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# INFRASTRUCTURE MANAGEMENT VIA BIM MODEL: INTEGRATION OF STRUCTURAL HEALTH MONITORING AND ANN-BASED DAMAGE ASSESSMENT

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***SUMMARY***: *Bridges and viaducts are critical infrastructure assets, yet their maintenance remains a challenge due to aging, increased traffic loads, and insufficient documentation. While Structural Health Monitoring (SHM) and Building Information Modelling (BIM) have independently advanced viaduct management, their integration is still underexplored. This study proposes a novel framework integrating SHM, BIM, and Artificial Neural Networks (ANNs) for comprehensive viaduct management. Field tests, including ambient vibration analysis, were conducted to capture the Rio Claro Viaduct's dynamic behaviour. This information was used for the calibration of a finite element model. Simulated damage scenarios were created to train ANNs that use modal curvature damage indices for damage detection and severity assessment. The integration of these components into an enriched BIM model centralizes data for efficient visualization and decision-making. The framework demonstrated high accuracy, with ANNs achieving an average precision of 85% in damage classification and an* $R^2$ *of 0.96 in severity prediction. Validation using a decade-separated dataset confirmed the framework's robustness, showing negligible structural deterioration over time. It is intended to provide an intuitive user interface so that asset managers can make data-driven decisions, overcoming the limitations of traditional visual inspections. This research attempts to bridge the gap between BIM and SHM applications by offering a replicable, efficient solution for infrastructure management.*

***KEYWORDS***: *structural health monitoring, building information modelling, artificial neural networks, damage assessment, infrastructure maintenance.*

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# 1. INTRODUCTION

Bridges and viaducts are essential infrastructure assets for the economic development of a region, as they support logistical routes. Maintaining the integrity of these structures is crucial to ensuring traffic flow and preventing significant losses. Subject to operational loads, environmental factors, and traffic accidents, these structures may develop damage over time, starting small and growing depending on the structure's use and the lack of corrective maintenance. Asset managers have been adopting structural health monitoring (SHM) systems to ensure safety and enable early damage detection in bridges and viaducts (Entezami et al., 2025). These technologies use non-destructive techniques to identify defects in structures by analysing changes in modal properties, such as natural frequencies and vibration modes (Figueiredo & Brownjohn, 2022). Assessing the condition of the structure provides valuable information for decision-making on interventions and helps build a database of these assets. In this context, information models of these structures serve as an alternative for consolidating data in an interactive and accessible way, encompassing both their current condition and historical information.

The aging of these infrastructures can be aggravated by the action of exceptional loadings, adverse environmental conditions and accelerated material degradation, requiring careful monitoring throughout their useful life. Mohamed et al. (2023) highlight the loss or fragmentation of essential information, such as original projects, inspections, and maintenance records, as a recurring problem, often scattered across paper documents or non-integrated systems. This gap can be exacerbated by changes in management or technical teams, which can disrupt the continuity of documentation history. Without a centralized repository, structural condition assessment can become uncertain, compromising decisions and raising maintenance costs (Huang et al., 2024). In this context, the use of Building Information Modelling (BIM) platforms, capable of preserving, organizing, and updating their database, can play an important role in extending the useful life of assets.

BIM is a methodology that involves creating and managing detailed, information-rich digital representations of built assets, including buildings and bridges. This collaborative approach integrates data and processes in a standardized digital environment, facilitating decision-making throughout the project's lifecycle (Davila Delgado et al., 2017). The application of BIM in infrastructure has shown promising results in infrastructure engineering. In asset management, works such as (Davila Delgado et al., 2017; Hagedorn et al., 2023; van Eldik et al., 2020) concluded that BIM optimizes processes, centralizes information, and enables a holistic view of the infrastructure lifecycle, facilitating strategic decision-making. In data management, (Alsharif et al., 2025; Aziz et al., 2017; Davila Delgado et al., 2017; McGuire et al., 2016) demonstrated that the methodology provides a unified platform for efficiently storing and analysing information, supporting maintenance interventions.

Structural Health Monitoring systems can enhance infrastructure management by supporting a continuous cycle of data collection, analysis, and integration. Using sensors and dynamic testing, these systems periodically gather structural condition information, which is then can be used to enrich an information model. This integration of up-to-date data enables a rapid response to adverse events, greatly improving condition monitoring (Fawad et al., 2023; Gragnaniello et al., 2024; Kwon et al., 2021; Truong et al., 2023). Furthermore, the adoption of the methodology allowed new inspection methods by providing visual and analytical tools that increase the accuracy and efficiency of this process (Boddupalli et al., 2019; Deng et al., 2022; Mohamed et al., 2023; Singh & Sadhu, 2020).

Digital Twins (DTs) are virtual models that replicate physical assets' characteristics and behaviour, using data to simulate performance and service life (Lu & Brilakis, 2019). Classification varies by data connectivity and automation levels. Honghong et al. (2023) distinguish between pre-Digital Twins, which are static models updated at intervals, and ideal Digital Twins that continuously ingest real-time sensor data for dynamic insights. In infrastructure management, these systems can facilitate early damage detection and more accurate integrity assessment (Heykoop et al., 2024). Additionally, they allow testing structural behaviour under various scenarios, including extreme loads and environmental changes, enabling identification of critical points and optimization of structural performance (Girardet & Boton, 2021; Honghong et al., 2023).

While Building Information Modelling (BIM) technologies and machine learning have advanced significantly, a gap remains in effectively integrating these tools for structural condition diagnosis. Existing literature has concentrated on data collection and visualization from sensors but has failed to explore how artificial intelligence algorithms can be applied to extract actionable insights for structural assessment decision-making. A practical obstacle that worsens this limitation is the lack of reliable data, reflected updated or missing digital inventories (especially for older structures), discrepancies between actual and design loads, and insufficient records of past damage and repairs. These information gaps hinder an accurate assessment of the structure's current condition and limit the reliability of predictions about its remaining service life.

This work proposes and validates a novel framework for structural integrity assessment that uses a pre-Digital Twin (pre-DT) as the backbone for integrating experimental, numerical, and data-driven methods within a collaborative BIM environment. The objective is to link in-service measurements to predictive diagnostics, so BIM model becomes a decision-ready repository for asset management. To achieve this, ambient vibration tests supply the viaduct's modal properties (natural frequencies and mode shapes), which are used to calibrate a finite element model. The calibrated model is then used to simulate damage scenarios and build a database of dynamic damage indices (modal curvature) at varying degradation levels; artificial neural networks are then trained using this database to map modal curvature patterns to locate damage and evaluate its extent. The main contribution is this closed-loop framework that integrates field measurements, model updating and simulation-driven ANN training with BIM. This approach generates actionable structural condition indicators directly that can be directly used for monitoring, risk assessment, and lifecycle decision-making. The framework's effectiveness and replicability are demonstrated through its application to the Rio Claro viaduct, highlighting how BIM can serve as a central hub for monitoring and strategic decision-making across infrastructure assets.

## 2. THEORETICAL BACKGROUND

### 2.1 Damage detection

In structural health monitoring (SHM), three approaches stand out: data-driven, model-based, and hybrid. Data-driven techniques employ statistical models on continuous monitoring data to detect changes in any of the structure's primary dynamic variables, usually natural frequencies. The structure's modal response is affected by environmental conditions, such as temperature changes, thus, the major challenge lies in creating algorithms that can distinguish whether a detected change was caused by stiffness loss or environmental action (Tibaduiza Burgos et al., 2020). The model-based approach uses numerical models or reduced-scale prototypes of the structure to simulate different damage scenarios and compare its results to the real scale structure's reference data (Bagchi et al., 2010). Recently, some works have proposed a hybrid approach to structural integrity monitoring (Figueiredo et al., 2019; Gordan et al., 2020; Svendsen et al., 2023), in which data and numerical models are used together to distinguish between the reference and damaged states. This approach attempts to overcome the disadvantages presented by each method when treated as distinct.

The choice of damage indicator in SHM systems is crucial for reliable damage detection, especially in the presence of environmental effects. The model-based and hybrid approaches share the use of damage indicators to identify changes in the structure's modal properties. An accurate damage indicator should be sensitive to structural changes caused by damage while being robust against changes due to environmental influences (Simoen et al., 2015). Natural frequencies are commonly used as damage indicators because they are easy to measure, although they are also significantly affected by environmental changes (Ho et al., 2021; Svendsen et al., 2023). Dynamic damage indicators are based on the principle that any alterations in a structure's physical properties - whether in its mass, damping, or stiffness - directly affect its modal characteristics, including natural frequencies and mode shapes. The development of a crack within a beam in an assembly leads to a decrease in stiffness. This change influences not only the dynamic characteristics of the beam itself but also the overall deformation pattern of the entire structure.

The modal curvature method (MCM) is an established damage index in structural analysis. This method, introduced by (Pandey et al., 1991), calculates the second derivative of modal displacement to assess structural damage. Its effectiveness has been documented across different bridge types. Studies have demonstrated its successful implementation in steel bridges, as shown by (Nick & Aziminejad, 2021). For reinforced concrete bridges, multiple researchers have validated its application, including the works of (Abdel Wahab & De Roeck, 1999; Dilena et al., 2015; Erduran et al., 2021; Sánchez-Aparicio et al., 2015). In one-dimensional applications, after the structure is discretized into elements of length $h$, the modal curvature can be computed using a centered difference scheme, as shown in Equation (1).

$$k_i = (w_{i+1} + w_{i-1} - 2w_i)/h^2 \tag{1}$$

where $w_i$ to represent the modal displacement at position $i$. To determine structural damage, the method compares the modal curvatures of the structure in both its damaged and undamaged states. This comparison is expressed mathematically in Equation (2), where the damage index is calculated as the difference between these curvatures.

$$\Delta k = \sum_{i=1}^{n} k_i - k_i^* \qquad (2)$$

where $k_i$ denotes the undamaged curvature, $k_i^*$ denotes the damaged curvature, and $n$ represents the number of mode shapes considered. The physical meaning of the MCM, as explained by (Pandey et al., 1991), lies in its ability to indicate localized changes in a structure due to damage. When a structural element experiences damage, such as a crack, it leads to a reduction in its flexural stiffness ($EI$), which in turn increases the curvature at that damaged section. Therefore, the difference in modal curvature between an intact and a damaged structure serves as a precise measure of how damage alters stiffness and structural behaviour at specific locations. This change is localized, effectively highlighting the area of damage.

## 2.2 Model calibration

Manual model calibration offers greater flexibility to the analyst, allowing for precise and iterative adjustments to the model. This approach has demonstrated effectiveness in previous studies (Altunisik & Bayraktar, 2017; De Angelis & Pecce, 2023; Oliveira et al., 2025; Talebi et al., 2023). The selection of parameters to be adjusted is crucial and depends on the analyst's expertise, allowing them to make a judicious selection based on real physical data and avoid arbitrary adjustments (Brownjohn et al., 2001). Both static and dynamic tests can provide data for model calibration. The need for traffic interruption makes static tests, though important for calibrating boundary conditions and element stiffness, logistically challenging. On the other hand, dynamic tests, which capture the global behaviour of the structure under operational conditions (Simoen et al., 2015), are more commonly used in practice (Garcia-Palencia et al., 2015; Malveiro et al., 2014; Ren & Chen, 2010; Svendsen et al., 2022). Few studies, such as (De Angelis & Pecce, 2023; Liu et al., 2021; Schlune et al., 2009), have explored the combination of both types of tests, despite the potential to enhance model update quality.

To evaluate the output progress at each step, it is common to compare natural frequencies measured in the field against those obtained through numerical calculations. According to Talebi et al. (Talebi et al., 2023) this comparison can be quantified using the objective function described in Equation 3:

$$\varepsilon = \frac{|f_i^{exp} - f_i^{num}|}{f_i^{num}} \qquad (3)$$

where $i$ represents the analyzed vibration mode, while $f_i^{exp}$ and $f_i^{num}$ denote the experimental and numerical frequency values, respectively.

In dynamic analysis, the Modal Assurance Criterion (MAC) serves as a key indicator for measuring correlation between different vibration mode shapes. As noted by (Allemang, 2002), higher MAC values indicate stronger correspondence between the compared modes. The MAC index is mathematically expressed as shown in Equation 4:

$$MAC(\phi_i, \phi_j) = \frac{|\phi_i^T \phi_j|^2}{(\phi_i^T \phi_i)(\phi_j^T \phi_j)} \qquad (4)$$

where $\phi_i$ and $\phi_j$ denote the modal displacements associated with vibration modes $i$ and $j$, respectively, and $\phi_i^T$ and $\phi_j^T$ represent their corresponding transposed forms. When analyzing the MAC matrix, the main diagonal elements show how each mode correlates with itself, while off-diagonal elements indicate a correlation between different modes. For optimal mode separation, the off-diagonal elements should exhibit low values.

## 2.3 Machine learning and health diagnosis

Data driven artificial neural networks (ANNs) learn by processing data through interconnected layers of nodes. The workflow begins with input data, which is fed into the first layer (input layer). Each connection between nodes has an associated weight, and each node in subsequent layers (hidden and output layers) applies a non-linear activation function to the weighted sum of its inputs. These activation functions introduce non-linearity, allowing the network to learn complex patterns. Common families of activation functions include sigmoid-like functions (e.g., logistic, tanh), which squash values to a limited range (often 0 to 1 or -1 to 1), and rectified linear unit (ReLU) families, which are piecewise linear and help mitigate the vanishing gradient problem. This process continues layer by layer until the output layer produces a prediction. The difference between the predicted output and the actual target value is quantified by a loss function. During training, the network adjusts the weights of the connections to minimize this loss. For regression tasks, the output layer typically uses a linear activation function (or no activation function), and the loss function often means squared error, aiming for a continuous output. For classification tasks, the output layer uses a softmax-like activation function, producing a probability distribution over the classes, and the loss function is typically cross-entropy, aiming for a categorical output representing class probabilities. By iteratively adjusting weights based on the loss, the network learns to map inputs to outputs, effectively performing regression or classification. The remarkable capacity of ANNs to process large datasets and recognize complex patterns has led researchers to apply them in structural damage detection and severity assessment (Jayasundara et al., 2019; Silva et al., 2016; Svendsen et al., 2023).

## 3. METHODOLOGY

The pre-DT workflow for infrastructure management integrates multi-source data through a systematic process (Figure 1). Initially, an infrastructure asset is selected, and comprehensive data, including design specifications (structural plans and material details) and field measurements (ambient vibration tests), are aggregated into a digital asset inventory. This centralized repository supports three critical parts: a Finite Element (FE) for structural analysis, Artificial Neural Networks (ANNs) for structure condition assessment, and a Building Information Modelling (BIM) for comprehensive representation and data storage. These components collectively contribute to the creation of the pre-DT, which provides a dynamic and data-driven representation of the infrastructure. Finally, asset management component utilizes the pre-DT for decision-making, monitoring, and maintenance planning, aiming to ensure the structure's optimal performance and safety. Additionally, a feedback loop from pre-Digital Twin to the asset inventory allows continuous updates based on new data and insights.

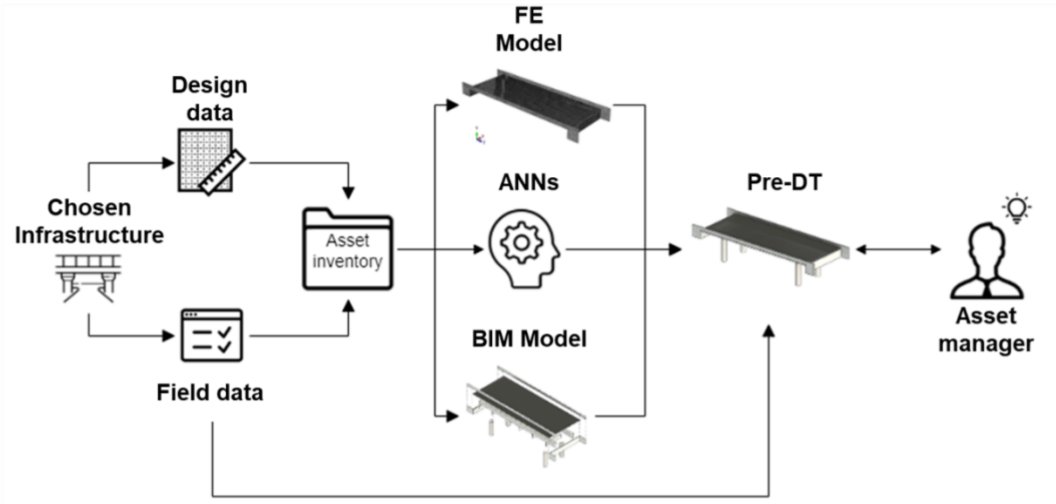


*Figure 1: Complete framework.*

The process involves four key stakeholders: Asset Management Team, Engineering Team, Modelling Team, and Data Science Team. The Asset Management Team initiates the process by selecting the assets to be monitored and determining maintenance interventions based on their condition. The Engineering Team, which includes experimentalists and structural specialists, conducts field tests, verifies design information, and generates periodic inspection reports to enhance the BIM model. The Modelling Team, composed of experts in numerical and information modelling, oversees the digital transformation by managing asset data requests, developing the BIM and FE models, and refining predictive state models to build the pre-DT. Lastly, the Data Science Team is responsible for establishing databases and training artificial neural networks (ANNs) to validate and improve predictive analytics, supporting the data-driven decision-making.

The process of pre-DT implementation (Figure 2) begins with the Asset Manager defining the target infrastructure. Subsequently, the Modelling Team creates a comprehensive document for the Engineering Team, outlining all necessary information to construct the structure's virtual models. This document specifies: verified actual and design measurements, dynamic test-derived modal properties, the structural elements to be analysed, and their physical properties. Guided by this scope, the Engineering Team plans and conducts field tests, determining the appropriate test types and experimental mesh. Upon completion, they provide the Modelling Team with critical data, including natural frequency values, vibration modes, and element compressive strengths. The Modelling Team then uses this data to calibrate the structure's finite element models and Building Information Model (BIM). With the calibrated finite element model, the Modelling Team generates simulated damage scenario results, which they deliver to the Data Science Team. These results are used to build databases for training and validating Artificial Neural Networks (ANNs) that will diagnose structural health. Finally, the pre-Digital Twin is consolidated by integrating these tools into the BIM model. The Engineering Team leverages the pre-Digital Twin to generate detailed reports that assist the Asset Manager in making informed decisions regarding potential interventions. Crucially, the Engineering Team documents all real-world interventions and shares this information with the Modelling Team to ensure the pre-Digital Twin remains up-to-date. This iterative process creates a continuous feedback loop, ensuring the pre-Digital Twin accurately reflects the asset's current state and enabling informed management decisions.

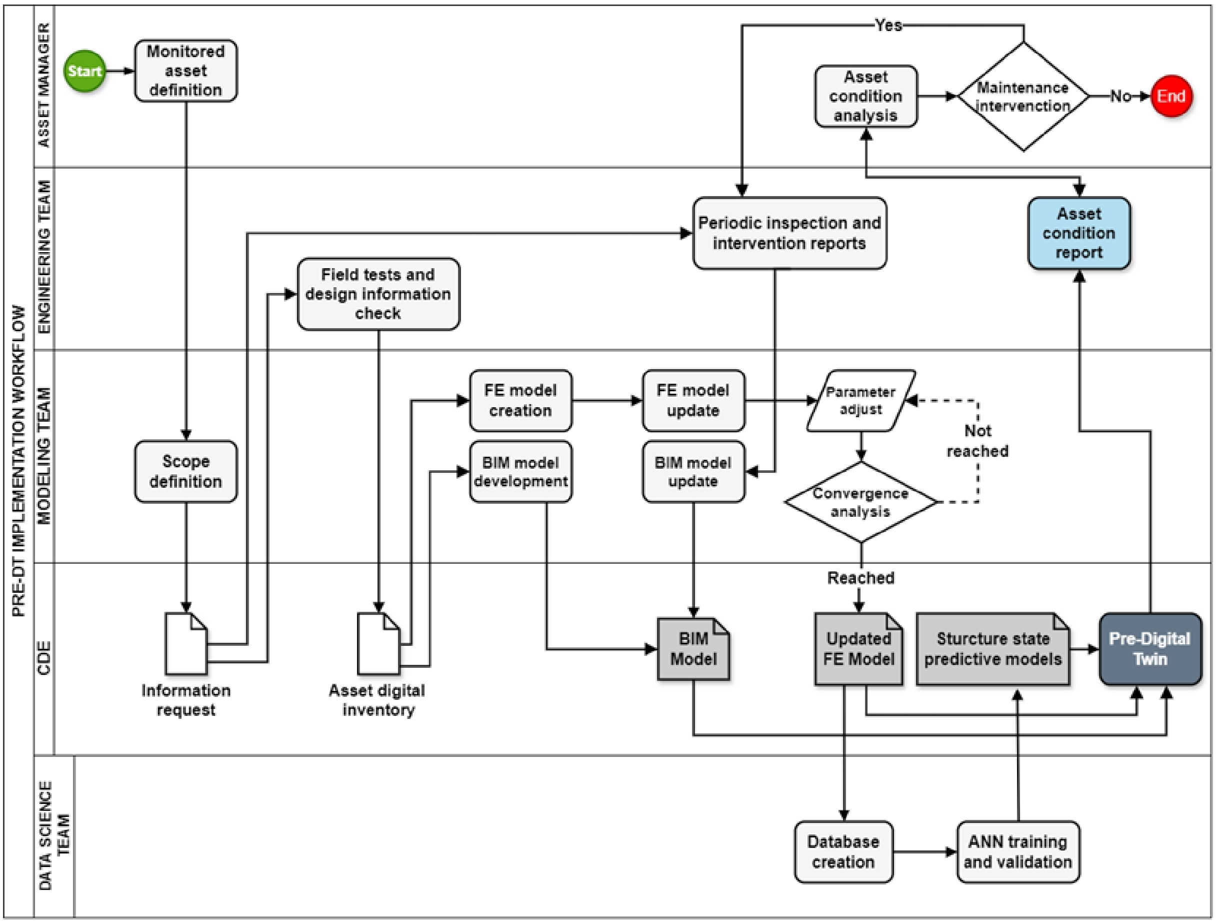


*Figure 2: Proposed process map.*

## 3.1 Asset digital inventory

The asset's digital inventory aims to create a comprehensive repository of data and attributes. Its primary goal is to facilitate continuous monitoring and efficient management of the asset's condition thorough the understanding of its state, therefore supporting proactive maintenance strategies. The process begins with the development of a 3D as-is BIM model based on design drawings, where critical attributes and relevant data are integrated. This inventory is organized as a database, consolidating all necessary information to enhance the efficiency of bridge management. The inventory includes general data and detailed information on design parameters, structural data, maintenance records, and structural condition diagnosis as shown in Figure 3. By serving as a centralized and structured repository, the inventory is intended to support effective management and informed decision-making for bridge maintenance and inspections.

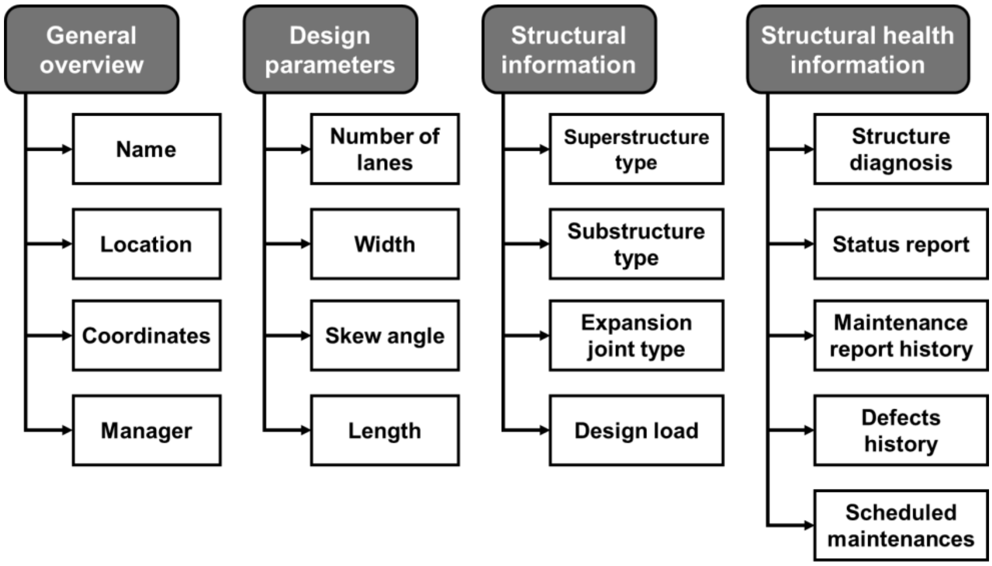


*Figure 3: Asset's inventory content.*

## 3.2 Field tests for structural characterization

The field tests play a key role in populating the structure's digital inventory. This data can be divided into two categories: structural behaviour and structural component properties. With respect to structural behaviour, the tests provide information on how the structure responds to external excitation, such as loads or wind effects. The choice of structural behaviour tests in practice is contingent upon the availability for traffic interruption (Figure 4). Ambient vibration tests, which can be conducted during the structure's operation, enables the determination of its natural frequencies, vibration modes and damping ratio. In contrast, static load tests, which can require traffic interruption, provide information on the stiffness of the structural elements and the structure's boundary conditions. The materials tests provide insight on the structural element's strength. This data affects the estimation of structural element's stiffness, which influences dynamic behaviour and updating process of the numerical model.

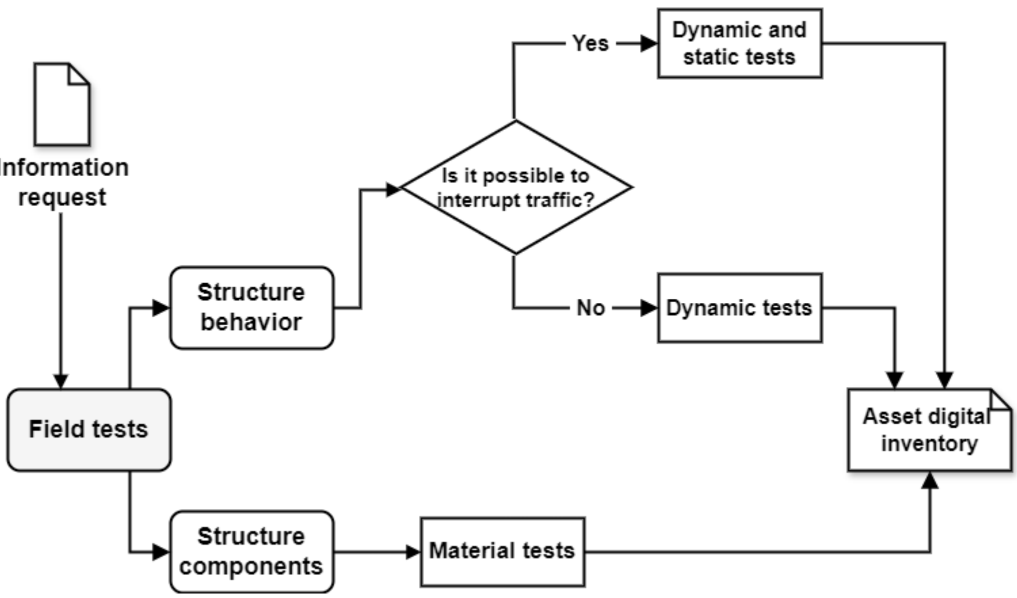


*Figure 4: Field test framework.*

## 3.3 Calibrated numerical model

By the end of the updating stage, the finite element model should accurately reflect the structure's behaviour as measured in the tests. Adjusting the model based on the results of the ambient vibration test requires assessing the similarity between the experimental and numerical results in terms of natural frequencies and vibration modes. The majority of the calibration effort focuses on the model's mass and stiffness, since these are the two main variables in the dynamic problem. In this work, the mass was adjusted by varying the asphalt layer's thickness, while the stiffness calibrated by changing the Young's modulus of the structure's material.

## 3.4 Assessment of structural condition using ANN

The structural condition diagnosis is performed in two sequential stages, using multilayer perceptron artificial neural networks. In the first stage, a classifier neural network analyses the structure and identifies the presence of damage, locating it in one of six predefined sections of the longitudinal beams. If damage is detected, the process advances to the second stage, where a regressive neural network estimates the severity of the damage identified in the previous stage. The architecture and parameters of each of these networks, presented in Table 1, were chosen and tuned to balance expressiveness with generalization. Multilayer perceptrons with a small number of hidden layers and progressively reduced neuron counts were adopted to capture the nonlinear relation between modal-curvature features and damage while avoiding over-parameterization. ReLU activations were used in hidden layers to speed convergence and mitigate vanishing gradients, softmax was used at the classifier output for stable multi-class probability estimates, and a linear output was used for the severity regressor to produce unbiased continuous predictions.

*Table 1: Artificial Neural Network's Architecture.*

| ANN | Input layer | Hidden layers | | | Output layer | | Training parameters | | |
|---|---|---|---|---|---|---|---|---|---|
| | Neurons | Layers | Neurons per layer | Activation function | Neurons | Activation function | Learning rate | Epochs | Loss function |
| Damage detection | 30 | 3 | 15 \| 12 \| 9 | Tanh | 7 | Sigmoid | 0,01 | 500 | Categorical cross entropy |
| Severity estimation | 30 | 3 | 25 \| 15 \| 5 | ReLU | 1 | Linear | 0,002 | 550 | Mean squared error |

Artificial Neural Networks (ANNs) must be trained with a dataset of damage indicators to assess a structure's condition accurately. To ensure reliable results, the training data must be free from noise and interference caused by environmental factors such as temperature variations and wind. In this context, dynamic damage indices provide a more robust alternative as damage indicator than the primary variables such as natural frequency and vibration modes, since they are less sensitive to noise and environmental fluctuations. This enhances the accuracy of damage detection and quantification. The dataset is generated by introducing artificial damage scenarios into a calibrated finite element model. Introducing damage in a finite element model for these analyses, rather than applying physical damage to the actual structure, is usually the only option due to the operational challenges and the risks associated with modifying a structure that is in service. In this work, artificial damage is simulated by reducing the bending stiffness ($EI$) in designated sections of the longitudinal beams.

The modal curvature index is adopted in this study as the input variable for the ANNs. This choice is justified because the proposed methodology is based on sporadic field tests rather than having to rely on continuous monitoring of the structure, which would allow filtering interferences from environmental effects using statistical methods.

## 3.5 Integration of BIM and SHM

The integration proposed in this work involves three key areas: general overview, asset inventory, and structural diagnosis. In the first one, a tool is used to display a *web dashboard* that consolidates reports from all the concessionaire's assets, including information about the location of bridges and viaducts, the main identified structural pathologies, and a ranking that orders these structures according to the severity of their deterioration.

Figure 5 describes in detail the general structure of the proposed *plugin* component. To populate the dashboard, asset condition reports are initially obtained, and stored in the Common Data Environment (CDE). Then, these reports update a *Power BI dashboard*, which is then published on the web, facilitating access to information. In parallel, a script integrated with the BIM tool interacts with the CDE and the online publication, ensuring data visualization and monitoring.

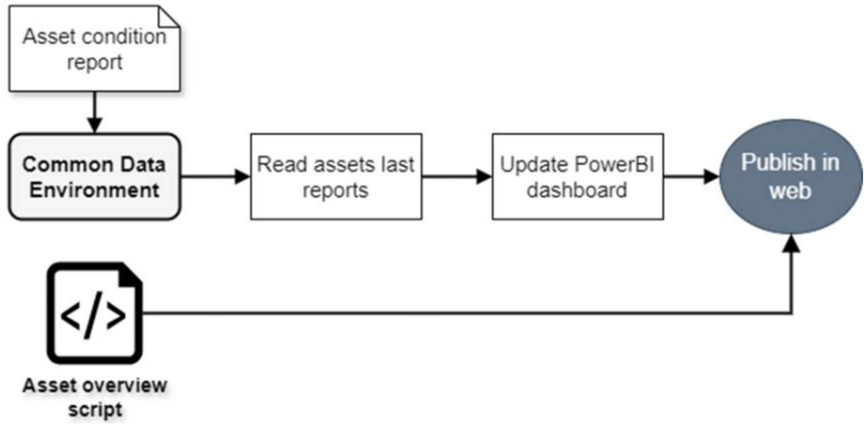


*Figure 5: Assets overview code framework.*

The viaduct inventory is divided into two parts: static and inspection data. The static part gathers information that remains unchanged or undergoes few changes during the infrastructure's lifespan, allowing it to be organized in a fixed database, accessible through a script. This section covers general, engineering, and structural data, as illustrated in Figure 6a, which details the operation of the code responsible for integrating them. This data, like all other structural data, is centralized in the CDE. Next, the *script* gathers and organizes the information, converting it to a format compatible with the BIM platform display. It then presents the result in a text window, offering a clear and consolidated view of the inventory. Figure 6b shows the operation of the code that displays inspection information. This code generates a list of all available inspection reports, which are displayed in a selection window, allowing the user to choose a specific report to view. Upon selecting a report, the system opens a new window to display the chosen report. This way, users can navigate and view different inspection reports on the BIM platform, facilitating the analysis and management of this information.

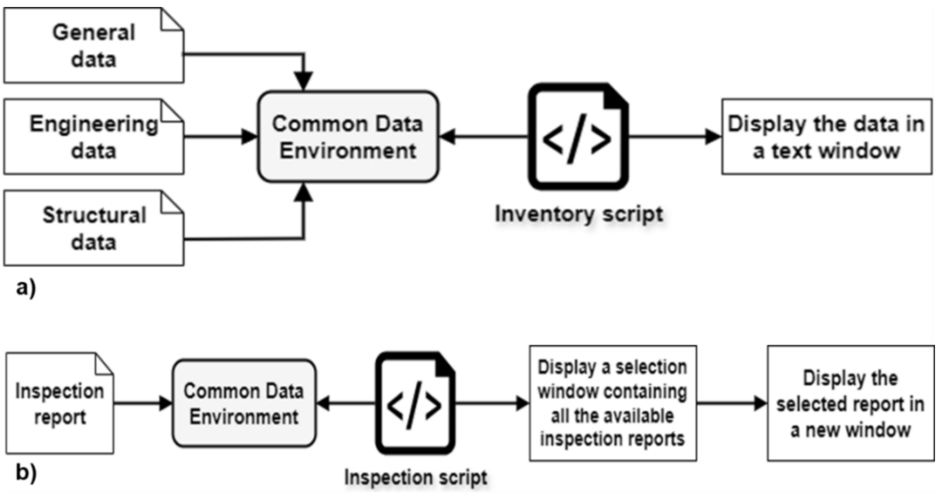


*Figure 6: Code framework for accessing and visualizing a) static and b) inspection data.*

The integration part of the system concludes with a structural diagnosis, executed through three sequential *scripts*. As depicted in Figure 7a, the *analysis script* initiates the diagnostic workflow. First, it retrieves the most recent modal curvature data, captured during ambient vibration tests and stored in the Common Data Environment (CDE), and processes it using two pre-trained neural networks. The *localization network* detects the presence and location of structural damage. If damage is identified, the *severity identification network* evaluates its intensity. These results are compiled into a diagnostic report, which states whether damage exists, specifies the affected structural element, pinpoints its location, and quantifies its severity. Next, the *incorporate* function (Figure 7b) integrates this report into the digital structural model. Using shared parameters, the function updates longitudinal beam model groups by assigning two key properties to the relevant elements: presence of damage and damage severity. These parameters are linked to specific structural members via their unique IDs, ensuring traceability. Finally, the results function (Figure 7c) generates an intuitive 3D view that visually highlights elements requiring attention. This view dynamically adjusts element appearances based on their shared parameter values, applying filters to emphasize compromised areas. Accessible online, the visualization supplements the manager's final report with actionable insights into structural health.

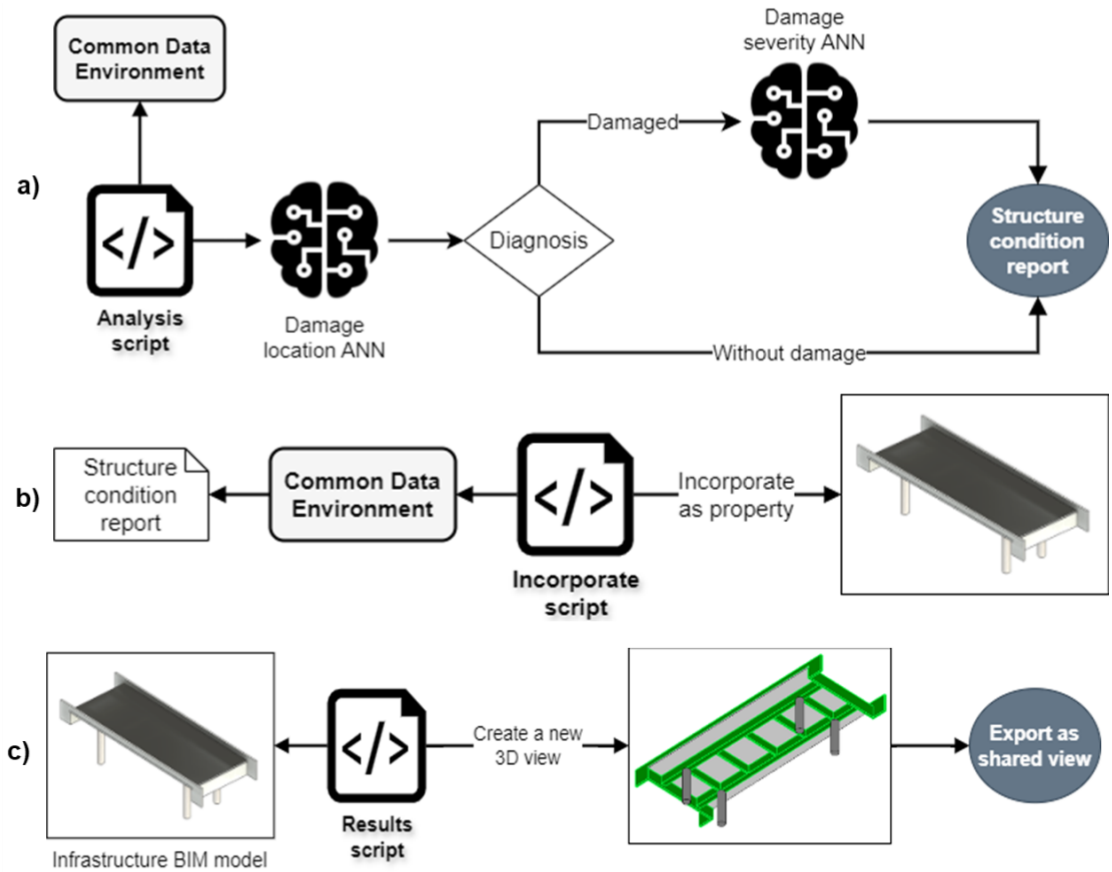


*Figure 7: Structure diagnosis code overview.*

The results related to the structural condition of the elements are integrated into the BIM model, enabling the generation of a report intended for the asset Management Team. This report displays all structural elements using a color-coded classification system that reflects the degree of degradation of each component. Structural conditions are categorized into four levels: undamaged (green), slightly deteriorated (yellow), highly deteriorated (purple), and potentially hazardous (red). Based on this report, which integrates SHM inspection data and the intervention history stored in the model, the manager can decide whether to carry out corrective maintenance, including it in the planned project schedule.

# 4. CASE STUDY

## 4.1 Structure and tests description

The Rio Claro-Viaduct is located in the city of Rio Claro, over the SP-340 highway. Situated in an urban area, the viaduct plays a crucial role in the region's infrastructure, serving as one of the main access routes to cities in the western part of the state of São Paulo, Brazil, particularly connecting to São Carlos (Figure 8).

*Figure 8: Rio Claro-Viaduct.*

Constructed in the 1980s, this reinforced concrete viaduct boasts a robust structural design. It comprises two main girders, five transverse beams connecting them, and four supporting piers. Two bracing beams enhance the columns stability, while the deck provides the roadway surface. The structure terminates on both ends with wing walls that anchor it to the surrounding earth slopes. Spanning 32.1 meters in length and 13 meters in width, it traverses three spans and is laterally secured by New Jersey barriers (Figure 9).

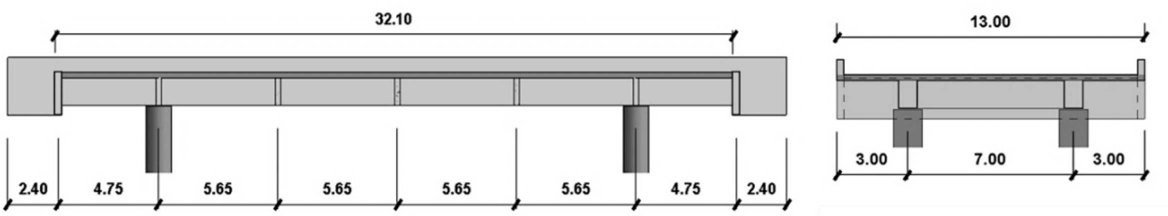


*Figure 9: Structure measurements (in meters).*

Two key factors motivated the choice of this viaduct for the case study. First, researchers had access to dynamic measurements taken ten years earlier, carried out by Gómez Araújo et al. (2019) in 2014, enabling a thorough assessment of how the structure's behaviour may have changed over this extended period. Second, since this viaduct shares design characteristics with many other bridges on Brazilian highways, the study's findings have broad applicability for evaluating similar infrastructure.

## 4.2 Field tests findings

The Rio Claro Viaduct's modal properties were determined by ambient vibration testing, which measures the structure's dynamic response to natural excitations such as wind and traffic. Accelerometers were installed at thirty strategically selected locations to record vibration time histories. This extensive experimental mesh enables a robust measurement of mode shapes, and consequently its use to damage detection task. The signals were processed with modal-identification techniques, notably Enhanced Frequency Domain Decomposition (EFDD), to extract natural frequencies, mode shapes and damping ratios. Because no artificial excitation is required, this method is especially well-suited for assessing structures in operation. Further details on the measurement layout and post-processing are discussed in (Oliveira et al., 2025).

The results from the 2014 ambient vibration test, illustrated in Figure 10, identified four distinct vibration modes with frequencies at 5.6Hz, 10.5Hz, 14.1Hz, and 19.3Hz. The second and fourth modes exhibited the highest damping coefficients, suggesting enhanced energy dissipation at these frequencies. While the first and second vibration modes displayed similar patterns, the third and fourth modes each showed unique characteristics. The modal shapes demonstrated increasing complexity in sequence, confirming effective data post-processing. These experimental measurements of natural frequencies ($f^{exp}$) and damping ratios ($\phi^{exp}$) were subsequently used to fine-tune the numerical model.

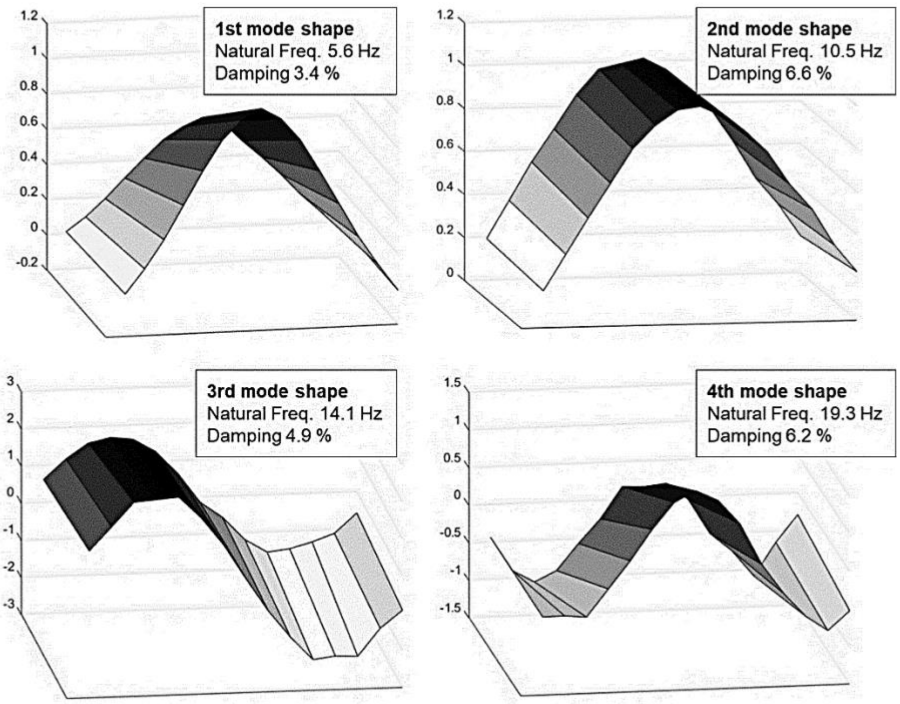


*Figure 10: 2014 ambient vibration test results.*

The study examined the structural behaviour at the component level, following the procedure outlined in Figure 4. Concrete girders' characteristic compressive strength ($f_{ck}$) was estimated using impact-hammer testing. An experimental grid was applied to the two longitudinal beams, showing characteristic strengths of 39.7 MPa and 45.0 MPa for the left and right stringers, respectively (Oliveira et al., 2025). These values were subsequently used to update the numerical model, the next stage of the framework.

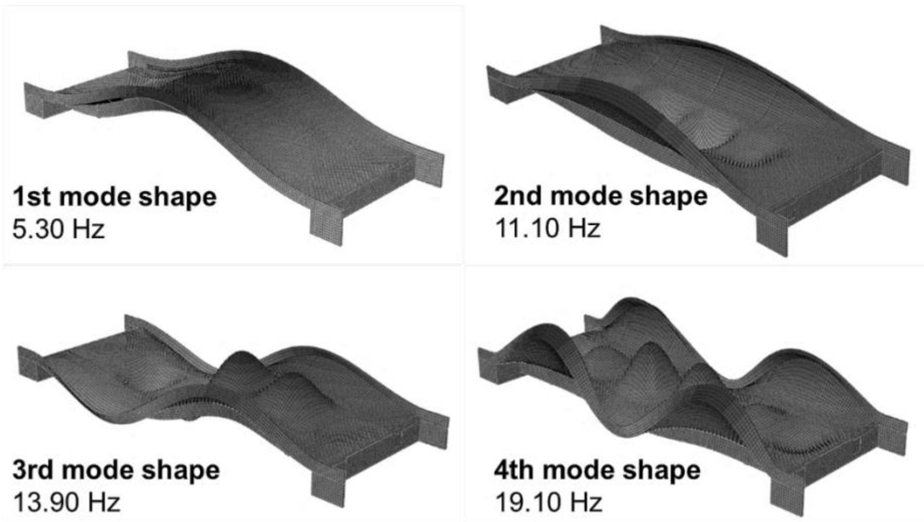


*Figure 11: Numerical mode shapes.*

## 4.3 FE model update

The finite element (FE) model construction began with design information. A model using quadratic solid elements for all structural elements was developed. This model was then manually updated by adjusting material properties, such as the concrete elasticity modulus and asphalt layer thickness, and boundary conditions to better match the structure's actual dynamic behaviour, as captured through field tests. The calibration process used experimental natural frequencies and mode shapes as references, with error metrics and the Modal Assurance Criterion (MAC) guiding the adjustments until the numerical results closely aligned with experimental data. The final values adopted for materials properties and boundary conditions can be found in Oliveira & Sotelino (2025).

Figure 11 shows the final numerical mode shapes, while Figure 12 displays a comparison between natural frequencies obtained numerically and experimentally. The differences between the numerical and experimental frequencies were 5% or less, indicating a good correspondence between the two.

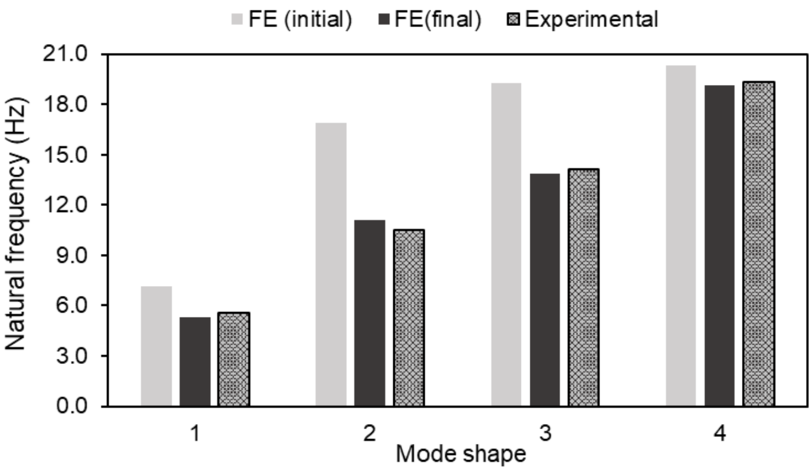


*Figure 12: Model update results.*

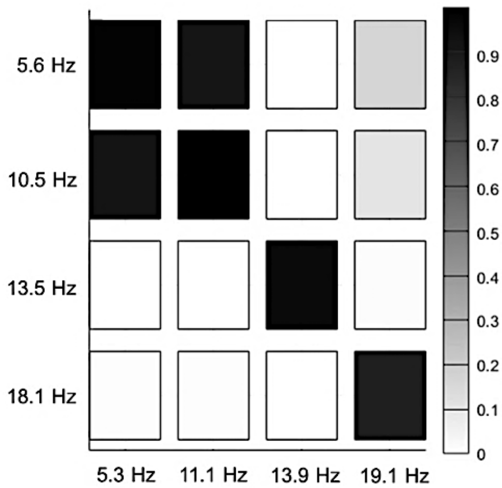


*Figure 13: Experimental x Numerical MAC.*

Figure 13 shows the Modal Assurance Criterion (MAC) matrix, applied to compare the mode shapes obtained experimentally and numerically. The values along the main diagonal of the matrix, all equal to or greater than 0.9, indicate a high degree of similarity between the mode shapes obtained after the calibration of the numerical model and the corresponding mode shapes obtained in the ambient vibration test. The proximity of the values adjacent to the main diagonal suggests a strong correlation between the first and second mode shapes. However, the 4.9 Hz difference between the natural frequencies of these two modes indicates that they correspond to distinct vibration modes. The near-zero values in the other off-diagonal positions demonstrate that the other mode shapes are independent. Based on all these results, it can be concluded that the calibration process was effective, resulting in a high similarity between the dynamic behaviours of the numerical and experimental models.

## 4.4 ANNs performance

Figure 14a and Figure 14b present the confusion matrices for the damage detection neural networks during the validation and training stages, respectively, using the modal curvature index as input. In these matrices, the vertical axis represents the true damage states, while the horizontal axis indicates the predicted states. The main diagonal consists of true positives, indicating accurate model predictions. Off-diagonal values denote incorrect predictions. Class 0 represents undamaged scenarios, and classes 1 through 6 represent the six sections of the longitudinal girders. A slight deficiency is observed in predicting damage in the first and third sections of the longitudinal beam, evidenced by a small number of false negatives. Nevertheless, the model demonstrates robust overall performance, achieving approximately 91% accuracy across all damage classes, alongside 91% precision, 93% recall, and a 91% F1-score.

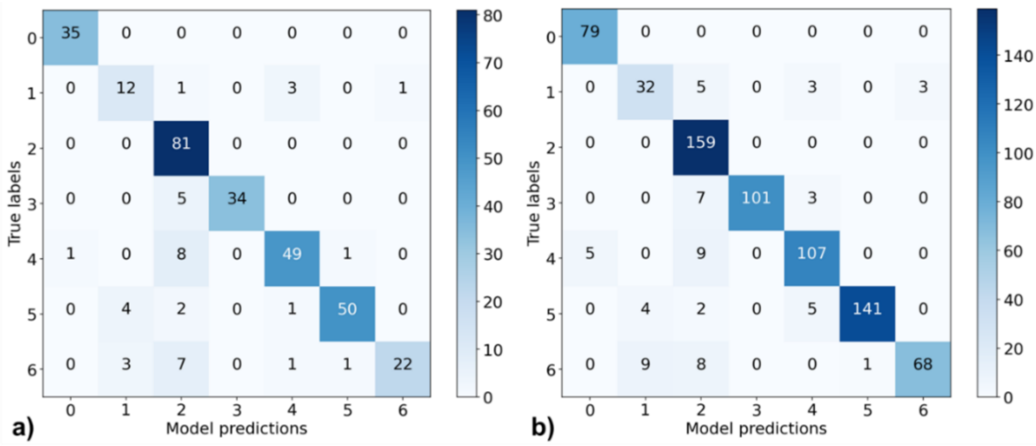


*Figure 14: Damage detection network a) Validation b) Training.*

The regression Artificial Neural Network (ANN) model demonstrated strong predictive performance, achieving an $R^2$ value of 0.92. This indicates that the model accounted for 92% of the variation in the data. Figure 15 presents a scatter plot of predicted versus real values, which confirms this accuracy, since the majority of data points cluster closely around the perfect fit line, suggesting high prediction reliability. However, a slight spread is observed, particularly for higher values, indicating potential areas for further model refinement.

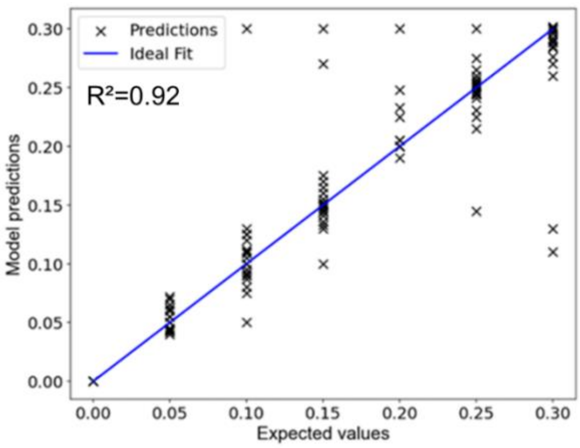


*Figure 15: Damage severity networks performance.*

## 4.5 BIM-SHM tools integration

The integration presented in section 3.5 was carried out through the *PyRevit* extension in a BIM model developed in Autodesk Revit. *PyRevit* enables the execution of Python extensions within the BIM environment, provided they follow a previously defined folder structure. As illustrated in Figure 16, this structure requires that the main folder, called *.extension*, contains all the extension content, organized into two subfolders: *.lib*, which includes the Python libraries used by the scripts — such as *TensorFlow* and *Scikit-Learn* for machine learning, and *Numpy* and *Pandas* for matrix operations and dataframe manipulation — and *.tab*, which contains all the extension tab components, organized in *.panel* type subfolders. Additionally, each extension function must be in a*.pushbutton* folder, which includes the Python *script* and the icon displayed in the graphical interface. The integration carried out in this work resulted in the SHM tab creation (Figure 17), divided into three panels: *Asset Overview, Bridge Inventory*, and *Structural Diagnosis*.

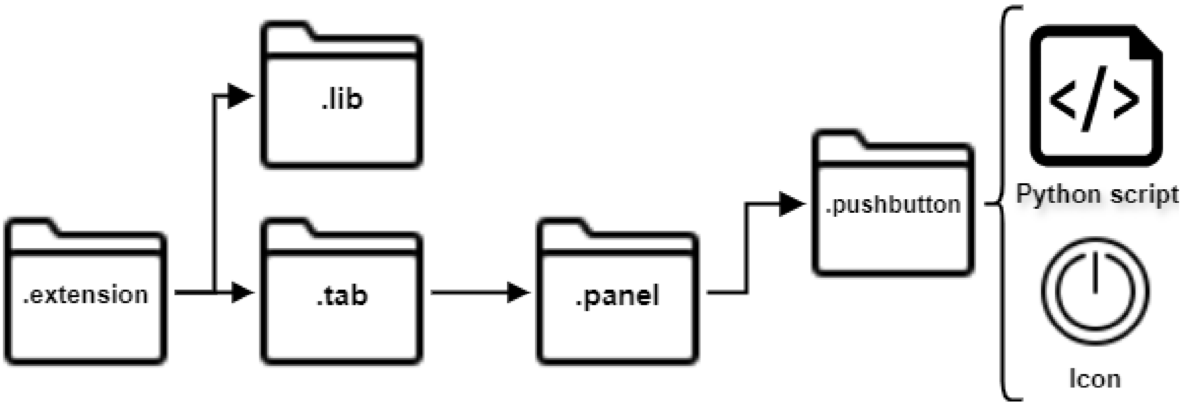


*Figure 16: PyRevit fold structure.*

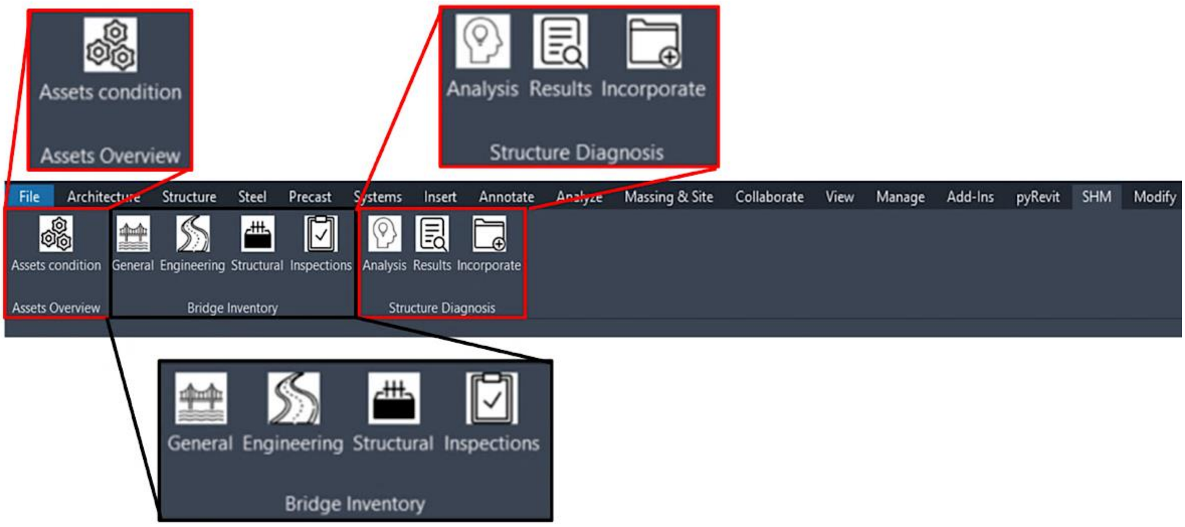


*Figure 17: SHM tab overview.*

The *Assets Overview* panel directs the user to an online dashboard with information about other managed assets (Figure 18). This dashboard provides a clear, visual summary of bridges and viaducts conditions, highlighting key issues such as joint deterioration and other concrete pathologies. By linking directly to a BIM platform via a PyRevit *.urlbutton*, the engineering team can seamlessly switch between the model and the dashboard, ensuring real-time updates and a single source of information. This integration enables collaboration among stakeholders, quicker identification of critical issues, and efficient resource allocation, ultimately improving the long-term management and maintenance of infrastructure assets.

Access to the viaduct inventory, available in the second panel of the SHM tab, is organized into specific buttons for *general*, *engineering*, *structural*, and *inspection history*. The first three options display the information in a single window (Figure 19a), while the *inspection history* button opens an initial screen for selecting the desired report before viewing the content (Figure 19b). This part of the integration enabled the use of the BIM model as a digital and centralized information repository. With all data concentrated in a single environment, decision-making becomes more agile and precise.

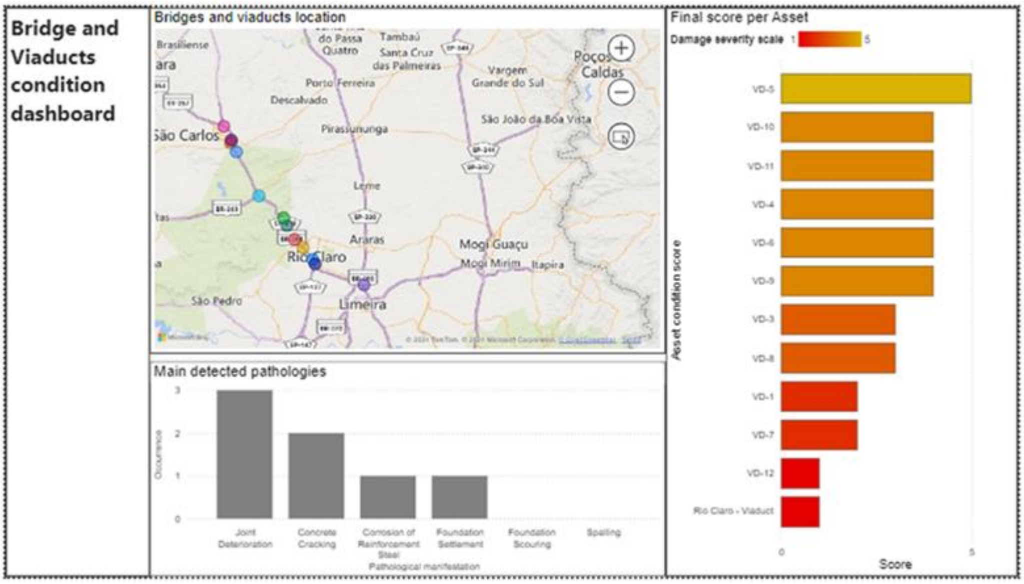


*Figure 18: Assets Overview dashboard.*

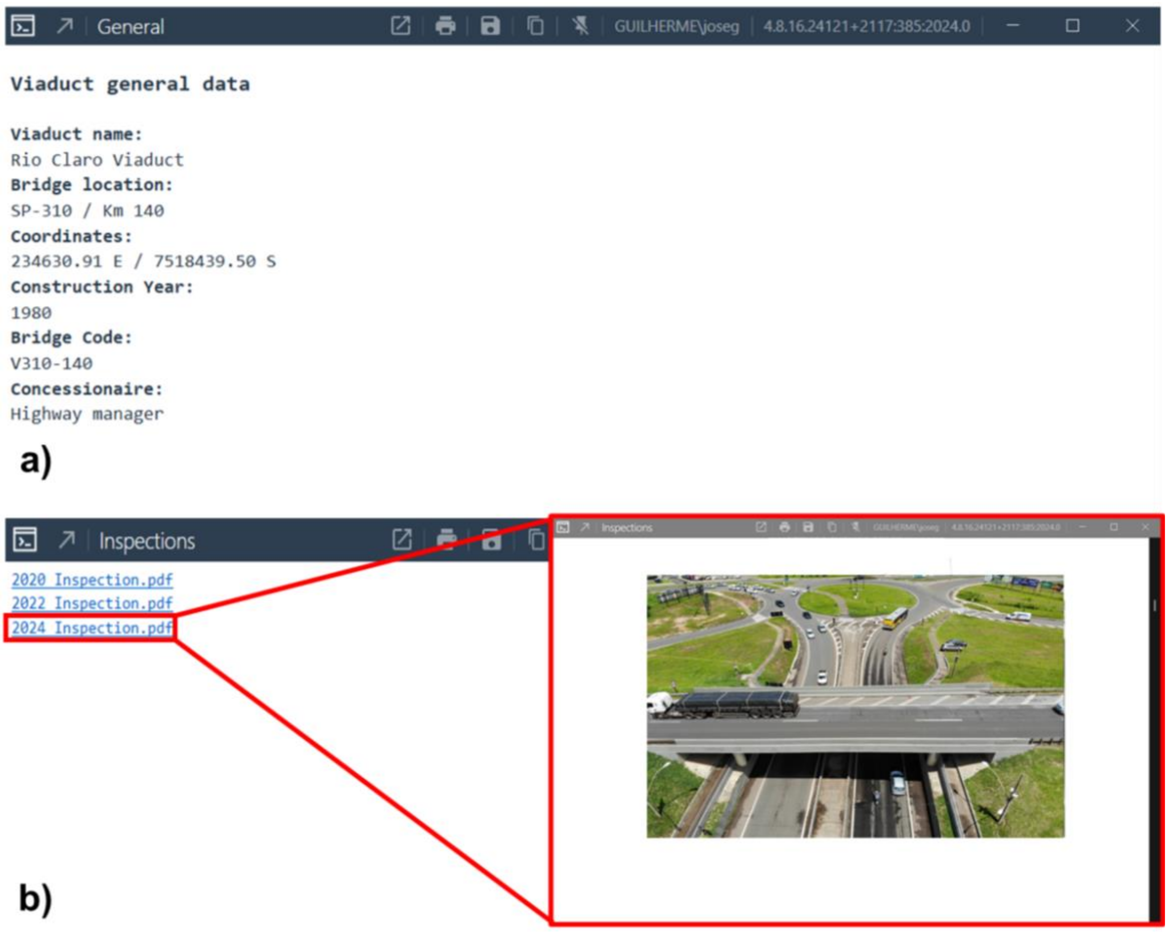


*Figure 19: Viaduct's a) General data window and b) Inspection history windows.*

The third panel is dedicated to structural diagnosis. The *analysis* button applies two pre-trained neural networks to identify damage and evaluate its severity. The results of this analysis are compiled into a report, which is stored in the Common Data Environment (CDE). To perform the analysis, an input file containing modal curvature data, experimentally collected from 30 points on the viaduct, must be available in the CDE. The *incorporate* button allows the report's findings to be integrated into the BIM model, updating the design properties of both intact and damaged longitudinal beams. This process ensures the pre-DT remains up-to-date and enhances the information model (Figure 20). Additionally, the *report* tool aggregates data from all girders, generating a color-coded visualization of the model. This visualization, accessible online, provides the manager with a clear and comprehensive overview of the structure's current condition.

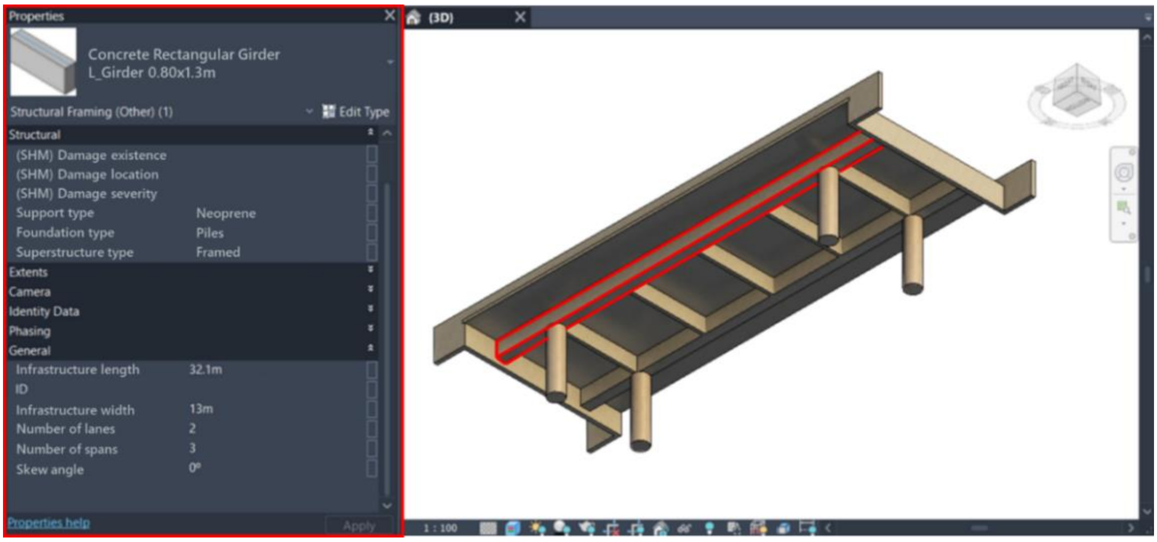


*Figure 20: Incorporate button result.*

## 4.6 System tests

Two tests were conducted using the developed system developed for the Rio Claro Viaduct. The first aimed to evaluate the neural network's ability to make predictions for data not used during their training. To this end, a new dataset was generated from the same numerical model but with different damage levels and distributions than those considered previously. The second test aimed to verify the full end-to-end functionality of the system. In this test, data from a second field experiment, conducted ten years after the first, were used. Note that the data was collected at the same thirty points on the viaduct.

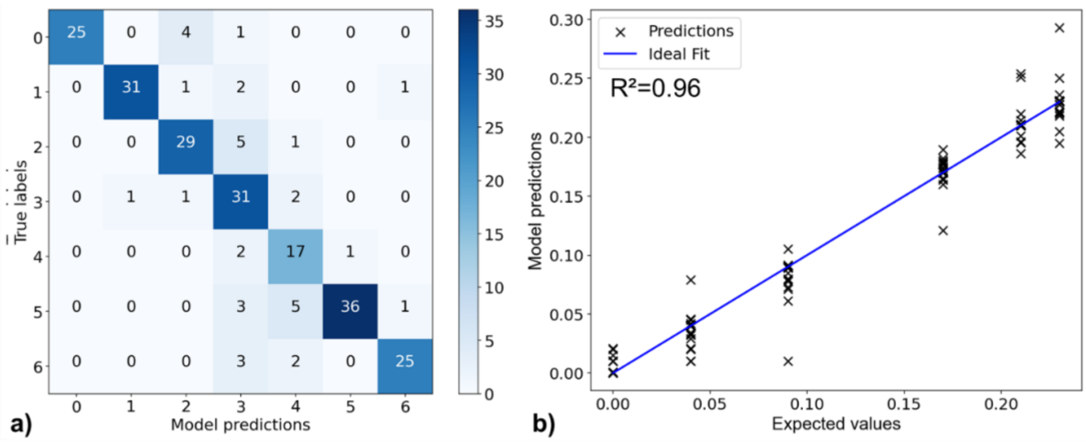


*Figure 21: a) Classification performance b) Regression performance.*

Figure 21 shows the neural network's results applied to the new dataset. Compared to the validation results, a slight drop in performance (5%) is observed for the adopted metrics (precision, recall, and F1-score) in the detection and localization ANN (Figure 21a). This variation is understandable, given the greater dataset diversity. Even so, the accuracy rate remains above 85%. The neural network responsible for assessing damage severity also maintains the previous performance, with a coefficient of determination ($R^2$) of 0.96 (Figure 21b). The mean absolute error of 0.005 is significantly smaller than the smallest difference in damage intensity present in the test data (0.02), indicating high prediction accuracy. These results demonstrate that the networks are able to generalize and do not suffer from overfitting.

The modal curvature used in the final benchmark was derived from the mode shapes obtained during the ambient vibration test conducted in 2024. These results were used as input to the proposed system, which is integrated to the BIM model, the output indicated no damage presence in the Rio Claro Viaduct longitudinal girders. The report generated from this result is shown in Figure 22 showing that the asset has preserved its structural integrity after the 10-year period.

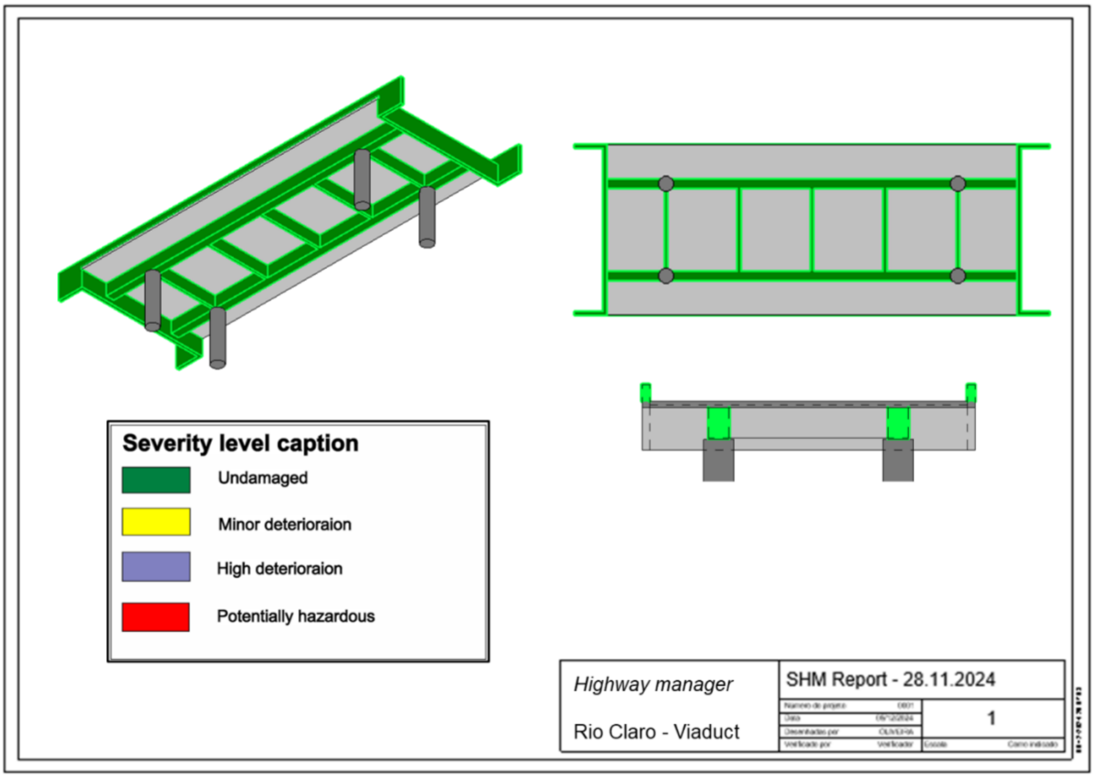


*Figure 22: Structure condition report.*

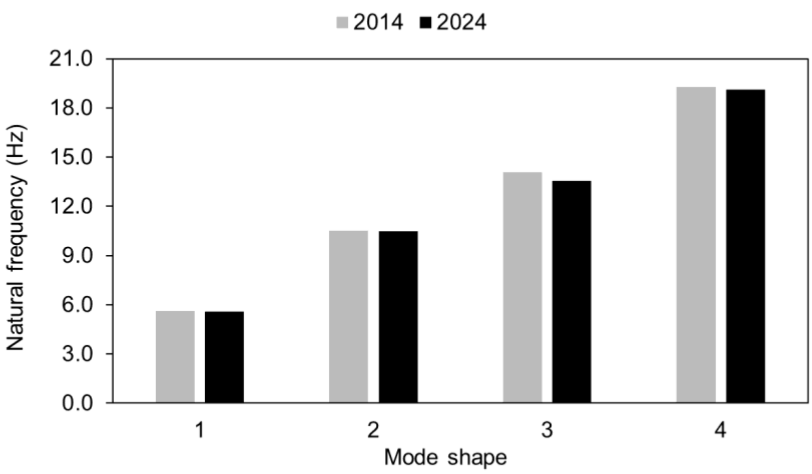


*Figure 23: Natural frequencies comparison.*

Figure 23 compares the post-processed natural frequencies from the ambient vibration tests carried out in 2014 and 2024. It can be noted that the natural frequencies remained relatively constant over the ten years, varying by an average of 1%, indicating that the analysed structure did not experience significant changes in its stiffness. This confirms results obtained from the developed system's result.

# 5. CONCLUSION

This research successfully developed and validated a novel framework for structural integrity assessment that leverages a pre-Digital Twin to integrate experimental field data, numerical modelling, and artificial neural networks within a collaborative BIM environment. To reach these objectives, the work addressed several key challenges in viaduct management, ranging from acquiring and applying reliable data to integrating assessment tools with the structure's maintenance records.

The case study of the Rio Claro Viaduct demonstrates the framework's potential. Field tests provided accurate dynamic characteristics, which were used to fine-tune the finite element model. Simulated damage scenarios enabled the training of ANNs that effectively correlated modal curvature indices with the extent and location of structural degradation. The detection and localization network maintained high performance, achieving over 85% accuracy even when tested on a dataset with varied damage levels, while the damage severity network yielded an $R^2$ of 0.96 with minimal mean absolute error. The framework successfully processed experimental data collected ten years apart, correctly identifying no structural deterioration in the viaduct, a conclusion validated by the minimal change in natural frequencies over time. These results affirm that the integrated system is not only accurate and replicable but also capable of supporting structural health monitoring and informed decision-making for infrastructure managers.

The proposed framework combines field data, numerical models, and predictive analytics in a Building Information Modelling environment using *PyRevit*. This unified three key structural health monitoring components, namely characterization of structural behaviour, model-based diagnostics, and data-driven prognostics using artificial neural networks. By centralizing this information, the pre-DT enables intuitive visualization, accurate structure's condition updates and reliable decision-making. The case study demonstrated the framework's replicability by using BIM's inventory and dynamic inspection data to address problems in existing SHM systems, such as fragmented historical records. The system automatically locates and quantifies damage, connecting theoretical models with practical insights by directly updating BIM elements with damage information. This integration improves data visualization and reporting, which can lead to effective maintenance planning decisions.

The current implementation focuses on damage to beam elements, extending the approach to other structural components (e.g., joints, foundations) would enhance its comprehensiveness. Automation of data ingestion and model updating could further reduce manual intervention and improve scalability of the framework. Finally, integrating real-time sensor data could transition the pre-Digital Twin into a dynamic Digital Twin, enabling continuous monitoring and even more responsive management. These directions will increase robustness and operational readiness while preserving the framework's advantages as a BIM-based decision support tool.

Overall, the research successfully bridges a gap between traditional SHM methods and modern digital asset management by merging BIM with advanced analytics. The demonstrated replicability and robustness of the framework underscore its potential to enhance the efficiency and reliability of infrastructure management practices. Future works could explore an expansion of the framework to other types of infrastructure, damage varieties or implement automation in part of the proposed method.

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