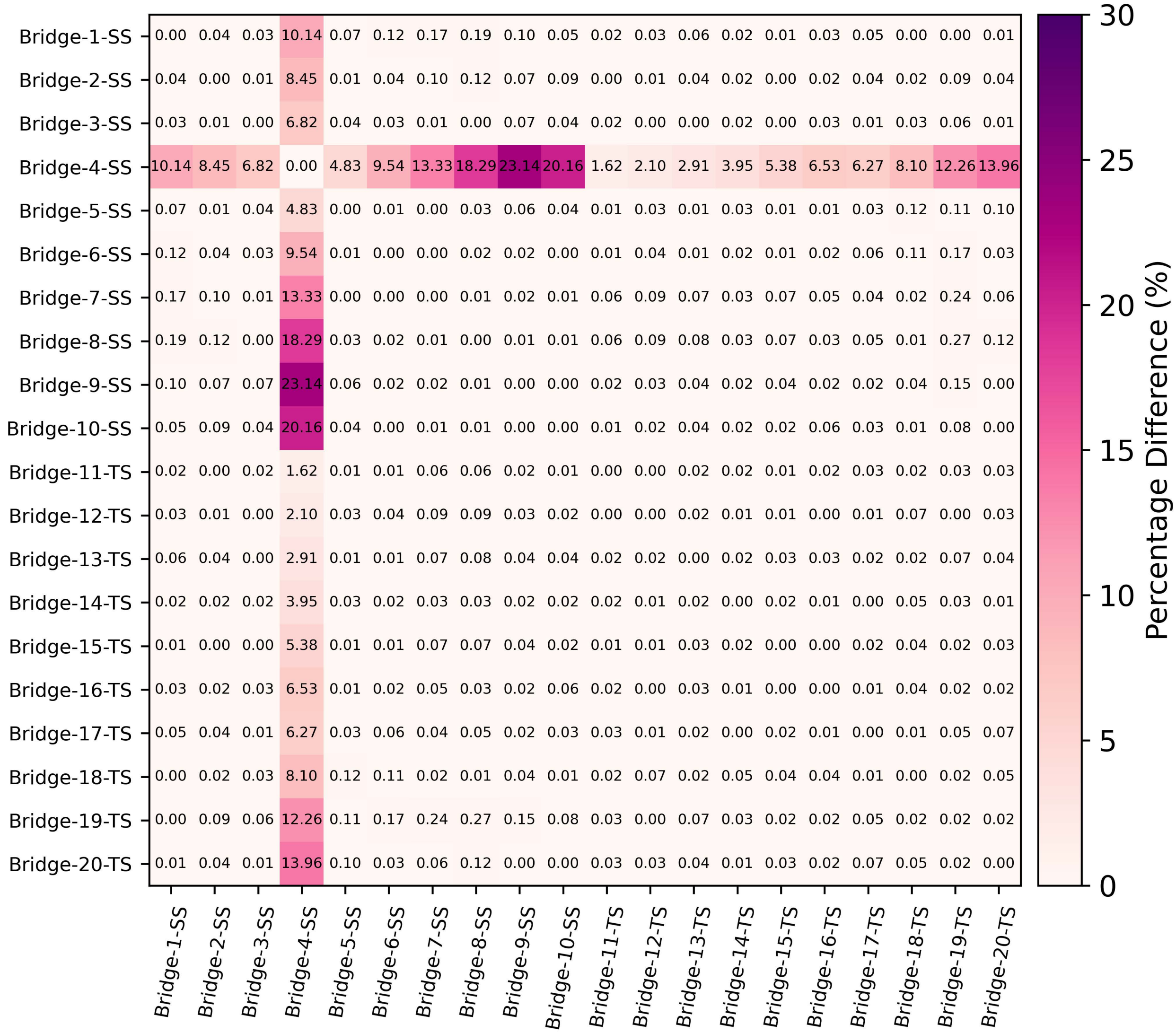


**Fig. 1** Percentage Difference Matrix for the damaged state: Bridge-4-SS.

In the case of Bridge-4-SS (Figure 1), the PDM exhibits pronounced differences, with values reaching as high as 23.14%. This indicates significant structural changes, particularly when comparing Bridge-4-SS with other bridges in the system. These elevated values reflect the localized damage and the limited ability of the single-span structure to redistribute the effects of the damage, making the changes more concentrated around the affected bridge. The high percentage difference clearly signals that the single-span structure is vulnerable to localized damage, and the signal-level comparison method is effective in detecting these changes.

Conversely, the PDM for Bridge-17-TS (Figure 2) shows much lower percentage differences, even though the same level of damage (30% stiffness reduction) was applied. The largest percentage differences remain below 4%, indicating a more subdued response to the damage. The lower PDM values suggest that the multi-span structure, with its more complex geometry and additional support at mid-span, is able to distribute the effects of the damage across multiple spans, thereby reducing the severity of localized structural responses[15, 16]. This highlights a key difference between single-span and multi-span bridges, where the structural complexity in the latter allows for better redistribution of stresses, leading to less pronounced changes in correlation coefficients.

While these visual insights from the PDMs provide an initial understanding of the changes in structural behavior, they are limited in detecting more subtle deviations that may occur across the bridge network. To address this, the RDI offers a more comprehensive, quantitative measure for assessing structural health.

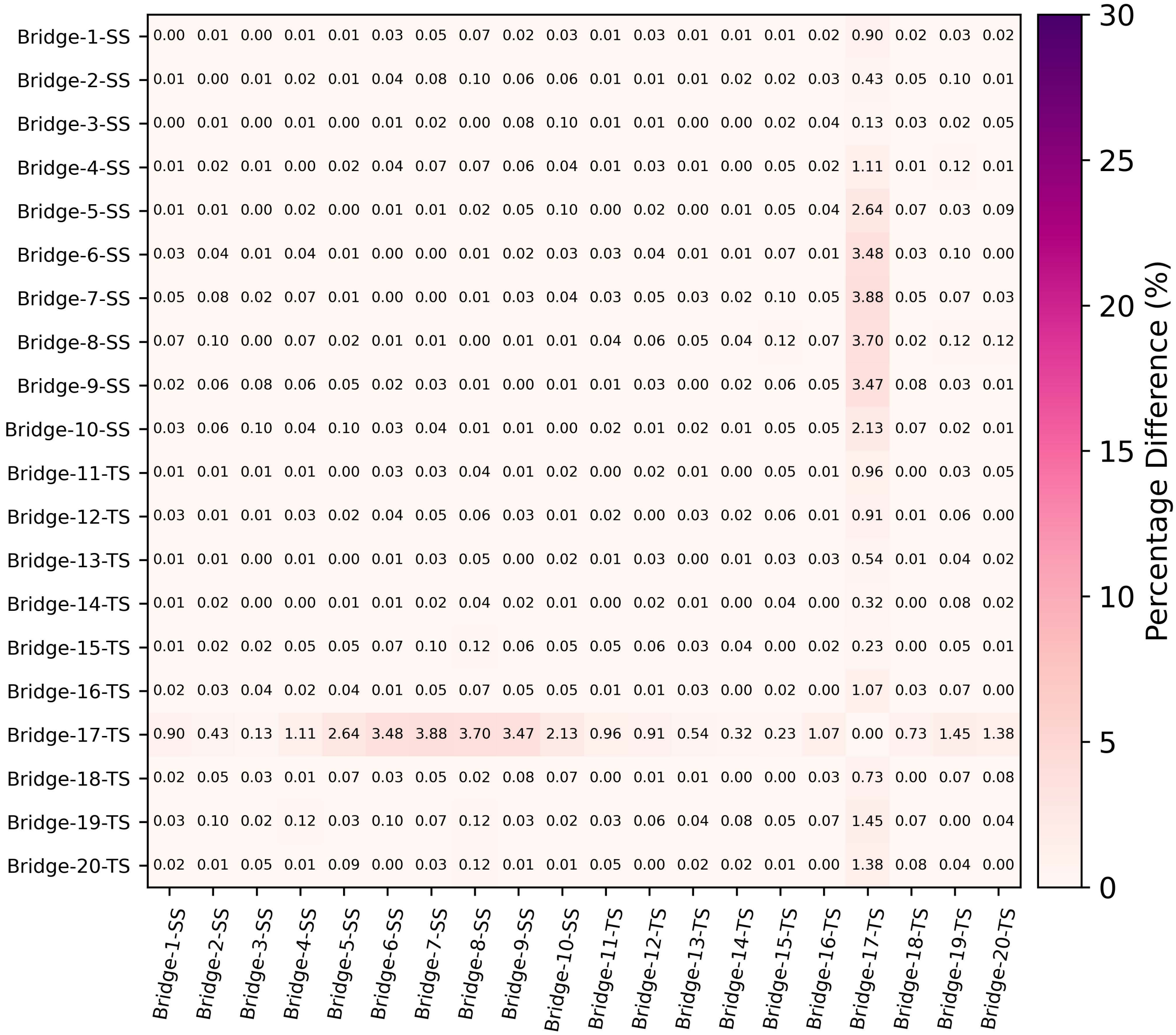


**Fig. 2** Percentage Difference Matrix for the damaged state: Bridge-17-TS.

### *RDI and TRDI results*

The RDI is particularly effective as it considers not just individual bridges, but the system-level comparison—i.e., the changes in correlation coefficients between a specific bridge and all other bridges in the network. By taking a system-wide approach, the RDI increases sensitivity to subtle changes in a bridge's behavior, which might be missed when analyzing the bridge individually. This is particularly important in cases like Bridge-17-TS, where stress redistribution across multiple spans might lead to less pronounced changes in the PDM.

Additionally, normalization in the RDI calculation helps reduce the impact of external factors like environmental conditions and traffic variations, isolating the changes caused by structural damage. The RDI is computed as shown in Equation 5. This normalization ensures robustness and emphasizes damage-related structural changes. Moreover, the exponential function amplifies even minor deviations, which further enhances the ability to detect damage even when the PDM differences are small, such as in the case of Bridge-17-TS.

Figures 3 and 4 display the RDI distributions for Bridge-4-SS and Bridge-17-TS under damaged conditions, calculated using five repeated experiments for each bridge.

For Bridge-4-SS (Figure 3), which represents a single-span bridge, the RDI values for the damaged bridge significantly exceed the threshold value, confirming the presence of structural damage. Specifically, Bridge-4-SS exhibits RDI values of approximately 16, well above the threshold. However, Bridge-9-SS's RDI values are slightly higher than its threshold, falling within 20% of the threshold, as indicated by the triangle markers. This suggests a possible false positive or minor sensitivity in the model for Bridge-9-SS. Nevertheless, all other bridges remain well below their respective thresholds, reinforcing the localized nature of the damage in Bridge-4-SS.

Similarly, for Bridge-17-TS (Figure 4), representing a two-span bridge, the RDI results indicate structural damage. The RDI values for Bridge-17-TS exceed the threshold, with values around 14 to 16. However, unlike the single-span bridge, the magnitude of the difference is slightly lower, reflecting the distribution of damage across the multiple spans. Despite this, the method effectively identifies the presence of damage in a more complex structural configuration, while other bridges maintain RDI values below their thresholds.

These observations demonstrate the effectiveness of the signal-level approach in detecting structural anomalies across both single-span and multi-span bridges, with the RDI values serving as a robust indicator of damage. The method's ability to consistently identify damage in various bridge types underlines its applicability in diverse structural health monitoring scenarios.

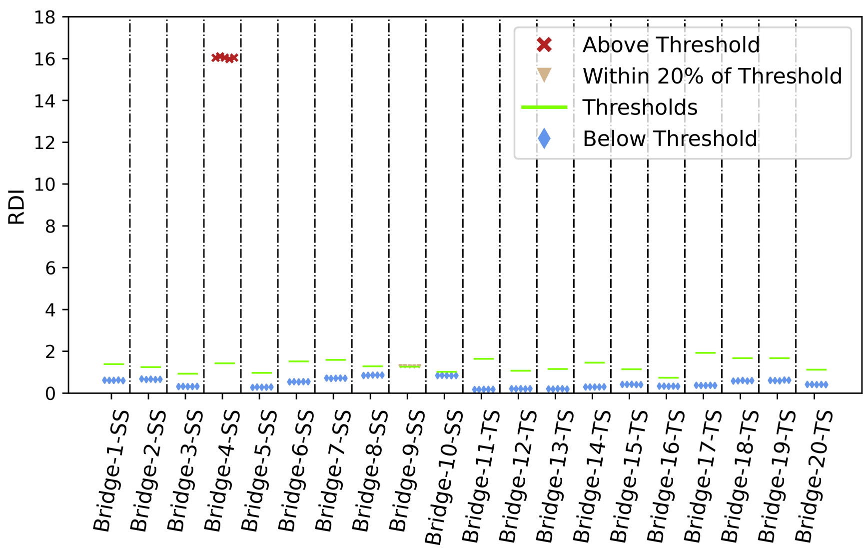


**Fig. 3** Distribution of RDI and TRDI values for the damaged state: Bridge-4-SS.

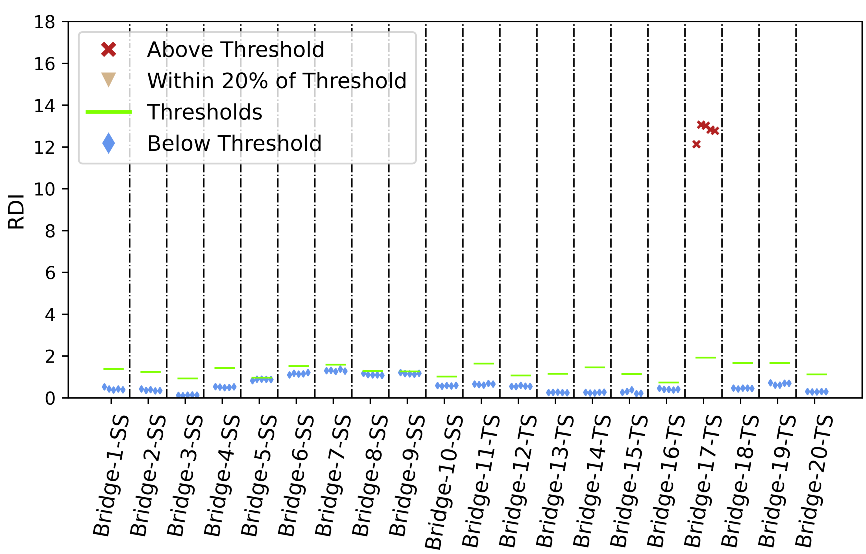


**Fig. 4** Distribution of RDI and TRDI values for the damaged state: Bridge-17-TS.

## Conclusion

This paper introduces an innovative signal-level approach for SHM that leverages information from multiple bridges to enhance damage detection accuracy. By utilizing correlation changes between dynamic responses across a network of bridges, this methodology departs from traditional SHM methods, which focus on monitoring individual structures in isolation. The ability to infer damage in a single bridge by analyzing data from the entire bridge network offers a more comprehensive understanding of structural health and reduces the likelihood of missed detections. Simulations for both single-span and multi-span bridges confirm the robustness of the proposed method. This approach is particularly well-suited for smart city applications, providing a scalable, cost-effective solution for monitoring large infrastructure networks.

## References


1. Wang, G. and Ke, J. "Literature Review on the Structural Health Monitoring (SHM) of Sustainable Civil Infrastructure: An Analysis of Influencing Factors in the Implementation". *Buildings*, 14(2):402 (2024)
2. Ntotsios, E., Papadimitriou, C., Panetsos, P., Karaiskos, G., Perros, K., and Perdikaris, P.C. "Bridge health monitoring system based on vibration measurements". *Bull Earthquake Eng*, 7(2):469–483 (2009)
3. Catbas, F.N., Gokce, H.B., and Gul, M. "Nonparametric analysis of structural health monitoring data for identification and localization of changes: Concept, lab, and real-life studies". *Structural Health Monitoring*, 11(5):613–626 (2012)
4. Gul, M. and Catbas, F.N. "Structural health monitoring and damage assessment using a novel time series analysis methodology with sensor clustering". *Journal of Sound and Vibration*, 330(6):1196–1210 (2011)
5. Yang, Y.B., Lin, C., and Yau, J. "Extracting bridge frequencies from the dynamic response of a passing vehicle". *Journal of Sound and Vibration*, 272(3-5):471–493 (2004)
6. Shirzad-Ghaleroudkhani, N. and Gül, M. "Inverse Filtering for Frequency Identification of Bridges Using Smartphones in Passing Vehicles: Fundamental Developments and Laboratory Verifications". *Sensors*, 20(4):1190 (2020)
7. Matarazzo, T.J., Santi, P., Pakzad, S.N., Carter, K., Ratti, C., Moaveni, B., Osgood, C., and Jacob, N. "Crowdsensing Framework for Monitoring Bridge Vibrations Using Moving Smartphones". *Proc. IEEE*, 106(4):577–593 (2018)
8. Matarazzo, T.J., Kondor, D., Milardo, S., Eshkevari, S.S., Santi, P., Pakzad, S.N., Buehler, M.J., and Ratti, C. "Crowdsourcing Bridge Vital Signs with Smartphone Vehicle Trips" (2022) arXiv:2010.07026 [cs].
9. Liu, J., Chen, S., Bergés, M., Bielak, J., Garrett, J.H., Kovačević, J., and Noh, H.Y. "Diagnosis algorithms for indirect structural health monitoring of a bridge model via dimensionality reduction". *Mechanical Systems and Signal Processing*, 136:106454 (2020)
10. Aalto University, Li, Z., Aalto University, Lan, Y., Aalto University, and Lin, W. "Crowdsensing-based automatic bridge health condition assessment using drive-by measurements and deep learning". *eJNDT*, 29(7) (2024)
11. Mei, Q., Gül, M., and Shirzad-Ghaleroudkhani, N. "Towards smart cities: crowdsensing-based monitoring of transportation infrastructure using in-traffic vehicles". *J Civil Struct Health Monit*, 10(4):653–665 (2020)
12. Catbas, F.N., Gokce, H.B., and Gul, M. "Nonparametric analysis of structural health monitoring data for identification and localization of changes: Concept, lab, and real-life studies". *Structural Health Monitoring*, 11(5):613–626 (2012)
13. Malekzadeh, M., Gul, M., and Catbas, F. "Application of multivariate statistically based algorithms for civil structures anomaly detection". In Catbas, F., Pakzad, S., Racic, V., Pavic, A., and Reynolds, P., editors, *Topics in Dynamics of Civil Structures, Volume 4*, Conference Proceedings of the Society for Experimental Mechanics Series. Springer, New York, NY (2013)
14. Riasat Azim, M. and Gül, M. "Damage Detection of Steel-Truss Railway Bridges Using Operational Vibration Data". *J. Struct. Eng.*, 146(3):04020008 (2020)
15. Zhang, Y., Xie, Q., Li, G., and Liu, Y. "Multi-Damage Identification of Multi-Span Bridges Based on Influence Lines". *Coatings*, 11(8):905 (2021)
16. Brinissat, M., Ray, R.P., and Kuti, R. "Multi-Span Box Girder Bridge Sensitivity Analysis in Response to Damage Scenarios". *Buildings*, 14(3):667 (2024)