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Research Paper

Damage detection for a large-scale truss bridge using Tranmissibility and ANNAOA

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A B S T R A C T

In this paper, we propose an efficient approach to enhance the capacity of Artificial Neural Network (ANN) to deal with Structural Health Monitoring (SHM) problems. Over the last decades, ANN has been extensively utilized for damage detection in structures. In order to identify damages, ANN frequently utilizes input information that is based on dynamic features such as mode shapes or natural frequencies. However, this type of data may not be able to detect minor damages if the structural defects are insignificant. To transcend these limitations, in this work, we propose utilizing transmissibility to create input data for the input layer of ANN. Moreover, to deal with local minimum problems of ANN, a combination between the Arithmetic Optimization Algorithm (AOA) and ANN is proposed. The global search capacity of AOA is employed to remedy the local minima of ANN. To evaluate the effectiveness of the proposed approach, a numerical model with different damage scenarios is considered. The suggested approach detects damage location precisely and with higher severity detection precision than the conventional ANN method.

1 Introduction

Modern societies crucially rely on large-scale bridges that are highly vulnerable to a wide range of potential threats such as environmental conditions, natural hazards, overload, accidental loads, and so forth. These adverse factors possibly significantly affect the operational effectiveness, safety, and lifespan of these systems. Therefore, over the last decades, SHM

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has been widely deployed and received meticulous attention from scholars and researchers worldwide [1-3]. For example, Janapati et al. [4] proposed using active and passive techniques based on ultrasound equipment to detect damage of composite structures. The active technique was employed to detect minor damages caused by delamination, corrosion, and fatigue, whereas the passive one was utilized to identify fiber breakage in the tested structures. Samir et al. [5] successfully identified damages of a numerical model of the Guangzhou TV Tower using enhanced damage indicators combined with metaheuristic optimization algorithms (Salp Swarm Optimizer and Atom Search Optimization). An improved Binary Bat Algorithm (IBBA) was proposed by [6] to detect defects in a multiprocessor system using the Malek model. The obtained results pointed out that the proposed approach combining IBBA and Malek model possibly identified defects exactly or even minor defects occurring in the tested structures with a lower computational cost.

Over the last decades, ANN has created ample opportunities for researchers to exploit its potential in various civil engineering problems, particularly in the SHM field [7, 8]. Randiligama et al. [9] applied ANN combined with mode shape curvature to localize and quantify the damages of a hyperbolic cooling tower. An effective approach based on ANN was also employed to identify damages of a spring-mass system, a simply supported beam, and a three-story plane frame [10]. Nevertheless, it should be noted here that the accuracy of the trained network relies critically on the input data. In terms of applying ANN for structural vibration-based-SHM, natural frequency and/or mode shape have been widely chosen as input data. However, in some cases, these features not only face numerous challenges to acquire in the field but also are not sensitive enough to detect minor defects properly.

Transmissibility, defined as the ratio of response amplitude to the applied amplitude of motion, has emerged as a promising technique for detecting damage in structures. It has gained popularity in the field of SHM due to its simplicity and effectiveness in identifying damage-related changes. The transmissibility function provides a quick and efficient way to assess the changes in the dynamic properties of a structure without the need for detailed knowledge of the underlying physical mechanism. In this study, we propose utilizing the transmissibility function in conjunction with ANN to identify damages in a large-scale truss bridge. The aim is to identify damage-sensitive features based on input data generated by the transmissibility function.

AOA is a method for optimization that involves using arithmetic operations to locate the global optimal solution for a mathematical function [11]. Its approach revolves around manipulating the mathematical expressions of the objective function to achieve maximum or minimum values. AOA is a heuristic technique that can effectively deal with both linear and nonlinear functions, and it is especially useful for solving optimization problems that involve numerous variables. With the global search, in this work, AOA is used to enhance the effectiveness and remedy the local minimal problems of ANN.

For comparison, we also use ANN based on natural frequencies to detect damages in the considered structure. Both single and multiple damage scenarios are taken into consideration, and the dynamic behavior of the structure is evaluated under the influence of moving loads. The paper is structured into four primary sections. Section 2 thoroughly explains the methodology of the proposed approach. Section 3 assesses the proposed method's efficacy by utilizing various damage scenarios in a numerical example. Finally, main conclusions are drawn.

2 Methodology

2.1 Artificial Neural Network

ANN is a type of Machine Learning (ML) algorithm inspired by the structure and function of the human brain. ANN is composed of interconnected nodes that process and transmit information, allowing them to learn patterns and make predictions from data [12]. ANN has been successfully applied in various fields such as image and speech recognition, natural language processing, and so on. An ANN (Fig 1) is typically structured into three main components:

Input Layer: The input layer receives the data, which is typically pre-processed and normalized, and passes it on to the hidden layers.

Hidden Layers: The hidden layers are where the majority of the computation in ANNs takes place. Each hidden layer is composed of multiple interconnected nodes or neurons, and the neurons in each layer receive inputs from the previous layer and transmit outputs to the next layer. The number of hidden layers and neurons per layer can vary depending on the complexity of the problem being addressed.

Output Layer: The output layer is the final layer of the ANN, where the model's prediction is made. The output layer can consist of one or more neurons, depending on the type of problem being solved (e.g., binary classification, multi-class classification, regression).

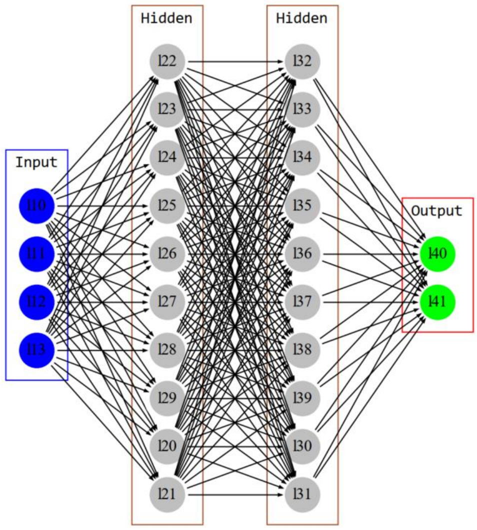


Fig. 1 – An illustration of ANN architecture

Step 1: Prepare the data for the input layer. Assume inputs have n features in m dimensions defined within the matrix X like as Eq. (1):

$$X = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^n \\ x_2^1 & x_2^2 & \cdots & x_2^n \\ \vdots & \vdots & \ddots & \vdots \\ x_m^1 & x_m^2 & \cdots & x_m^n \end{bmatrix} \tag{1}$$

Convert the columns in the $m \times n$matrix of X into a vector whose number of elements is equal to $m \times n$ elements. This is expressed as the following Eq. (2).

$$\vec{x} = \begin{Bmatrix} x_1^1 \\ x_1^2 \\ \vdots \\ x_1^n \\ x_1^2 \\ \vdots \\ x_m^n \end{Bmatrix} \tag{2}$$

Step 2: The data after entering the input layer, the next target will go through the first hidden layer. The data from the input layer is calculated as a linear equation $W^T x + b$ and the result of this linear equation is passed through a function called the activation function to calculate the output. One of the most popular function, namely Sigmoid (Eq.(3)), is used for this activation function.

$$\vec{a}^{[1]} = S(W^T \vec{x} + \vec{b}) \tag{3}$$

$$S(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

Where:

$\vec{a}^{[1]}$	:	Output of hidden layer 1
$S(z)$	:	activation function
W	:	Weight matrix
$\vec{b}$	:	Bias vector

Step 3: The process of transferring from the hidden layer to the hidden layer or the output layer is similar to steps 1 and 2.

Step 4: Calculate the deviation between the calculated and desired outputs using Eq.(5).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{5}$$

Where:

Y_i : Calculated output of the output layer

$\hat{Y}_i$: Target output of the output layer

2.2 *Transmissilbity Damage Index*

In vibration-based SHM, the core idea is to find a sensitive feature capable of distinguishing damaged structure versus healthy state. Transmissibility is a useful method for detecting damage in structures that has become increasingly popular in SHM. The transmissibility function offers a convenient and efficient way to evaluate a structure's dynamic properties, without requiring extensive knowledge of its underlying physical mechanism.

2.2.1 Transmissilbity

Transmissibility is defined as the ratio between the magnitude of the response amplitude and the magnitude of the applied amplitude of motion. Considering a linear system with multiple degree-of-freedom, the dynamic equilibrium equation is described through an equation such as the following Eq. (6) by the well-know second-order differential equation:

$$M\ddot{\Delta}(t) + C\dot{\Delta}(t) + K\Delta(t) = \mathrm{F}(t) \tag{6}$$

Where M, C, and K are the mass, damping, and stiffness matrices, respectively, of the system, $\mathrm{F}(t)$ is the input force vector, and $\Delta(t)$ contains the responses of each degree-of-freedom of the system. To calculate the transmissibility, independently of the real technique or the experimental analysis, apart from the direct extraction from the two answers, it can be derived in different ways, for example using the Frequency Response Functions (FRFs). This can be estimated as described in Eq. (7) and (8) :

$$X_i(\omega) = H_{(i,l)}(\omega)F_l(\omega) \tag{7}$$

$$X_j(\omega) = H_{(j,l)}(\omega)F_l(\omega) \tag{8}$$

Where $H_{(i,l)}$and $H_{(j,l)}$ represent the FRF at point i and $j$to l. $F_l$is a force vector impact on node l, X_i is a vector is responses (amplitude of displacement) at point i. Similarly X_j is the reaction at point j. Herein, the transmissibility is an estimation of structural dynamic responses. This was calculated as described in Eq. (9)

$$TR_{(i,j)} = \frac{H_{(i,l)}(\omega)}{H_{(j,l)}(\omega)} = \frac{X_i(\omega)/F_l(\omega)}{X_j(\omega)/F_l(\omega)} \tag{9}$$

Under the influence of a harmonic function at a given coordinate, the transmission between point i and a reference point j can be estimated as described in Eq.(10):

$$TR_{(i,j)}(\omega) = \frac{X_i(\omega)}{X_j(\omega)} \tag{10}$$

2.2.2 Damage Indicator (DI)

Using a similar approach as [13], a DI damage indicator, defined here based on DI long-frequency range accumulation as follows, Eq. (11):

$$DI = \int_{f_{min}}^{f_{max}} TR\, df \tag{11}$$

Where the interval $[f_{max}; f_{min}]$ is the frequency bandwidth of interest for our problem.

Transmissibility functions can be computed from numerical simulations and then generating the data to train the ANN.

2.3 ANNAOA

In this section, the methodology of ANNAOA used to train the optimal weight and bias parameters are discussed. The used network architecture (Fig. 2) has 4 layers including one input layer, one output layer, and two hidden layers. The number of hidden layers is chosen by using try-and-error.

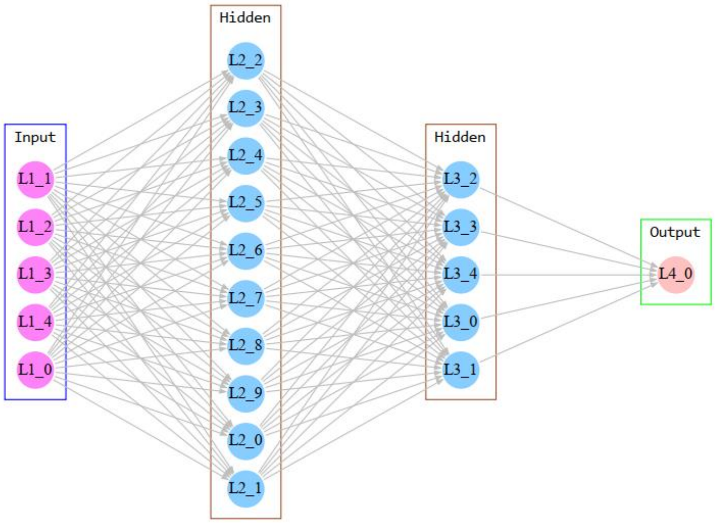


Fig. 2 – Four-layer neural network architecture.

Step 1: The input data is inserted in the input layer and transferred to the hidden layer. The outcome of hidden layer 1 was calculated for each sample as described in Eq. (12)

$$\vec{z}^{[h\_1]} = \sum_{k=1}^{m} \vec{w}_k \cdot \overrightarrow{output}^{[input\_layer]} + b_k \tag{12}$$

Where $\overrightarrow{output}^{[h_1]}$is the output vector of hidden layer 1; $\vec{w}_k$, $b_k$specify training parameters that connect the input layer and the hidden layer. $\vec{z}^{[h_1]}$is a vector that is the product of Eq.(12). The activation function (Eq. (13)) is used.

$$\overrightarrow{output}^{[h\_1]} = S(\vec{z}^{[h\_1]}) = \max(0, \vec{z}^{[h\_1]}) \tag{13}$$

Step 2: Elements of the hidden layer 1 are transferred to the hidden layer 2. This process uses Eq.(14)

$$\vec{\mathbf{z}}^{[\boldsymbol{h\_2}]} = \sum_{k=1}^{m} \vec{w}_k \cdot \overrightarrow{output}^{[h\_1]} + b_k \tag{14}$$

The activation function (Eq. (15)) is employed.

$$\overrightarrow{output}^{[h\_2]} = S(\vec{z}^{[h\_2]}) = \max(0, \vec{z}^{[h\_2]}) \tag{15}$$

Step 3: Elements of the hidden layer 2 are transferred to the output layer. This process utilises Eq. (16)

$$\vec{z}^{[output\_layer]} = \sum_{k=1}^{m} \vec{w}_k \cdot \overrightarrow{output}^{[h\_2]} + b_k \tag{16}$$

The activation function (Eq. (15)) is employed.

$$\overrightarrow{output}^{[h\_2]} = S(\vec{z}^{[h\_2]}) = \frac{1}{1 + e^{-\vec{z}^{[h\_2]}}} \tag{17}$$

The (Mean Square Error) MSE between predicted and real output is calculated in Eq.(18)

$$MSE(X) = \frac{1}{n}\sum_{i=1}^{n}(output_i - \widehat{output_i})^2 \tag{18}$$

If the network is entrapped in the locally optimal solution, it means that the MSE between predicted and real outputs of the next step is not smaller than that of the previous one (shown in Eq.(19))

$$MSE^{t+1}(X)\ \boldsymbol{is\ not} < MSE^{t}(X) \tag{19}$$

t is t^{th} iteration.

In this case, AOA is employed to escape the network from local minima. Specifically, AOA is used to determine the new weight and bias coefficients (X^{net}) for the network. $X^{net} = [w_1^{net}, w_2^{net}, \dots, w_{wn}^{net}, b_1^{net}, b_2^{net} \dots, b_{bn}^{net}] = [x_1^{net}, x_2^{net}, \dots, x_{we}^{net}]$. Weight and bias values from the ANN are then organized as a single vector (Eq (20)), which is used as the initial parameters of AOA.

$$X^0 = \begin{bmatrix} x_1^{net} & x_2^{net} & \cdots & x_{we}^{net} \\ x_{1,1}^0 & x_{1,2}^0 & \cdots & x_{1,we}^0 \\ x_{2,1}^0 & x_{2,2}^0 & & x_{2,we}^0 \\ \vdots & \vdots & \ddots & \vdots \\ x_{(N-1),1}^0 & x_{(N-1),1}^0 & \cdots & x_{(N-1),we}^0 \end{bmatrix} \tag{20}$$

Where: $X^0$is weight and bias values from ANN; wn indicates the number of weight, bn is the number of bias and we denotes the number of all elements; $we = wn + bn$.

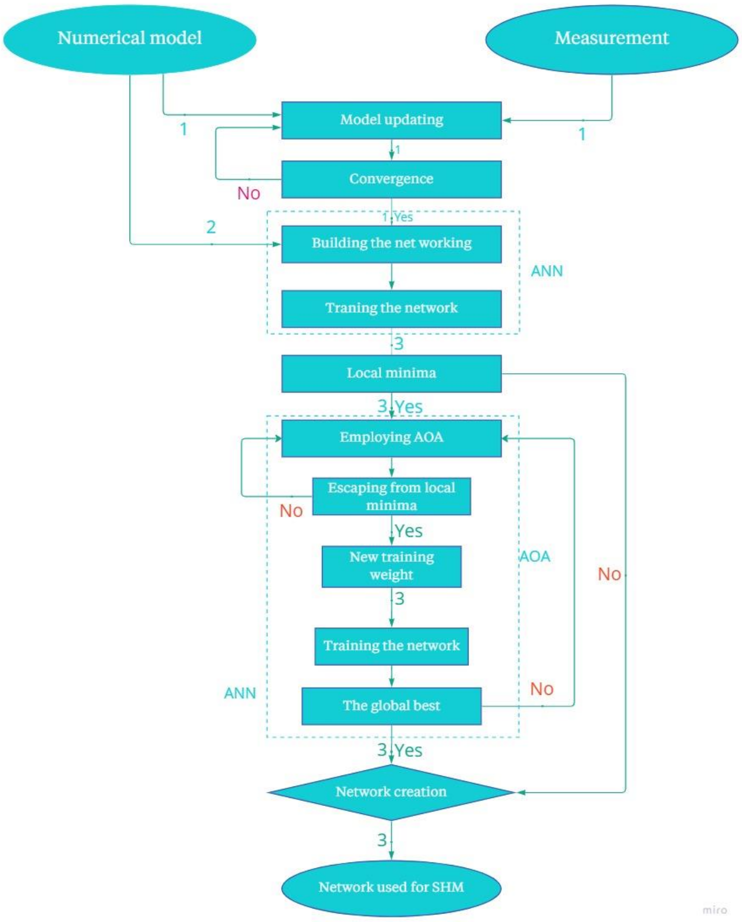


Fig. 3 – The flowchart of ANNAOA

Caculate the values of $MSE(X^0)$ of the initial solution's positions randomly based on Eq.(21)

$$E(X^0) = \sqrt{\sum_{k=1}^{N} \|MSE(X_k^0)\|} \tag{21}$$

The probability ratio is chosen by using Eq.(22).

$$MOP(\text{it}) = 1 - \frac{it^{1/\alpha}}{Max\_Iter^{1/\alpha}} \tag{22}$$

MOA is calculated by Eq.(23)

$$\text{MOA } (it) = \text{ MOP\_Min } + it \times \left(\frac{\text{MOP\_Max } - \text{ MOP\_Min}}{Max\_Iter} \right) \tag{23}$$

Updating the solution of multiplication and division through Eq. (24)

$$x_{i,j}(C\_\text{Iter } + 1) = \begin{cases} \text{best } (x_j) \div (MOP + \epsilon) \times \left((UB_j - LB_j) \times \mu + LB_j \right), & r2 < 0.5 \\ \text{best } (x_j) \times MOP \times \left((UB_j - LB_j) \times \mu + LB_j \right), & \text{otherwise} \end{cases} \tag{24}$$

Subtraction and addition solutions Eq. (25)

$$x_{i,j}(\text{it} + 1) = \begin{cases} \text{best}(x_j) - MOP \times \left((UB_j - LB_j) \times \mu + LB_j \right), & r3 < 0.5 \\ \text{best } (x_j) + MOP \times \left((UB_j - LB_j) \times \mu + LB_j \right), & \text{otherwise} \end{cases} \tag{25}$$

The working principle of ANNAOA is depicted in Fig. 3.

3 Application of the proposed method to damage detection of a large-scale bridge

3.1 Finite Element Model (FEM)

To investigate the effectiveness of ANN, a large-scale truss bridge is used. Fig. 4 shows the Chuong Duong Bridge that connects the $1A$ National road with one of the most heavily trafficked routes in Hanoi (Vietnam). With nearly 40 years of service, the structure has suffered degradation and damage after being built in the 1980s.

Fig. 4 – Chương Dương Bridge

In the context of this paper, only span number 10^{th} is selected for data measurements. Fig. 5 illustrates the sections of span 10th.

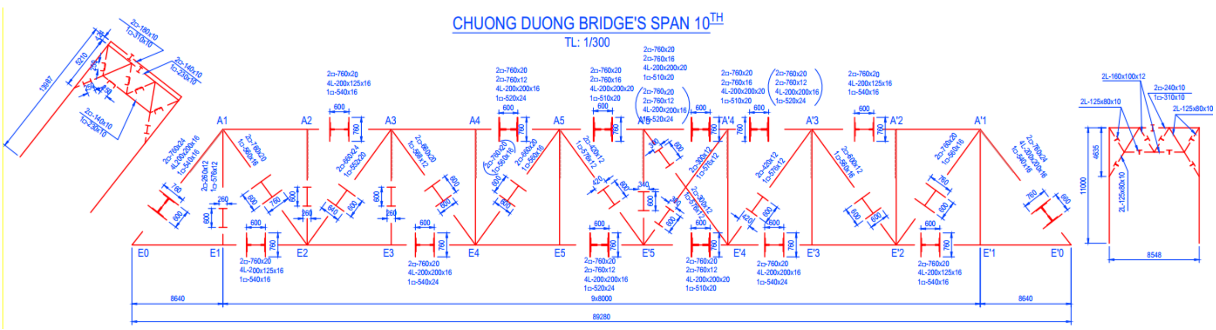


Fig. 5 – Typical sections of the main span

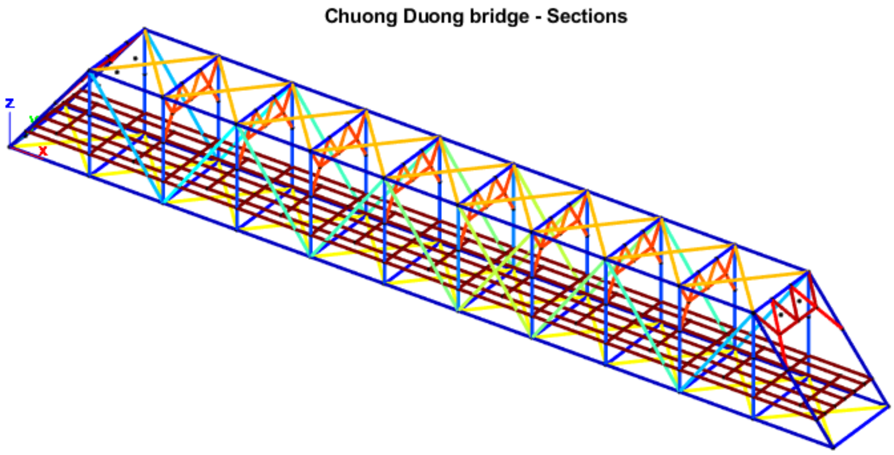


Fig. 6 – FEM model of Chương Dương Bridge

Fi. 6 provides an overview of the FEM of Chuong Duong bridge which is constructed using Stabil toolbox in Matlab [14]. The model uses "beam" elements with 6 Degree-of-Freedoms (DoFs) at each node including rotational and translational displacements in the x, y, and z-axis.

As result, the model consists of 264 nodes, 562 elements, and 1275 DoFs. A summary of the section's properties is given in Table 1 - Young's modulus is 200 GPA and the density of the structure is 7850 kg/m^3.

Table 1 – Properties of sections in Chuong Duong bridge

No	**Types of elements**	**ID**	**Areas (m^2)**	**Moment of Inertia Iyy (m^4)**	**Moment of Inertia Izz (m^4)**
			A	Iyy	Izz
1	Bottom chord - Main beam	1	0.059136	0.001657	0.004052
2	Bottom chord - Main beam	11	0.059136	0.004052	0.001657
3	Strut - Cross beam	2	0.007700	0.000128	0.000023
4	Vertical chord	3	0.013152	0.000731	0.000035
5	Vertical chord	31	0.015072	0.000897	0.000079
6	Diagonal chord	41	0.027456	0.000878	0.001832
7	Diagonal chord	42	0.024576	0.000524	0.001583
8	Diagonal chord	43	0.023616	0.000432	0.001500
9	Diagonal chord	44	0.019296	0.000148	0.001126
10	Diagonal chord	45	0.016416	0.000054	0.000877
11	Under Bracing systems	5	0.008600	0.000023	0.000228
12	Upper bracing systems	51	0.007700	0.000023	0.000128
13	Cantilever beam	6	0.005952	0.000033	0.000008

Concrete and steel are the materials used in the model. Table 2 lists the parameters used in the model.

Table 2 – Properties of section in the bridge

Elements	ID	Young's modulus	Poison's ratio	Volumetric mass density
		Gpa	μ	kg/m^3.
Truss elements	$\boldsymbol{E}$	200	0.2	7850

Boundary conditions of model include fixed bearing at Pier T9 and movable bearing at pier T10. The force is applied with stochastic forces. The response of strucutre in frequency domain and time domain is shown in Fig. 7.

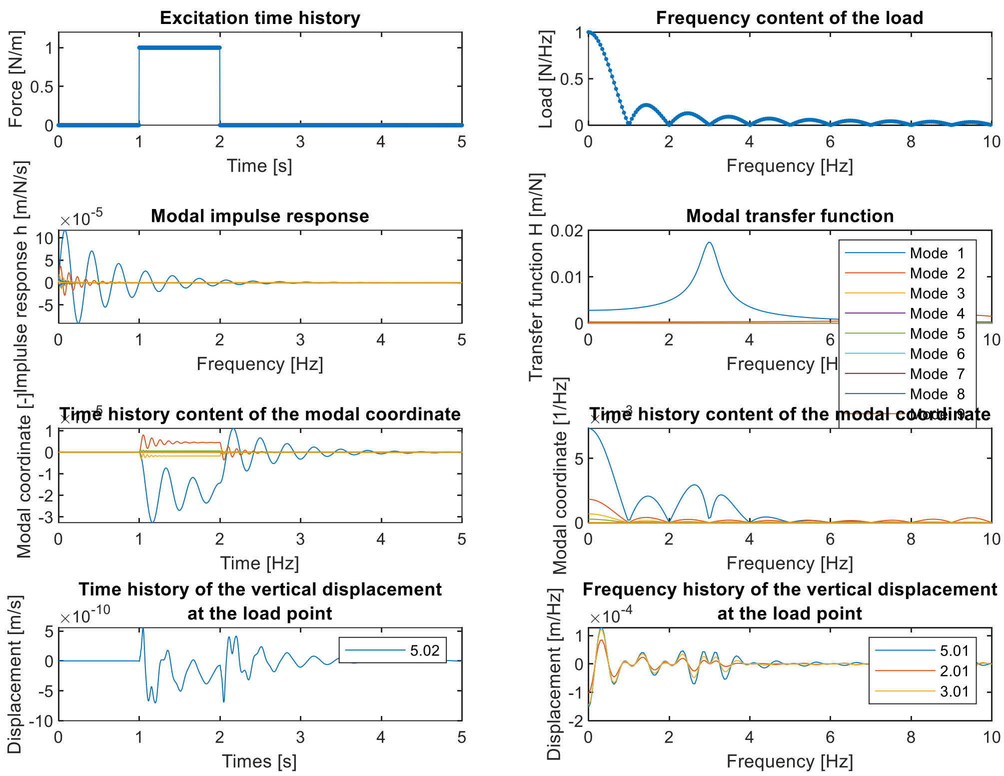


Fig. 7 – Response of the strucutre (Hz).

3.2 Input data

For the purpose of comparison, two sets of data are created. The first set uses frequency as input, while the second set uses Transmissibility. The same method is applied to both data sets. In the case of single damage, a 1% reduction in stiffness is applied to individual truss nodes, reducing the overall stiffness by 50%. For the scenario of multiple damages, two nodes are combined and their stiffness is reduced by 1% in increments, until the total stiffness reaches 50%. Fig. 8 shows one of step to create data by Transmillbility function.

Considering the bridge affected by harmonic forces, transmissibility functions have been calculated are TR2324, TR2325, TR2326, and TR2327 which respond to the transmissibility factor from node 23 to each other nodes 24, 25, 26, and 27 (Eq.(10)). In the next stage, the transmissibility damage index has been calculated by using equation (Eq. (11)). This factor responds to the area of transmissibility function in the frequency domain. As shown in Fig. 8, the areas that have been calculated are combination of green and blue area.

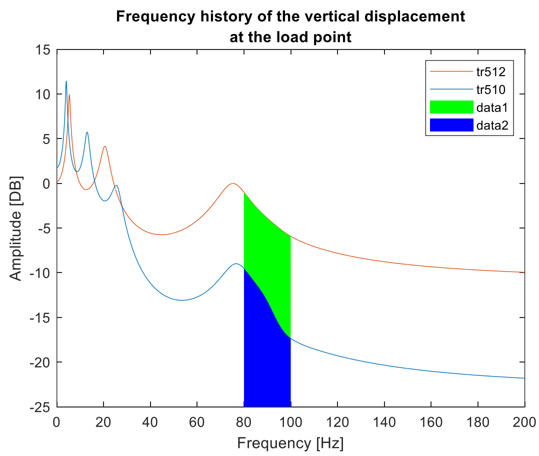
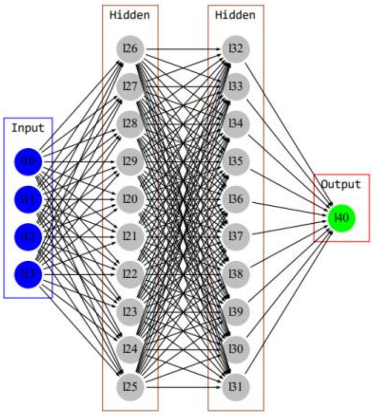


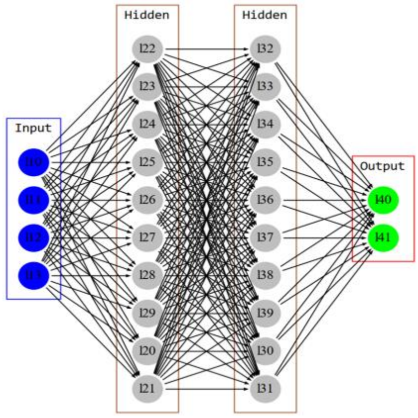
Fig. 8 – Transmissibility functions of Chuong Duong bridge

3.3 Target data

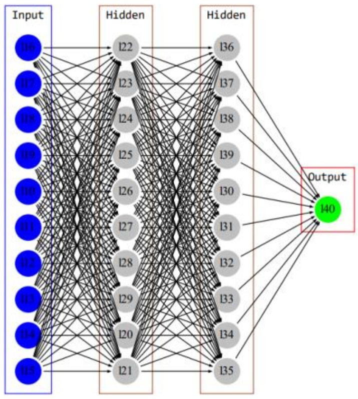
The target data for ANN are damage level and damage location, respectively. Damage applies to four elements 114, 115, 116 and 117. In each scenario, we have damage location and damage level. The ANN architecture used in this paper is shown in Fig. 9.



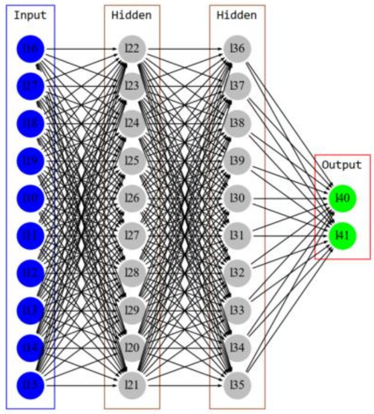
(a) The artchitechture of ANN for single damage using transmissibility data



(b) The artchitechture of ANN for two damage elements using transmissibility data



(c) The artchitechture of ANN for single damage using frequency data



(d) The artchitechture of ANN for two damage elements using frequency data

Fig. 9 – The arichitecture of network

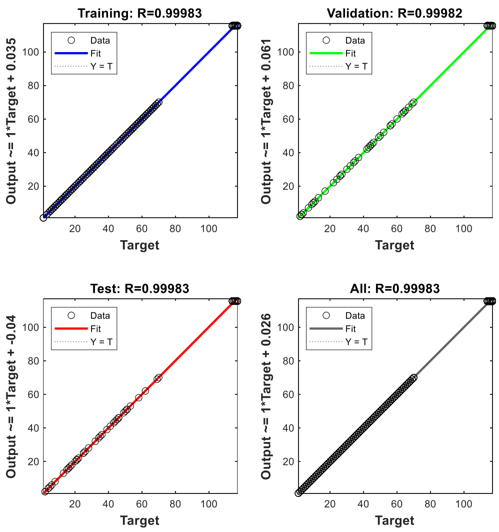


Fig. 10 – **R**-***value of ANNAOA for single damage using frequency data***

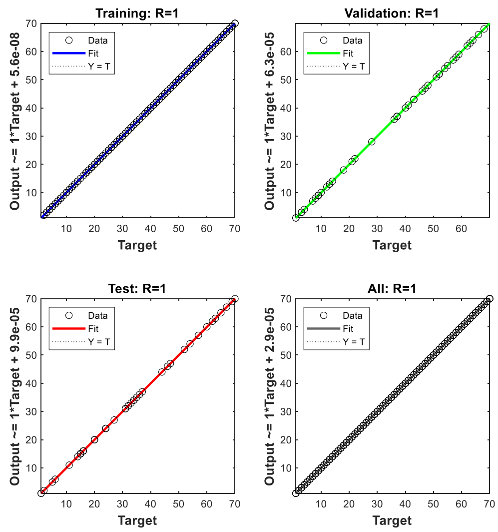


Fig. 11 – **R**-***value of ANNAOA for single damage using transmissibility data***

3.4 Results

3.4.1 Single damage

The R-values in (Fig. 11) are higher than those calculated using frequency data (Fig. 10). On the other hand, ANNAOA using transmissibility data spend 81.03 (s) to train the network, whereas, traditional ANN using frequency data 146.47 (s) for this process. Fig. 12 shows calculated and target values which demonstrate a high accuracy.

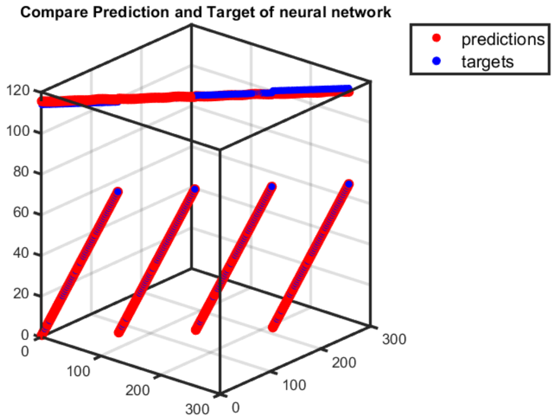


Fig. 12 – Prediction and Target of ANN

3.4.2 Multiple damage

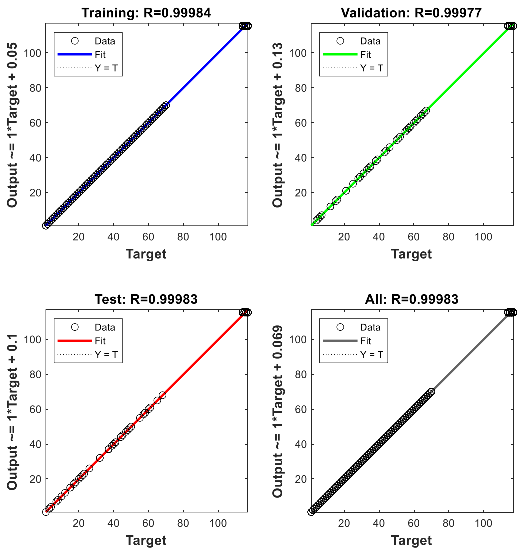


Fig. 13 –* R*-value of ANNAOA for multiple damages using frequency data

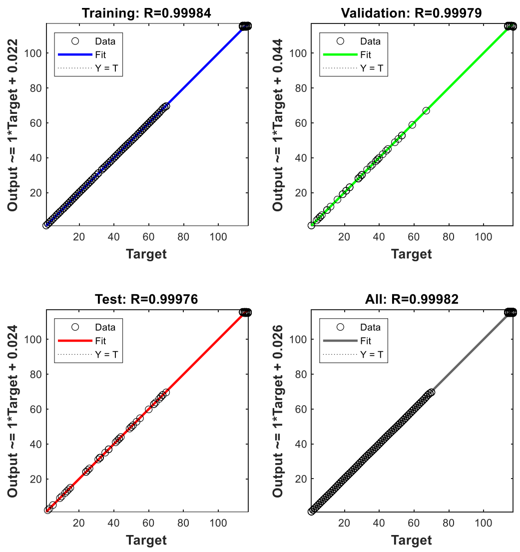


Fig. 14 –* R*-value of ANNAOA for multiple damages using transmissibility data

In Fig. 13 and 14, it is evident that using the transmissibility function as input data outperforms using natural frequencies in two ways. Firstly, in terms of R-values, the former method achieves 0.999 and 0.914 compared to the latter's values. Additionally, the first method requires less time to train the network than the second, taking only 312.63 seconds compared to 567.63 seconds for the latter.

4 Conclusions and future works

This study aims to use a combination of the transmissibility function and ANN to detect damages in a large-scale bridge. We suggest using the input data produced by the transmissibility function to identify features that are sensitive to damage. Moreover, a novel hybrid ANNAOA is proposed. The core idea of this approach is that the stochastic capacity of AOA is applied to prevent the network from trapping in local minima throughout the process of training the network. To evaluate the performance of the proposed method, a large-scale truss bridge with both single and multiple damages is employed. The methods we have proposed, along with the frequency-based ANN, offer highly accurate results. This is supported by the R-values (which are higher than 0.9) and the convergence level (which is close to 0). In addition, our proposed method can also reduce computational time when compared to the frequency-based ANN. The subsequent studies will employ this methodology to detect damages for real-world models.

5 Acknowledgement

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