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# Damage detection for a cable-stayed Bridge under the effect of moving loads using Transmissibility and Artificial Neural Network

***Thanh Bui-Tien [a], Thang Le-Xuan [a], Hung Tran-Viet [b], Tung Nguyen-Xuan [b], Long Nguyen-Ngoc [a], Linh Dao-Thuy [a], Hoa Tran-Ngoc [a,*]***

[a] *The Department of Bridge Engineering & Underground Infrastructure, Faculty of Civil Engineering, University of Transport and Communications, Hanoi, Vietnam;*

[b] *Structural Engineering Department; Faculty of Civil Engineering, University of Transport and Communications, Hanoi, Vietnam;*

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A B S T R A C T

Artificial Neural Network (ANN) has been widely used for Structural Health Monitoring (SHM) in the last decades. To detect damage in the structure, ANN often uses input data consisting of natural frequencies or mode shapes. However, this data is not sensitive enough to accurately identify minor structural defects. Therefore, in this study, we propose to use transmissibility to generate input data for the input layer of ANN. Transmissibility uses output signals exclusively to preserve structural dynamic properties and is sensitive to damage characteristics. To evaluate the efficiency of the proposed approach, a cable-stayed bridge with a wide variety of damage scenarios is employed. The results show that the combination of transmissibility and ANN not only accurately detect damages but also outperforms natural frequencies-based ANN in terms of accuracy and computational cost.

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## 1 Introduction

In the last decades, Artificial Neural Network (ANN) has been used successfully in Structural Health Monitoring (SHM) [1-3]. To detect damages in the structures, ANN often uses input data consisting of natural frequencies and/or mode shapes. For instance, Hyeon-Jong Hwang *et al.* [4] applied ANN to identify the binding performance of tensile slap splices. The authors pointed out that the proposed approach offered higher correctness than current design equations. Eissa Fathalla *et al.* [5] used ANN to determine the remaining service life of a concrete bridge. However, the accuracy of the obtained results was low, since the overfitting phenomena occurred during the network training process. Eui-YoulKim *et al.* [6] coupled Wavelet

* *Corresponding author.*
E-mail address: *ngochoa@utc.edu.vn*
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Packet Transform (WPT) with ANN to detect damages of a mechanical machine. WPT was applied to extract abnormal sounds (significant features) when the machine operated and ANN was utilized for error classification.

Most of the previous studies have mainly focused on improving algorithms to increase the efficiency of ANN. However, it must be noted that the accuracy of the obtained results after training the network depends crucially on the input data. In terms of using ANN for damage detection based on structural dynamic properties, natural frequency, mode shape, or mode shape curvature have been commonly used as input data. Nevertheless, these properties not only face major challenges to obtain in the field but also are not sensitive enough to accurately identify minor structural defects

In recent years, the transmissibility function has demonstrated its ability to apply to damage detection problems, since this approach solely uses output signals to preserve structural dynamic properties, which are more sensitive to damage properties [7] Transmissibility is defined as the ratio between the magnitude of the response amplitude and that of the applied amplitude of motion.

The application of the transmissibility function to detect damages has been conducted by many researchers. For instance, Maia et al. [8] employed the transmissibility function to identify the damages of a simply supported beam and a steel beam in the laboratory. To compare with the transmissibility function, the Frequency Response Function (FRF) was also utilized. The authors concluded that the proposed method outperforms FRF-based data in terms of accuracy. The transmissibility function was also applied to detect damages for a simply supported beam in the work of [9]. In this research, transmissibility was created by the response of the structure and the vehicles. Zhou et al. [10] proposed combining transmissibility with Hierarchical Clustering Analysis (HCA) to detect damages for a numerical model of a 10-floor structure and a free-free beam in the laboratory.

Based on the potential capacity of the transmissibility function for damage detection problems, in this work, we propose applying the transmissibility coupled with ANN to detect damages for a cable-stayed bridge. The core idea is to seek sensitive features of damaged structures based on input data generated from the transmissibility function. To compare with transmissibility-based ANN, natural frequencies-based ANN is also employed. Both single and multiple damages are taken into account. Moreover, structural dynamic behaviors are considered under the effect of moving loads.

Some of the main contributions are summarized as follows:

- Propose using transmissibility coupled with ANN for damage detection of a cable-stayed bridge under the excitation of moving loads. With the best knowledge of the authors, this is the first time, the application of ANN for damage detection of a cable-stayed bridge using input data from transmissibility generated by the response of moving loads is considered.

- To compare with the proposed approach, natural frequencies–based ANN is also employed.

- To evaluate the practical applicability of the method, the influence of noise is fully taken into account.

- A wide variety of damage scenarios including both single and multiple damages are considered.

## 2 Methodology

### *2.1 Artificial Neural Network*

The ANN models Fig. 1 were invented and inspired by the principle working of the human nervous system. An ANN model includes nerve cells (neurons) linked to each other by parameters (weight and bias). An ANN model includes three layers (input layer, hidden layer, and output layer) as shown in ***Fig.1.***

These layers are connected with each other based on neurons. The numbers of neurons in the input layer and the output layer rely on the specific problems that need to be dealt with. An ANN model can employ one or many hidden layers. However, no study demonstrates that the network with more hidden layers is more effective than the network using one hidden layer. Therefore, to identify the most suitable number of hidden layers for a specific problem, the trial-error process should be applied.Training a network consists of two steps including forward and backward processes.

- Forward process

Data set from the input layer is transferred to the hidden layer using the summation function $S_1$ Eq (1).

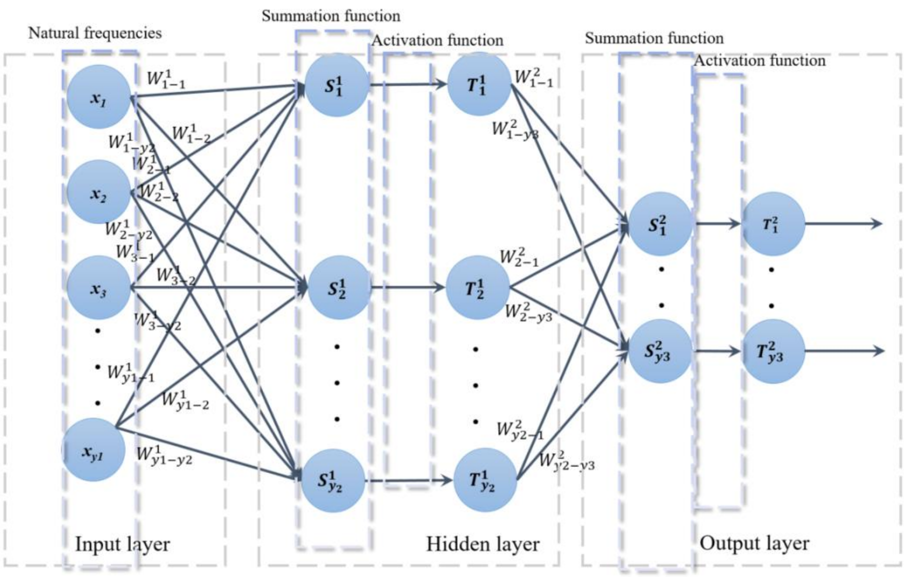


***Fig. 1 - ANN artchitechture***

$$S_1 = \sum_{1,1}^{Y_1,Y_2} W_{y_1 y_2} * x_{y_1} + b_{y_2}, \qquad y_1 \in (1{:}\,Y_1);\;\; y_2 \in (1{:}\,Y_2) \tag{1}$$

$\boldsymbol{x}_{y_1}$ is input data; $W_{y_1 y_2}$ and $b_{y_2}$ are training parameters; $y_{1,}y_2$ are $y_1{}^{th}$and $y_2{}^{th}$neurons in the input layer and the hidden layer; $Y_1$ and $Y_2$ are the total numbers of neuron in the input layer and the hidden layer. After that, the output ($T_1$) of the hidden layer is obtained using the sigmoid function $T_1$ Eq(2).

$$T_1 = \frac{1}{1 + e^{-S_1}} \tag{2}$$

The same process is applied to transfer data from the hidden layer to the output layer using Eq (3)-(4).

$$S_2 = \sum_{1,1}^{Y_2,Y_3} W_{y_2 y_3} * T_1 + b_{y_3}, y_3 \in (1{:}\,Y_3) \tag{3}$$

$S_2$ is the input of the output layer; $y_3$ and $Y_3$ are $y_3{}^{th}$ in the output layer, and the total number of neurons in the output layer, respectively.

$$T_2 = \frac{1}{1 + e^{-S_2}} \tag{4}$$

$T_2$is the output of the output layer.

The differences between calculated and desired outputs ($T_2^i$ and $\bar{T}_2^i$) are computed.

$$\nabla(W, b) = \sum_{i=1}^{n} 0.5 * \frac{(T_2^i - \bar{T}_2^i)^2}{n} \tag{5}$$

$i$ and $n$ in turn are $i^{th}$ data and the total number of data.

To reduce the deviation of $\nabla(\mathrm{W}, \mathrm{b})$, the backward process is employed by tuning training parameters $(\mathrm{W}, \mathrm{b})$ depicted in Eq (6) to Eq (22).

- Backward process (backpropagation)

Turn training parameters that connect the hidden layer and the output layer.

$$\frac{\partial\nabla(W,b)}{\partial W_{y_2y_3}} = \frac{\partial\, S_2}{\partial W_{y_2y_3}} * \frac{\partial T_2}{\partial\, S_2} * \frac{\partial\nabla(W,b)}{\partial T_2} \tag{6}$$

$$\frac{\nabla(W,b)}{\partial b_{y_3}} = \frac{\partial\, S_2}{\partial b_{y_3}} * \frac{\partial T_2}{\partial\, S_2} * \frac{\partial\nabla(W,b)}{\partial T_2} \tag{7}$$

$$\frac{\partial\nabla(W,b)}{\partial T_2} = -(\overline{T_2} - T_2) \tag{8}$$

$$\frac{\partial T_2}{\partial\, S_2} = \frac{e^{-S_2}}{(1+e^{-S_2})^2} \tag{9}$$

$$\frac{\partial\, S_2}{\partial W_{y_2y_3}} = T_1; \frac{\partial\, S_2}{\partial b_{y_3}} = 1; \tag{10}$$

$$W_{y_2y_3}{}^{+} = W_{y_2y_3} - \tau * \frac{\partial\nabla(W,b)}{\partial W_{y_2y_3}} \tag{11}$$

$$b_{y_3}{}^{+} = b_{y_3} - \tau * \frac{\nabla(W,b)}{\partial b_{y_3}} \tag{12}$$

Turn training parameters that connect the input layer and the hidden layer.

$$\frac{\partial\nabla(W,b)}{\partial W_{y_1y_2}} = \frac{\partial\, S_1}{\partial W_{y_1y_2}} * \frac{\partial T_1}{\partial\, S_1} * \frac{\partial\nabla(W,b)}{\partial T_1} \tag{13}$$

$$\frac{\nabla(W,b)}{\partial b_{y_2}} = \frac{\partial\, S_1}{\partial b_{y_2}} * \frac{\partial T_1}{\partial\, S_1} * \frac{\partial\nabla(W,b)}{\partial T_1} \tag{14}$$

$$\frac{\partial T_1}{\partial\, S_1} = \frac{e^{-S_1}}{(1+e^{-S_1})^2} \tag{15}$$

$$\frac{\partial\, S_1}{\partial W_{y_1y_2}} = x_{y_1}; \frac{\partial\, S_1}{\partial b_{y_2}} = 1; \tag{16}$$

$$W_{y_1y_2}{}^{+} = W_{y_1y_2} - \tau * \frac{\partial\nabla(W,b)}{\partial W_{y_1y_2}} \tag{17}$$

$$b_{y_2}{}^{+} = b_{y_2} - \tau * \frac{\nabla(W,b)}{\partial b_{y_2}} \tag{18}$$

$\boldsymbol{W_{y_2y_3}}^{+}$ , $\boldsymbol{b_{y_3}}^{+}$, $\boldsymbol{W_{y_1y_2}}^{+}$, $\boldsymbol{b_{y_2}}^{+}$are new training parameters between the input layer - the hidden layer, and the hidden layer - the output layer, respectively. $\boldsymbol{\tau}$ is the learning rate.

### *2.2 Transmissilbity*

Transmissibility performs the response ratio between two Degrees of Freedom (DoF) [11]. The process of calculating the transmissibility is depicted below.

If $F_l$ is a force vector at node $l$; $X_i$, and$X_j$ are responses (amplitude of displacement) at point $i$, $j$, respectively, the relationship between $F_l$ and $X_i, X_j$ can be estimated as Eq. (19) and (20):

$$X_i(\omega) = H_{(i,l)}(\omega)F_l(\omega) \tag{19}$$

$$X_j(\omega) = H_{(j,l)}(\omega)F_l(\omega) \tag{20}$$

Where $H_{(i,l)}$and $H_{(j,l)}$ represents the Frequency Response Function (FRF) at point $i$ and $j$ to $l$. The transmissibility ($T_{(i,j)}$) is calculated by using Eq. (21).

$$T_{(i,j)} = \frac{H_{(i,l)}(\omega)}{H_{(j,l)}(\omega)} = \frac{X_i(\omega)/F_l(\omega)}{X_j(\omega)/F_l(\omega)} \tag{21}$$

The short form of Eq. (21) can be presented in Eq.(22):

$$T_{(i,j)}(\omega) = \frac{X_i(\omega)}{X_j(\omega)} \tag{22}$$

Where $X_i$ and $X_j$ are responses at points $i$ and $j$ in the frequency domain.

Using a similar approach as**Erreur ! Source du renvoi introuvable.**, a Damage Indicator (DI) can be identified using Eq. (23):

$$DI = \int_{f_{min}}^{f_{max}} TR\, df \tag{23}$$

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

# 3 Application of the proposed approach for damage detection problem

### *3.1 Numerical model*

To investigate the effectiveness of the proposed approach, a cable-stayed bridge (Kien bridge) is employed. Kien bridge is located in Hai Phong (see ***Fig. 2)*** that crosses the Cam river, is on Highway 10 and connects Thuy Nguyen and An Duong districts. The bridge includes three spans with a length of 85m + 200m + 85m. The bridge has a total of 72 stay cables distributed on two tower plane with the length from 20m to 103m.

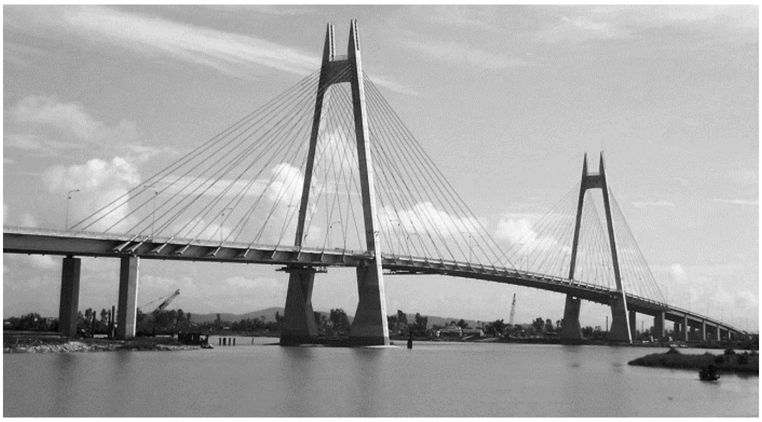

***Fig. 2 - Kien bridge.***

**Fig**. 3 provides an overview of the Finite Element Model (FEM) of Kien bridge. This model is constructed using Stabil toolbox in Matlab [12]

The model consists of 645 nodes, 1354 elements, and 3093 DoFs. The bridge is modeled utilizing three-dimensional beam elements including 6 DoFs at each node. The bottom of the tower is fixed and movable bearings are put at the end of the bridge. A summary of the section’s properties of components is given in **Table 1**.

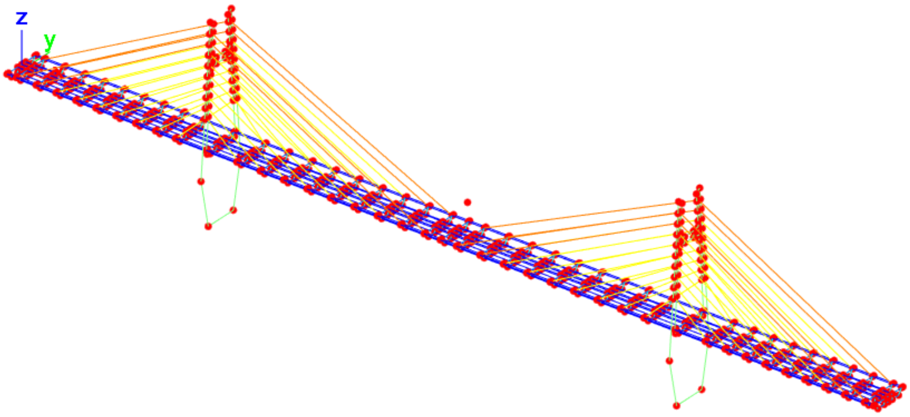


*Fig. 3 - FEM of Kien Bridge*

**Table 1 - The section's properties of components in Kien bridge**

| No | Types of elements | ID | Areas (m$^2$) | Moment of Inertia (m$^4$) | Moment of Inertia (m$^4$) |
|---|---|---|---|---|---|
| | | | $A$ | $I_{yy}$ | $I_{zz}$ |
| 1 | Main Beam | 1 | 8 | 2.980833333 | 2.98083333 |
| 2 | Cross beam | 2 | 3 | 2.125 | 2.125 |
| 3 | Web | 3 | 3 | 2.125 | 2.125 |
| 4 | Tower | 4 | 8 | 7.06666667 | 1.666666667 |
| 5 | Cable type 1 | 5 | 0.070686 | 0.000397608 | 0.000397608 |
| 6 | Cable type 2 | 6 | 0.113411 | 0.001023539 | 0.001023539 |

Table 2  lists the material parameters used in the model.

Table **2** lists the material parameters used in the model.

**Table 2 - Material properties**

| Elements | ID | Young's modulus | Poison's ratio | Volumetric mass density |
|---|---|---|---|---|
| | | Gpa | $\mu$ | kg/m$^3$ |
| Main beam | $E1$ | 23.00 | 0.35 | 2400 |
| Cross beam | $E2$ | 23.00 | 0.35 | 2400 |
| Web | $E3$ | 40.00 | 0.35 | 2400 |
| Tower | $E4$ | 38.68 | 0.35 | 2400 |
| Cable type 1 | $E5$ | 160.00 | 0.2 | 7850 |
| Cable type 2 | $E6$ | 173.00 | 0.2 | 7850 |

### *3.2* Input and target data for the network.

For comparison, two data sets including natural frequencies and transmissibility are used. We assume that the damages are generated by reducing the stiffness of elements (only consider damages for cable elements). For single damage, the stiffness of each cable element reduces from 0% to 50% with an interval of 1%. In this case, there are 50 (the number of damaged scenarios of one element)*36 (the number of cables) = 1800 damage scenarios. For multiple damages, the stiffness of two elements is reduced at the same time. Therefore, a total of 706860 damaged cases are created. To consider the practical applicability of the method, 2% of the noise is used. The ANN architecture is shown in Fig. 5.

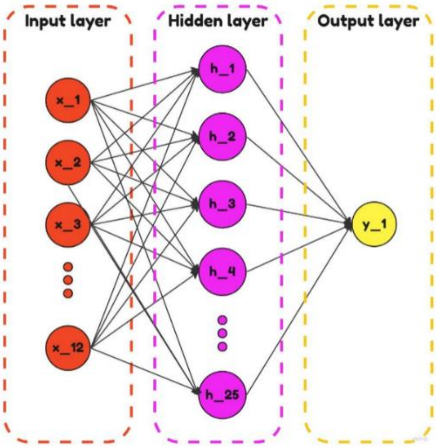


***Fig. 4 – ANN architectures***

The input data for the two models is the transmissibility damage index calculated by Eq.(23) and the natural frequencies of the first 12 modes. The input layer and the hidden layer include 12 neurons and 25 neurons, respectively, whereas the output layer consists of the damage level and damage location.

## 4 Results

In this section, the obtained results are analyzed for both single and multiple damage cases.

### *4.1* Single damage.

Fig. 5 and Fig. 6 show that the $R$-value calculated using input data of the transmissibility function (0.99999) is higher than using input data of natural frequencies (0.99974). On the other hand, the second approach (input data based on transmissibility function) also reduces computational time compared to the first one (input data based on natural frequencies), at 37.52 (s), and 58.26 (s), respectively.

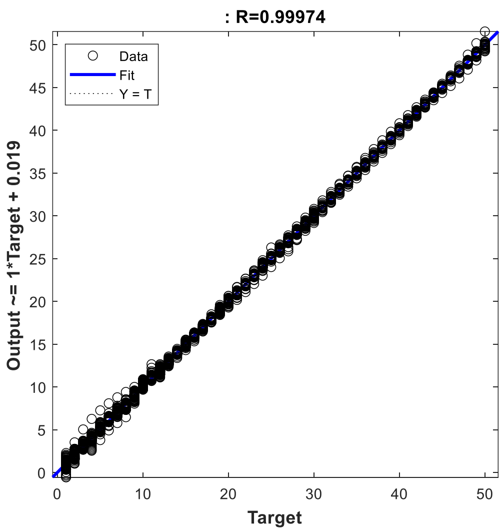


***Fig. 5 – R-value in single damage using natural frequencies – based ANN***

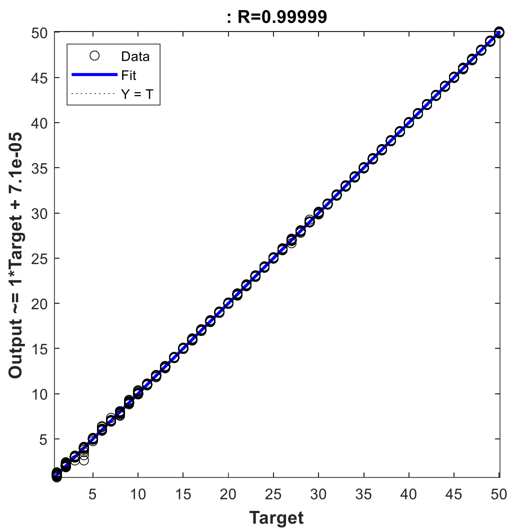


***Fig. 6 – R-value in single damage using transmissibility function– based ANN***

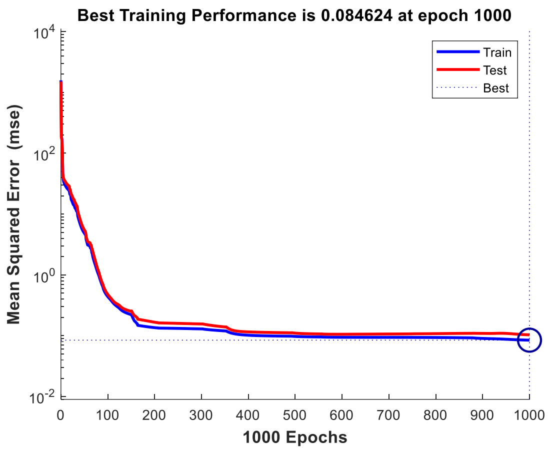


*Fig. 7 – MSE-value in single damage using natural frequencies – based ANN*

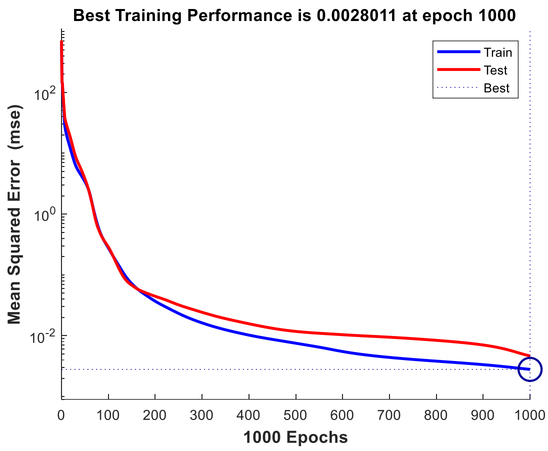


*Fig. 8 – MSE-value in single damage using transmissibility function– based ANN*

In terms of accuracy, ***Fig. 7*** and ***Fig. 8*** show that the method using input data based on the transmissibility function also surpasses that applying input data based on natural frequencies. The error between the calculated and real values of the first and the second approach is **0.0028011** and **0.084624**, respectively.

In this work, we only apply 1000 epochs to train the network for both cases. The reason is that after 1000 epochs, the convergence of the network using natural frequencies-based ANN almost does not change. In the contrast, the convergence of the network applying transmissibility-based ANN still improve (go down). In the other word, the main aim of this work is to compare the effectiveness of transmissibility-based ANN with that of natural frequencies-based ANN. Therefore, the network using 1000 epochs can satisfy the aim.

### *4.2 Multiple damage*

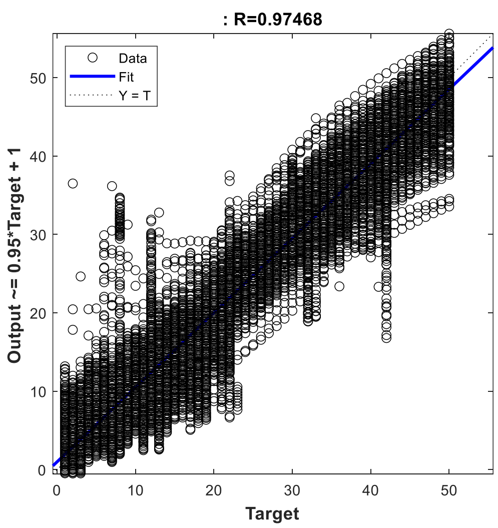


*Fig. 9 – R-value in multiple damage using natural frequencies – based ANN*

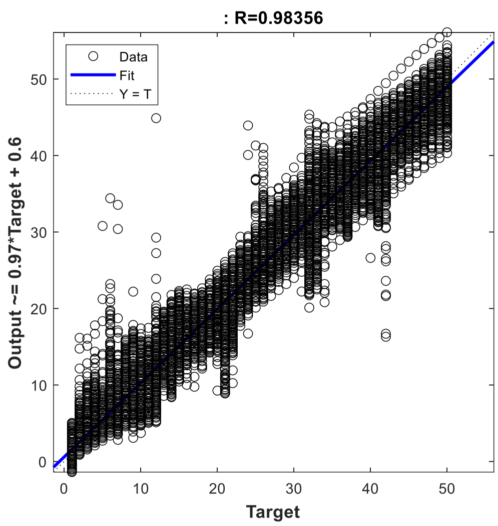


*Fig. 10 – R-value in multiple damage using transmissibility function– based ANN*

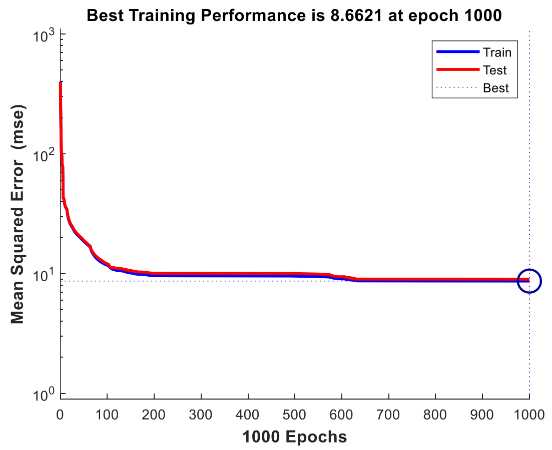


*Fig. 11 – MSE-value in multiple damage using natural frequencies – based ANN*

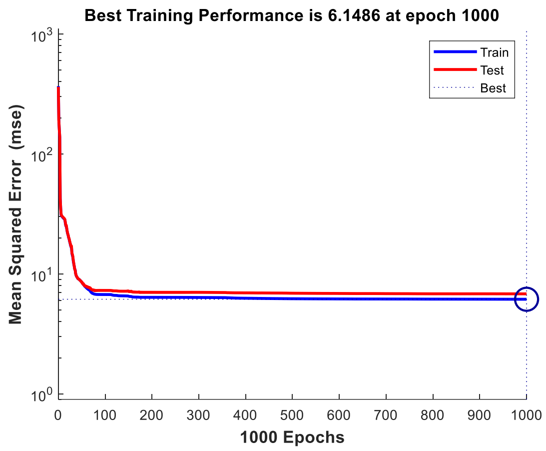


*Fig. 12 – MSE-value in multiple damage using transmissibility function– based ANN*

From ***Fig. 9*** to ***Fig. 12***, we can see that the method using input data based on the transmissibility function outperforms the method using input data based on the natural frequencies in terms of both $R$-value (**0.98356, 0.97468**) and MSE-values (**6.1486**, and **8.6621)**, respectively. Moreover, the first method requires lower computational time to train the network than the second one, with **354.98** (s) and **422.36**(s),respectively.

## 5 Conclusions

In terms of using ANN for damage detection based on structural dynamic properties, natural frequency, mode shape, or mode shape curvature have been commonly used as input data. However, these methods not only face major challenges to obtain in the field but also are not sensitive enough to accurately identify minor structural defects. Therefore, we propose using data obtained from the transmissibility function as input data to train the network. Besides, in this work, structural dynamic behaviours are collected under the effect of moving load. To compare with the proposed approach, natural frequency-based ANN is also employed. Based on obtained results, some main conclusions are drawn. Both the proposed methods and frequency-based ANN provide results with a high degree of accuracy. This demonstrates via $R$-values ( $R$-values higher than 0.9) and convergence level (convergence level close to 0). Transmissibility-based ANN outperforms frequency-based ANN in terms of accuracy even the effect of noise is taken into account. The proposed method also reduces computational time compared to frequency-based ANN.

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