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Probabilistic Damage Detection in a Post-Tensioned Concrete Bridge Using Bayesian Neural Networks for Continuous Model Updating: a Numerical Study

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ABSTRACT
In Structural Health Monitoring (SHM), ensuring the integrity of infrastructure faces notable challenges due to uncertainties stemming from limited information about the structural properties to be used in numerical modeling. Leveraging recent advancements in artificial intelligence, this study introduces a Bayesian Neural Network (BNN) tailored for identifying both undamaged and damaged states in structures over time by integrating multi-source data from various monitoring instruments. The BNN framework, unlike traditional neural networks, excels in handling smaller datasets while providing probabilistic outputs, including mean and standard deviation estimates, which quantify prediction uncertainty. A key advantage of the BNN is its adaptability allowing it to incorporate new data from experimental campaigns or ambient vibration tests to refine predictions in a Bayesian manner as more data becomes available. For this study, a prestressed concrete box-girder bridge with vertically prestressed internal joints is used as an illustrative case. A Finite Element Model (FEM) of the bridge is built and calibrated using Ambient Vibration Test data. Measurement points along the bridge girder in the FEM represent the SHM system, where both dynamic features and static responses are monitored under simulated damage scenarios. The BNN is trained with sensor data as inputs, aiming to predicting the variations in girder stiffness, to address the inverse problem of damage identification and quantification. Parametric investigations demonstrate that the BNN effectively identifies probable damage configurations over time and provides confidence levels for each prediction. Importantly, the Bayesian approach, included in the training process, enables continuous updates, enhancing predictive accuracy with ongoing data from field experiments or additional campaigns, thereby improving the robustness of SHM-driven decisions over the structure's lifecycle.

Keywords: Structural Health Monitoring, Damage detection, Damage localization, Artificial intelli-

gence, Bayesian Neural Networks

1. INTRODUCTION

Aging infrastructure worldwide demands urgent attention and the limited economic resources for maintenance makes prioritizing interventions across entire networks a critical challenge. SHM offers a promising solution by employing sensor networks to collect heterogeneous data, such as strains, accelerations, and temperature. However, effectively processing and integrating these diverse data types, and critically inferring damage from its effects on structural behavior, necessitates advanced computational methods. In this sense, SHM approaches are broadly categorized as data-driven and model-based. Data-driven methods analyze raw or processed sensor data directly, searching for anomalies and persistent deviations that may indicate damage [1, 2]. These methods often rely on statistical analysis or machine learning to identify patterns in the data without explicitly modeling the underlying physics. Model-based approaches, on the other hand, take a more mechanistic approach. They involve calibrating numerical models of the structure to connect observed sensor data with the underlying structural behavior, enabling not only damage detection but also localization and quantification [3–5]. This ability to pinpoint the location and extent of damage is a significant advantage. While powerful, model-based SHM faces significant challenges. Accurately calibrating complex numerical models, especially with the large datasets generated by extensive sensor networks, is computationally demanding. Furthermore, the inherent complexity of real-world structures, coupled with the increasing number of variables in the model, often leads to ill-conditioned problems. In these situations, multiple, and often unreliable, solutions can correspond to the same set of sensor data, making it difficult to confidently identify the actual damage scenario. This ill-conditioning arises because the inverse problem of inferring damage from sensor readings can be highly sensitive to small changes in the data or model parameters sometimes hidden by noise and environmental effects. Artificial Neural Networks (ANNs) have demonstrated their value in various engineering fields for both classification and regression tasks [6, 7]. However, traditional ANNs, with their fixed weights, struggle with the ill-conditioning problem prevalent in model-based SHM. They tend to provide a single, deterministic output, even when multiple plausible solutions exist. In SHM, a set of measured structural data can correspond to various damage scenarios. A probabilistic approach, therefore, offers a more robust and interpretable solution, acknowledging the inherent uncertainty in the problem. This paper addresses these challenges by employing a Bayesian Neural Network (BNN) as a surrogate model. Unlike traditional ANNs, which assign fixed, deterministic values to the network's weights, BNNs represent these weights as probability distributions. This fundamental difference allows the BNN to capture the uncertainty associated with the model parameters. Consequently, the calibrated BNN-based surrogate model generates probabilistic predictions, providing not just a single estimate of the damage state, but a distribution of possible outcomes along with a measure of uncertainty. This capability is crucial for addressing ill-conditioned problems and significantly improving the reliability and interpretability of damage assessment [8–12]. To underscore the practical applicability and reliability of the proposed algorithm, its effectiveness is demonstrated on a real-world case study involving a complex structure: a post-tensioned concrete box girder bridge with vertically prestressed internal joints.

2. THE PROPOSED METHODOLOGY

1. The offline phase focuses on preparing and training the Bayesian Neural Network (BNN) to serve as an accurate surrogate model for damage detection. This involves several key steps:

   (a) Finite Element (FE) model calibration: adjustment of the model parameters (e.g. material properties, boundary conditions), starting from the available design information, until the model predictions closely match the non-destructive campaign observations of the actual structure. This calibrated FE model becomes the basis for generating training data for the

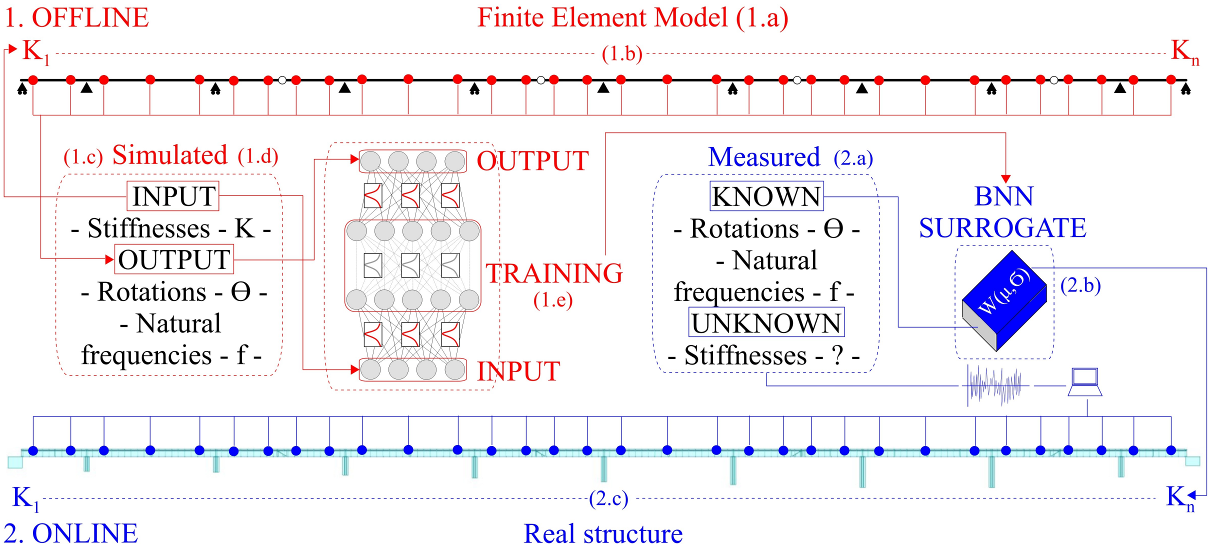

Figure 1: Scheme of the methodology

BNN.

(b) Damage-sensitive parameter identification and measurement point definition: identification of quantities that are significantly affected by the presence of damage and can be reliably measured or calculated. Corresponding measurement points are then defined in the FE model to mimic the sensor configuration on the real structure. This ensures that the BNN is trained on data that reflect the information available from the actual sensor network.

(c) Input-output dataset generation: generated by combining design values and any available experimental values of relevant mechanical parameters. To efficiently explore the space of possible structural conditions, sampling techniques like Latin Hypercube Sampling (LHS) are employed. LHS ensures good coverage of the parameter space with a relatively small number of samples, maximizing the information gained from each simulation. This input dataset represents a variety of potential scenarios, including both healthy and damaged states.

(d) Structural response simulation: using the calibrated FE model, the structural response is simulated for each combination of input parameters in the generated dataset. This collection of input-output pairs forms the training dataset for the BNN.

(e) BNN model training and optimization: the BNN model is trained using the generated training dataset. This involves experimenting with different BNN architectures (number of layers, neurons per layer), activation functions, and prior distributions for the weights through the Bayesian optimization algorithm. The goal is to optimize the BNN's performance, ensuring reliable predictions.

2. The online application phase involves deploying the trained BNN for real-time monitoring and analysis of the structure. This phase consists of the following steps:

   (a) Real-Time data acquisition: real-time data is collected from the sensors installed on the structure. These sensors' readings, related to the previously identified damage-sensitive parameters, serve as the input for the trained BNN surrogate model.

   (b) Stiffness prediction with the BNN: having learned the relationship between sensor readings and structural behavior during the offline training phase, the BNN predicts the stiffness of each structural element. Because of the probabilistic approach, the output isn't a single stiffness value but rather a probability distribution representing the likely range of stiffness values for each element.

(c) Damage scenario identification and analysis: the probability distributions of the predicted stiffness values are analyzed to identify potential damage scenarios. Deviations from baseline distributions corresponding to the healthy state can indicate the presence and extent of damage. By defining appropriate thresholds and evaluating the probability of exceedance, it is possible to quantify damage with different levels of tolerance. Critically, the probabilistic nature of the BNN's output allows for a comprehensive assessment that considers the entire distribution rather than a single point estimate, providing a robust framework for estimating the likelihood of various damage scenarios.

3. THE CASE STUDY BRIDGE

The proposed methodology is applied to a real-world case study involving a post-tensioned concrete box girder bridge constructed in 1984 [13–15]. The bridge has a total length of approximately 630 meters and consists of ten spans. The first and last spans measure 35 meters each, while the intermediate spans are 70 meters long. The prestressing system comprises three distinct sets of cables within the girder. The first set, located between the web and the upper slab, consists of more than 600 cables. The second set, embedded within the upper slab, includes 160 cables, while the third set, positioned within the lower slab, comprises 180 cables. The superstructure is supported by piers and abutments made of cast-in-place reinforced concrete, with heights varying between 7.5 meters and 18.5 meters, following the natural ground slope. The bridge was constructed using the balanced cantilever method and the frames are connected by four vertically prestressed internal joints. These joints, located at spans 3, 5, 7, and 9, are designed to accommodate horizontal thermal displacements while maintaining structural continuity between adjacent cantilevers. Each joint incorporates two sets of sliding supports (an upper and a lower one) to facilitate movement. Additionally, 30 prestressed Dywidag bars are installed at the lower supports to ensure continuous contact under positive bending moments. Visual inspections of the bridge revealed significant vertical deflections that warranted further investigation. Specifically, the spans incorporating the internal joints exhibited noticeable lowerings, resulting in the formation of cusps that disrupt the longitudinal continuity of the superstructure. These lowerings are substantial, such that the spans without joints exhibit the opposite behavior, displaying appreciable upward displacements. For the reasons outlined above, a calibrated FE model was developed and validated using data from static and dynamic experimental campaigns. This model serves to investigate the underlying causes of the observed structural condition and to develop algorithms for predicting and mitigating the impact of future adverse scenarios. Within the FE model, the complex cable system is simplified by representing the upper and lower cable systems with resultant cables. 51 strategically positioned measurement points simulate a sensor network, capturing both dynamic (e.g., modal frequencies) and static (e.g., rotations) structural features. The girder is divided into 21 segments, each assigned distinct material properties to simulate varying stiffness configurations. The positions of the sensors and of the segments are schematized in Figure 2. The concrete's elastic modulus, defined as the damage-sensitive parameter, is modeled for each segment using log-normal probability distribution functions with a variation coefficient of 0.20 around the design modulus of 32860 MPa. LHS generates approximately 5000 combinations of varying stiffness distributions across the segments to ensure a well-generalized dataset. Simulated sensor measurements, reflecting structural conditions under different stiffness degradation levels, are extracted for each combination. This dataset serves as input for the BNN, which is trained to predict the elastic modulus of concrete for each segment, enabling the localization and quantification of damage through stiffness reduction assessment.

4. BNN SURROGATE MODEL

Following dataset generation, a probabilistic framework is established using a Bayesian Neural Network (BNN). With sensor data as input and the concrete Young's moduli of individual segments as output, an optimal network architecture was identified. This architecture consists of a single hidden layer con-

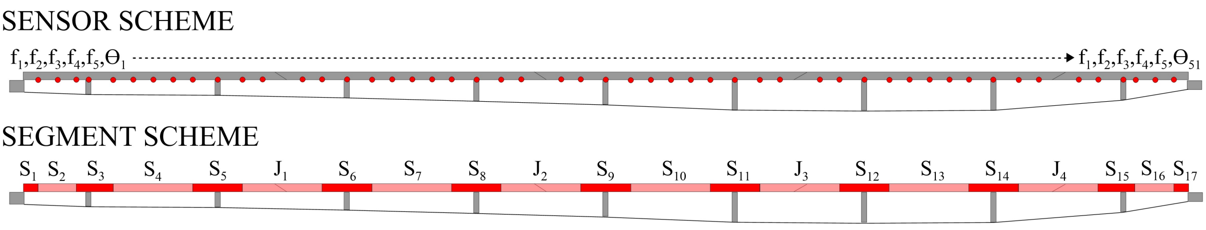

Figure 2: Schemes of the case study: sensor and segment positions

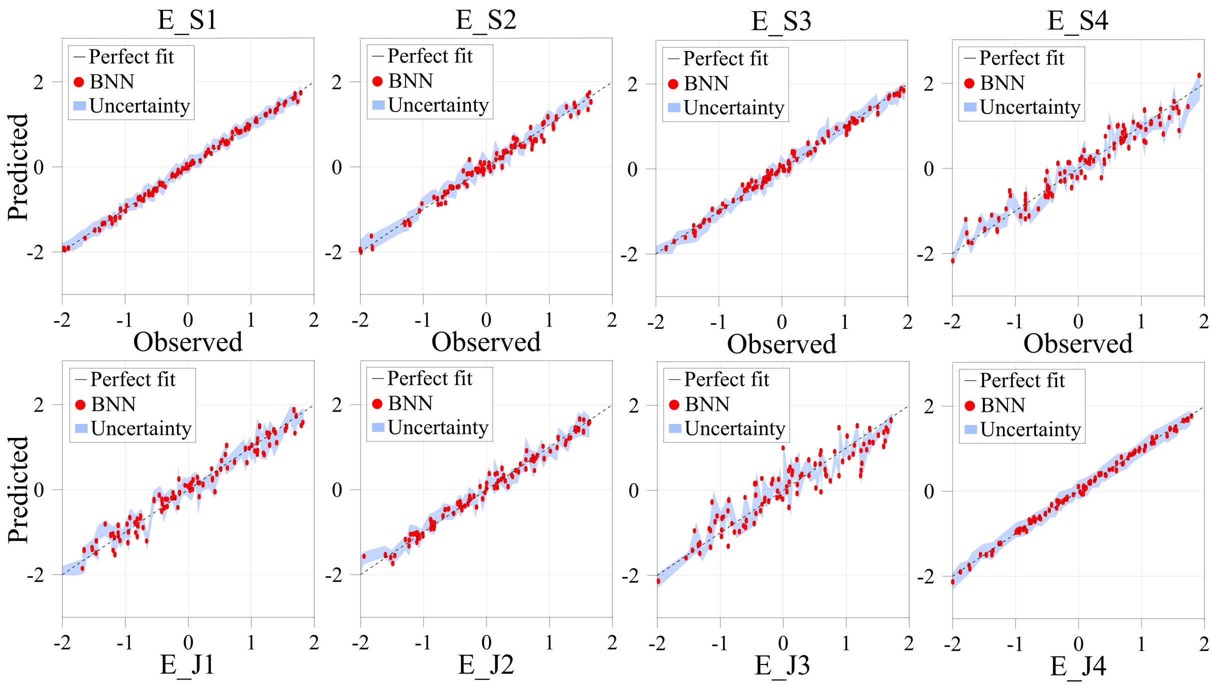

Figure 3: Examples of Bayesian Neural Network performance on the test dataset

taining 20 neurons and utilizes the hyperbolic tangent (Tanh) activation function. Weight distributions are estimated via the Markov Chain Monte Carlo (MCMC) sampling method, generating 100 samples per weight. A train-test split was performed on the dataset during training, varying the number of training samples. This analysis revealed that approximately 500 samples were sufficient to train a reliable network. The remaining 4,500 samples were then used to evaluate the network's ability to accurately infer structural behavior from the sensor data. Figure 3 presents the test results, demonstrating strong agreement between predicted and actual values, as evidenced by the close alignment of data points along the bisector. These results also indicate a greater degree of uncertainty in the relationship between sensor measurements and the properties of the vertically prestressed internal joints.

5. RESULTS

Following training, the resulting BNN surrogate model was evaluated on a new dataset comprising various realistic damage scenarios. For each prediction, the BNN, having generated 100 weight samples, produces a distribution of 100 predicted values. To assess the BNN's ability to accurately identify both the location and severity of damage, the observed (deterministic) elastic moduli values for each segment were compared with the median of the corresponding predicted distribution. Examples of this comparison are shown in Figure 4. Figure 4a demonstrates the BNN's ability to identify severe damage concentrated within a single segment along the girder, while avoiding false positives in undamaged segments. In this scenario, the Young's modulus is reduced by approximately 25% from the nominal value in mid-span 4 (segment 8), and the damage is accurately identified in both location and severity. Subsequently, two

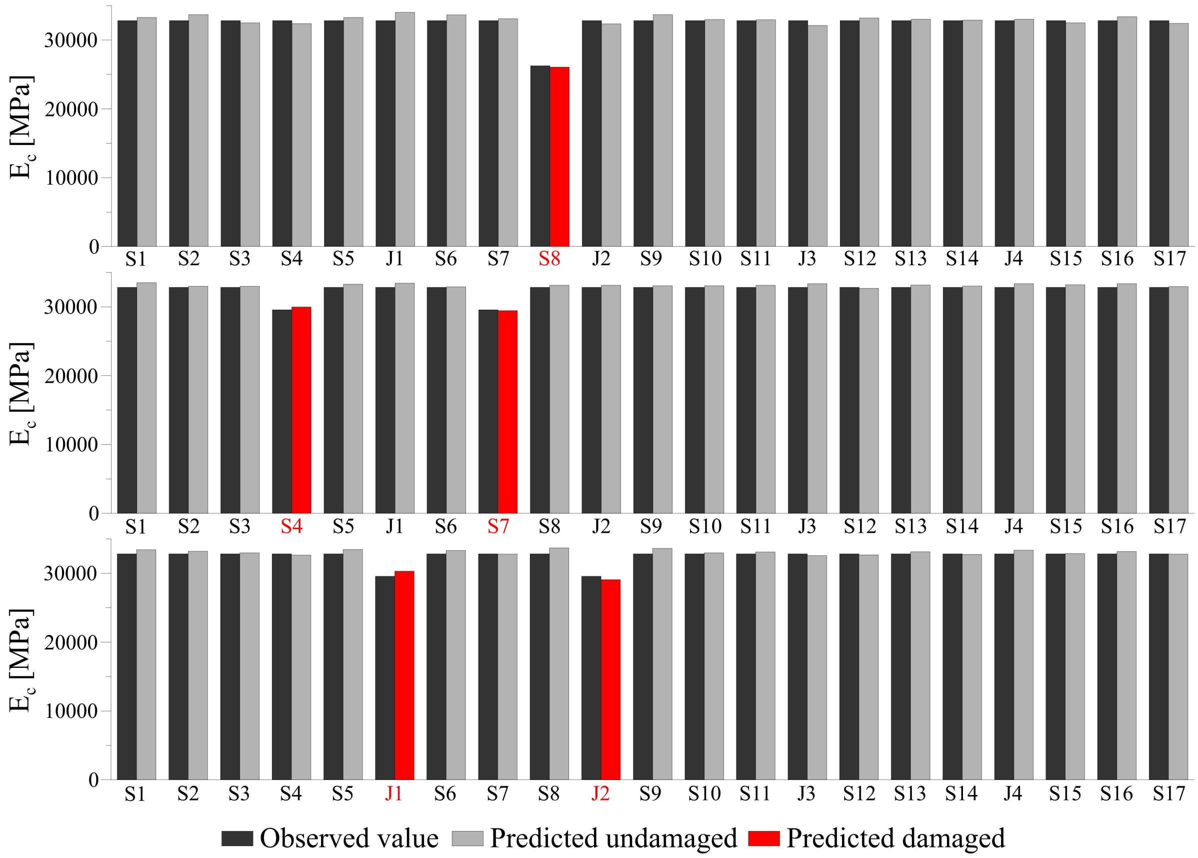

Figure 4: Examples of prediction on different damage scenarios: a) 25% Young's modulus reduction on a single segment; b) 10% Young's modulus reduction on two segments; c) 10% Young's modulus reduction on two internal joints

simultaneous damage instances were introduced in two separate segments, each with a reduced intensity of 10% Young's modulus reduction. The BNN's predictions in this scenario, shown in Figure 4b, remain quite reliable. Finally, a test was conducted on the elements exhibiting the highest uncertainty: two of the joints. The elastic modulus of these joints was reduced by 10%. Figure 4c demonstrates that the BNN is still capable of localizing and quantifying the damage in both elements. After the evaluation of the BNN's predictive capabilities, the advantages of a probabilistic approach are highlighted by analyzing the statistical parameters of the predicted distributions. Figure 5 illustrates two distinct damage scenarios. Within each graph, two thresholds, representing reductions in the nominal concrete elastic modulus, are defined. The first threshold is set at a 5% reduction, while the second represents a 10% reduction. These thresholds divide the space into three distinct regions. From top to bottom, these regions represent: ordinary damage due to time-related degradation; sensitive damage requiring ongoing monitoring; and critical damage necessitating immediate investigation. In this case, the scenarion in Figure 5.a consists on the critical degradation of the four vertically prestressed internal joints simultaneously. While this scenario is clearly identified by the trained BNN, some observations are needed. The distributions for all undamaged elements show approximately 75% of the samples above the nominal elastic modulus, with only a small number of samples (false positives) falling within the 5-10% reduction zone. Crucially, the distributions for the damaged joints exhibit a significant number of samples bordering this zone and the critical damage region, thus correctly prompting further investigation of these elements. Figure 5b displays the network's performance under extreme conditions, where all structural elements exhibit a reduced elastic modulus due to uncertainties in the cast-in-place concrete mixture properties. While this combination of values falls outside the BNN's training range, the model still correctly categorizes all elements as having a significant probability of being severely or critically damaged ensuring the capability of the BNN of understanding the structural behavior in unseen conditions.

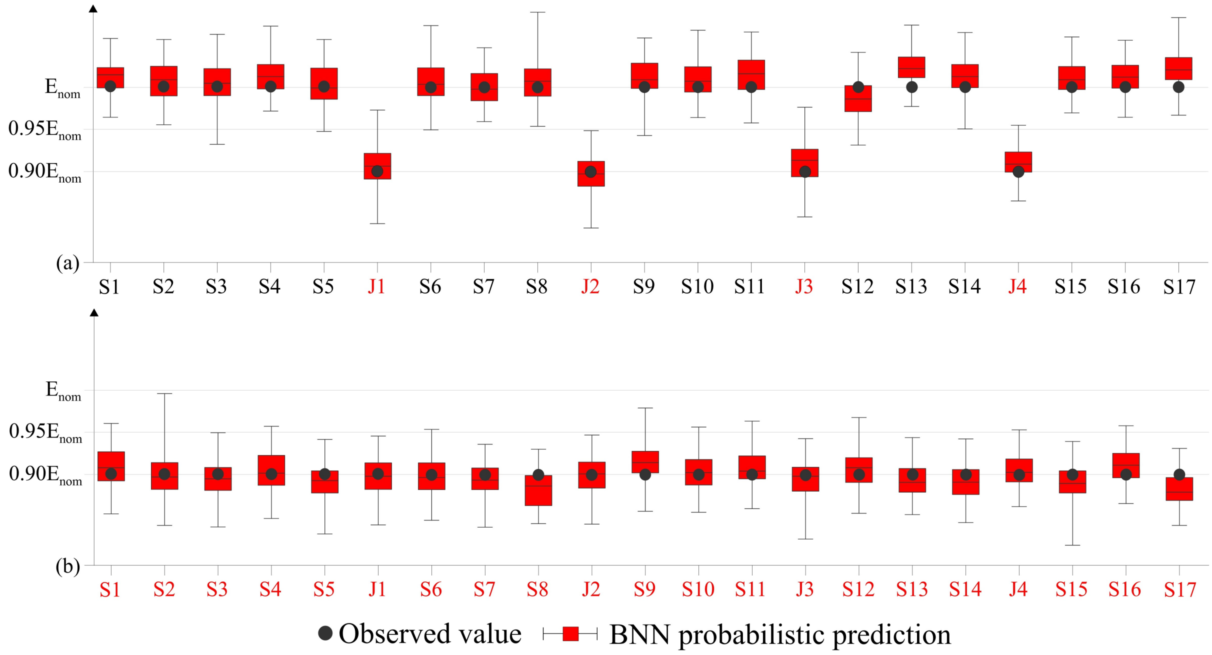

Figure 5: Examples of probabilistic predictions on different damage scenarios: a) simultaneous 10% reduction of stiffness on the four joints; b) simultaneous 10% reduction of stiffness along the whole girder

6. CONCLUSION

This study presents a BNN framework for damage detection and quantification in a complex, real-world post-tensioned concrete box girder bridge. The methodology demonstrates the BNN's ability to achieve reliable results with relatively small datasets, a significant advantage over traditional machine learning algorithms, particularly in real-world applications where data acquisition can be challenging. Furthermore, the BNN's probabilistic output, providing a distribution of possible damage states rather than a single deterministic value, enables a more nuanced interpretation of structural health. This probabilistic information empowers decision-makers to prioritize inspections and maintenance, focusing resources on areas with a higher probability of critical damage while maintaining surveillance over adjacent segments that may exhibit early signs of degradation. The analysis of the predicted probability distributions further demonstrates the framework's potential for classifying damage severity and informing proactive maintenance strategies.

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