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Prediction of Damage Severity in Steel Bridges Using Natural Frequency Data and Artificial Neural Networks

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Abstract

Steel bridges are essential to transportation systems and must be regularly inspected to guarantee their robustness and safety. Conventional methods of identifying damage are subjective and time-consuming, frequently depending on manual inspections. This study aims to overcome these limitations by using Artificial Neural Networks (ANNs), which are sensitive to changes in mass and stiffness caused by damage, to predict the severity of damage in steel bridges based on natural frequency data. This research proposes a new method for detecting damage in steel girder bridges by integrating natural frequency data with ANNs. This vibration-based fault detection method addresses the shortcomings of traditional approaches by employing natural frequency as a dependable indicator of structural irregularities. An ANN model was trained and validated using an extensive dataset that included natural frequency data from experimental modal analyses conducted under various damage conditions. To assess the model's accuracy in predicting the severity of damage, its performance was studied on a different dataset. The findings indicate that ANNs can effectively analyze frequency data to accurately predict the severity of damage, reducing the reliance on manual inspections. In addition to improving the effectiveness of structural health monitoring systems, this strategy supports the robustness and safety of steel bridge infrastructure. Overall, the findings demonstrate that ANNs trained using modal curvature data provide a reliable and effective solution for early damage detection in steel girder bridges, substantially improving safety and operational performance. This novel approach advances the field of structural health monitoring and offers a valuable means of preserving the integrity of critical infrastructure, including steel girder bridge systems.

1. Introduction

Steel bridges are vital in civil engineering because they provide durable, strong and flexible structures capable of spanning long distances while supporting heavy loads efficiently. Their structural integrity may eventually be threatened though by aging, environmental conditions and ongoing load exposure. Time-consuming, expensive, and prone to errors are the traditional methods of evaluating bridge conditions which frequently depend on visual or manual inspections. Several methods have been applied for detecting structural faults. While visual inspections are widely used, they frequently miss problems that are not immediately visible, particularly in early-stage or hidden damage [1-4]. Therefore, continuous monitoring of structural performance, even in the absence of obvious defects, is crucial to maintain structural integrity. In recent years, artificial neural networks (ANNs) have become valuable tools for assessing structural damage, offering precise predictions of both the severity and location of damage in civil structures [5-7]. When provided with suitable input parameters and well-chosen training data, ANNs can accurately capture complex relationships. The ability of ANNs as a recent development in artificial intelligence to handle complex, non-linear relationships in data and produce precise predictions with little human intervention has shown great promise in structural health monitoring [8-10].

ANNs that apply vibration parameters have become increasingly popular in structural assessment due to their capability to detect patterns and handle data efficiently. For example, Nguyen and Wahab [11] proposed a novel technique that integrates the mode shape method with ANNs to identify damage in slab structures. Their approach not only precisely identifies damaged locations but is also straightforward to implement, without necessitating in-depth knowledge of structural behavior. Similarly, Tan et al. [12] developed a method to determine both the location and severity of damage in steel beams by integrating modal strain energy with ANNs, using damage indices as inputs to demonstrate accurate damage detection. In another research, Chang et al. [13] employed ANNs to identify damage in a steel-frame building through analysis of dynamic parameters, achieving precise detection despite variations in stiffness. Gu et al. [14] combined ANNs with novelty detection to evaluate changes in modal frequencies caused by temperature-related damage, providing reliable damage evaluations. Additionally, Aydin and Kisi [15] used vibration data, specifically the first four natural frequencies, as inputs to ANNs for effective detection of beam cracks. Ravanfar et al. [16-17] suggested a technique for damage detection that combines information entropy and wavelet packet transform. Structural response signals were broken down using the wavelet packet transform, and information entropy measured the signals' complexity and variations, suggesting possible harm. These studies showed how well this method works to precisely identify damage, providing a strong method for structural health monitoring.

A fuzzy-based artificial intelligence method for identifying structural degradation was presented by Hakim et al. [18-19]. The approach analyzes structural response data and accurately locates damage by combining fuzzy logic with sophisticated computer algorithms. The study demonstrates how well this method works to enhance structural health monitoring and offers a trustworthy instrument for identifying problems and scheduling maintenance. In a study done by Paridie [20], an analysis is carried out to determine the extent of damage to which the location of the preload affects the natural frequencies of the beam. Subsequently, an ANN is used in order to predict the natural frequency of the beam with respect to beam cross-sections, preload, and preload distribution. The extent of the effectiveness of the ANNs predictions is evident from the comparison with results from the FEM-based modeling. In general, the results are in reasonable agreement with each other. FEM has also demonstrated that the natural frequency reduces for equivalent beam cross-section and preload magnitude as the position of the preload moves closer or nearer to the end of the beam where it is rigidly fixed as a cantilever.

In recent years, the use of ANNs combined with modal parameters for structural damage detection has gained considerable attention, with numerous studies exploring the application of vibration data to train ANNs for assessing damage in various structures [21–28]. Despite these advancements, challenges persist, particularly in accurately evaluating structural damage through the integration of natural frequencies and neural networks. This study seeks to address these gaps by evaluating the effectiveness of ANNs trained on natural frequencies from experimental modal analysis of both intact and damaged steel girder bridges for damage severity. In particular, the research examines the limitations of conventional approaches, highlighting vibration-based detection methods and emphasizing natural frequencies as a reliable and precise tool for identifying structural damage.

2. Methodology

Using changes in natural frequency data, this study suggests a methodology that uses ANNs to model the severity of damage in steel bridges. Natural frequencies are good indicators of dynamic behavior and are strongly impacted by changes in a structure's mass or stiffness. The extent of structural damage can be assessed by monitoring changes in these frequencies. ANNs provide an effective framework for interpreting variations in natural frequencies to assess the extent of structural damage, owing to their ability to model complex and nonlinear relationships. The methodology involves collecting natural frequency data from steel bridge models subjected to various damage scenarios. This data is then used to train, validate, and test the neural network model, thereby enhancing the accuracy of damage detection and severity prediction. Natural frequencies are critical indicators of structural condition because they are directly influenced by changes in mass, stiffness, and boundary conditions caused by damage. As structural damage progresses, reductions in stiffness typically lead to measurable shifts in natural frequencies, allowing not only the detection of damage but also the assessment of its severity. Monitoring these frequency variations provides a reliable, non-destructive, and global approach for evaluating structural

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integrity, making natural frequencies particularly valuable in vibration-based structural health monitoring systems.

2.1 Artificial Neural Networks

The architecture and operation of the human brain serve as the inspiration for artificial neural networks. Similar to the brain, which is a highly parallel, nonlinear and adaptive computing system, ANNs use interconnected units called neurons to process information. To mimic human-like learning processes, these neurons modify their internal structures and learn from examples [29]. Figure 1 presents a schematic of the ANN architecture, showing how information is transmitted from the input layer through the hidden layer to the output layer. Figure 1 depicts a multilayer neural network structure consisting of an input layer with five neurons, a hidden layer with three neurons, and an output layer with four neurons.

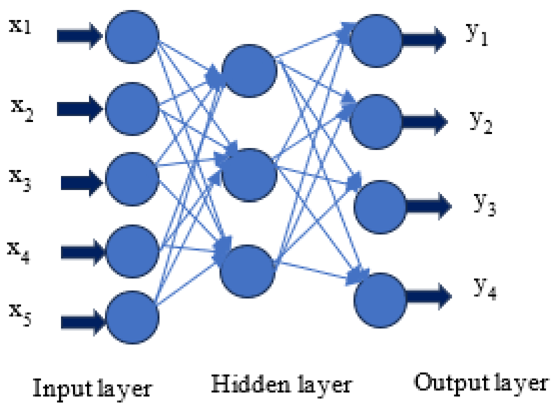

Fig. 1 *A sample of multi-layer neural network architecture with three layers*

Backpropagation is a widely used algorithm in multilayer networks due to its effectiveness in modeling complex problems [30-31]. In structural damage detection, the Multi-Layer Perceptron (MLP) is commonly employed, with its performance typically evaluated using metrics such as Mean Square Error (MSE), which measures the difference between predicted and actual outputs. The backpropagation (BP) algorithm minimizes the MSE through a gradient-descent optimization process, iteratively updating network weights by following the negative gradient of the error across all input patterns. ANNs offer notable advantages, including robust damage detection capabilities even in the presence of imperfect or noisy training data. Moreover, ANNs progressively improve their diagnostic performance through continued training, enhancing accuracy over time as they learn from new data inputs [32-33].

This study utilizes the Orange toolbox to perform the training, testing, and validation of the ANN model. The Neural Network widget in Orange toolbox, which is based on scikit-learn, enables users to construct models with programmable parameters like hidden layers, activation functions, and optimization strategies. With Python scripting, advanced users can expand orange's capabilities and integrate platforms like TensorFlow or PyTorch for complex applications. Because of this, Orange is a useful tool for researchers and machine learning consumers to gain insights and facilitate data-driven decision-making. Tools for managing, cleaning, and getting data ready for analysis or transformation are available in the orange toolbox's Data group. The File widget allows users to import data from a variety of sources, including CSV, Excel, and repositories. These widgets serve as the cornerstone of any orange workflow, guaranteeing more efficient and clean datasets for analysis.

Strong preprocessing features offered by Orange software allow users to scale, normalize, reduce, encode, and create features, among other operations to change and get data ready for analysis. These tools make use of sophisticated algorithms like t-SNE [34], in addition to feature scaling techniques frequently found in scikit-learn libraries. While Box Plot compares data distributions across categories, Scatter Plot shows correlations between two numerical values. Orange's Model category is dedicated to developing machine learning models for tasks involving prediction. It contains training tools for algorithms like Tree, which creates decision trees for regression or classification, and Neural Network, which is perfect for identifying relationships. With the help of these tools, users can build, train, and optimize models according to their goals and data.

2.2 Model Setup

A steel girder bridge model served as the experimental test specimen in this study. In Figure 2, the model is depicted as a plate with length, width, and thickness of 1200 mm, 210 mm, and 5 mm, respectively, with a 100 mm overhang at both support ends. As seen in Figure 2, three stiffeners, each measuring 1200 mm by 50 mm by 5 mm in length, height, and width, were affixed along the plate's length.

(a) **(b)**

Fig. 2 *Test specimen (a) View from above; (b) View from below*

Different damage scenarios were presented for the bridge girder in the experimental study. Each of the seven locations in these scenarios had 25 different levels of severity. Investigations were conducted into 175 cases of single damage. L/13, 2L/13, 3L/13, 4L/13, 5L/13, 6L/13, and L/2 of the span length were the seven damaged locations. The structure was subjected to 25 different levels of damage severity, each with a fixed width of 5 mm and a depth that varied from 2 mm to 50 mm with a 2 mm increment. The experimental modal analysis was conducted for all damage severities, starting from the middle stiffener's soffit at L/13th of the span length. Modal testing was carried out to identify the dynamic characteristics of the steel girder bridge. The initial phase involved testing the intact girder to extract its modal parameters, after which multiple damage scenarios were introduced by simulating faults of varying severity at different locations along the structure.

3. Results and Discussion

Results of the study on predicting the magnitude of damage in steel girder bridges using ANNs and natural frequency data are shown in this section. The results are examined to determine how well the ANN model predicts the severity of damage. The effectiveness of the model is assessed using performance metrics like error rates and predictive accuracy. With its user-friendly, graphical, drag-and-drop capabilities, Orange Data Mining software is used to preprocess data, train neural network models, and compare them with results from experiments. The method improves research accuracy and fosters developments in analytical and experimental techniques by bridging the gap between theoretical predictions and experimental data. The training datasets were generated via experimental modal analysis, which offered natural frequency data for single damage scenarios.

A total of 300 datasets, including both damaged and undamaged states, were used. The evaluation of damage prediction accuracy using ANNs involved a systematic multi-step procedure. The complete dataset encompassed a broad range of scenarios to reflect variability under real-world conditions. After preprocessing, the data were randomly partitioned into training, validation, and testing subsets, each containing a representative distribution of scenarios to minimize bias. Of the 300 total datasets, 210 (70%) were allocated for training, while the remaining 90 (30%) were used for validation and testing. Statistical analyses were performed on each subset to confirm adequate coverage of input parameter ranges. The ANN was initially trained using the training dataset, with performance monitored on the validation set, and early stopping was applied to prevent overfitting. Damage scenarios were simulated at seven different places, each with 25 levels of severity. Table 1 shows the equivalent reductions in the second moment of area (I) for each damage level. This approach illustrates the ability of ANNs trained with vibration data to accurately anticipate the severity of structural damage in scaled girder bridge deck.

ANNs have proven useful in assessing structural damage levels and locations. They can learn and improve utilizing a variety of datasets, even when trained on partially wrong data. When designed with the right input parameters, training data, and computational algorithms, ANNs may accurately map complex input-output relationships. This work looks into improving ANN approaches for determining damage levels utilizing dynamic structural behavior data, specifically natural frequencies. ANNs were trained, tested, and verified using vibration data derived from experimental modal analysis of healthy and damaged structures. Natural frequencies have been demonstrated to be reliable markers of damage severity. The quality and quantity of training data have a major impact on the performance of neural networks. Insufficient data restricts training, whereas abundant data might hinder efficiency. To provide credible forecasts, datasets must fully represent the problem environment, including balanced samples of both damaged and undamaged situations. Scaling input-output datasets reduces unpredictability in raw data and improves network performance. Accuracy depends on proper classification and dispersion of incoming data.

Table 1 *Loss of the second moment of area (I) for different damage severities*

Cut slot (mm)	I (%)	Cut slot (mm)	I (%)
2	11.5	18	73.78
4	22.10	20	78.40
6	31.85	22	82.44
8	40.73	24	85.94
10	48.80	26	88.94
12	56.10	28	91.48
14	62.67	30	93.60
16	68.55	-	-

In this study, the first five flexural natural frequencies of steel girder bridges were used, and 300 datasets from experimental modal studies served as the foundation for ANN training and evaluation.The ANN's output parameters, which indicate the degree of damage, were the ratio of the cross-section loss of the second moment of area for damaged to undamaged cases. Table 2 provides the damage severity index value based on various damage severities.

Table 2 *Damage severity index for the girder bridge deck*

Cut slot (mm)	DI	Cut slot (mm)	DI
2	0.8850	18	0.2622
4	0.7790	20	0.2160
6	0.6815	22	0.1756
8	0.5927	24	0.1406
10	0.5520	26	0.1106
12	0.4390	28	0.0852
14	0.3733	30	0.0640
16	0.3145	-	-

This study used the hyperbolic tangent activation function in the hidden and output layers of the ANN because it is suitable for damage identification problems. ANN designs with varied numbers of hidden layers and neurons were tested and assessed using metrics such as coefficient of determination (R^2), mean squared error (MSE), and absolute error (AE). The training process tried to reduce MSE, and it ended when the MSE reached 0.00001, or the maximum iteration limit of 80,000.

The study used the first five natural frequencies of steel bridge girders as input data, and the damage index values as outputs. Weights were iteratively adjusted until the ANN outputs roughly matched the goal values. The ideal network structure was discovered by trial and error, taking into account characteristics such as the number of hidden layers, neurons, activation functions, learning rate, and momentum.

Therefore, the architecture of the ANN in this study was constrained to include two hidden layers, resulting in a total of four layers in the network configuration. As a result, the chosen network architecture adopts a configuration of 5-12-6-1, comprising a total of four layers. The ANN model has high predictive accuracy, with MSE of 0.014, RMSE of 0.119, MAE of 0.042, and R^2 of 0.978**.** The mean absolute percentage error (MAPE) of 3.46% demonstrates minimal departure from the actual damage index, even for different damage levels.

The results further showed that the developed ANN attained its minimum error at a learning rate of 0.3 and a momentum value of 0.7. These parameters were determined through a series of preliminary experiments aimed at achieving optimal convergence and minimizing validation error. The learning rate was tuned to balance training efficiency and stability, while the momentum coefficient was adjusted to accelerate gradient descent and avoid entrapment in local minima. The final parameter values were selected based on the configuration that delivered the best overall performance in terms of accuracy and convergence, with training continuing until the error reached its minimum and the network stabilized.

The error metrics demonstrate that the model efficiently maps the dataset's nonlinearity, with errors close to zero and relatively consistent mean square errors over the damage index range. These findings outperform or coincide with earlier research, demonstrating the ANN's suitability for structural health monitoring. This technology is cost-effective, safe, and efficient, allowing damage assessment in steel bridge structures. Results showed a good correlation between ANN predictions and actual damage index values, which further validates the model's accuracy. Figure 3 shows a comparison between the damaged severity values identified by the ANN and the actual values for the training datasets.

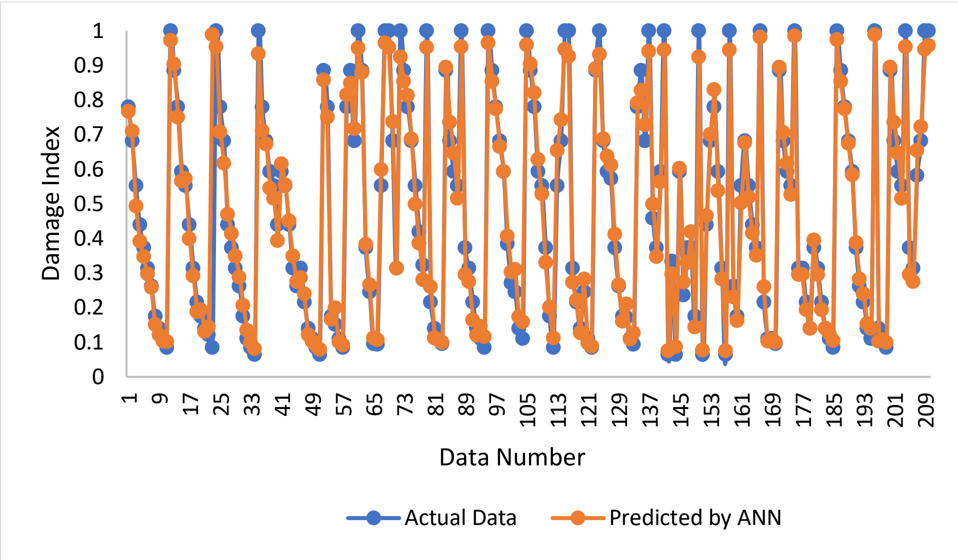

Fig. 3 *Damage severity identified by ANN and the actual values from training datasets*

Figure 4 uses a scatter plot to show the relationship between neural network predictions (x-axis) and actual damage index values (y-axis). The significant positive connection, with most points clustered along the diagonal, indicates the model's ability to predict damage indices in training datasets. These results demonstrates the effectiveness of employing ANNs to predict damage severity in steel girder bridges using natural frequency data. Figures 3 and 4 illustrate the comparison between the ANN-predicted damage index values and the corresponding actual values for the training dataset, which consists of 210 samples. Following the training phase, the network learned the underlying patterns in the data, enabling it to predict damage indices for new inputs with an acceptable level of error.

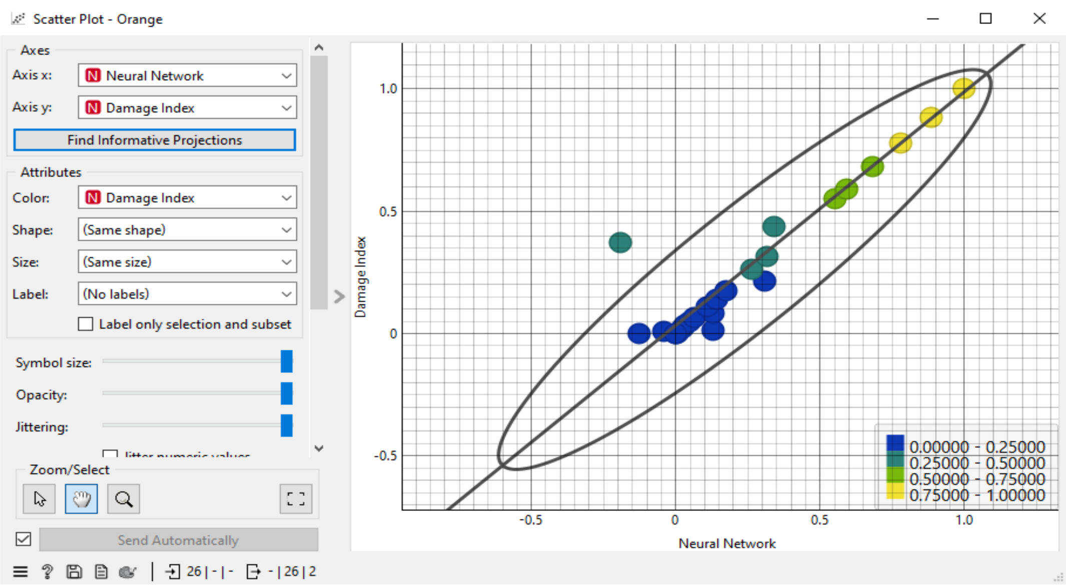

Fig. 4 *Scatter plot of the training datasets*

Once training was completed, the network was tested on new datasets that were not included in the training phase to examine its effectiveness in accurately predict the severity of damage within an acceptable error. The results of testing is shown in Figure 5. From the results shown in Figure 5, it is clear that the selected network matched inputs to outputs well, which means it has predictive value, demonstrating its ability to precisely capture the relationship between the variables.

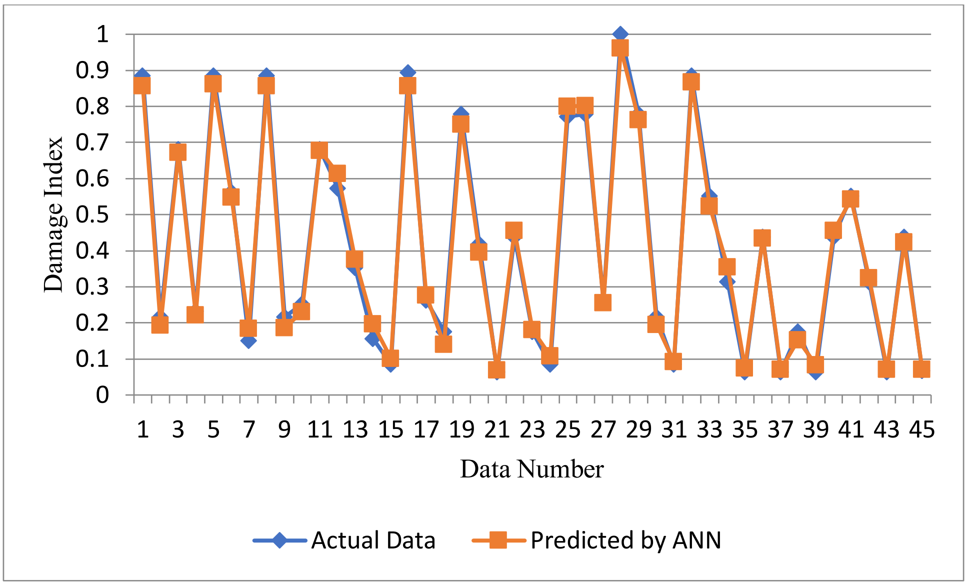

Fig. 5 *Damage severity identified by ANN and the actual values from testing datasets*

Validation datasets were performed to mitigate overfitting and to ensure the suitability of the selected ANN architecture for damage detection. Figure 6 compare the damage severity results predicted by the ANN with the actual values for the validation datasets.

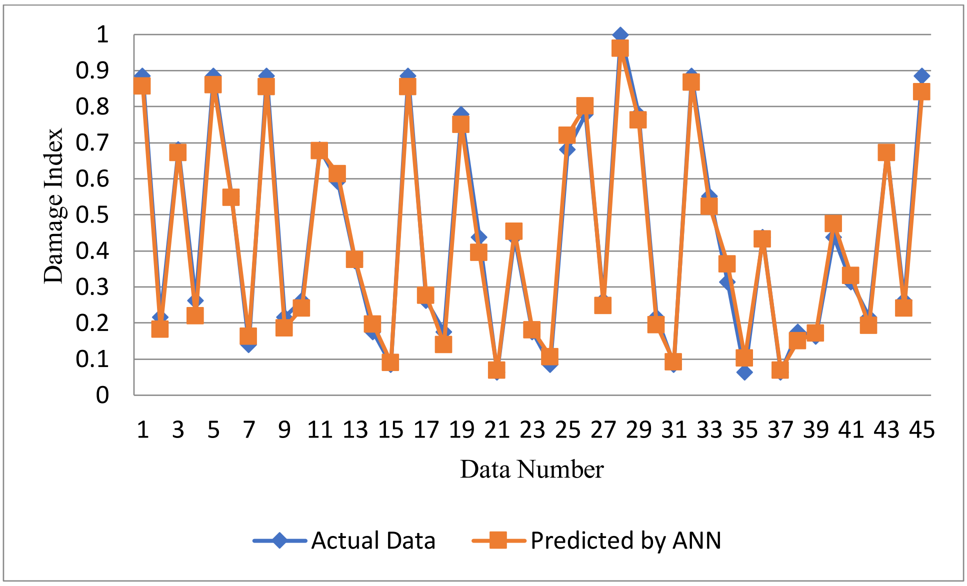

Fig. 6 *Damage severity identified by ANN and the actual values from validation datasets*

The damage severity evaluation across the training, validation, and testing datasets reveals a high level of agreement between predicted and measured values. The ANN effectively predicted damage severity, yielding Mean Square Error (MSE) of 0.0161 and 0.0169 for the testing and validation datasets. Furthermore, the correlation coefficient(R^2) of 0.965, and 0.9759 for the testing and validation datasets confirm the robustness of the model. Based on the testing and validation results, the model demonstrated strong performance, as evidenced by the close agreement between predicted and actual damage levels, indicating effective generalization to new inputs. The strong overlap between the predicted and actual curves underscores the potential of ANNs for structural health monitoring (SHM), particularly in identifying minor damage variations through frequency response analysis.

4. Conclusion

This study demonstrated the effectiveness of ANNs in predicting damage severity in steel bridges using natural frequency data. Variations in natural frequencies, which are highly sensitive to changes in structural stiffness, were successfully employed as input parameters for damage evaluation. The proposed ANN model was trained, validated, and tested using comprehensive datasets representing different damage scenarios, ensuring reliable performance and generalization capability.

The results showed a strong agreement between the predicted and actual damage severity levels across training, validation, and testing datasets, as evidenced by low prediction errors and high correlation coefficients. These findings confirm that the ANN can precisely capture the nonlinear relationship between frequency alterations and damage severity. Furthermore, the use of suitable training strategies, including hyperparameter tuning and early stopping, effectively avoided overfitting and heightened model robustness.

Overall, the outcomes highlight the potential of combining natural frequency-based indicators with ANN-based models as a practical and efficient approach for structural health monitoring of steel bridges. The proposed methodology offers a data-driven solution for early damage detection and severity prediction, which can support maintenance decisions and improve the safety and serviceability of bridge structures.

According to this study's findings, ANNs demonstrate strong capabilities to predict damage severity by identifying complicated patterns in structural response. Analyzing the results allows for precise damage predictions and strengthens the structural integrity. While ANNs are able to accurately capture overall damage trends, explicitly detecting failures remains a challenge. Enhancing model efficiency requires larger, various datasets and additional input parameters, such as real-time structural health monitoring data to improve predictive accuracy.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

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