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Implementing Artificial Neural Networks and Mode Shape Curvature for Locating damage in Bridge Structures

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Abstract

Structural damage manifests as changes in a system's geometry and material properties, leading to stiffness reduction and adversely impacting performance. These reductions alter modal parameters like natural frequencies and mode shapes, which can be analysed to identify damage. Modal analysis allows for the extraction of modal frequencies and shapes, enabling a detailed examination of mode shape curvature to locate structural issues accurately. Recently, artificial neural networks (ANNs) have proven to be highly effective in structural health monitoring, particularly due to their exceptional pattern recognition capabilities. This study presents a novel approach that combines mode shape curvature analysis and ANNs to detect damage in steel girder bridge structures. Through vibration-based fault detection, this approach overcomes limitations of traditional methods by using mode shape curvature as a reliable indicator of structural anomalies. Experimental evaluations compare the modal responses of intact and damaged structures, providing critical insights into changes in structural behaviour. A feed-forward neural network with two hidden layers is employed, trained on damage indices generated from mode shape curvature data. This trained ANN is then used to identify unknown damage locations within the structure, demonstrating high precision. Validation results further confirm the accuracy and reliability of this damage detection method. Overall, the study shows that ANNs trained with modal curvature data offer a robust and efficient approach for early damage detection in steel girder bridge structures, significantly enhancing safety and operational reliability. This innovative method contributes to advancing structural health monitoring, offering a valuable tool for maintaining the integrity of infrastructure, such as steel girder bridges.

1. Introduction

Assessing the integrity of existing structural systems and ensuring their ongoing safety requires effective identification of any signs of damage, which is critical for preventing potential collapse. Structural damage often leads to weakened areas within the structure, possibly causing undesired displacements that reduce overall performance. Monitoring structures for defects is therefore essential, as damage can alter a structure's mass and stiffness, leading to changes in dynamic responses, such as natural frequencies and mode shapes. Early damage detection plays a crucial role in preventing sudden collapses, enhancing safety and functionality, and minimizing maintenance costs [1-5].

Various approaches have been utilized for structural fault detection. Visual inspections are commonly employed but often fail to detect issues that are not readily visible, especially in cases where early-stage damage is concealed [6-8]. Thus, consistent monitoring of structural performance, even when defects are not visually apparent, is essential to uphold structural integrity. Recently, artificial neural networks (ANNs) have emerged as powerful tools in structural damage assessment due to their accuracy in predicting damage severity and location in civil structures [9-12]. With appropriate input parameters and careful selection of training data, ANNs are highly effective at capturing complex relationships with precision.

ANNs utilizing vibration parameters have gained attraction in structural evaluation for their ability to recognize patterns and process data effectively. For instance, Nguyen and Wahab [13] introduced an innovative method that combines the curvature mode shape approach with Convolutional Neural Networks (CNNs) to detect slab damage. Their approach accurately identifies damage locations and is easy to implement without requiring extensive knowledge of structural behaviour. Similarly, Randiligama et al. [14] developed a technique for identifying defects in cooling towers using changes in mode shape curvature along with ANNs. By training the network on damage indices derived from mode shape data, their method enabled early detection of structural damage in cooling towers.

In related research, Liu [15] explored the use of modal curvature analysis and neural networks for identifying defects in rail bases, employing a series of numerical simulations validated by modal tests. The neural network was trained to locate and quantify base damage, providing a novel approach to rail defect detection. Additionally, Mai et al. [16] introduced a Damage-Informed Neural Network (DINN) designed to locate and assess damage in structural elements. Through numerical studies on truss and frame structures, their method demonstrated accurate damage localization and faster convergence compared to other algorithms.

Tan et al. [17] proposed a method for identifying damage location and severity in steel beams using modal strain energy and artificial neural networks (ANN). Damage indices served as ANN inputs, showcasing the method's accuracy in detecting structural damage. Similarly, Chang et al. [18] applied ANN to pinpoint damage in a steel-frame building by analysing dynamic parameters, demonstrating precise identification even with varying stiffness reductions. Gu et al. [19] integrated ANN with novelty detection to evaluate modal frequency changes from temperature-induced damage, yielding robust damage assessments. Moving on, Aydin and Kisi [20] utilized vibration data, specifically the first four natural frequencies, as ANN inputs for diagnosing beam cracks effectively.

In recent years, there has been increased interest in using ANNs with modal parameters for structural damage detection, as several studies have explored the use of vibration data to train ANNs for damage assessment across various structures [21-27]. Despite significant progress, challenges remain, particularly in achieving precise localization and evaluation of structural damage through the integration of mode shape curvature and neural networks. This research aims to address these gaps by examining the feasibility of utilizing ANNs trained with modal curvatures obtained from experimental modal analysis on both intact and damaged steel girder bridge structures for damage detection. Specifically, this study investigates the limitations of conventional methods by focusing on vibration-based damage detection, with an emphasis on mode shape curvature as a reliable, accurate approach for identifying structural damage.

2. Materials and Methods

2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are advanced parallel processing systems modelled after the human brain's biological structure. By emulating brain functions, ANNs are designed to solve specific problems using rule-based learning mechanisms to achieve desired results [28-29]. They are particularly valuable for generating insights even with incomplete or imprecise data and excel at rapidly processing information to tackle complex, real-world issues [30-32]. Figure 1 provides an overview of ANN architecture, illustrating the flow of information from the input layer through the hidden layer to the output layer. Figure 1 illustrates a multi-layer neural network architecture comprising an input layer with 5 neurons, a hidden layer containing 3 neurons, and an output layer with 4 neurons.

One of the most used algorithms in multi-layer networks is the backpropagation (BP) algorithm, prized for its ability to accurately model intricate problems mathematically. Among various ANN architectures, the Multi-Layer Perceptron (MLP) is widely utilized for structural damage detection [33-35]. The performance of MLPs is often evaluated using indices like the Mean Square Error (MSE), which assesses the deviation between the target and actual outputs produced by the network.

The BP algorithm minimizes MSE using a gradient-descent method, adjusting network weights iteratively to follow the error gradient's downward slope across all input patterns. ANNs offer significant advantages, notably their ability to reliably detect damage even with imperfect training data. Additionally, ANNs continuously improve through training, enhancing diagnostic accuracy over time by learning from new data inputs.

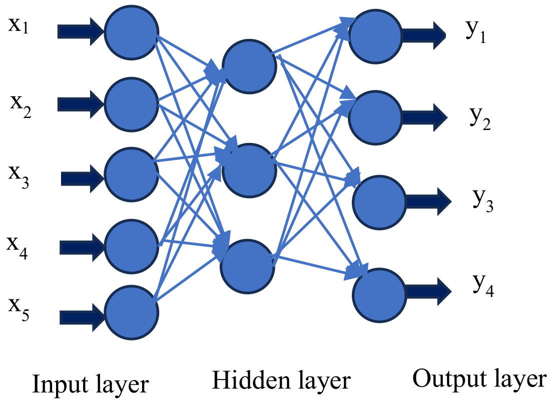

Fig. 1 *A multi-layer neural network architecture with three layers*

2.2 Mode Shape Curvatures

Mode shape curvatures provide a distinct advantage over basic mode shapes for identifying damaged locations within structures, as they are particularly sensitive to local stiffness variations. This sensitivity enables the detection of even minor damage, as mode shape curvatures emphasize localized stiffness changes more effectively than mode shapes alone. By revealing variations in the slope of deformation patterns, mode shape curvatures enhance damage localization, offering a more precise indication of affected areas. This approach also magnifies damage effects, thereby creating clearer contrasts between damaged and undamaged regions, making it a highly effective tool in structural health monitoring.
Derived by taking the second derivative of mode shape functions with respect to spatial coordinates, mode shape curvatures illustrate the curvature distribution throughout the structure, providing detailed insights into localized bending and deformation characteristics [36]. Typically, mode shape curvatures are calculated from displacement mode shapes using the central difference approximation method, as represented in Equation 1. This method enables the transformation of displacement data into curvature, which is crucial for accurately assessing and monitoring the structural integrity.

$$\varphi"_{ji} = \frac{\varphi_{j-1,i} - 2\varphi_{j,i} + \varphi_{j+1,i}}{l^2} \qquad (1)$$

Where $\varphi"_{ji}$ refers to the curvature of the mode shape of the jth element for ith mode. Also, φ_{ji} is the mode shape of the jth element for ith mode and l is the distance between two successive nodes in grid line. The damage detection algorithm used in this study calculates the absolute change in mode shape curvature by comparing curvature data from the undamaged state with data from the damaged state, as shown in Equations 2 and 3.

$$\mathrm{DI}=\left(\frac{\varphi_{j-1,i}-2\varphi_{j,i}+\varphi_{j+1,i}}{l^2}\right)^{\mathrm{d}}-\left(\frac{\varphi_{j-1,i}-2\varphi_{j,i}+\varphi_{j+1,i}}{l^2}\right)^{\mathrm{h}} \qquad (2)$$

$$\mathrm{DI}=\varphi_h^{"} - \varphi_d^{"} \qquad (3)$$

In Equation (2), letter d represents the damaged state, while letter h represents the healthy state. In Equation (3), $\varphi_h^{"}$ and $\varphi_d^{"}$, represent healthy and damaged mode shape curvatures. When considering multiple modes, the average damage index across all modes is defined as the total of individual damage indexes, as shown in Equation 4.

$$\mathrm{DI}=\frac{1}{N}\sum_{m=1}^{N} DI_m \qquad (4)$$

In Equation (4), NNN denotes the total number of modes measured. For this study, the analysis focuses on the first five modes.

2.3 Experimental Modal Analysis

Experimental modal analysis assesses a structure's dynamic properties by artificially inducing vibrations and identifying its response patterns. When damage occurs, it changes the structure's physical and material properties, along with its boundary conditions, leading to variations in its dynamic parameters. In this study, a steel girder bridge model served as the specimen for experimental testing. As illustrated in Figure 2, the model comprised a plate measuring 1200 mm in length, 210 mm in width, and 5 mm in thickness, with a 100 mm overhang at each support end. Three stiffeners, each measuring 1200 mm in length, 50 mm in height, and 5 mm in width, were fixed along the plate's length. The spacing between each stiffener was 70 mm, and the distance between the outermost stiffener and the plate edge was 35 mm.

Fig. 2 *Steel girder bridge as a test specimen*

The bridge girder and its test set up are illustrated in Figure 3. To determine the dynamic characteristics of the steel girder bridge, modal testing was conducted. Initially, the testing focused on the undamaged bridge girder to extract its modal parameters. Following this, various damage scenarios were introduced by simulating faults of different severities at distinct locations along the structure.

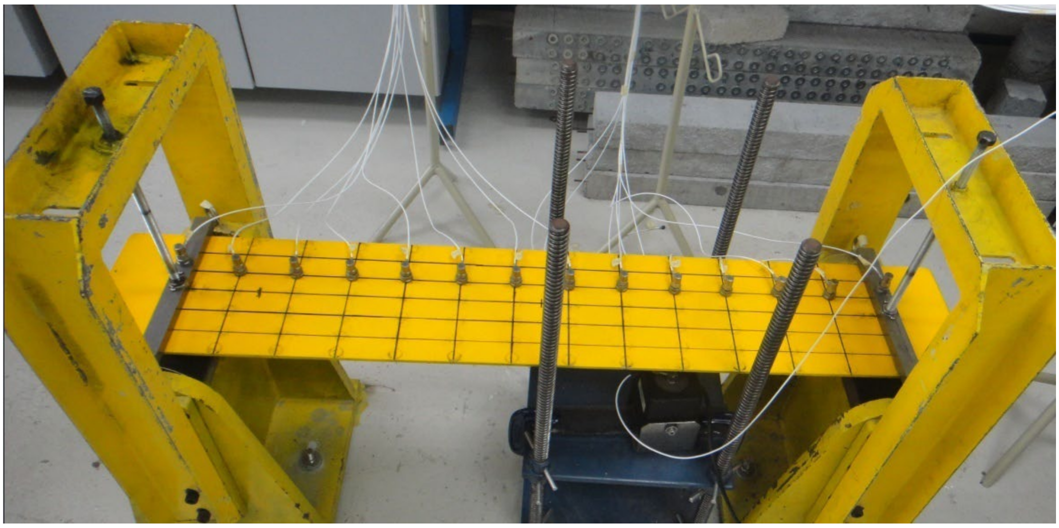

Fig. 3 *Experimental set up*

In this research, time-history response signals were transformed into the frequency domain using Fourier transforms. During modal testing, the structures were excited with a shaker, and accelerometers captured the responses. A sampling rate of 5.14 kS/s was used, producing a frequency bandwidth of 2500 Hz with 6401 FRF data points, resulting in a frequency resolution of 0.39 Hz. Signals were amplified, analyzed, and converted into FRFs, followed by modal analysis via specialized software to extract modal parameters. Through modal testing, the vibration characteristics of the structures were analyzed for both intact and damaged states, enabling the identification of mode shapes and their corresponding curvatures.

3. Results and Discussion

In this section, the bridge girder was initially tested in its undamaged state to determine its dynamic properties. Subsequently, the structure was subjected to various damage scenarios, and the corresponding modal parameters were derived. The modal characteristics of the intact girder were extracted from the frequency response functions

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(FRFs) using the post-processing tools available in the ICATS software. In the experimental study, multiple damage scenarios were applied to the bridge girder, covering seven specific locations: L/13, 2L/13, 3L/13, 4L/13, 5L/13, 6L/13, and L/2 along the span. Each location included 25 levels of damage severity, characterized by a fixed slot width of 5 mm and depths ranging from 2 mm to 50 mm increments. The damage was introduced by grinding a slot into the soffit of the middle stiffener, simulating varying severities at each location.

Since identifying damage locations using ANNs is a key goal of this study, the mode shapes of the structure were carefully analysed. Mode shapes, which illustrate the vibrational deformation pattern, provide more insight into localized damage than natural frequencies and are particularly sensitive in detecting damage locations. The results showed that as damage severity increased, changes in the mode shapes became more significant. The differences in mode shapes were more pronounced with higher damage levels. These mode shape data were then used to train and test ANNs for damage localization. Various neural networks were considered for damage prediction, and the results of damage identification are discussed.

Several numbers of ANNs using all mode shape values consisting of twelve inputs at the points on the centerline of the scaled girder bridge deck (except the points at supports) were constructed and designed to identify the location of the structure. In this study, 372 different datasets from undamaged and damaged structures were collected from the experimental modal analysis and numerically simulated model.

In this study, divisions of the datasets were carried out randomly into training, validation and testing datasets. Of the total of 372 datasets, 260 datasets, representing 70% of the data, were used for training purposes. The remaining datasets were evenly divided between validation and testing procedures. Various damage scenarios were given to the test structure. These scenarios consisted of seven locations with twenty-five severities for each location. The output parameter of the ANN was damage location from the support to the length of deck, representing the location of damage. The damage location indices for the bridge girder at positions L/13, 2L/13, 3L/13, 4L/13, 5L/13, 6L/13, and L/2 were 0.077, 0.154, 0.231, 0.308, 0.385, 0.462, and 0.5, respectively.

The input layer of the ANN consisted of 12 neurons, each representing one of the mode shape curvature values at specific points along the centerline of the structure. The output layer contained a single neuron, which indicated the damaged location. Thus, the input and output data were structured as follows:

$$\{\phi_{1,2},\ \phi_{1,3},\ \phi_{1,4}, \phi_{1,5}, \phi_{1,6}, \phi_{1,7}, \phi_{1,8}, \phi_{1,9}, \phi_{1,10}, \phi_{1,11}, \phi_{1,12}, \phi_{1,13},\ l_d/L\}$$

The training process was performed using the BP algorithm and repeated until the error between the actual and predicted output by the ANN was minimized. A network with 12-7-4-1 architecture, which produced the lowest MSE and highest correlation, was selected as the optimal model for identifying the damage location. The low error rates and high correlation indicate that the dataset was accurate, and the ANN successfully captured the underlying patterns within the data. Figure 4 shows a comparison between the damaged localization values identified by the ANN and the actual values for the training datasets.

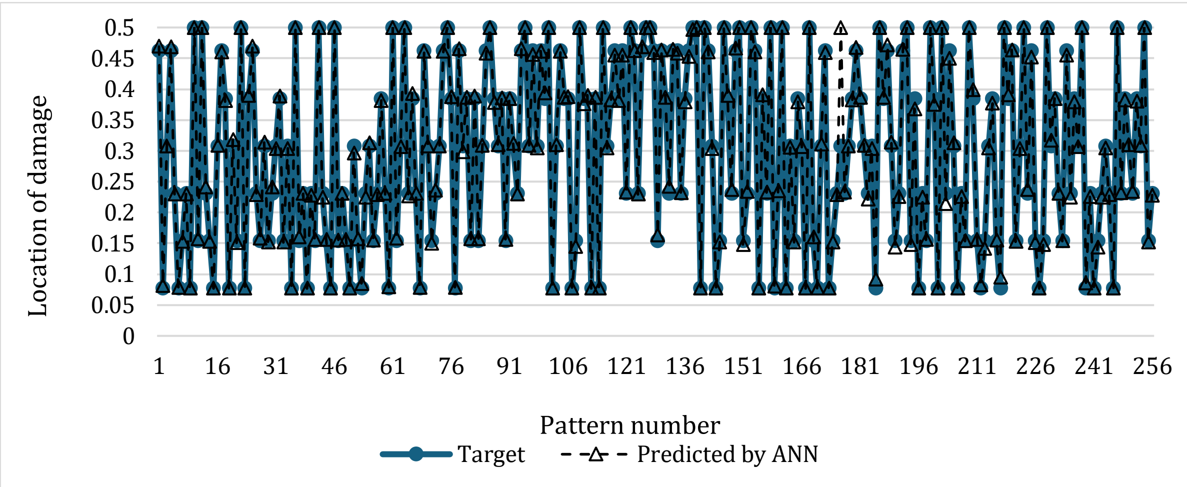

Fig. 4 *Damage location identified by ANN and the actual values from training datasets*

Once the network was trained, it was tested with new datasets that were not part of the training set to verify its ability to identify the damaged location with an acceptable error margin. To avoid overfitting and ensure the accuracy of the chosen architecture for damage detection, the ANN underwent thorough validation and testing.

Figures 5 and 6 present a comparison between the damaged localization values predicted by the ANN and the actual values for the testing and validation datasets, respectively.

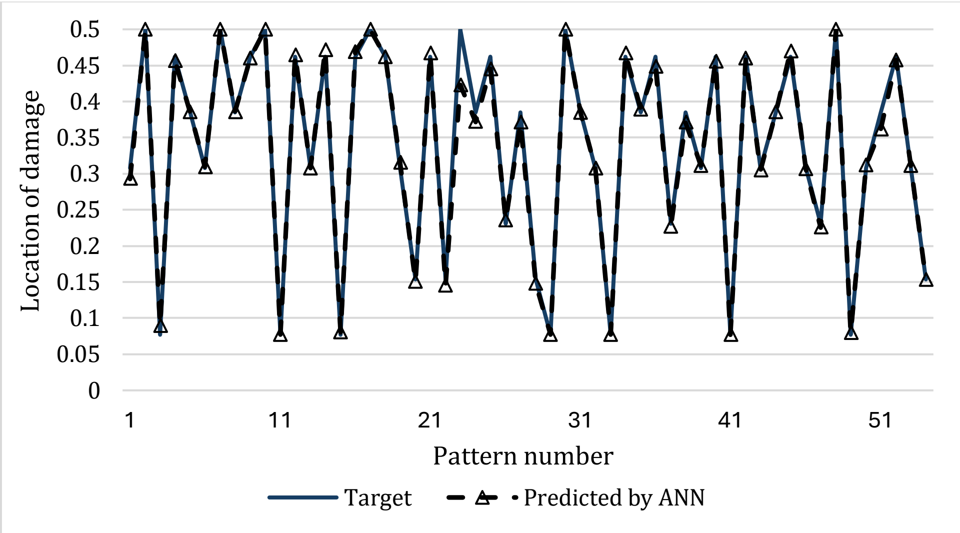

Fig. 5 *Damage location identified by ANN and actual values from validation datasets*

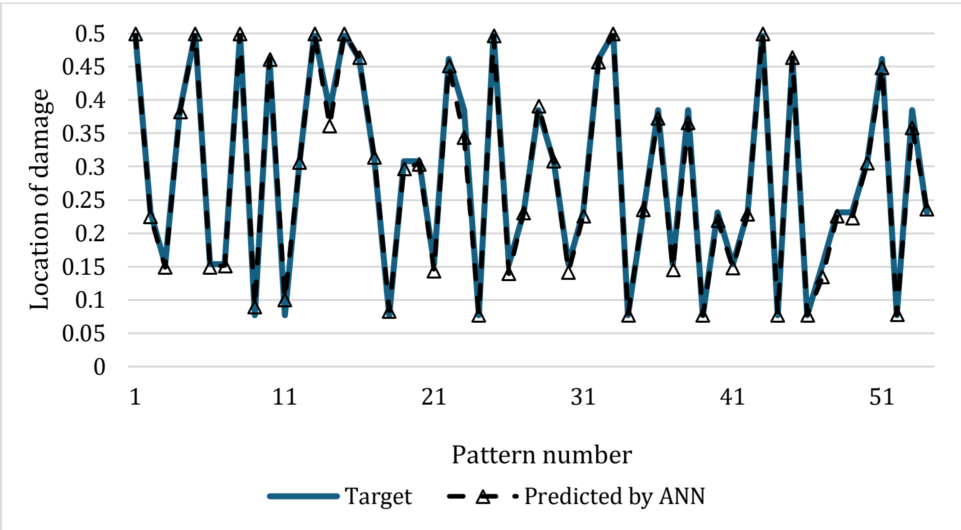

Fig. 6 *Damage location identified by ANN and actual values from testing datasets*

The damage localization accuracy for training, validation, and testing datasets is clearly demonstrated in Figures 4 to 6, proving strong alignment between predicted and actual values. The ANN successfully predicted the damage location with an Absolute Error (AE) of 2.33%, 2.47%, and 2.65% for the respective datasets. Additionally, the correlation coefficients were 0.9902, 0.9788, and 0.9734 for training, validation, and testing datasets, respectively. Figure 7 further illustrates the comparison of AE for the damaged location across all datasets.

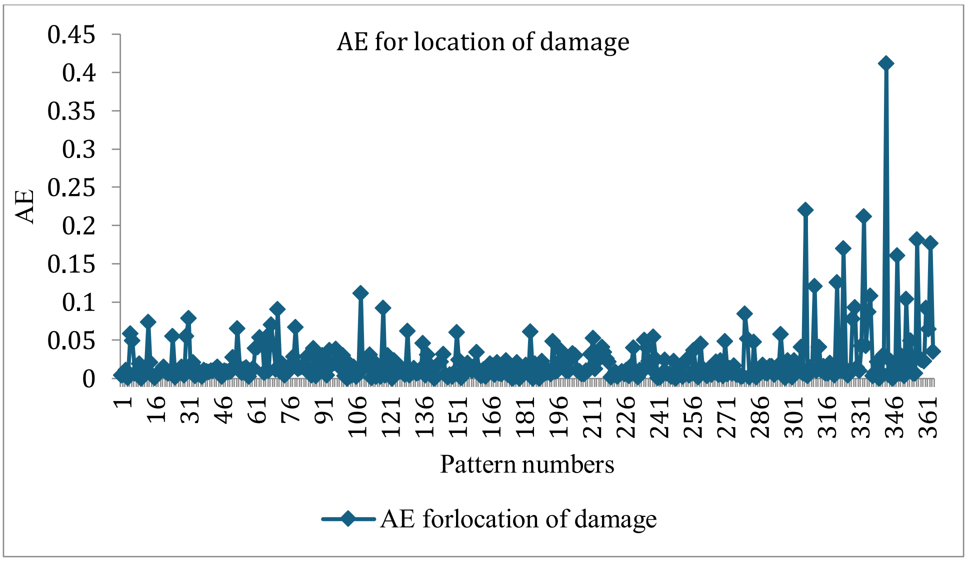

Fig. 7 *AE performance for damage location for all datasets*

As apparently seen in Figure 7, the AE values for all datasets to identify the location of damage were low which indicates that the ANN could recognize the location of damage with high accuracy. Also, the comparison of the damaged location through the ANN and the actual value for all datasets is illustrated in Figure 8.

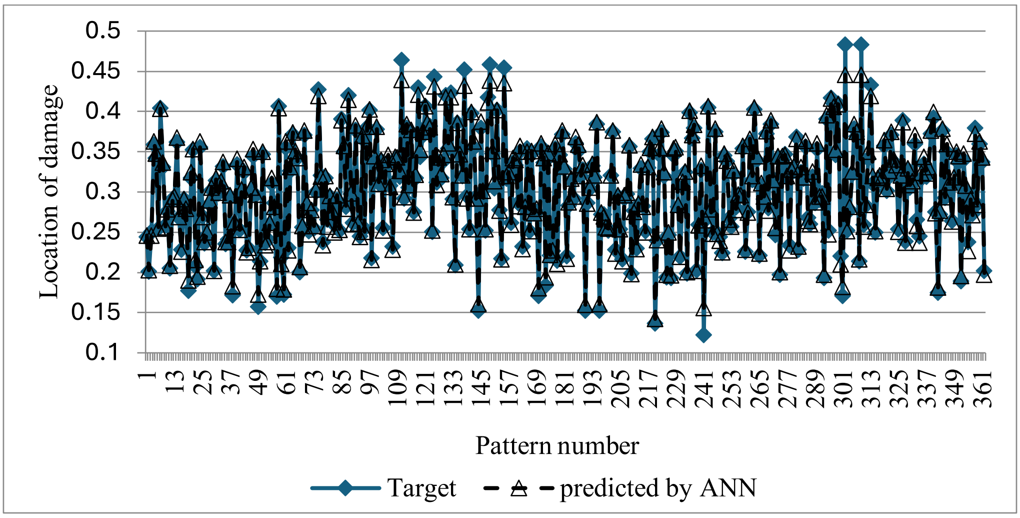

Fig. 8 *Damage location through ANN and actual values for all datasets*

Figure 8 illustrates that nearly all damage cases were accurately identified. Minor errors were observed, which could be attributed to material property uncertainties or inhomogeneity. Additionally, some incorrect damage locations may have resulted from noise and environmental factors affecting the experimental modal analysis. Despite these challenges, the network demonstrated strong performance in localizing damage on the girder bridge, yielding reliable results.

4. Conclusion

This research addresses the limitations of conventional damage detection methods by employing vibration-based techniques, particularly focusing on artificial neural networks (ANNs) trained using mode shape curvature. It introduces an innovative and accurate approach to locating damage in steel girder bridge structures. Experimental modal testing provided vibration data under diverse damage scenarios, capturing both healthy and damaged conditions. The mode shape curvature was processed into damage indices, serving as inputs to ANN models for damage localization. The findings emphasize that damage induces substantial alterations in vibration characteristics, including natural frequencies and mode shapes, near damaged states. This deviation is efficiently captured by the ANN, demonstrating high accuracy in damage localization with marginal prediction error. By integrating mode shape curvature analysis with the predictive power of ANNs, this method enhances the reliability of structural health monitoring, offering a robust framework for the evaluation of steel girder bridge integrity. This approach plays a crucial role in advancing vibration-based diagnostics with practical applications in infrastructure maintenance.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

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