Wesleyan Scientific Review

Wesleyan University-Philippines
journals.wesleyan.edu.ph

ISSN Online: 2945-4085

Application of Artificial Neural Networks in Beam Damage Diagnosis

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Abstract

This paper studies the application of Artificial Neural Networks (ANN) to diagnose cracks in beam structures. In this study, FGM beams are considered. This prediction method is based on input parameters to find the parameters of cracks, which are location and depth in the beam structure. In this study, vibration characteristics are used as input parameters for ANN to give output results. The prediction results from the Neural Network method are compared with previously measured data by experimental methods to evaluate the effectiveness of this method in diagnosing damage in beam structures. This study aims to evaluate the accuracy and effectiveness of the ANN method in solving the current problem of detecting structural damage.

Keywords: Artificial Neural Network (ANN), Crack Diagnosis, Beam Structures, Vibration Characteristics.

How to cite this paper. Ho, Q.Q., Nguyen, T.L., Le, K.T., Nguyen, T.K. (2025). Application of Artificial Neural Networks in Beam Damage Diagnosis. Wesleyan Scientific Review 3(1).

http://doi.org/10.54788/wsr.v3i1.107

Received: November 25, 2024
Reviewed: February 26, 2025
Accepted: April 4, 2025
Published: June 26, 2025

INTRODUCTION

Engineering diagnostics play an important role in ensuring the safety and durability of construction works. It helps to detect potential problems before they become serious, providing important data for timely maintenance and repair measures. This not only prolongs the life of the works and machinery but also helps to save repair costs and prevent unfortunate accidents. The structure is an important part of the architecture of construction work or machinery in engineering. Any change in the structure of a work compared to its original state (considered intact) is called structural damage. Structural damage can occur due to changes in the properties of materials, geometry or connections in the structure of the work. These damages often reduce the load-bearing capacity and performance of the work or machinery. If not detected and handled promptly, they can lead to serious accidents, causing economic losses as well as affecting social safety.

In the modern context, the application of advanced technologies such as artificial neural networks in damage diagnosis brings higher efficiency, greater accuracy and better forecasting ability, thereby improving the quality and reliability of the project. Artificial Neural Network (ANN) is a part of the field of artificial intelligence; it simulates human thinking and is assisted by computers, thus overcoming the limitations of conventional mathematical models. ANN in structural damage diagnosis is a model that connects the input (measured data) with the output (damage parameters to find). This relationship is built using machine learning tools and optimization algorithms, approximating human inference. Among structural damage identification methods applied in recent years, thanks to their strong computational power and ability to detect structural deformations, ANNs have been widely used. Features such as natural frequencies are often input into ANN models; after training, results are tested, compared, classified, and predicted regarding damage status within allowable error bounds. In vibration-based damage diagnosis, Frequency Response Function (FRF) is often used as input to backpropagation neural networks (BPNNs). The ANN predictions are then compared with experimental results, typically yielding acceptable error levels. Some studies propose hybrid methods combining Neural Network and Wavelet Transform to detect cracks in beams; input parameters derive from vibration patterns (e.g. via finite element simulation) and produce high-accuracy predictions of damage condition.

Recent advances further push the frontier of structural health monitoring (SHM) by integrating machine learning, deep learning, physics-guided networks, and explainable AI into damage diagnosis workflows. For instance, recent work has provided a comprehensive review of machine learning–based structural health diagnosis, discussing challenges like incomplete monitoring data and multi-modal fusion, and highlighting trends in digital twin and reliability assessment integration. In beam damage detection, a two-stage method combining displacement difference analysis and an ANN has been proposed to localize and quantify damage with positional errors under ~1.4% and severity errors ~2.8%. Another study introduced a physics-guided residual neural network (PhyResNet) to enhance robustness and accuracy in structural damage identification by embedding physical constraints within the learning process. A convolutional neural network (CNN) group framework has also been developed to handle sensor faults by diagnosing abnormal sensors and excluding their data before damage inference, achieving near-perfect accuracy in controlled tests. Furthermore, recent works explore explainability: techniques from explainable AI (XAI) have been incorporated into convolutional damage diagnosis frameworks to interpret model decisions and improve trustworthiness. Also, the concept of unsupervised or semi-supervised damage detection is gaining traction like for example, an unsupervised quantitative damage identification method has been proposed that does not rely on labeled damage data, helping reduce dependence on expensive ground truth data.

The purpose of this study is to emphasize the application of advanced technologies in mechanics, specifically focusing on the use of artificial neural network models (and potentially their hybrid or physics-augmented variants) to diagnose damage in beam structures, leveraging both classical and contemporary techniques.

METHODOLOGY

Artificial Neural Networks

Artificial Neural Network (ANN) is an information processing model consisting of artificial neurons that operate and process similarly to biological neurons in the human brain. ANN is formed from a large number of neurons connected together in a layered structure. The most commonly used ANNs are Multilayer Layer Perceptron (MLP) and Radial Basis Function (RBF).

Figure 1 shows node i as an artificial neuron in an MLP network. The neuron consists of inputs xk with corresponding weights wki, bias i and transfer function f (or activation function) [16]. The transfer function is used in common for all layers. The choice of transfer function depends on the type of problem that needs to be solved by the ANN network, in which the Sigmoid and Tan-Sigmoid transfer functions are often used in MLP

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networks using backpropagation algorithms for training due to its continuous differentiability (Figure 2). The neuron will perform the sum of the products of input values x1,…,xk with the corresponding weights wki and add the bias wki . The weights and biases are random numbers at network initialization and they are updated during the network learning process. The result ni is the input value for the given transfer function f. The output of node i is

$$y_i = f_i = f\left(\sum_{j=1}^{k} w_{ji} x_j + \theta_i\right) \qquad (1)$$

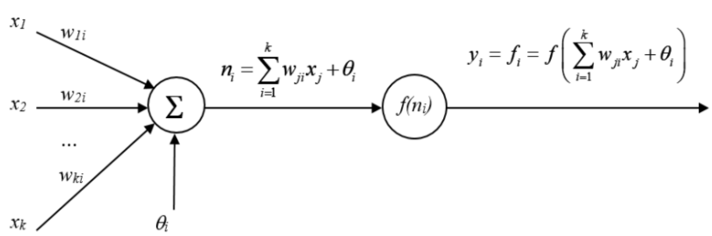
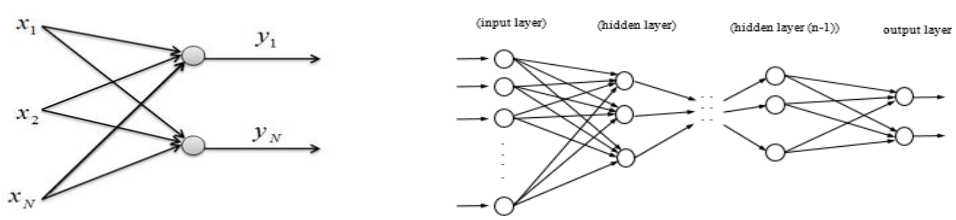


Figure 1: An artificial neural network node in an MLP network

Connecting neurons in parallel and serial patterns will form an MLP (Multilayer Layer Perceptron) network. An MLP network consists of an input layer, a number of hidden layers and an output layer. Based on the number of layers and the connections between the layers, ANNs can be divided into different groups [16]:



(a) (b)

Figure 2: Single-layer network (a) and multi-layer network (b) structure.

Figure 2b shows a typical MLP network consisting of k inputs, 1 hidden layer with 3 neurons, and an output layer with 2 neurons with transfer function f. The output value y_i , $i=1,2$ of this MLP network is:

$$y_i = f\left(\sum_{j=1}^{3} w_{ji}^2 f(\mathrm{n}_j^1) + \theta_j^2\right) = f\left(\sum_{j=1}^{3} w_{ji}^2 f\left(\sum_{j=1}^{k} w_{kj}^1 x_k + \theta_j^1\right) + \theta_j^2\right) \qquad (2)$$

Thus, the MLP network is a nonlinear mapping from the input space $\mathbf{x}\in\mathbf{R}^k$ to the output space $\mathbf{y}\in\mathbf{R}^m$. The ANN network parameters that need to be determined are the weights w_{ji}^k and biases θ_j^k . The transfer function f is often assumed to be known and the same in the ANN network.

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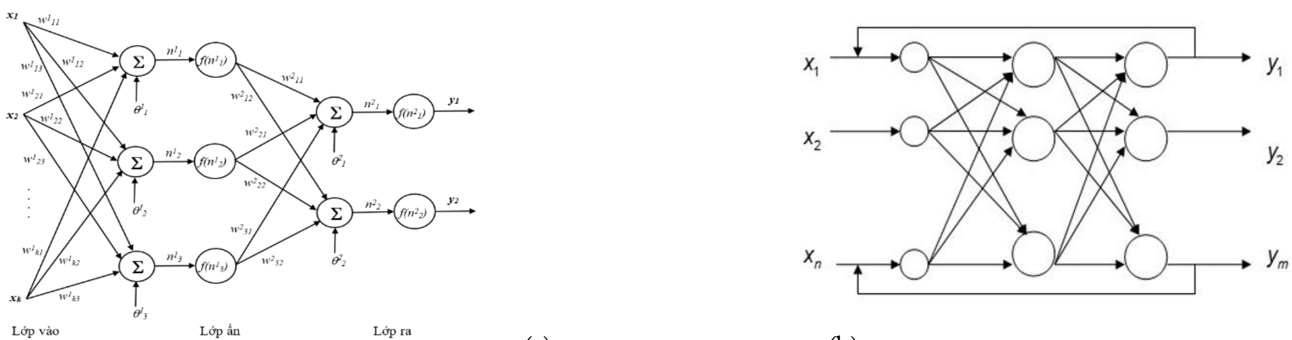

(a) (b)

Figure 3: (a) Multi-layer MLP network with one hidden layer, (b) Recurrent network

Feedforward neural networks: The data flow from the input layer to the output layer is only transmitted straight, without any backward connections as shown in Figure 3a, 3b.

Recurrent neural network: Recurrent networks, also known as feedback networks, contain backward connections, meaning there is a connection between the output neurons and the input neurons as shown in Figure 3b. ANNs retain previous states, and the next state depends not only on the input signals but also on the previous states of the ANN.

The functionality of an ANN is determined by the network architecture (number of layers, number of neurons in each layer and how the layers are connected) and the network parameters w_{ji}^k, θ_j^k. For each problem, the network structure is usually determined in advance, and the values of the network parameters are determined later by learning or training algorithms. This is the process of determining the most optimal network parameters so that the ANN network can establish the relationship between the input and output according to the desired function, similar to the parameter estimation algorithm in technical diagnostic problems.

There are many algorithms used to train ANN networks, of which the back-propagation algorithm is commonly used. This is an ANN network training method to determine the most optimal parameters through the repeated calculation of 2 processes: Forward propagation to calculate the output value of the network, from which the error between this value and the desired value is calculated; Backward propagation of errors is based on the error to update the parameters using the algorithm based on gradient descent and the Levenberg - Marquardt algorithm [16, 17]. The correlation between the number of hidden layers in the model and the output error will be inversely proportional, meaning that the more hidden layers there are in the ANN model, the smaller the error will be. But there cannot be too many hidden layers because it will consume memory and slow down the calculation process. The MLP network training process includes 4 sequences as follows: first is determining the network structure, choosing the operating function. Initializing the network parameters w_{ji}^k, θ_j^k. Next is to choose the parameters related to the training algorithm such as the desired error, the maximum number of samples (iterations) to call the training algorithm. After the network is trained, the results are tested by simulating the output value of the network with measured input data. This result is compared with the measured output. The final accuracy of the network must be determined through independent data.

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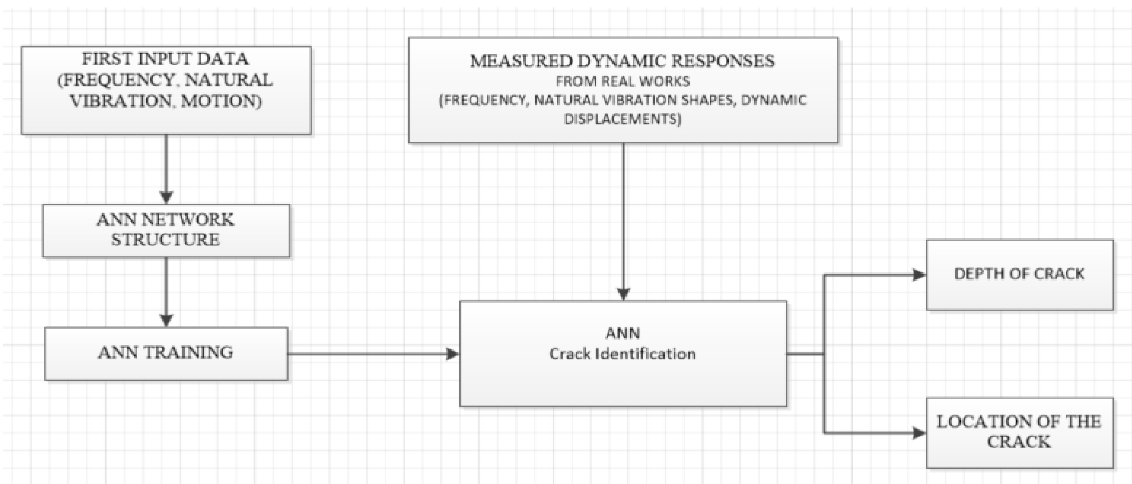
Crack Diagnosis Using Ann

The problem of crack diagnosis consists of two main stages. The first stage is to prepare suitable and accurate data sets that can be used to train the network. The second stage is to link the input and output data (including the location and size of the crack). ANN is used as a tool to solve the inverse problem to find the damage parameters of the structure. Ideally, this data set should be taken from the actual response data of the test results in the structural model or through the numerical model or a combination of all these types of data sets [18]. Figure 4 shows the application of ANN to diagnose the location and depth of cracks on FGM beams with input data being frequency, natural oscillation mode, dynamic displacement or SWT analysis of natural oscillation modes.



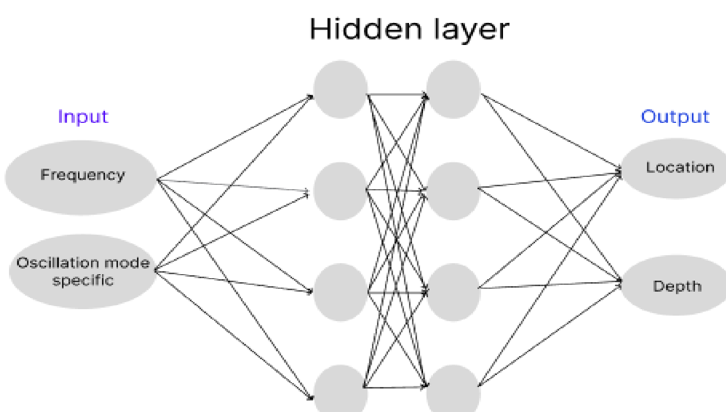


Figure 4: Diagram of crack diagnosis method using ANN

Structural model of an ANN with 2 inputs with corresponding activation functions x_1 , x_2;

Formula for calculating the output of the corresponding hidden neuron at the jth position:

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$$k_j = f(\omega_{j1} * x_1 + \omega_{j2} * x_2 + b_j). \qquad (3)$$

Where: ω_{j1}, ω_{j2} is the connection weight and with the jth hidden neuron j , f is the bias coefficient of the jth hidden neuron, is the activation function of the hidden layer.

Each neuron in the output layer receives input from the neuron in the hidden layer through different weights to generate Y_1, Y_2 .

$$Y_1 = g(\omega_{11} * h_1 + \omega_{12} * k_2 \ldots + \omega_{1n} * k_n + b_1^{'}) \qquad (4)$$

$$Y_2 = g(\omega_{21} * k_1 + \omega_{22} * k_2 \ldots + \omega_{2n} * k_n + b_2^{'})$$

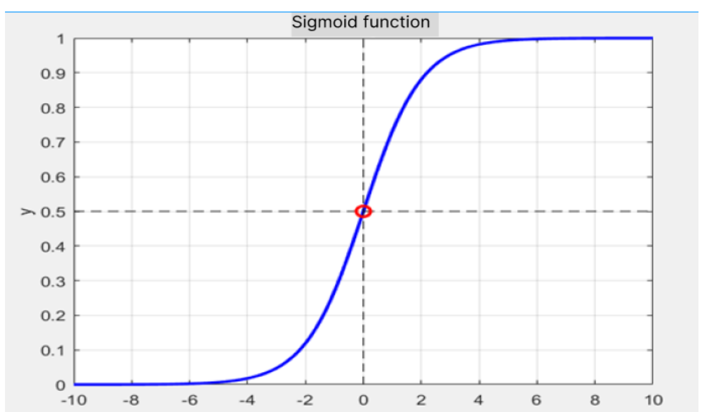
In which: $k_1, k_2, \ldots k_n$ is the output of the hidden layer neurons, g is the activation function.

In the specific case of a hidden layer with 2 neurons ($n = 2$) then the value k_1, k_2, Y_1, Y_2 .

$$\begin{aligned} k_1 &= \sigma(\omega_{11} * x_1 + \omega_{12} * x_2 + b_1) \\ k_2 &= \sigma(\omega_{21} * x_1 + \omega_{22} * x_2 + b_2) \end{aligned} \qquad (5)$$

$$\begin{aligned} Y_1 &= \sigma(\omega_{11}^{'} * k_1 + \omega_{12}^{'} * k_2 + b_1^{'}) \\ Y_2 &= \sigma(\omega_{21}^{'} * k_1 + \omega_{22}^{'} * k_2 + b_2^{'}) \end{aligned} \qquad (6)$$

With sigmoid $\sigma(x) = \frac{1}{1+e^{-x}}$



Hình 5: Sigmoid Function

In the case of no activation function, equation (3) will have the form:

Formula for calculating the output of the corresponding hidden neuron at position j (in the case of no activation function f)

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$$k_j = \omega_{j1} * \mathrm{x}_1 + \omega_{j2} * \mathrm{x}_2 + \mathrm{b}_j \tag{7}$$

$$\begin{aligned} Y_1 &= \omega_{11} * k_1 + \omega_{12} * k_2 \ldots + \omega_{1n} * k_n + \mathrm{b}_1^{'} \\ Y_2 &= \omega_{21} * k_1 + \omega_{22} * k_2 \ldots + \omega_{2n} * k_n + \mathrm{b}_2^{'} \end{aligned} \tag{8}$$

Substituting k_j the hidden layer into the equation Y_1, Y_2 becomes:

$$\begin{aligned} Y_1 &= \omega_{11} * (\omega_{11} * \mathrm{x}_1 + \omega_{12} * \mathrm{x}_2 + \mathrm{b}_1) + \omega_{12} * (\omega_{21} * \mathrm{x}_1 + \omega_{22} * \mathrm{x}_2 + \mathrm{b}_2) + \ldots + \mathrm{b} \\ Y_2 &= \omega_{21} * (\omega_{11} * \mathrm{x}_1 + \omega_{12} * \mathrm{x}_2 + \mathrm{b}_1) + \omega_{22} * (\omega_{21} * \mathrm{x}_1 + \omega_{22} * \mathrm{x}_2 + \mathrm{b}_2) + \ldots + \mathrm{b} \end{aligned} \tag{9}$$

In which: Y_1 and Y_2 in equation (9) are linear combinations x_1 and x_2 respectively are input variables, it is seen that the nonlinear function does not appear in the equation, which proves that without the activation function, the Neural Network will only be a linear system, which also means that the model will not be able to learn or find the relationship between input and output data.

The study presents the application of ANN to detect damage in steel girder bridges using the natural oscillation form as dynamic parameters. The input parameters of this ANN are easy to implement and can be directly linked to the beam's connection structure. The natural oscillation form is obtained through actual testing. After the training process, the output result (an array or matrix) is compared with the known result to find the error, the output of the process will be the damage index of the considered object. The training process wants to achieve good results, the correlation coefficient must be approximately 1.

Validation phase

The validation set was applied as a further test step for generalizing the neural network and checking the accuracy of the selected structure. The main task was to predict the severity of damage in the validation sets against the experimental data. It is clear from the figure that there is a good correlation between the predicted results and the target results, the values are close to each other. These results demonstrate that the ANN has been successful in finding and making the connection between the parameters, input data and output (crack depth and location).

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RESULTS AND DISCUSSION

Crack diagnosis on FGM cantilever beams using ANN using natural vibration modes
Consider the beam model:

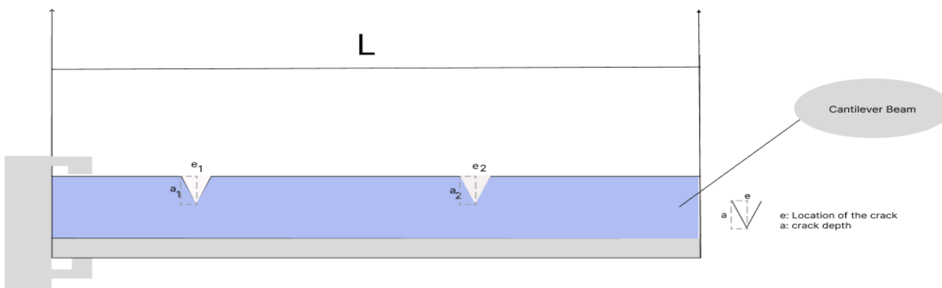

Figure 6: Beam model with 2 cracks with depth a and location e

FGM cantilever beam with the left end tightly clamped and the right end free has the following material parameters: E_t=70GPa; ρ_t=2780kg/m^3; μ_t=0.33; E_b/E_t=0.5; ρ_b=7850kg/m^3; μ_b=0.33, n=0.5 and geometry: L=1.0m, b=0.1m, h=0.1m. The beam has 2 cracks at 0.4m and 0.8m from the left end with crack depths of 20% and 30%. The problem is to re-diagnose the location and depth of the 2 cracks using an ANN network with input data of 1, 2, 3, 4 natural oscillation frequencies of the beam, respectively. The ANN network has 20 hidden layers and 4000 "epochs". The results of crack location and depth diagnosis are shown in tables 1, 2, 3, where R is the correlation coefficient between the output value and the desired value of the ANN network. R has a value of 1, which means that the output value of the ANN has an exact linear relationship with the desired value, R has a value of 0 if the output value of the ANN does not have a linear relationship with the desired value.

Table 1: Diagnosis results of crack location and depth based on 1 specific oscillation frequency

Location and depth of cracks		1st frequency		2nd frequency		3rd frequency		4th frequency	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
0.4m	0.8m	0.28	0.7265	0.2399	0.6921	0.2546	0.7167	0.2560	0.7340
0.20	0.30	0.1423	0.224	0.2203	0.2121	0.2737	0.2718	0.1697	0.2138
Error	L_i	30.0%	9.18%	40.0%	13.5%	36.4%	10.4%	36.0%	8.25%
	ah_i	28.9%	25.3%	26.6%	29.3%	36.9%	9.4%	15.2%	28.7%

Table 2: Results of crack location and depth diagnosis based on 2 natural oscillation frequencies

Location and depth of cracks		1st,2nd frequency		2nd,3rd frequency		3rd,4th frequency		1.4th frequency	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
0.4m	0.8m	0.3168	0.6914	0.2679	0.7434	0.2758	0.7462	0.3245	0.6853
0.20	0.30	0.1660	0.2315	0.2394	0.2496	0.1462	0.2940	0.1664	0.2402
Error	L_i	20.8%	13.6%	1.15%	7.07%	31.1%	6.73%	18.9%	14.3%
	ah_i	17.0%	22.8%	19.7%	16.8%	26.9%	2.00%	16.8%	19.9%

Table 3: Diagnosis results of crack location and depth based on 3.4 natural oscillation frequencies

Location and depth of cracks		1st, 2nd, 3rd frequency		2nd,3rd,4th frequency		1st, 3rd, 4th frequency		First 4 frequencies	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
0.4m	0.8m	0.3243	0.7903	0.3185	0.7138	0.3252	0.7399	0.3881	0.7928
0.20	0.30	0.1631	0.2676	0.1621	0.2895	0.1685	0.2846	0.1970	0.2925
Error	L_i	18.9%	1.21%	20.4%	10.8%	18.7%	7.51%	2.98%	0.9%
	ah_i	18.5%	10.8%	18.9%	3.50%	15.8%	5.13%	1.50%	2.5%

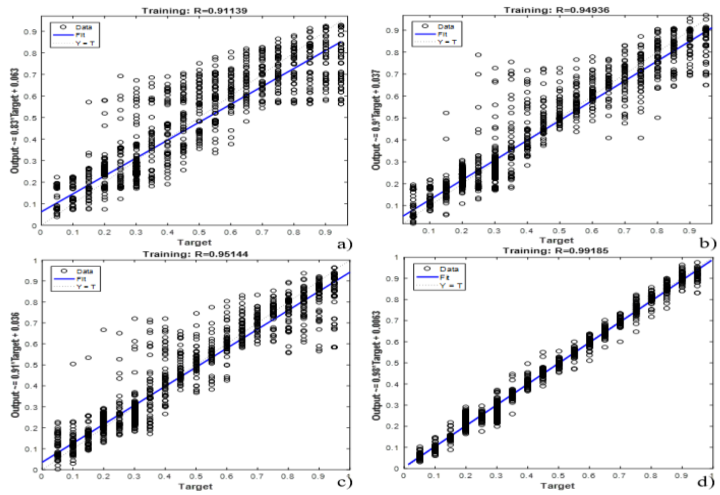

Figure 7: Correlation coefficient R chart of ANN network using 1(a); 2(b); 3(c) and 4 (d) natural oscillation frequencies

Figure 7a is the correlation coefficient R graph of the ANN network using 1 natural oscillation frequency (frequency 1). Figure 7b is the correlation coefficient R graph of the ANN network using 2 natural oscillation frequencies (frequency 1,2). Figure 7c is the correlation coefficient R graph of the ANN network using 3 natural oscillation frequencies (frequency 1,2,3). Figure 7d is the correlation coefficient R graph of the ANN network using the first 4 natural oscillation frequencies.

From the calculation results, it can be seen that although the ANN network can diagnose the location and depth of cracks in a beam with 2 cracks (each crack has 2 parameters: location and depth) with the number of input frequencies being less than the number of crack parameters, the diagnosis result is reliable when the number of measured input frequencies is equal to the number of crack parameters on the beam.

Crack diagnosis on FGM cantilever beams using ANN using natural vibration modes

For a cantilever beam with the geometric and material parameters as in section 3.1, consider the problem of re-determining the location and depth of cracks using an ANN network based on the measurement results of the first three natural oscillation modes, respectively. The research team chose a data split ratio of 80% for the training set (Train) and 20% for the test set (Test). MSE (Mean Squared Error) calculates the average of the error between the actual value and the prediction. The gradient of each data sample represents the “unresolved” level of the model. Points with small gradients contribute very little to the parameter update, so their frequency of appearance can be reduced while keeping the learning direction the same. The ANN network has 10 hidden layers and 4000 “epochs” iterations. The results of the diagnosis of the location and depth of cracks are shown in Table 4. Figure 8 is the plot of the mean square error (MSE) during training (a) and the correlation coefficient

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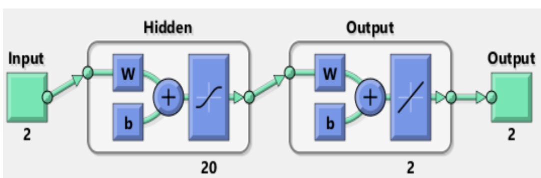
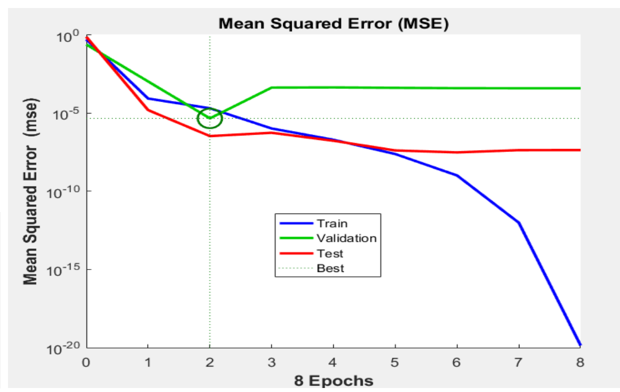
R of the ANN network using the first natural oscillation mode.

Table 4: Results of crack location and depth diagnosis based on natural vibration patterns

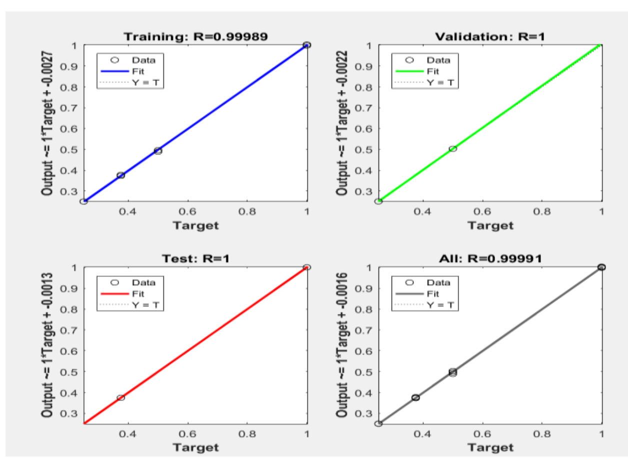
Location and depth of 2 cracks		Oscillation mode #1		Oscillation mode #2		Oscillation mode #3	
		(1)	(2)	(1)	(2)	(1)	(2)
0.4m	0.8m	0.3944	0.8027	0.4037	0.7896	0.3890	0.7971
0.20	0.30	0.1980	0.3031	0.2021	0.3052	0.1907	0.2984
Error	Location	1.40%	0.34%	0.93%	1.30%	2.75%	0.36%
	Depth	1.00%	1.03%	1.05%	1.73%	4.65%	0.53%
Coefficient R		0.9998		0.9997		0.9988	



(a)



(b)



(c)

Figure 8. ANN model training and evaluation: (a) network architecture with two inputs, one hidden layer, and two outputs; (b) mean square error (MSE) curves during training, testing, and validation; and (c) regression plots with correlation coefficients.

The results obtained in Figure 8 show that: the use of Artificial Neural Network (ANN) when the input data is used in Table 4 and the output data is predicted. The neural network is trained to optimize the model based on

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the actual input and output data (crack depth). This means that the output is the predicted version of the crack depth.

CONCLUSIONS

Through research on the application of artificial neural networks (ANN) in structural damage diagnosis, some main results have been obtained as follows: Firstly, when using only natural oscillation frequencies and individual oscillation modes as input data, the diagnosis results show that ANN can identify damage with a certain reliability, but then the number of measured frequencies must be equal to the number of crack parameters that need to be identified on the beam. Secondly, when using natural oscillation modes or forced displacements as input, the ANN is capable of diagnosing the number, location and depth of cracks on the structure with quite high accuracy. However, the process of building the database and training the network often takes a long time. Finally, to overcome this limitation, ANN has been combined with SWT analysis based on natural oscillation modes or forced displacements to reduce the number of unknowns in the inverse problem. The results show that this integrated method not only improves the accuracy but also significantly reduces the calculation time compared to the case of using only pure ANN.

The novelty of the study is that it has shown the relationship between vibration characteristics and crack parameters, and introduced the ANN–SWT model as an effective diagnostic tool. Technically, the research results provide a feasible solution for structural health monitoring, in which the detection and diagnosis of cracks effectively and accurately play a key role in maintenance and safety assurance of the construction.

The next research direction of the group is to focus on building a deep learning model and extending the ANN to integrate with measuring devices to improve the diagnostic ability. At the same time, verifying the method with experimental data in complex environmental conditions and in conditions with interference will be an important step to evaluate the practical application of this method.

CONFLICT OF INTEREST

This research has been supported by The Vietnam Academy of Science and Technology, Projects numbers VCH.ĐTT.04/2024.

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