



## ROBUST AI-BASED DRIVE-BY DAMAGE DETECTION FOR RAILWAY BRIDGES UNDER OPERATIONAL AND ENVIRONMENTAL VARIATIONS

Cássio Bragança<sup>1</sup>, Edson Florentino Souza<sup>1,2</sup>, Isabela Ames<sup>1</sup>, Diogo Ribeiro<sup>3,4</sup>, Túlio N. Bittencourt<sup>1</sup>

<sup>1</sup> Department of Structural and Geotechnical Engineering, University of São Paulo, Brazil

<sup>2</sup> Department of Civil Engineering, Federal University of Technology – Parana, Brazil

<sup>3</sup> CONSTRUCT - LESE, Faculty of Engineering, University of Porto, Portugal

<sup>4</sup> iBuilt, ISEP, Polytechnic of Porto, Portugal

### Abstract

Ensuring the integrity of railway infrastructure is paramount for transport safety, particularly amid network expansion and aging assets. Conventional monitoring strategies, reliant on direct sensor installation on bridges, are often prohibitively expensive and logistically impractical for large-scale, system-wide deployment. While indirect drive-by monitoring techniques offer a promising alternative, existing methods often struggle to effectively handle environmental and operational variations (EOVs). This significantly limits their reliability and applicability under real-world conditions. This study addresses these gaps by developing a novel, automated, AI-based drive-by methodology for detecting structural damage in railway bridges. The framework's efficacy was tested using comprehensive numerical simulations focused on freight railway operations, employing a detailed three-dimensional finite element model of a Warren-type truss bridge combined with vehicle-track interaction simulations. This numerical investigation, which affords essential flexibility for technique development, constitutes a critical preparatory step preceding experimental validation. The proposed damage detection framework integrates an initial preprocessing for noise reduction, followed by feature extraction using Continuous Wavelet Transform. Deep learning analysis, via Convolutional Autoencoders, is then used to learn normal structural behavior patterns from the extracted features. Finally, damage assessment is conducted using Structural Similarity Index Measure error maps, which are combined with statistical outlier detection to pinpoint anomalies indicative of damage. The results demonstrated successful structural damage detection across various challenging scenarios, including at early stages. The methodology proved sensitive to different levels of damage severity and exhibited strong robustness against the influence of EOVs. This research provides a scalable and cost-effective alternative to traditional railway bridge monitoring systems, maintaining robust detection capabilities without direct instrumentation.

*Keywords: drive-by damage detection, indirect monitoring, convolutional autoencoders, structural health monitoring*

### 1 Introduction

Railway bridges are vital components of transport infrastructure, ensuring the movement of goods and safety across networks [1]. To maintain these aging assets in a context of increasing traffic and axle loads, and climate changes, Structural Health Monitoring (SHM) has become essential for assessing structural integrity and preventing catastrophic failures [2, 3].

However, conventional SHM strategies rely on direct sensor installations, which are often prohibitively expensive and logistically impractical for large-scale, system-wide deployment. Consequently, recent research has shifted toward indirect drive-by monitoring, where sensors on a passing vehicle capture the bridge's dynamic response, offering a more scalable and cost-effective alternative [4, 5].

Despite their advantages, indirect methods struggle with reliability under real-world conditions due to environmental and operational variations (EOVs) [6]. To overcome these challenges, advanced signal processing and deep learning are required to isolate damage-sensitive features from non-structural disturbances [5]. In this context, this work presents an innovative, automated methodology that utilizes Continuous Wavelet Transform (CWT) and Convolutional Autoencoders (CAE) to learn normal structural behavior. Damage is then assessed through Structural Similarity Index Measure (SSIM) error maps and statistical outlier detection, specifically designed to remain robust against EOVs. The efficacy of this framework is demonstrated through comprehensive 3D finite element simulations of a Warren-type truss bridge and freight wagon interactions. This study contributes to the field by:

- introducing a robust, unsupervised AI-based drive-by framework for freight railway bridges
- utilizing complex, calibrated numerical models that provide a realistic preparatory step before experimental validation
- evaluating the methodology's sensitivity to incipient damage (as low as 1%) across diverse scenarios involving various speeds, noise levels, and temperature-induced material changes.

## 2 Methodology

The methodology is composed of four main steps: i) Data acquisition, ii) feature extraction, iii) feature fusion and iv) feature discrimination. All these steps were implemented in Mat-Lab® [7] and are depicted below:

- **Data acquisition:** consists in acquiring acceleration data from points distributed along the wagon in different levels of its suspension systems (axles, bogies and carbody). In the case of this work eight points were used, four on the axle boxes and four on the carbody right above the suspensions.
- **Feature extraction:** this step involves the extraction of damage sensitive information from the acceleration time series. The proposed approach uses CWT coefficients from the acceleration as damage sensitive features. A normalization step is then performed in these features based on a CAE, trained to reconstruct these coefficients under regular operational scenarios. Since the CAE is trained only on undamaged bridge data it is expected that it will fail to reconstruct abnormal situations, therefore the SSIM between the pixels in original and reconstructed image are used as normalized damage features. This normalization is of paramount importance for reducing the influence of operational and environmental disturbances.
- **Feature fusion:** Once extracted and normalized the features consist of 2D matrix of SSIM values, whose interpretation is not very intuitive and direct. Therefore, a feature fusion step enhances the sensitivity of the features by combining them in a single damage index (DI). A two-step fusion approach is adopted. First, the SSIM values along the temporal dimension are averaged, since it is expected that damage detectable by a drive-by technique might affect the complete behavior of the bridge. After, the averaged indexes along the frequency dimension are fused based on a multivariate statistical approach, using the square value of the Mahalanobis distance, as well as the resulting indexes from each sensor. The average in frequency dimension is not adequate since errors in different frequencies might represent intrinsic characteristics of the damage.

- **Feature discrimination:** finally, the detection is performed based on an outlier analysis of the single DI resulting from the fusion process.

In summary, the result of the presented methodology is a DI, which is defined as a unified scalar metric calculated via the squared Mahalanobis distance. It statistically fuses the temporally-averaged SSIM reconstruction errors across all sensors and frequency bands, translating complex 2D feature maps into a single robust indicator where outliers denote structural anomalies. The flowchart in figure 1 depicts the steps of the presented methodology for onboard-monitoring based bridge damage detection.

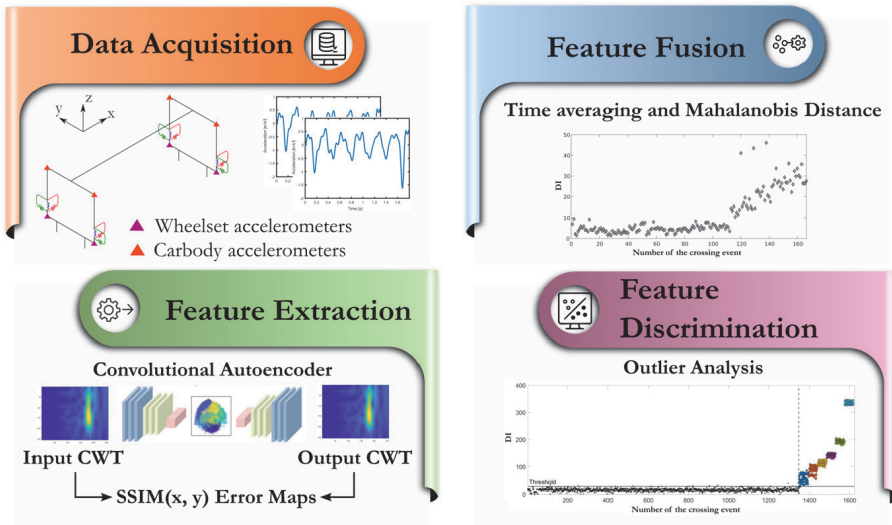


Figure 1 Flowchart of the proposed methodology

### 3 Case study

For the validation of the methodology presented in Section 2 a numerical case study is used for generating synthetic acceleration time series, for different damage cases. The numerical models, vehicle structure interaction tool and simulation scenarios are depicted in this section.

#### 3.1 Numerical models

Numerical models were developed for different railway systems (vehicle, track and bridge) based on real data from these elements. In this section the modelling strategy adopted for each of these systems is presented.

##### 3.1.1 Vehicle

The vehicle used in this study is a two axle Laagrss-type freight wagon (figure 2a) used as a platform for transporting paper roll containers along the beira alta railway line in Portugal. The numerical model (figure 2b) was developed in ANSYS® [8] based on a multibody approach in which the vehicle structural parts are modelled with rigid elements with proper inertial properties and suspensions are modelled by spring dashpot assemblies.

This approach combines good representation of vehicle global behavior with acceptable computational costs [9]. This model was calibrated by Bragança et al. [10] based on experimental modal information. The properties of the elements in the vehicles' numerical model are depicted in [10].

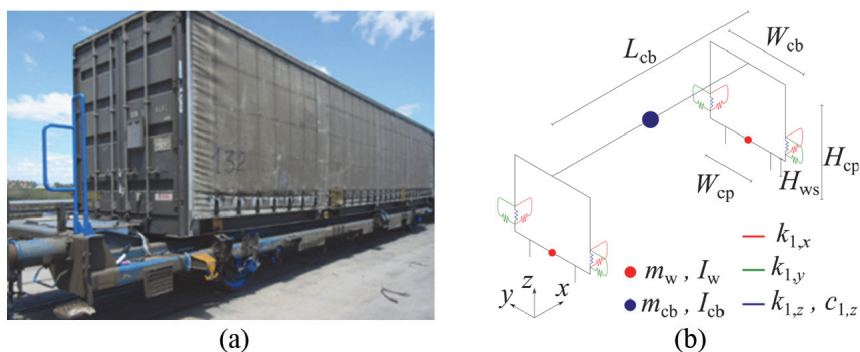


Figure 2 Laagrss-type freight wagon: (a) Overview and (b) numerical model

### 3.1.2 Bridge

The bridge chosen for the study is a 21.42 m open Warren-type truss. The model was developed in ANSYS® [8] using 3D frame elements (BEAM188). The geometry and elements cross section were derived from the work of Bernardini et al. [11] and the model was calibrated based on experimental modal information available in [11]. For the damage scenarios depicted in Section 3.2.2 one main and one secondary element were chosen, these are indicated in figure 3c.

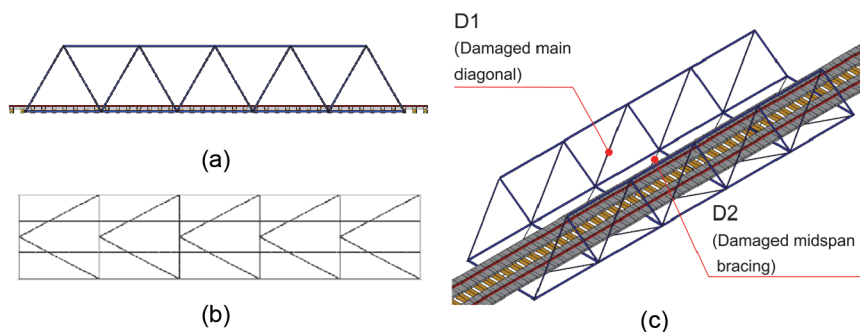


Figure 3 Bridge numerical model: (a) side view, (b) top view and (c) perspective with indication of damaged elements

### 3.1.3 Track

The track was modelled using a multilayer approach in which the interfaces between the different elements were represented by spring-dashpot assemblies. The mechanical properties of the track elements are listed in Neto et al. [12]. Figure 4 depicts the multilayer track structure adopted for the ballasted section outside the bridge (figure 4a) and ballastless section over the bridge (figure 4b).

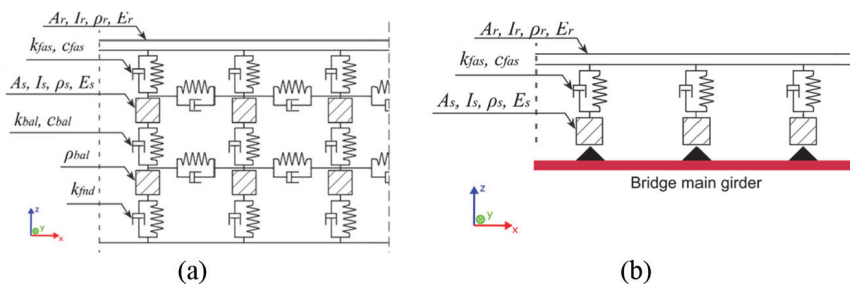


Figure 4 Track numerical mode – schematic representation: (a) Outside bridge and (b) inside bridge

## 3.2 Numerical simulations

To validate the drive-by methodology, several vehicle-track-structure interaction simulations were conducted encompassing different EOVs as well as damage scenarios. These simulations are discussed during this section.

### 3.2.1 VSI numerical tool

The dynamic simulations of the train crossing the bridge were carried out with the in-house software VSI, developed by [13, 14]. The framework of this tool is depicted in figure 5.

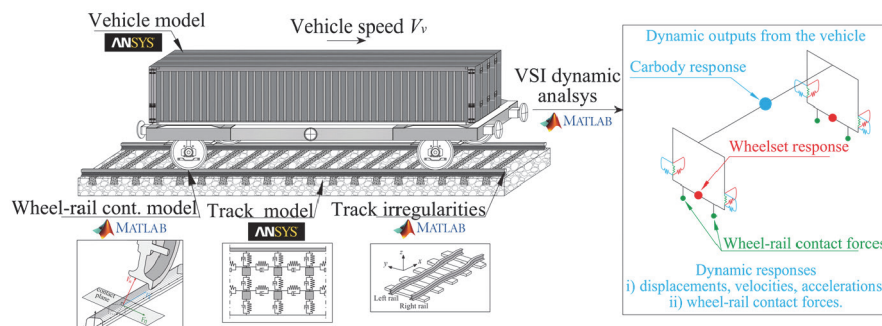


Figure 5 Framework of the numerical tool used in the VSI simulations

### 3.2.2 Simulation scenarios

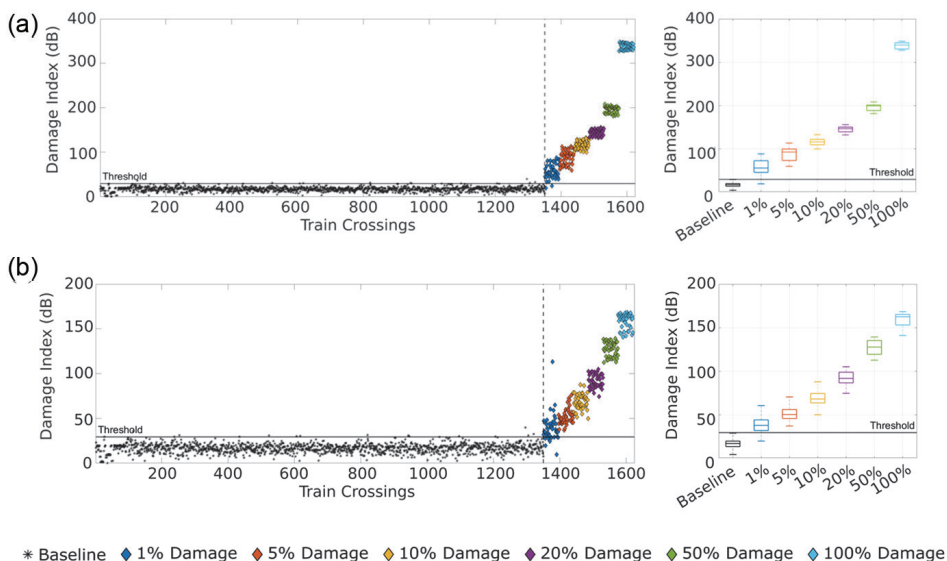
The simulations explored a range of scenarios, incorporating baseline and damaged conditions with various EOVs which are depicted in table 1. Minor damage scenarios assessed the methodology's sensitivity to corrosion-induced stiffness loss, while severe damage included structural failures like large cracks or ruptures. This comprehensive framework offers vital insights into bridge health monitoring under realistic operational conditions.

**Table 1** Simulation scenarios

Condition	Baseline		Damaged
	Undamaged	Slightly damaged	
LAAGRSS type wagons	5	5	5
Speeds [km/h]	45/50/55	45/50/55	45/50/55
Irregularity profiles	2	1	1
Wagon mass variation [%]	90-110 ( $\Delta 5$ )	90-110 ( $\Delta 5$ )	90-110 ( $\Delta 5$ )
Change in elastic modulus with temperature [%]	97.5/100/102.5	97.5/100/102.5	97.5/100/102.5
Positioning accuracy [m]	$\pm 1$	$\pm 1$	$\pm 1$
Measurement noise [%]	5	5	5
Damage severities [%]	-	< 0.5	1/5/10/20/50/100
Damaged elements	-	4	2
Number of simulations	90	1, 260	540 (2x270)

## 4 Results

Figures 6a and 6b present the results of the DI calculated for damage conditions in the main diagonal and the central bracing. The results are displayed as both scatter plots and boxplots, where the boxes represent the 25<sup>th</sup> and 75<sup>th</sup> percentiles. These plots clearly demonstrate that the methodology can detect damage in both scenarios, even for levels as low as 1%. It is also observed that the proposed indicator is sensitive to damage severity, yielding progressively higher values as damage increases, particularly for more severe cases such as those in the main diagonal. The boxplots reveal that despite the presence of some outliers, the overall data trend confirms the robustness and efficacy of the proposed indicator.



**Figure 6** Damage Indices for: a) main diagonal, b) center bracing

## 5 Conclusion

This study demonstrated the feasibility of an innovative and automated methodology for damage detection in railway bridges through indirect drive-by monitoring. The integration of CWT, CAE, and SSIM enabled the extraction of anomaly-sensitive features, overcoming common limitations of traditional methods in handling EOVs. Numerical results obtained from a Warren-type truss bridge model validated the efficacy of the approach, showing a high sensitivity capable of identifying structural damage at incipient levels, starting from 1%, in both primary and secondary elements. The robustness of the proposed damage indicator was confirmed by its clear progression trends as damage severity increases, even in the presence of several EOVs. Therefore, this research provides a scalable and cost-effective alternative to monitoring systems based on fixed sensors, eliminating the need for direct instrumentation on the infrastructure. This work establishes a solid foundation for future experimental validation, positioning the use of AI and on-board monitoring as fundamental tools for managing the integrity and safety of railway networks.

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