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An Artificial Neural Network Approach to Structural Condition Assessment of a Reinforced Concrete Viaduct

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Abstract. Bridges and viaducts are critical to transportation infrastructure and require effective monitoring strategies to ensure long-term safety and performance. Traditional inspection methods are often limited by subjectivity, accessibility issues, and the inability to detect early-stage damage. Although Structural Health Monitoring (SHM) using dynamic parameters offers a more reliable alternative, its effectiveness can be hindered by environmental and operational noise. To address this challenge, this study proposes an Artificial Neural Network (ANN)-based framework for detecting and quantifying structural damage in reinforced concrete viaducts. The methodology combines experimental vibration data and a calibrated finite element model to generate synthetic damage scenarios. Mode shapes extracted from these models are used to calculate the modal curvature index, with white noise added to simulate real-world measurement conditions. Two ANNs are trained: one to classify damage location and another to estimate its severity. Results demonstrate the framework's robustness, with damage localization accuracy above 90% and severity estimation achieving an R^2 of 0.87, even under noisy conditions. The findings confirm that the proposed approach is effective for condition assessment, offering a reliable tool to support data-driven infrastructure maintenance decisions.

Keywords: Structural Health Monitoring, Artificial Neural Networks, Infrastructure Maintenance, Damage Detection, Finite Elements Method.

1 Introduction

Bridges and viaducts are essential for infrastructure, facilitating logistics and urban transportation. Although designed to endure, their service life relies on regular maintenance and periodic inspections, since load-bearing capacity degrades over time. Vehicle traffic and environmental effects can initiate small cracks that, if not detected promptly, propagate and compromise safety [1]. Effective maintenance strategies depend on early problem detection, which requires consistent, comprehensive, high-quality inspections.

Structural health monitoring (SHM) uses non-destructive methods to detect defects by tracking changes in dynamic properties like natural frequencies [2]. Two primary approaches exist: data-driven SHM continuously analyzes sensor data, statistically comparing measurements against an undamaged baseline to flag damage-indicating deviations [3]. Model-based SHM employs calibrated models (often finite element) simulating structural responses under damage and loads. Environmental factors cause modal property variations that mimic damage, complicating detection. Machine learning algorithms overcome this by training on datasets incorporating both environmental and damage-induced variations, effectively discriminating true defects from benign fluctuations.

This paper proposes an alternative methodology based on periodic structural monitoring using a calibrated finite element model informed by field data from a full-scale viaduct. A database of simulated damage scenarios is generated, with added noise to reflect real-world conditions, and used to train two artificial neural networks (ANNs): one for detecting and locating damage, and another for estimating its severity. The goal is to support asset managers by guiding inspections toward potentially damaged regions, improving the efficiency and accuracy of structural health assessments.

2 Theorical background

2.1 Damage indicator

Choosing the right damage indicator is vital for reliable structural health monitoring (SHM), especially under varying environmental conditions. An ideal indicator must respond strongly to damage-related changes in stiffness and mass while resisting shifts due to temperature or operational loads [4,5]. Natural frequencies are popular because they are easy to measure, but they can drift significantly with environmental changes. Dynamic damage indicators instead track alterations in a structure's physical parameters (mass, damping, or stiffness) through changes in modal properties, such as frequencies and mode shapes. A crack reduces local stiffness, modifying both the beam's vibrational response and the overall deformation pattern. Mode-shape-based metrics offer greater reliability, distinguishing true damage from harmless environmental fluctuations.

The modal curvature method (MCM), introduced by Pandey et al. [6], is a well-established damage index that evaluates the second derivative of modal displacement to detect structural damage. Its efficacy has been demonstrated in reinforced concrete bridges [7,8]. In one-dimensional models, with the structure discretized into elements of length h, curvature is calculated via a centered difference scheme (Eq. 1).

$$\phi_i = (\phi_{i+1} + \phi_{i-1} - 2\phi_i)/h^2 \tag{1}$$

Here, ϕ_i denotes the modal displacement at position i. To detect structural damage, the method contrasts the modal curvature profiles of the damaged and undamaged states. Eq. (2) formalizes this comparison by defining the damage index as the point-by-point difference between the two curvature distributions.

$$\Delta\phi = \sum_{i=1}^{n} \phi_i - \phi_i^* \tag{2}$$

In this equation, ϕ_i represents the undamaged curvature at position i, ϕ_i^* is the corresponding damaged curvature, and n is the total number of mode shapes included in the analysis.

2.2 Artificial neural networks

Artificial Neural Networks (ANNs), particularly multilayer perceptron (MLP), process inputs through successive layers of interconnected neurons. Each neuron computes a weighted sum of its inputs, applies a nonlinear activation function, and forwards the result to the next layer. The network architecture includes an input layer, one or more hidden layers, and an output layer. Activation functions introduce nonlinearity and determine whether a neuron turns on, enabling the model to capture complex relationships. During training, hyperparameters such as learning rate and number of epochs govern how weights and biases are adjusted via backpropagation to minimize error. Gradient descent optimization iteratively updates parameters along the negative gradient of the loss function. Due to their ability to learn intricate patterns from large datasets, ANNs have proven effective for damage detection and severity estimation [5,9].

2.3 White noise layer

Eq. (3) simulates noise measurement in experimental mode shapes. Proposed by Shi et al. [10], it perturbs each mode shape component ϕ_{ij} of the ith DOF in the jth mode shape by a term proportional to the maximum amplitude in that mode ($\phi_{max,j}$) and a random factor γ_i^{ϕ}, scaled by a noise level ρ^{ϕ}. Introducing noise into FEM signals is essential to assess the robustness of the damage detection method. It highlights performance thresholds, e.g., success with 7% noise in single-damage cases versus failure under 5% for multiple damages. This practice validates theoretical models, quantifies limitations, and ensures real-world applicability in structural health monitoring (SHM) systems.

$$\overline{\phi}_{ij} = \phi_{ij}\left(1 + \gamma_i^{\phi}\rho^{\phi}\left|\phi_{max,j}\right|\right) \tag{3}$$

3 Methodology

Figure 1 illustrates the framework proposed in this study, which integrates field test data and numerical simulations. Dynamic and material tests characterize the structure's actual state and are applied to calibrate and update a finite element model until it accurately reflects the structure's real behavior. This calibration process results in a reliable model that can faithfully represent the studied viaduct. The updated model is then used to generate a database of various damage scenarios, which serves to train and validate the ANNs. White noise is added to the model-generated database signals to replicate practical field measurement conditions. Two ANNs are applied: the first network identifies the presence and location of damage, while the second evaluates its severity.

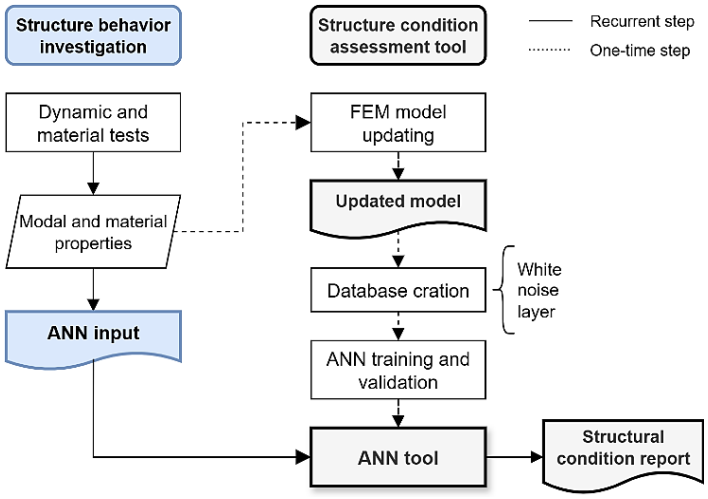


Figure 1. Methodology framework

3.1 Case study

The Rio Claro Viaduct spans the SP-340 highway in the city of Rio Claro, serving as a vital transportation link in the urban infrastructure (Figure 2). As one of the primary access routes connecting to western São Paulo cities, particularly São Carlos, the viaduct handles significant regional traffic flow.

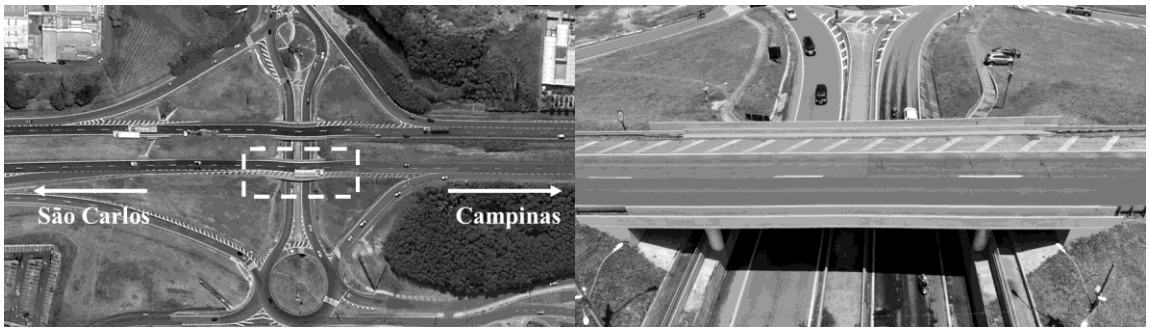


Figure 2. Rio Claro Viaduct

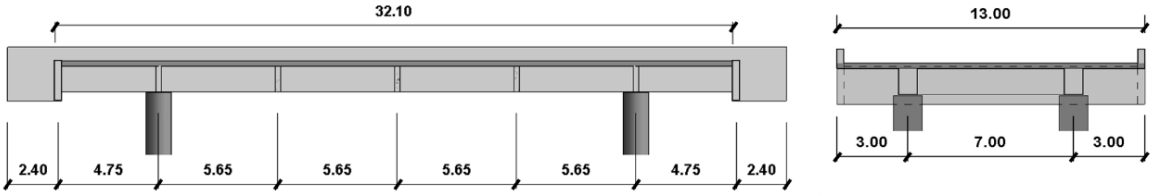


Figure 3. Structure measurements

Built in the 1980s, this reinforced concrete structure features a robust design consisting of two main girders interconnected by five transverse beams, supported by four concrete piers. Column stability is reinforced through two bracing beams, while the deck surface accommodates vehicular traffic. Wing walls at both ends anchor the structure to the adjacent earth slopes. The viaduct measures 32.1 meters in length and 13 meters in width, encompassing three spans with New Jersey barriers providing lateral protection (Figure 3).

3.2 Dynamic and material tests

Structural characterization for model updating utilized data from a 2024 ambient vibration test [11]. Employing nine uniaxial piezoelectric accelerometers, vertical acceleration was measured at 30 points along the viaduct's span. Ambient testing was chosen due to traffic constraints precluding controlled excitation. Concurrently, material property assessment addresses spatial variability in concrete properties (caused by batch, curing, and construction differences), crucial for model accuracy. Compressive strength was evaluated using a concrete hammer test at three points per longitudinal girder (critical elements). Average readings provided compressive strength estimates, which were converted to Young's Modulus values for incorporation into the numerical model. This integrated testing characterized dynamic behavior and material properties essential for reliable model updating.

3.3 FEM modeling and update

The model updating process aims to achieve agreement between the finite element model and experimental test results. Calibration involves comparing natural frequencies and vibration modes from ambient vibration tests with numerical predictions to assess similarity. Since mass and stiffness are the primary variables governing dynamic behavior, calibration efforts concentrate on adjusting these parameters. In this study, mass was modified by varying the asphalt layer thickness, while stiffness was calibrated through changes to the structural material’s Young’s modulus. This systematic adjustment process ensures the updated model accurately represents the structure's actual dynamic characteristics.

3.4 Database creation and ANN structure

ANN training requires reliable damage indicators derived from data free of environmental noise (e.g., temperature, wind) for accurate structural condition assessment. Dynamic indices provide a more robust alternative to primary variables (natural frequencies, mode shapes) due to their lower sensitivity to such disturbances, enhancing detection and quantification accuracy. The dataset was generated using a calibrated finite element model to simulate artificial damage scenarios. This numerical approach is essential, circumventing the impracticality and risk of physically altering the in-service structure or accessing specific damaged locations. Damage was induced by selectively reducing the bending stiffness in sections of the longitudinal beams, creating the necessary scenarios for training the ANNs on representative structural responses.

Two Multilayer Perceptron (MLP) networks were designed: a classification ANN for damage detection/location and a regression ANN for severity estimation. Both utilize 30 input neurons processing the Modal Curvature Method (MCM) data. The classification network employs three hidden layers (15, 12, 9 neurons) with Tanh activation and a 7-neuron sigmoid output layer (undamaged + 6 sections), trained for 500 epochs (0.01 learning rate, categorical cross-entropy loss). The regression network features three hidden layers (25, 15, 5 neurons) with ReLU activation and a single linear output neuron, trained for 550 epochs (0.002 learning rate, mean squared error loss). This progressive reduction in hidden-layer neurons enhances feature generalization for both tasks.

4 Results

4.1 Model update

Manual model updating enabled monitoring, stage by stage, of the changes in natural frequencies from specific modifications. Manual updating also reduces the risk of introducing parameters without physical basis that

automatic updating may incur [12]. Figure 4 plots the percentage error between the natural frequencies measured in physical tests and those predicted by the numerical model for the first four mode shapes on its vertical axis, with the horizontal axis tracking each model-updating stage. Concurrently, spring stiffness at the end supports was refined using soil coefficients for stiff clay, derived from Terzaghi's plate-load tests. In stage 5, the concrete's elastic modulus was updated, using field-measured f_{ck}, to better match girder behavior. Stage 6 incorporated the New Jersey barrier mass on the deck, and stage 7 added the approach slab mass (totaling 19,500 kg). Stage 8 adjusted intermediate column spring stiffness per field tests. Finally, stages 9 and 10 added the asphalt layer using

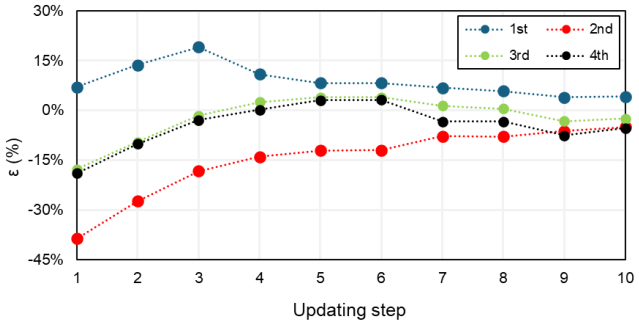


Figure 4. Model updating steps results

densities of 2,400 kg/m³, first at 0.15 m thickness (150,228 kg over 417.3 m²) and then at 0.25 m (250,380 kg) to achieve a modal response that closely matches experimental results.

4.2 Noise introduction

Figure 5 compares original and noise-corrupted mode shapes for the viaduct girder under two noise levels. In each plot, the horizontal axis shows girder length in meters, while the vertical axis represents modal amplitude. Subfigures (a) and (b) display the first and second mode shapes, respectively. 3% random noise (green squares) is superimposed on the clean response (blue circles), producing only slight deviations around the peaks and troughs. These results illustrate how increasing noise level gradually obscure precise mode-shape features, potentially affecting damage detection accuracy.

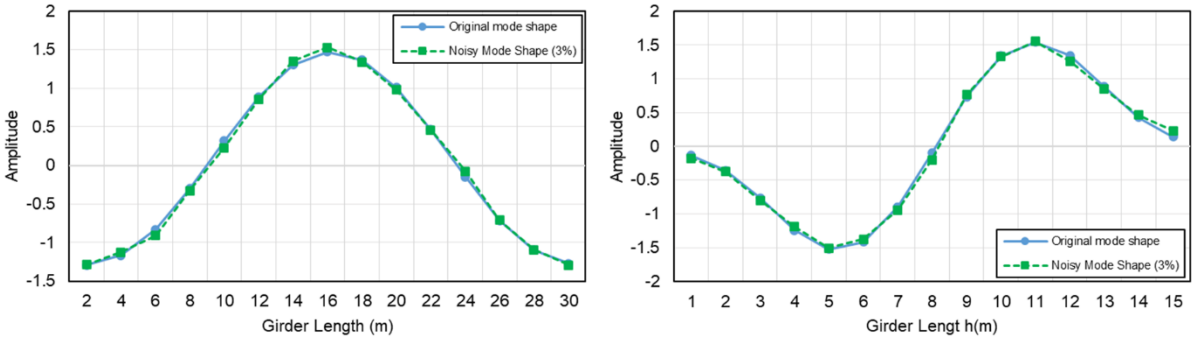


Figure 5. Comparison of original and noise-contaminated a) First mode shape b) Second mode shape

A modal curvature difference between original and noisy signals can be seen in Figure 6, which compares modal curvature distributions along the girder length under varying damage levels (5 %, 10 %, 15 %, 20 %, 25 % and 30 %) with curvature change Δk on the vertical axis. Figure 6 a) shows the original modal curvature profiles: each dashed line rises smoothly to a pronounced peak around midspan before tapering off toward the supports. Figure 6 b) illustrates the same damage scenarios after adding 3 % random noise to the mode shapes. While the overall peak location and trend remain, the noisy curves exhibit greater scatter and slightly elevated local maxima, indicating how measurement interference can blur precise curvature changes and complicate damage quantification.

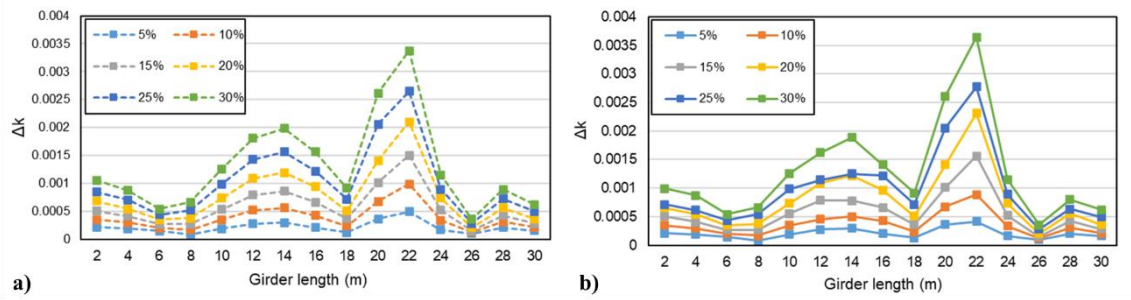


Figure 6. Modal curvature change: a) Original and b) Adding 3 % white noise

4.3 ANN performance

The neural network damage detection results are shown in Figure 7. In its confusion matrix, the vertical axis represents the true condition (ground truth), and the horizontal axis represents the model's predictions. Cells along the main diagonal indicate correct predictions (true positives), whereas cells off this diagonal signify prediction errors. The label '0' corresponds to undamaged states, while labels 1-6 identify the six predefined sections of the longitudinal girders. Results for the validation and training stages using modal curvature index input are displayed in Figures 7a and 7b, respectively. While the model shows slight difficulty (false negatives) in detecting damage within sections 2, it achieved an average accuracy of 90% across all classes, which is acceptable.

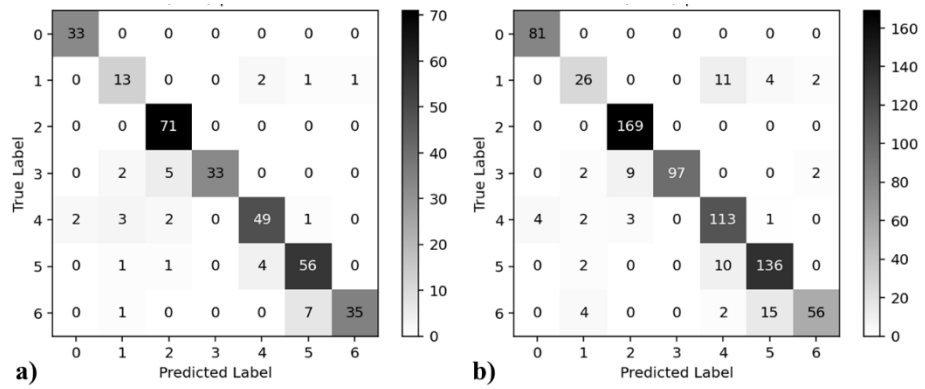


Figure 7. Damage detection network a) Validation b) Training

The regression's artificial neural network performance is demonstrated in Figure 8, which achieved a high coefficient of determination. This indicates the model explains 87% of the variance in the target variable. Predicted values range from 0.00 to 0.30, closely aligning with the real values and confirming the model's accuracy.

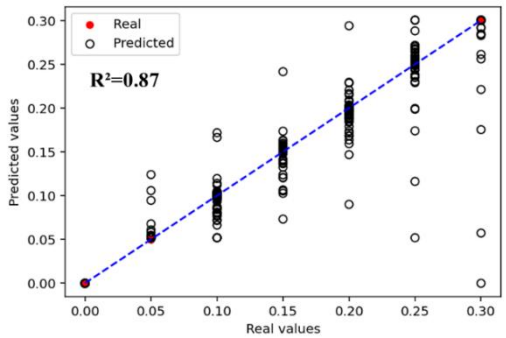


Figure 8. Damage severity network performance

5 Conclusions

This study successfully integrated numerical modeling with ANNs for viaduct damage assessment, explicitly evaluating robustness against measurement noise. Introducing white noise (simulating field sensor inaccuracies) revealed critical performance thresholds. While 3% noise caused minor deviations in mode shapes (Figure 5), it induced noticeable scatter in modal curvature differences (Figure 6), complicating precise damage quantification. Despite this, the ANNs demonstrated significant resilience. The damage detection network achieved 90% accuracy in locating damage across six girder sections under noisy conditions (Figure 7), though sensitivity varied slightly. Crucially, the severity estimation ANN maintained high predictive capability (R^2=0.87) even with noise-corrupted inputs (Figure 8). This confirms the framework's practical viability, as both ANNs tolerated noise levels (≤3%) representative of real-world SHM systems, ensuring reliable damage identification and severity assessment despite signal contamination.

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