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A multi-scenario approach for structural health monitoring of existing bridges

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ABSTRACT

This paper presents a methodology for structural health monitoring (SHM) of existing bridges, designed to operate at progressively detailed levels and capable of detecting multiple structural damage scenarios. The SHM system is tailored based on the potential damage the structure may experience throughout its lifespan. By considering the bridge's structural type, materials, construction technology, and current health conditions, a comprehensive list of possible damage scenarios can be identified. The effects of these scenarios can be effectively characterized and either directly or indirectly monitored through the SHM system. Following a data-driven approach, the acquired static and dynamic data are processed using pre-defined algorithms to evaluate and track key parameters associated with the analyzed scenarios over time. The proposed methodology is applied to an existing bridge equipped with an SHM system, with a focus on structural scenarios to demonstrate its practical implementation and effectiveness.

Keywords: Structural Health Monitoring, Bridges, Multi-risk, OMA

1. INTRODUCTION

The management of bridges has become today a critical need, involving high numbers of assets and a variety of managing authorities (from national infrastructure administrators down to local administrators managing limited territories). What is more, the large number of bridges that have to be managed are often structurally deficient, different in terms of materials and structural schemes and exposed to different hazards. The scientific community is facing the issue of developing theoretically sound, harmonized technical methods that can support road managers in knowing and analyzing structures, detecting damage, and supporting decisions [1][2]. In this regard, data-driven SHM is a powerful approach that uses data deriving from dedicated devices to directly or indirectly control global/local structures' response/parameters and their evolutions over time. With many options, by developing proper methods

to post-process the acquired data, and knowing the phenomena to be observed, devices can be selected and installed on the bridges with the purpose of monitoring their structural behavior under traffic load [4], or their response when interfering with natural hazards, such as landslides [5]. On the other hand, model-based approaches are emerging, such as Bayesian-based methods [6][7]. As a further development, Bayesian Belief Networks (BBNs) have gained significant attention as effective tools for addressing challenges in SHM [8][9]. These networks utilize probabilistic graphical models to integrate data from multiple sources while accounting for uncertainties and interdependencies between variables. One of their key advantages is the ability to manage incomplete or uncertain data while incorporating prior knowledge, making them highly suitable for informed decision-making in bridge management. When extended to include a temporal dimension, the so-called Dynamic Bayesian Networks (DBNs) [10] enable the tracking of system evolution over time, capturing damage progression and structural deterioration. This capability is particularly beneficial for long-term monitoring, risk assessment, and predictive maintenance. In SHM applications, BBNs enhance diagnostic accuracy, facilitate prognosis, and support risk-informed decisions, making them a transformative approach to infrastructure monitoring. Based on the reviewed literature, the primary challenge now is to develop a structured approach that leverages existing SHM methods, scaling and standardizing them for application across all bridge types while considering their unique structural characteristics.

2. THE PROPOSED METHODOLOGY

This study proposes a unified framework for handling bridge monitoring data, integrating various damage scenarios, damage models, sensor-based monitoring, and data fusion techniques to support decision-making. The proposed framework enhances early damage detection, predictive maintenance, and risk assessment, ensuring sustainable and cost-effective bridge management.

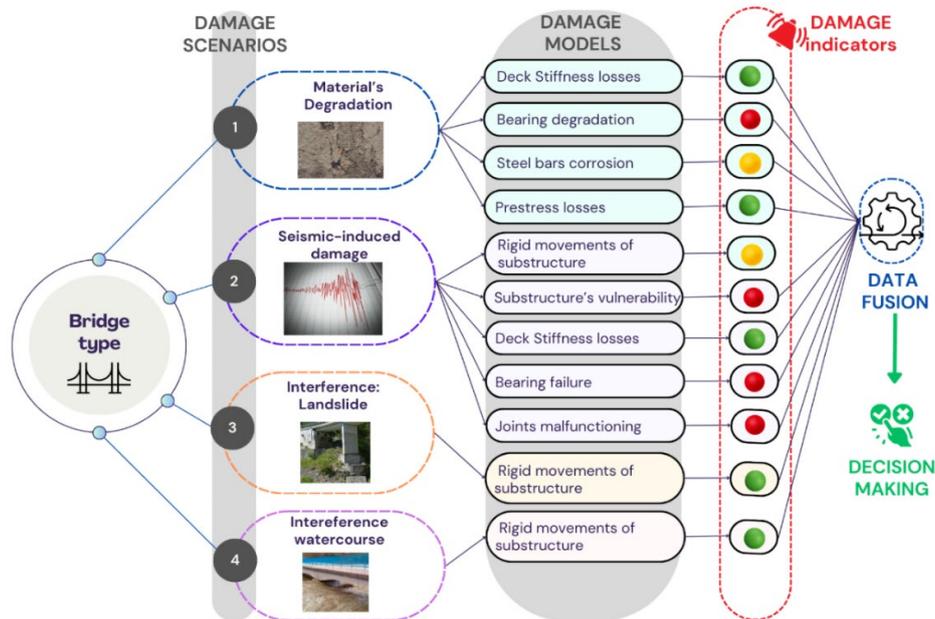


Figure 1. The proposed methodology

The proposed framework consists of six key steps (see Fig. 1): (1) *bridge type classification*, i.e., identification of bridge typologies to tailor monitoring strategies, this includes bridge static schemes and construction material; (2) *damage scenarios identification*, i.e., categorization of potential damage sources affecting structural integrity; (3) *definition of damage models*, i.e., specification of damage mechanisms corresponding to each scenario; (4) *damage indicators & sensor-based monitoring*, i.e., deployment of sensors and corresponding damage indicators to detect damage-related anomalies, where the tag of the indicator provides the following insights: no, no anomaly detected; yes, anomaly detected requiring attention; (5) *data fusion*, i.e., integration of sensor information to provide a comprehensive assessment of bridge health; (6) *decision-making support*, based on the fused data, stakeholders can

decide whether maintenance, repairs, or immediate interventions are necessary. Table 1 summarizes frequent damage scenarios and damage models, suitable sensors, and damage indicators for each scenario. The main objective is to use real-time monitoring data to assess the condition of these damage models, continuously over time, where a damage model can be associated with different damage scenarios. It is worth noticing that the optimal sensor placement is crucial to ensure a correct tracking of the damage indicators associated with each damage model.

Table 1. Comparison between experimental and numerical results.

Damage Scenario	Damage Model	Sensor Type	Damage Indicator
Material Degradation (DS-D)	Deck stiffness losses	Accelerometers	Frequency
	Bearing degradation	Displacement transducers	Displacement
	Steel bar corrosion	Electrochemical sensors	electrical conductivity
	Prestress losses	Tiltmeters	Deck rotation
Seismic-induced damage (DS-S)	Rigid movements of substructure	Tiltmeters	Rotation
	Substructure vulnerability	Accelerometers	Max peak acceleration
	Deck stiffness losses	Accelerometers	Frequency
	Bearing failure	Displacement transducers	Displacement
Interference: Landslide (DS-L)	Deck stiffness losses	Displacement transducers	Displacement
	Joints malfunction	Displacement transducers	Displacement
Interference: Watercourse (DS-W)	Rigid movements of substructure	Tiltmeters	Differential displacement, increased tilt
	Rigid movements of substructure	scour depth sensors, Tiltmeters	Scour depth, increased tilt

2.1. The use of statistical pattern recognition methods for anomaly detection

Usually, SHM systems generate vast amounts of raw data from multiple sensors (e.g., accelerometers, tiltmeters, and displacement sensors). However, the data are often affected by environmental variations, sensor noise, and operational loads, making it challenging to distinguish damage-related anomalies from non-damage variations. To ensure reliable damage detection and diagnosis, the raw data undergoes systematic preprocessing; environmental effect removal using regression models, neural networks, or cointegration methods; statistical pattern recognition for anomaly detection. More specifically, control charts can be used for real-time anomaly detection. A control chart is a statistical tool that monitors data trends over time and detects deviations from normal operating conditions, helping to track structural performance and identify potential damage. Among the various control charts available in the literature, the well-known Hotelling's T^2 control chart [11] appears to be the most suitable, as it can detect anomalies in multidimensional datasets. This method involves defining a training period in which data is collected and analyzed. A regression model, which relates the data to temperature variations, is used to reconstruct the expected response. The residual vector R i.e., the difference between the acquired data and the data reconstructed through the regression model, serves to build the control parameter. From the cumulative distribution function (CDF) of a suitable statistical distance, such as the Mahalanobis distance T^2 , computed during the training period, the upper control limit (UCL) of T^2 is established. The same regression model is then applied to data outside the training period. If T^2 exceeds the UCL with a sustained deviation, the system identifies a potential damage event.

2.2. Bayesian Networks for data fusion

A BBN is a probabilistic graphical model used to represent causal relationships between variables and update beliefs in light of new evidence. In SHM, BBNs can provide a systematic way to integrate multiple sensor data sources for damage diagnosis and decision-making under uncertainty. Generally speaking, a BBN consists of: (i) nodes, representing random variables (e.g., sensor readings, structural conditions, environmental factors); (ii) edges: representing probabilistic dependencies (causal or correlational) between variables; (iii) conditional probability tables (CPTs): quantifying the probability distribution of each node given its parent nodes (prior knowledge). BBNs allow Bayesian inference, meaning

that when new sensor data or information is received, the system updates its beliefs about damage occurrence and severity in a probabilistically sound way.

3. THE CASE STUDY

To validate and illustrate the proposed framework, a monitored viaduct on the highway connecting Turin to Bardonecchia is selected as pilot case study. The viaduct consists of two continuous single-box girders made of segmental post-tensioned prestressed concrete, one for each carriageway, following a curvilinear layout in plan (Fig. 2a). The radius of curvature is approximately 535 m for the carriageway in the direction of Bardonecchia and 587 m for the carriageway in the direction of Turin. The present study focuses on the carriageway from Turin to Bardonecchia. The selected carriageway consists of seven spans of varying lengths. The first and last spans are 50 m long, while each of the five intermediate ones measures 100 m. The piers have approximately square box sections and are characterized by different heights due to the site's topography and features. The base section dimensions vary depending on the pier height, while the section located 7 m below the bearing pads is constant across all piers, measuring 5.4 m (transversely to the viaduct) by 5 m (longitudinally to the viaduct). Above this section, two 7 m-high blades with a rectangular cross-section of 5.4 m × 1.1 m are positioned (Figure 2b). On top of the blades, three transversely aligned bearings are placed on each for a total number of six bearings per pier.

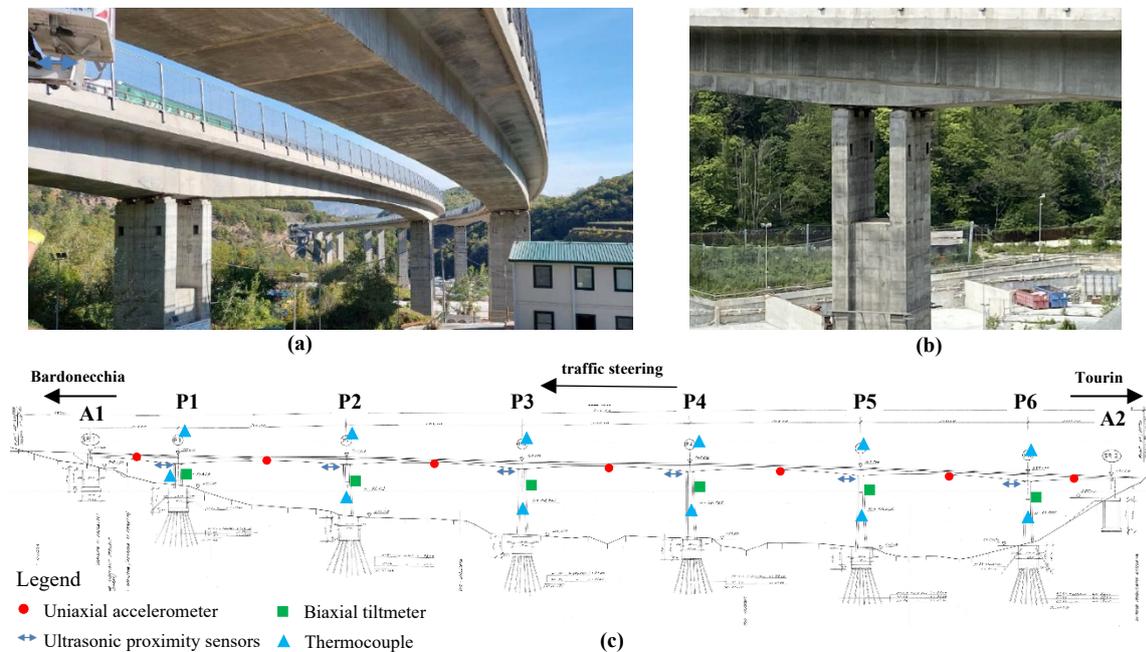


Figure 2. Image of the real case study bridge and sensor positioning: (a) view of the monitored bridge; (b) detail of the top of the piers; (c) schematic representation of sensor positioning

The central bearing provides horizontal restraint in the transverse direction, while the external ones provide only vertical restraint. Figure 2 presents a view of the viaduct and a detailed view of the top of the piers. The bridge is equipped with static and dynamic SHM systems. For dynamic monitoring, each span is fitted with a uniaxial vertical accelerometer. For static monitoring, a biaxial tiltmeter (measuring rotation about the longitudinal and transverse directions) and an ultrasonic displacement sensor are installed at the top of each pier. The ultrasonic displacement sensor monitors the relative displacement between the top of the piers and the deck. For environmental monitoring, each inclinometer and accelerometer are equipped with a thermocouple, and each pier is also equipped with multiple thermocouples (one per each side of the external section, plus an internal one). In addition, an internal thermocouple is installed inside of the single-box girders at each pier position. Figure 2c illustrates the sensors installed on the bridge. For the present paper, the following damage indicators are selected and analyzed: (i) natural frequencies and vibrations modes; (ii) rotations of the deck; (iii) rotations of the piers. As can be observed from Table 2, a single damage indicator can be associated with different damage scenarios.

Table 2. Damage indicators with corresponding damage models and possible associated damage scenarios.

Damage indicator	Acr.	Sensor type	Location	Damage Model	Damage scenarios
Frequencies, vibration modes	DI-F	Accelerometers	Deck	Deck stiffness losses	DS-D DS-S
Rotations	DI-RP	Tiltmeters	Piers	Rigid movements of substructure	DS-S DS-L, DS-W
Displacements	DI-D	Ultrasonic	Piers-deck	Bearing degradation	DS-D

3.1. The proposed BBN for data fusion

To highlight the potential of the proposed approach, a BBN for data fusion is summarized in Fig. 3.

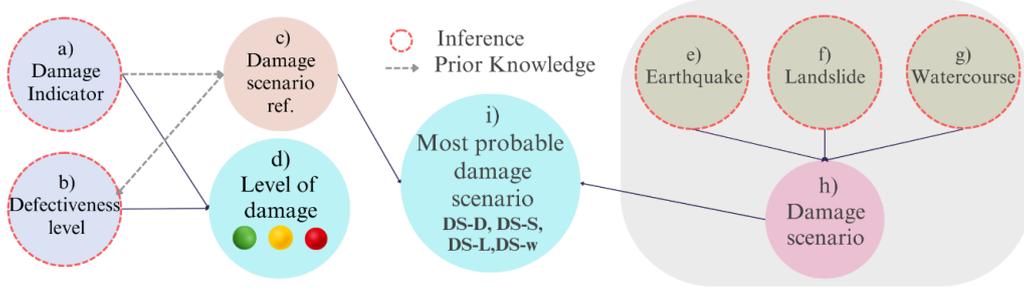


Figure 3. The proposed BBN for real-time data fusion

The BBN consists of multiple hierarchical levels, each representing a different aspect of the damage assessment process: node a) damage indicator, which has binary outcomes (yes/no) based on the results of anomaly detection; node b) defectiveness level derived from visual inspection cues and linked to a reference damage model, it has categorical outcomes (e.g., low, medium, high, add knowledge – when the information acquired are not consistent), for example, if the damage model pertains to deck stiffness losses, the deck’s defectiveness level serves as the relevant parameter; node c) reference damage scenario, predefined based on prior knowledge, i.e., in the case of a damage model involving deck stiffness losses, possible associated scenarios might include DS-D and DS-S, which are assigned higher prior probabilities; node d) level of damage, which assigns a severity score (e.g., low, medium, high) based on information from nodes a) and b); nodes e), f), g) which are related to external interference indicating (binary outcome Yes or No) whether external factors such as earthquakes, landslides, or watercourse variations may influence the structural health; node (h) most probable DS synthesizing the information inferred from nodes e), f), and g); node i) final most probable DS, which integrates all previous information, particularly from nodes c) and h), to characterize the results derived from the damage indicator. In a complete framework, multiple damage indicators contribute to a fused dataset that provides fundamental insights into the causal factors of bridge damage. The outcomes of the key nodes (d) and (i) vary depending on the specific combination of damage indicator, reference damage scenario, and defectiveness level being analyzed.

4. PRELIMINARY RESULTS

As reported in Table 2, three main damage indicators are preliminarily analyzed: DI-F, DI-RD, and DI-RP. Regarding DI-F, data from November 16th to 22nd, 2024, are extracted. Each day, two windows of signals are analyzed, from 9:00 to 9:30 AM and from 9:30 to 10:00 AM, with an acquisition sampling rate of 200 Hz. The signals were bandpass filtered to the frequency range between 0.5 and 18 Hz using a third-order Butterworth filter, followed by a decimation to 40 Hz. Based on this, the dynamic identification was conducted using the covariance-driven Stochastic Subspace Identification (SSI) method implemented in the software MOSS [12]. In particular, the covariance functions between the sensors were extracted with a maximum time lag of 3.2 s. The order of the state-space model was analyzed between 2 and 120 with steps of 2. The poles were classified as stable or unstable, considering as a hard criterion a maximum damping ratio of 10% and, as soft criteria, tolerances in the relative variations in frequencies and damping ratios of 1% and 3%, and MAC values of 0.01. The resulting sets of stable

poles were automatically clustered into different groups of physical poles using a hierarchical clustering algorithm with a cut-off distance of 0.03 (relative variations in frequencies and 1-MAC values), and a minimum cluster size of 10 poles (refer to reference [12] for further details of the OMA implementation). The stabilization diagram for the first acceleration record, shown in Fig. 4(a), highlights the identification of nine lines of stable poles, corresponding to the first nine physical models of the structure.

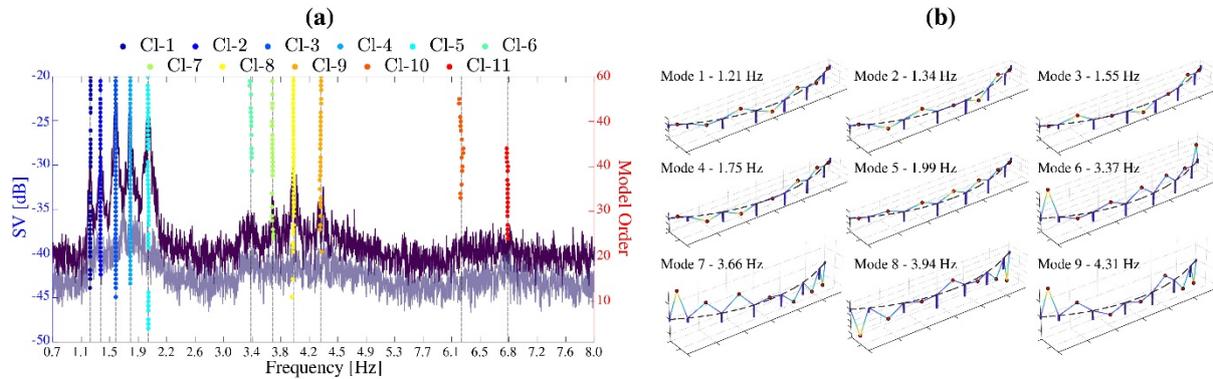


Figure 4. Dynamic identification using the first acceleration record: (a) stabilization diagram; (b) identified vibration modes from 1 to 9

The same procedure was iteratively applied to the remaining acceleration records. Figure 5(a) depicts the identified time series of resonant frequencies. Note that all the modes were consistently identified in the 14 available records, except for Modes 6 and 9 whose identification success ratio was below 50%, so they were omitted from this analysis. On this basis, although the available dataset is not representative, a statistical pattern recognition model was trained for illustrative purposes. In particular, a principal components analysis (PCA) model was trained, considering the seven time series of identified resonant frequencies as estimators and one single principal component (explaining 90% of the variance).

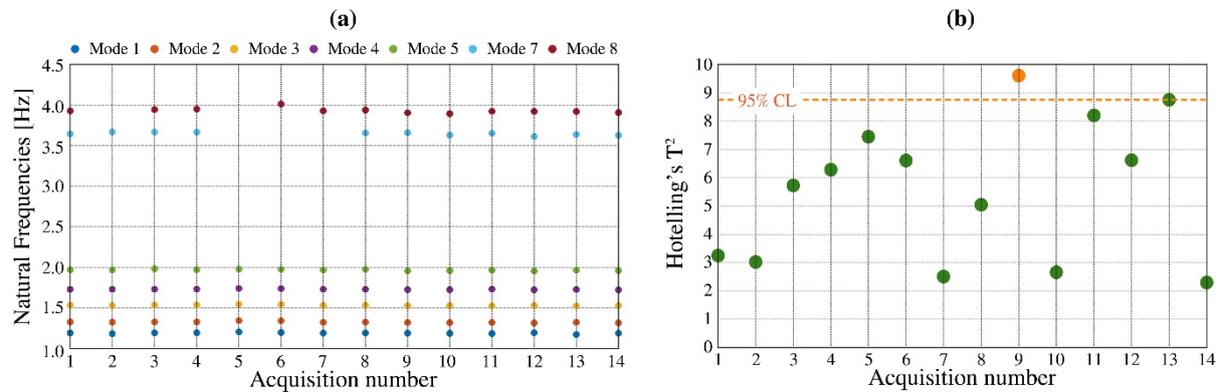


Figure 5. Anomaly detection for DI-F: (a) Frequencies tracking; (b) Hotelling's T^2 control chart

Finally, the residuals between the time series of resonant frequencies and the predictions of the PCA model were used to create a Hotelling's T^2 control chart, as shown in Fig. 5(b). For further details on the theoretical basis of these procedures, the reader can refer to reference [13]. However, the results indicate that the selected training period is insufficient to fully capture environmental influences, particularly during colder temperatures from November 2024, where the model had not yet been trained. This limitation is reflected in the control chart of Fig. 6(b), where outliers (red dots) appear after the training period. A similar trend is observed in Figs. 7(a)-(b), which analyze DI-D at P1, measuring the relative displacement between the deck and the pier. Also in this case, the anomalies detected in the control chart are likely attributable to the limited training period, underscoring the need for an extended dataset to improve model reliability. Finally, a parametric analysis of the proposed BBN (Fig. 3) for DI-F was performed, and the results are summarized in Figs. 8. More specifically, figures illustrate the probability of a certain damage level (node d) and the likelihood of a damage scenario developing, based on evidence from nodes a), b), e), and f). The analysis considers the following scenarios: (1) no evidence, the BBN is initially calibrated to a low damage level and the absence of watercourse-related

effects; (2) anomaly no to DI-F; (3) anomaly yes ; (4) defectiveness medium-node b); (5) defectiveness high-node b); (6) earthquake yes-node e); (7) earthquake no-node f); (8) landslide yes-node g); (9) landslide no-node g. The results indicate that as visual inspection and SHM data reveal anomalies, the probability of a high level of damage increases.

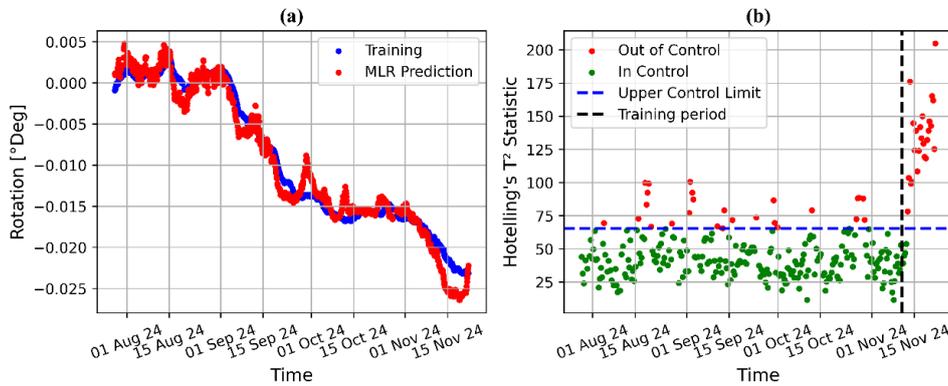


Figure 6. Anomaly detection for DI-RP: (a) Rotation tracking; (b) Hotelling's T^2 control chart

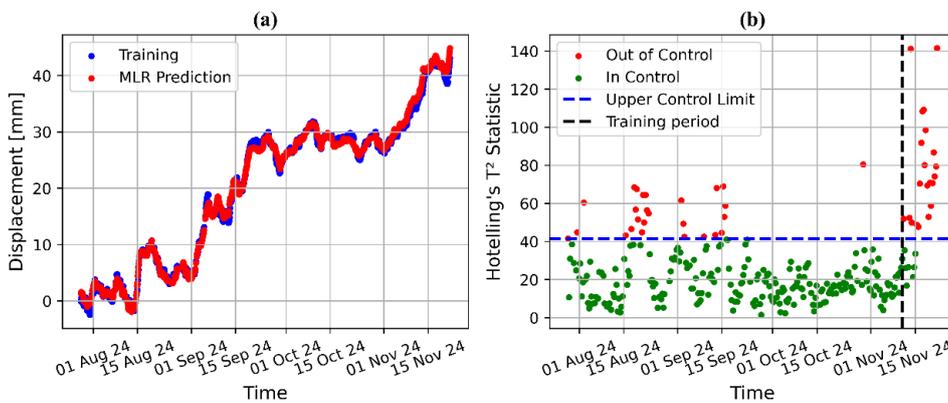


Figure 7. Anomaly detection for DI-D: (a) Rotation tracking; (b) Hotelling's T^2 control chart

Furthermore, according to Table 2, DI-F is primarily associated with scenarios linked to material degradation or seismic events. However, the BBN framework also accounts for alternative causal factors. For instance, if a landslide occurs and an anomaly is detected, the model considers the associated DS as a potential candidate, acknowledging possible secondary effects.

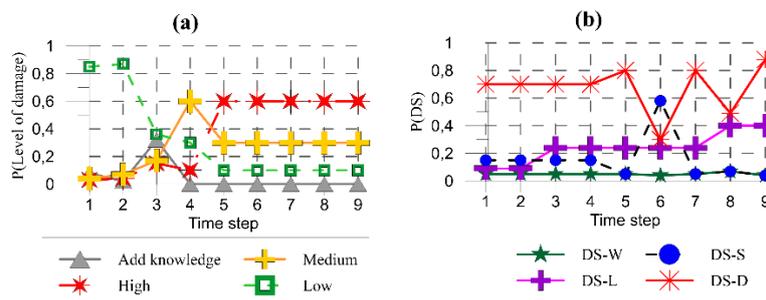


Figure 8. A BBN-based parametric analysis: (a) outcomes of node d); (b) outcomes of node i).

5. CONCLUSIONS

This study presents a comprehensive methodology for SHM, designed to assess existing bridges at progressively detailed levels and detect multiple structural damage scenarios. By integrating a data-driven approach, the proposed framework enables continuous monitoring and evaluation of a bridge's health

status through static and dynamic data processing. The effectiveness of the methodology was demonstrated through its application to a box girder bridge, selected as a pilot case study. By defining a set of potential damage scenarios based on the bridge's structural type, materials, construction technology, and current condition, the SHM system was tailored to monitor both direct and indirect indicators of structural integrity. A BNN is used to fuse all possible information acquired. The results highlight the capability of the system to identify and track damage evolution over time, leveraging predefined algorithms to process instrumental data. Overall, the proposed framework offers a systematic and scalable solution for bridge health assessment, providing valuable insights for maintenance and decision-making.

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