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PERFORMANCE ANALYSIS OF DAMAGE IDENTIFICATION BASED ON VIBRATION IN CANTILEVER BEAMS USING ARTIFICIAL NEURAL NETWORKS

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Abstract. In this study, the effectiveness and potential of Artificial Neural Networks (ANN) and Genetic Algorithm (GA) optimization methods were evaluated in vibration-based damage detection applications in beam structures. Damage in the beam was modeled by reducing the stiffness (modulus of elasticity) in the corresponding elements. In the first stage of the study, a cantilever beam model was created using ANSYS Workbench software, and 1,000 different damage scenarios were randomly simulated using the Design of Experiments (DOE) method. This dataset was used to train the ANN. The performance of the trained network was evaluated on 10 different damage scenarios. In the second stage of the study, damage detection was performed based on GA optimization. For this purpose, an objective function that considers changes in frequency and mode shapes for two different states of the structure was minimized, and corresponding stiffness loss sets were searched. The Guyan reduction method was applied to the numerical model to compare limited observation results with those obtained from the finite element model. As a result, the performances of the ANN and GA methods were evaluated individually and compared with each other.

Keywords: *Artificial Neural Networks, Genetic Algorithm, Damage Detection, Structural Health Monitoring, Optimization, Finite Element Method*

Introduction: In the modern era, the safety and resilience of infrastructure systems have become one of the most critical issues in the field of engineering. To ensure human safety, prevent economic losses, and guarantee the long-term usability of structural systems, continuous monitoring of the health of existing structures has become an essential requirement (Farrar & Worden, 2012). Structural Health Monitoring (SHM) has been developed for this purpose and is used to continuously track structural performance, detect potential damage at an early stage, and analyze such damage.

Traditional SHM methods—such as visual inspections, acoustic emission, and ultrasonic testing—are widely used for monitoring structural systems. However, these methods have limitations such as high dependency on user experience, expensive equipment, and difficulties in application under certain conditions (Amafabia et al., 2017; Kahya et al., 2022). Therefore, in recent years, there has been a significant increase in interest in vibration-based damage detection methods, which are easier to implement and more economically viable. These methods are based on the principle that changes in a structure's elasticity and stiffness affect its modal parameters.

The application of advanced computational techniques—such as optimization methods, Artificial Neural Networks (ANN), Machine Learning, and Deep Learning models—has further enhanced the effectiveness of vibration-based damage detection approaches. The rapid advancement of technology has spurred increased research in this area, and particularly ANN methods have shown promising results in structural health monitoring and damage detection. In this context, the presented study investigates the identification of possible damage in cantilever beam structures using ANNs.

Within the scope of the study, a three-dimensional cantilever beam model was created in ANSYS Workbench using SOLID186 type finite elements. To simulate various damage scenarios within the structure, different damage levels were modeled by reducing the modulus of elasticity (E). The beam was divided into 10 elements, and the modulus of elasticity for each element was defined as $\hat{E} = (1-\alpha)E$. Here, the parameter α represents the damage severity, varying between 0 and 1; $\alpha=0$ indicates a healthy element, while $\alpha \neq 0$ indicates the presence of some degree of damage.

To effectively train the ANN model, 1,000 different damage scenarios were simulated in ANSYS. Thanks to this large dataset, the ANN model was able to predict both the location and severity of damage with high accuracy using vibration data. Thus, this study demonstrates that large datasets generated from numerical simulations play a significant role in enhancing the performance of ANN models and that a practical, economical, and reliable approach to structural health monitoring can be developed.

Methodology: In this study, a multilayer artificial neural network (ML-ANN) was used for detecting damage in a cantilever beam. For this purpose, the beam was first modeled using the finite element method, followed by simulation of damage scenarios, and then the performance of the multilayer artificial neural network was evaluated using various performance metrics. A detailed description of each step is provided below.

At the beginning of the study, a finite element model of a steel cantilever beam with a length of L = 1 m, width b = 35 cm, and height h = 25 cm was created. The modeling process was carried out using ANSYS Workbench software. In the three-dimensional model of the beam, SOLID186 type finite elements were selected. These elements have 20 nodes and 3 degrees of freedom at each node (Figure 1). To represent the damage in the beam, the modulus of elasticity of each element was modified. The damage was modeled by reducing the elasticity modulus in the form of $\hat{E} = (1-\alpha)E$. Here, the α parameter varies between 0 and 1 and represents the severity of the damage in the beam.

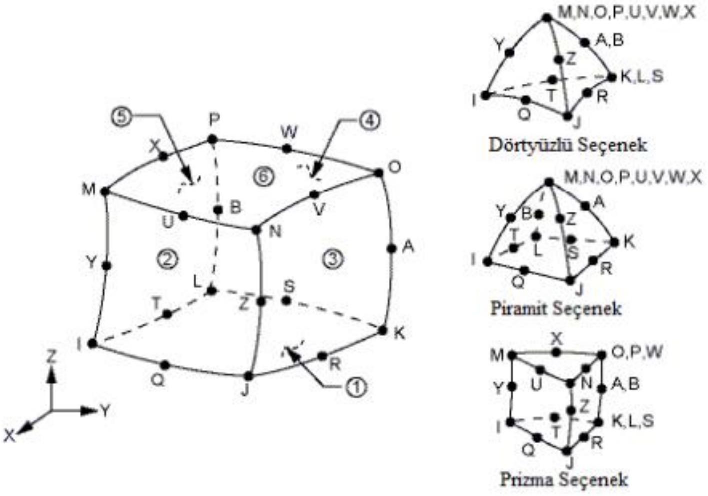

Figure 1. SOLID186 element (ANSYS, 2013)

In the undamaged condition, the modulus of elasticity of the beam was assumed to be $E = 2\times10^{11}$ Pa. Damage was introduced in each element of the beam with varying levels of severity. The modulus of elasticity assigned to each element randomly ranged from 1×10^{11} Pa to 2×10^{11} Pa. In this study, a total of 1,000 different damage scenarios were created.

The data obtained from the damaged beam using the finite element model were divided into three different sets to be used in the training, validation, and testing stages. Of these sets, 60% was allocated for training, 20% for validation, and the remaining 20% for testing. To ensure that the varying scales in the dataset did not complicate the optimization process, the data were normalized. The following equation was used for the normalization process:

$$\text{Normalization equation} = \left[\frac{\text{Raw value } - \text{Min value}}{\text{Max. valur} - \text{Min. value}}\right](0{,}9 - 0{,}1) + 0{,}1 \qquad (1)$$

In this equation, the x variables were normalized to fall between 0.1 and 0.9. After the training process was completed, the normalized data were transformed back to their original scale so that the results could be easily analyzed.

A multilayer artificial neural network (ML-ANN) architecture was constructed for damage detection. In this model, a variable number of hidden layers, ranging from 5 to 25, were placed after the input layer. The Levenberg-Marquardt (LM) algorithm was used for the training process of the model. The LM algorithm helps to speed up the learning rate of the network and obtain faster and more accurate results. It updates the network’s weights by minimizing the training function.

The performance of the ML-ANN model was evaluated using various metrics. For this purpose, the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Nash-Sutcliffe Efficiency (NSE) coefficients were used. Below are the definitions and calculation formulas for these metrics:

Root Mean Squared Error (RMSE):

$$\text{KHOK} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - yt_i)^2} \qquad (2)$$

Mean Absolute Error (MAE):

$$\text{OMH} = \frac{1}{N}\sum_{i=1}^{N}|(y_i - yt_i)| \qquad (3)$$

Nash-Sutcliffe Efficiency (NSE):

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N}(y_i - yt_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (4)$$

In these equations:
N- the number of samples,
y_i- the measured values,
yt_i- the values predicted by the model and,
$\bar{y}$- the mean of the measured values

The RMSE and MAE metrics indicate how closely the model's predictions align with the measured values. Lower values of RMSE and MAE indicate better fit of the model. The NSE is a more complex indicator that shows how well the model fits the measured values. When the NSE value is close to 1, it means the model perfectly fits the measured values. When the NSE is closer to 0, it indicates a weak model.

After the training process was completed, the performance values of the model, such as the number of hidden layers, learning rate, and momentum parameter, were analyzed to obtain the best results. Additionally, the NSE values obtained during the validation and testing stages of the model were compared. The best results were obtained with the model having 25 hidden layers. With this model, more accurate results were achieved even in regions closer to the ends of the beam. In regions near the ends of the cantilever beam, the accuracy level for the elements reached over 80% according to the NSE metric.

Analysis: The findings obtained from the analyses conducted on Multilayer Artificial Neural Network (ML-ANN) models with different numbers of hidden layers are presented in Figures 2-6 and Figures 7-11. When evaluating these results in general, it was observed that increasing the number of hidden layers significantly improved the model’s prediction performance. Specifically, as the number of hidden layers increased, the predicted values of the modulus of elasticity (E) were closer to the real observed values.

The low standard deviation (STD) values obtained in all models indicated that the predictions of the ANN models demonstrated high reliability and stability. However, a slight decrease in prediction accuracy was observed in elements near the ends of the beam. Increasing the number of hidden layers did not provide a significant improvement in prediction accuracy in these regions. Furthermore, the increase in the number of hidden layers significantly prolonged the computation time, which could reduce efficiency in practical applications.

Considering all these factors, a 25-layer hidden network was chosen as the optimal architecture for the ANN model. This model provided the best results both in terms of high prediction accuracy and practical computation time. The scatter plots related to the model are presented in Figure 11, where it is clearly seen that the model fits the observed values very well.

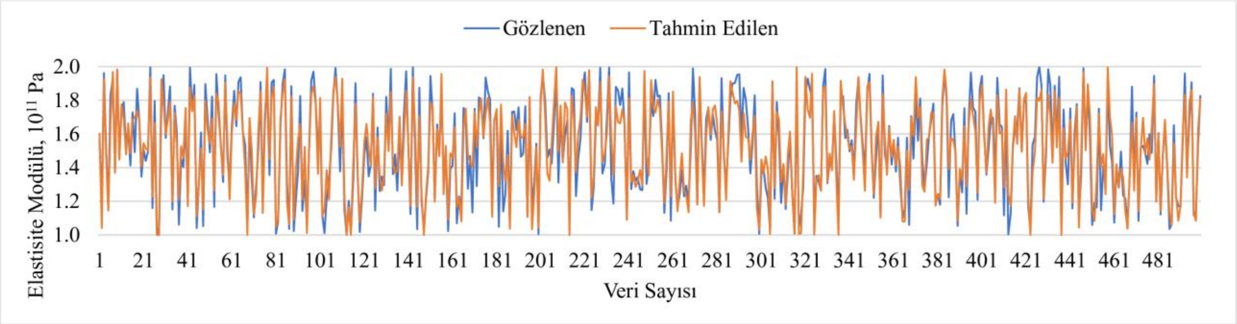

Figure 2. Time series of the prediction model obtained with a 5-hidden-layer ANN

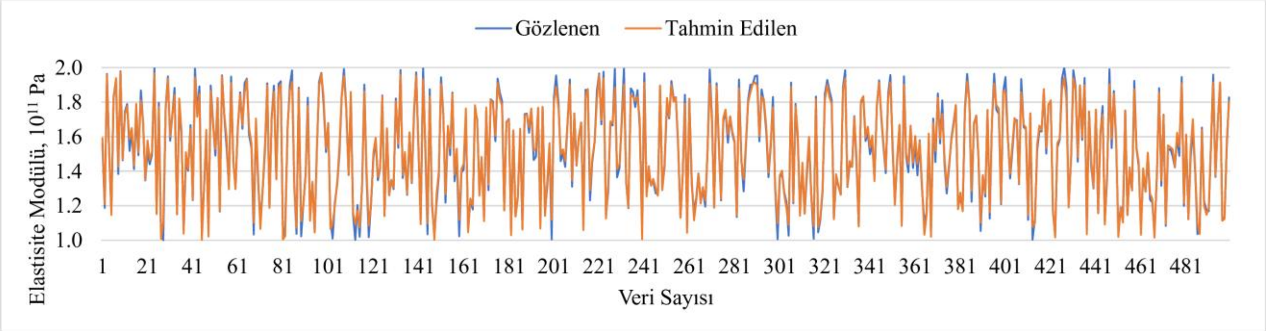

Figure 3. Time series of the prediction model obtained with a 10-hidden-layer ANN

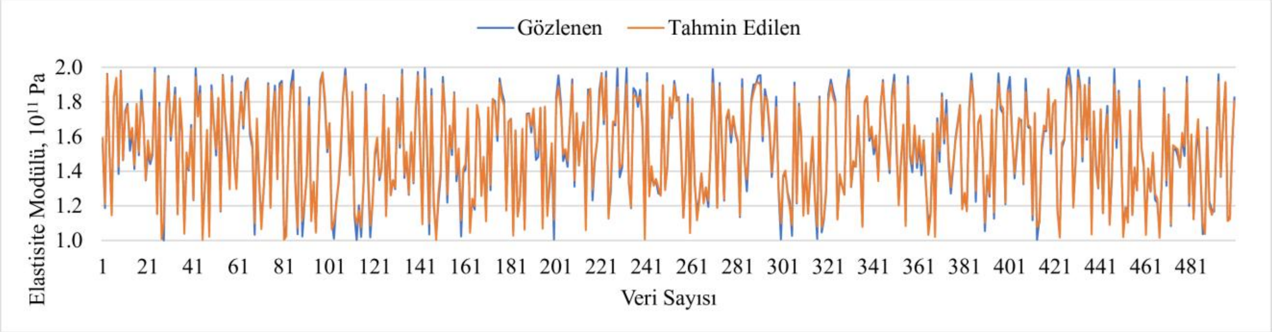

Figure 4. Time series of the prediction model obtained with a 15-hidden-layer ANN

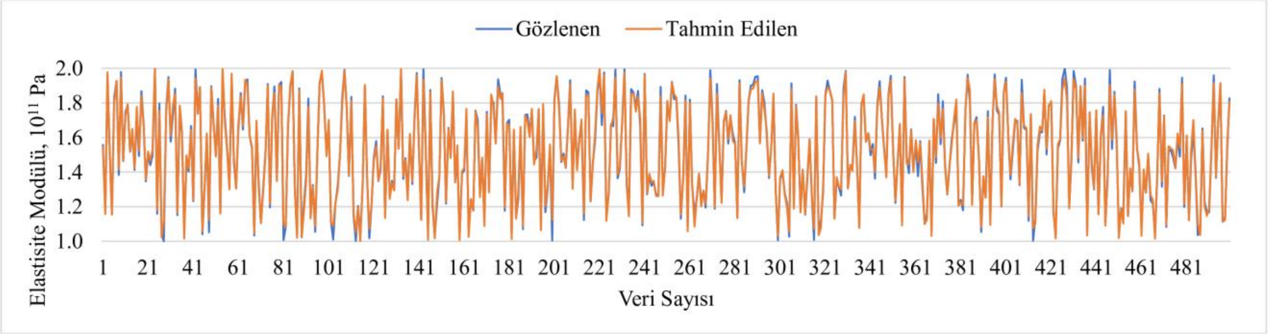

Figure 5. Time series of the prediction model obtained with a 20-hidden-layer ANN

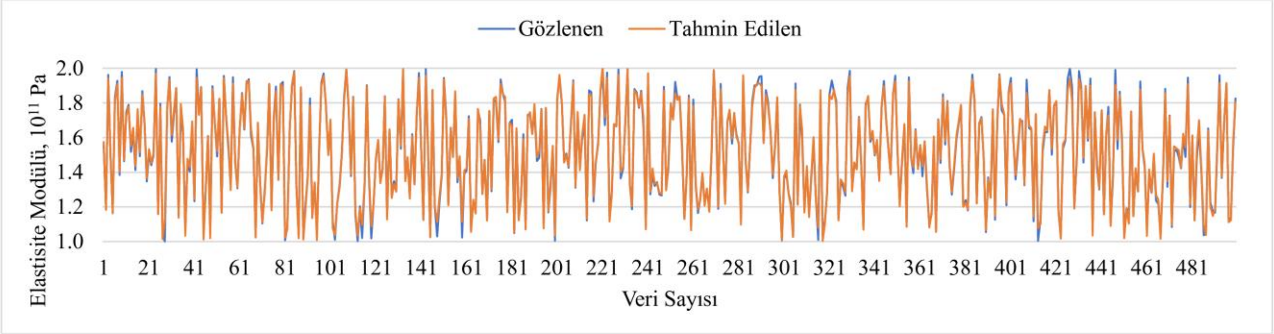

Figure 6. Time series of the prediction model obtained with a 25-hidden-layer ANN

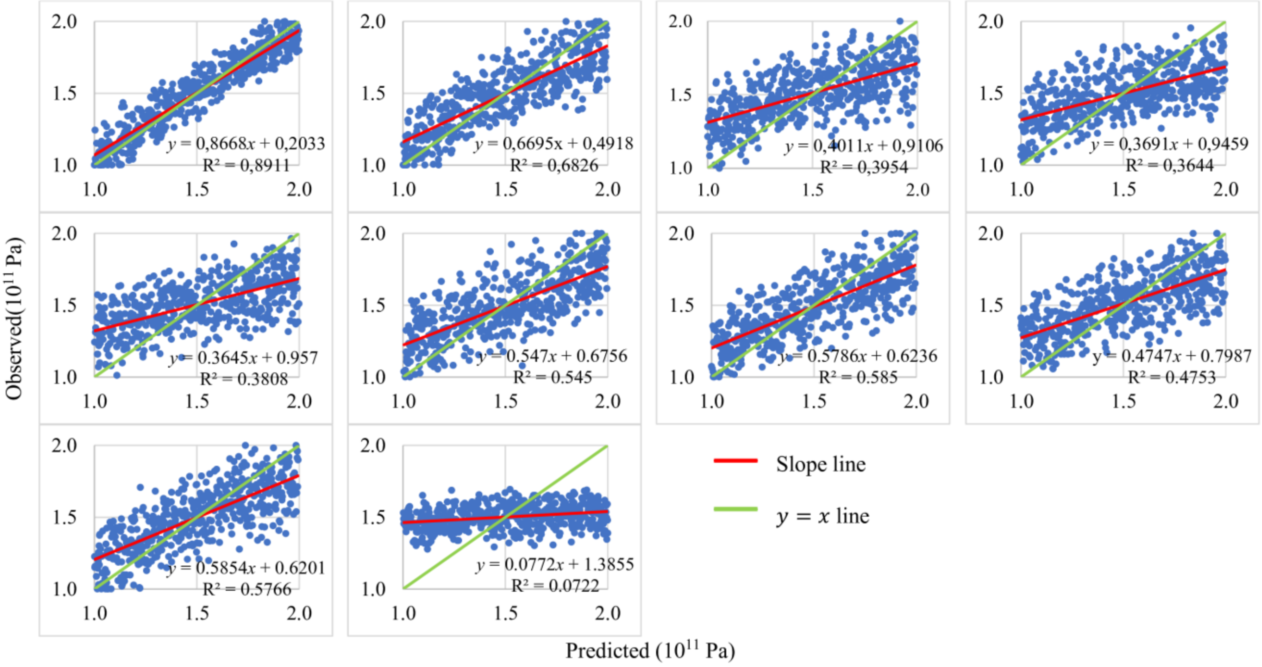

Figure 7. Scatter plots of the prediction model obtained with a 5-hidden-layer ANN

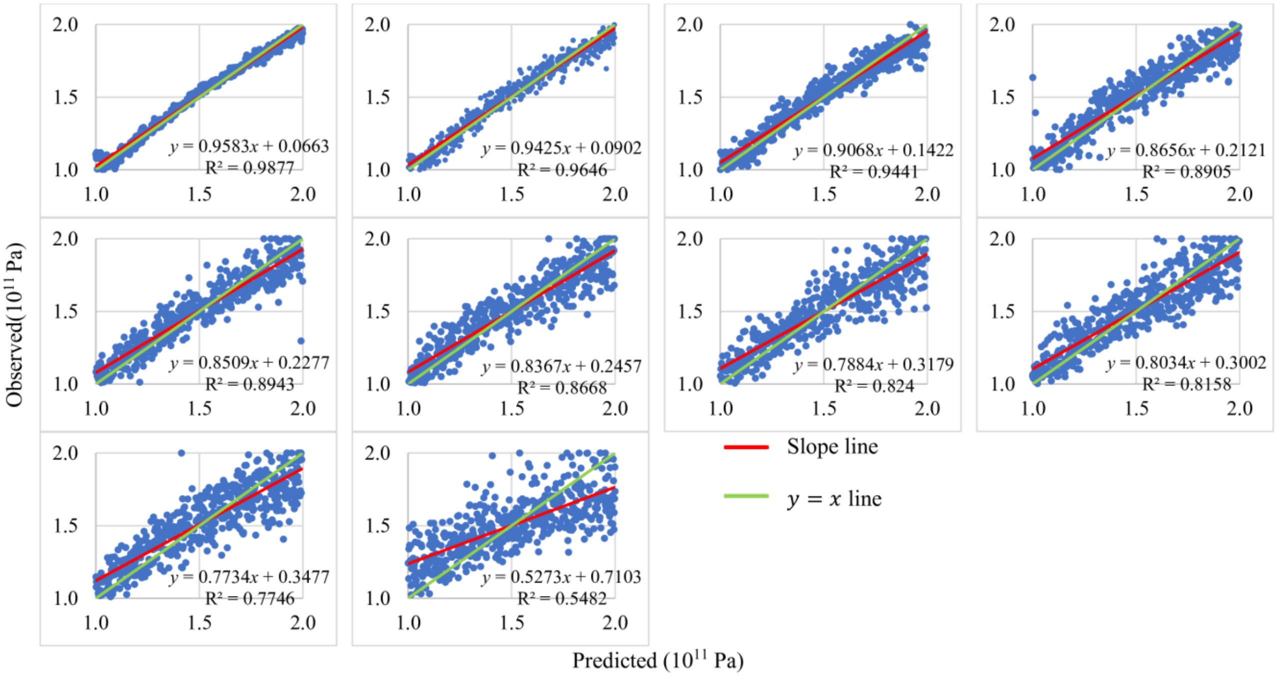

Figure 8. Scatter plots of the prediction model obtained with a 10-hidden-layer ANN

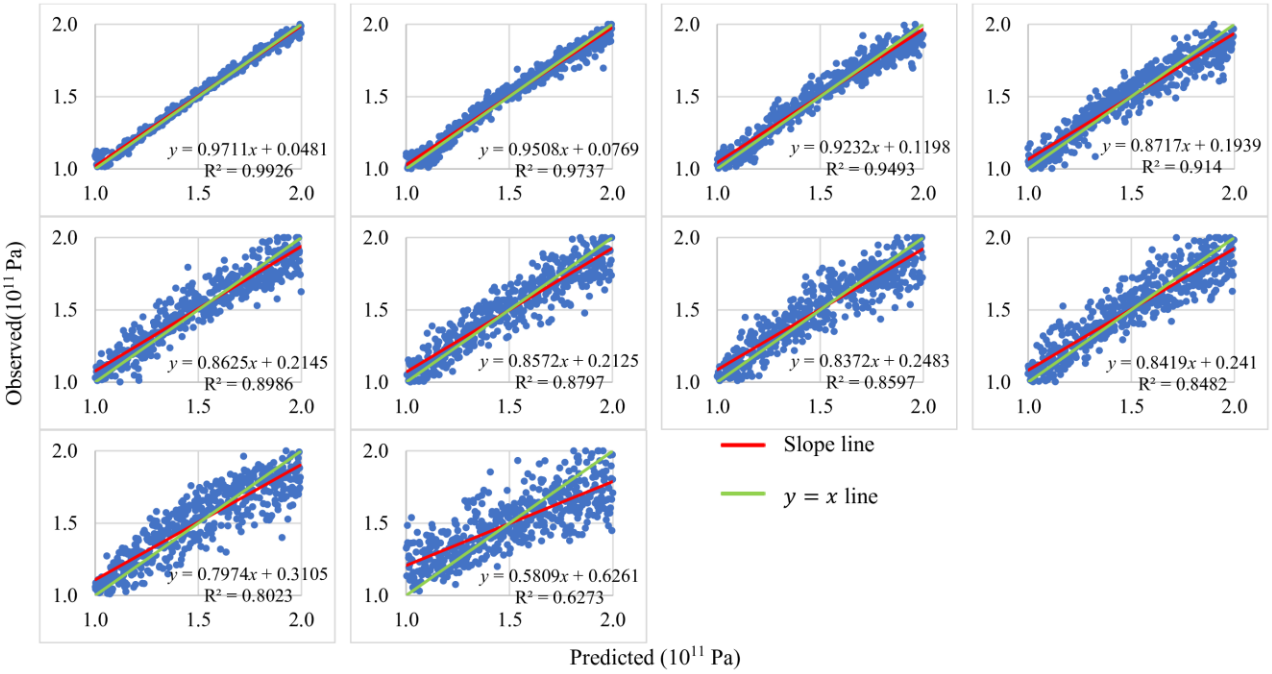

Figure 9. Scatter plots of the prediction model obtained with a 15-hidden-layer ANN

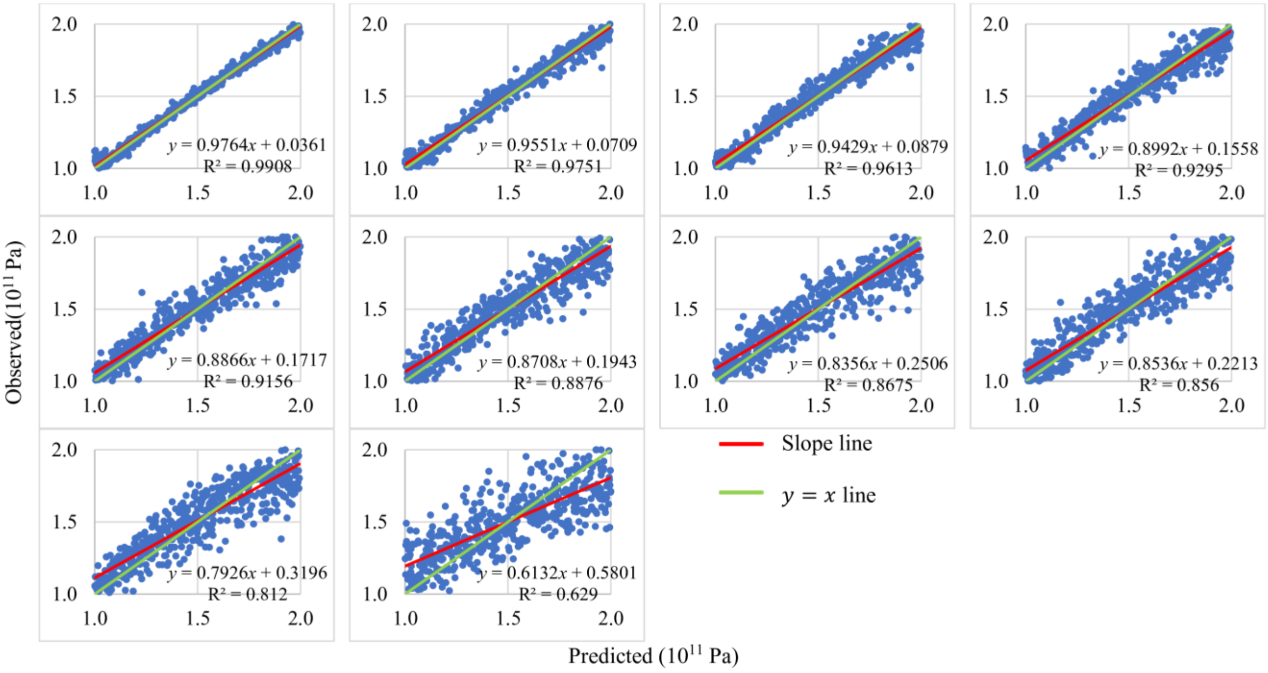

Figure 10. Scatter plots of the prediction model obtained with a 20-hidden-layer ANN

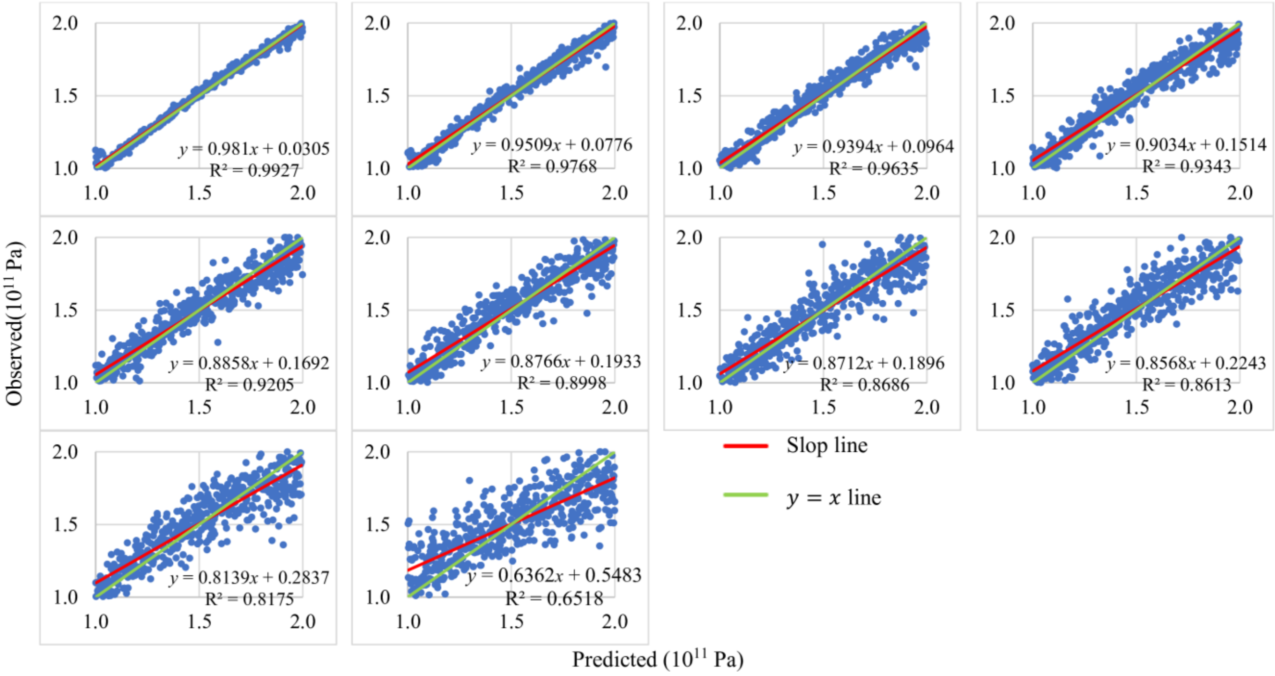

Figure 11. Scatter plots of the prediction model obtained with a 25-hidden-layer ANN

The decrease in prediction performance near the ends of the beam is due to several key reasons. First, the free end of the beam has less stiffness due to boundary conditions, and the impact of changes in the modulus of elasticity is less measurable in this region. This results in the ANN model being unable to fully distinguish changes in the end regions during the training phase.

The second reason is related to the characteristics of the training data. In the training data set, damage scenarios were created completely randomly, and a certain damage value was assigned to all elements. Since there were no elements in a free or undamaged state, the model did not learn about undamaged conditions during training. As a result, the model's performance decreased in the end regions of the beam, where there were elements with small changes or in an undamaged state.

Additionally, in elements near the free ends, the amplitude of natural vibration modes is higher, meaning that local changes in these regions could cause more distortion in the overall response signal. This distortion can disrupt the learned relationships during training, weakening the model's prediction performance.

In conclusion, the lower prediction performance near the free ends of the beam resulted from both physical boundary conditions and the insufficient diversity of the training data. In future work, addressing these shortcomings could be achieved by developing more diverse and balanced training data sets that also include undamaged conditions.

Discussion. One of the main challenges encountered in this research on structural health monitoring based on vibration data for cantilever beams was the limited number of measurement points. In real structures, measuring all degrees of freedom presents technical and financial challenges, meaning that the data obtained from measurable degrees of freedom could not be directly matched with the full finite element model of the structure.

To overcome this issue, it was necessary to use model reduction techniques. One of the traditional and simple methods applied was the Guyan model reduction. The Guyan method, based on a static equilibrium approach, allowed the reduction of the number of degrees of freedom in the system while preserving the stiffness matrix of the structure.

This technique, while significantly reducing the analysis and computation time, caused some deviations in the accuracy of the system’s natural frequencies and mode shapes due to the neglect of dynamic effects. Nevertheless, the reduced models obtained provided sufficiently reliable results for matching with the available measurement data and damage detection.

This challenge became more pronounced, especially during the training of the Artificial Neural Network (ANN) models. Missing measurements from the full model limited the ability of the ANN to learn the entire system behavior. However, the analysis conducted on the data obtained through the model reduction approach proved effective for determining the health condition of structures.

Suggestions: Improving Performance by Including Undamaged Elements in Training Data

The results of the research indicated that the data set used in the training of the ANN models only included damaged condition scenarios. As a result, the ANN did not learn the healthy (undamaged) states and provided inaccurate results for identifying undamaged elements.

As a solution to this problem, it is recommended to apply an approach that includes both damaged and completely healthy states in the training data set. Such a methodology would allow the ANN model to differentiate more accurately between healthy and damaged elements, thereby improving the overall accuracy of the damage detection process.

At the same time, this approach is expected to bring the ANN performance closer to the high-performance levels obtained with Genetic Algorithm (GA) optimization.

Additionally, the development of more systematic and diverse scenario generation methods for creating training data sets presents significant future prospects. This will be especially important for improving the ANN’s learning capability in modeling various boundary conditions and damage types.

Ultimately, the correct model reduction approach, considering measurement limitations, and the creation of a wide-ranging training data set will significantly improve the performance of machine learning methods used in structural health monitoring processes.

Results:

1. In this research, two major innovations were introduced in the field of structural health monitoring:

2. Systematic Evaluation of ANN Training with Large-Scale (1000 Samples) Stochastic Damage Data in ANSYS

3. In previous works, the data used for structural health monitoring were typically based on a limited number of damage scenarios. In this study, however, 1000 different damage scenarios covering random and various levels of damage were generated using the "Design of Experiments" module of the ANSYS Workbench program.

4. This dataset provided a broad and diverse set of examples for training the ANN, thereby enhancing the model's ability to learn various damage conditions.

5. This approach contributed significantly to the field by providing a learning environment that not only covered specific and limited damage cases but also encompassed a broader damage space.

6. The results obtained showed that the extensive and stochastically generated training data not only improved the ANN's damage detection performance but also facilitated the development of more generalizable and robust models.

7. Comparative Analysis of ANN Performance in Different Regions of the Beam (Tip vs. Mid-section)

8. In this work, a detailed comparative analysis of ANN performance in different regions of the beam was conducted.

9. The analysis results showed that in regions closer to the middle of the beam, the ANN's damage detection performance was higher (with accuracy of approximately 90% or more). Conversely, in regions near the free end of the beam, the performance was relatively lower (with accuracy of less than 90%).

10. This difference arises from the more complex and mixed vibration modes at the free end of the beam, making it more difficult for the ANN to learn the changes in vibration data caused by damage.

11. This observation highlights the importance of giving specific attention to the region when preparing measurement strategies and training datasets for beam structures in future work.

12. These two major innovations highlight the importance of creating large-scale datasets and conducting region-specific performance analyses in the field of structural health monitoring, thereby establishing new directions for future research.

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