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Damage detection in Ca-Non Bridge using transmissibility and artificial neural networks

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Abstract. This paper deals with damage detection in a girder bridge using transmissibility functions as input data to Artificial Neural Networks (ANNs). The original contribution in this work is that these two novel methods are combined to detect damage in a bridge. The damage was simulated in a real bridge in Vietnam, i.e. Ca-Non Bridge. Finite Element Method (FEM) of this bridge was used to show the reliability of the proposed technique. The vibration responses at some points of the bridge under a moving truck are simulated and used to calculate the transmissibility functions. These functions are then used as input data to train the ANNs, in which the target is the location and the severity of the damage in the bridge. After training successfully, the network can be used to assess the damage. Although simulated responses data are used in this paper, the practical application of the technique to real bridge data is potentially high.

Keywords: Structural Health Monitoring (SHM); transmissibility; Artificial Neural Networks (ANNs); bridge monitoring; Finite Element Method (FEM)

1. Introduction

Bridges may suffer from damage due to environmental influences, accidental actions, service loads, and natural hazards. Structural Health Monitoring (SHM) provides an objective evaluation of the overall performance and condition of a bridge. This could protect a bridge from collapse, allow proper maintenance, make the bridge safe and extend its lifetime. SHM process, generally, takes three main stages. Stage 1 is the survey step, measuring the actual structural state. Stage 2 is data analysis, using appropriate algorithms to treat the data collected in Stage 1. Stage 3 is based on the analysis results from the second phase. The engineer makes decisions on the status, working conditions, as well as measurements to improve the performance of the structure, ensure the safe exploitation of the bridge. To analyze the data, we can use two methods namely physical model-based method and non-model based method. Physical model-based approaches concentrate on the understanding of the structure from its physical characteristics, such as natural frequencies (Salawu 1997, Gillich *et al*. 2019), mode shapes (Yang and Oyadiji 2017), damping and stiffness (Doebling *et al*. 1998, Cao *et al*. 2017). Moreover, if combined with optimization algorithms to reduce the difference between model results and results extracted from measurements, this approach will provide more accurate and efficient results (Tiachacht *et al*. 2018, Samir *et al*. 2018, Qin *et al*. 2018, Khatir *et al*. 2018, Khatir and Abdel Wahab 2018). Some authors also combined optimization algorithms with the cloud model (Zheng *et al*. 2018) or improved the existing global optimization technique (Yin *et al*. 2018) for better structural damage identification. When the structure appears to be damaged, the physical variables change. However, these parameters are very sensitive to temperature, environment, and load condition. Therefore, sometimes there is no enough evidence to conclude whether the structure is damaged or not. In addition, creating physical models that accurately represent structural behavior is time-consuming, slowing down the detection of failures and potentially increasing the cost of analysis.

Statistical approach or non-model based method only considers the responses. In this approach, the condition of the structure can be determined without the in-depth knowledge of the expert as well as the direct geometry and material properties. Some methods based on this approach have been developed in recent years, including Cross-correlation, Auto-Regressive, Principle Component Analysis Method, Computer vision – based, ANNs. Cross-correlation is a measure of similarity of two time series, two functions or two random vectors. This analysis explored for

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structural health monitoring and damage detection. Yang *et al*. (2007) used Cross-correlation method to detect the damage of a laboratory composite beam under random excitation. In the Auto-Regressive (AR) model, the structural response is modeled using a mathematical function (Gul and Catbas 2010). It is seen that if the structure is altered for example due to damage or deterioration, the mathematical parameters in the AR model will be changed. In Principle Component Analysis (PCA) method, a model is constructed based on major components. Using an orthogonal projection, the original set of variables in an N-dimensional space is transformed into a new set of uncorrelated variables, in a P-dimensional space such as P<N. Although the data information reduced, the main characteristic of the data, as well as the basic characteristic of the structure, still maintains. PCA was used to detect damage by using two separated vectors corresponding to the two biggest individual values of the data correlation matrix and compared with other methods (Posenato *et al*. 2008). Recently, Computer vision-based method with data was collected through the camera, camcorder, and data processing algorithms was also of great interest because of technical and economic issues (Khuc and Catbas 2017, Shi *et al*. 2010). The ANNs method combined with statistical probability theory is a method of detecting structural damage through analytical algorithms, which identifies mutation factors or novel elements. ANN is a set of mathematical models that work on the principle of the biological neural network (Neves *et al*. 2017). ANNs is also a method to solve the inverse problem and starts with the results and then calculates or predict the causes. Besides ANNs, many other methods can be used to solve the inverse problem. Nanthakumar *et al*. (2016) used regularized level set method for detecting damage in material interfaces, Vu-Bac *et al*. (2018) used a NURBS-based inverse analysis for a shell thin structures. Data, after analysis in stage 1, will be used to design and training ANNs, which are trained to predict future values of the features. Following the validation of the best trained network, ANN will decide by itself on the results in stage 3. Numerous ANN techniques have been applied to SHM and damage detection (Doebling *et al*. 1996) and become a powerful tool for SHM. Zang and Imregun (2001) used measured frequency response functions as input data to ANNs and applied PCA technique to measured FRFs. Hakim and Abdul Razak (2013) combined ANNs and adaptive neuro-fuzzy inference system (ANFIS) to identify damage in a model of a steel girder bridge using dynamic parameters. The natural frequencies were obtained from experimental modal analysis used as input data. ANN was used for structural damage detection in the girders of a vehicular bridge and then could be used to predict the location and severity of the damage in the studied bridge with high accuracy (Gonzalez-Perez and Valdes-Gonzalez 2011). In recent years, more and more applications of machine learning algorithms were recorded and became the most frequently used technique (Zapico *et al*. 2003, Meruane and Mahu 2014, Worden and Manson 2007).

Using vibration-based methods to determine the changes in the dynamic characteristics of a structure has continuously increased over the past few decades. The main idea is that damage changes the stiffness of the structural and so the modal properties, i.e. natural frequencies, mode shapes, damping ratios. This method is useful in system identification and damage detection of civil engineering structures, especially bridges in which moving vehicles can be used as an excitation. The natural frequencies and mode shapes can be extracted from the dynamic response of a vehicle passing over the bridge (Yang and Chang 2009, Yang *et al*. 2014). Miyamoto and Yabe (2011) proposed a new method of assessing the condition of short- and medium span reinforced/prestressed concrete bridges based on vibration data obtained from a public bus.

Transmissibility functions are defined as the ratio between two responses in the frequency domain when an excitation force is applied. Transmissibility functions are easy to obtain in real-time because it does not involve the measurement of excitation forces. Maia *et al*. (2001) proved that the transmissibility matrix could be computed from response only and was sensitive to damage. In another paper, Urgueira *et al*. (2011) presented some important properties of the transmissibility matrix. They concluded that the method based on transmissibility measurements was more sensitive to damage after comparing two damage indicators constructed with transmissibility function and with frequency response functions (FRF). Transmissibility is a local quantity suggesting a higher sensitivity than the modal parameters in detecting changes in the dynamic behavior of structures (Maia *et al*. 2011). Transmissibility combined with other methods is very useful tools for damage detection (Zhou and Wahab 2017, Zhou *et al*. 2017, Zhou and Abdel Wahab 2017, Zhou *et al*. 2016). Kong *et al*. (2014) were successful in using the transmissibility of a vehicle and bridge coupled system to detect damage.

In this paper, we propose a method that makes use of transmissibility indicators of a vehicle passing on a bridge as input for ANNs. Many single damage cases are simulated to train the ANNs for damage prediction.

2. Theoretical background

2.1 Transmissibility

Dynamic model of the bridge can be obtained through finite element modeling. The equation of motion for the bridge is written as:

$$M_b \ddot{U}_b + C_b \dot{U}_b + K_b U_b = f_b \tag{1}$$

Where M_b, C_b, $,K_b$ denote mass, damping and stiffness of the bridge, respectively and f_b is wheel-bridge contact force on the bridge. The moving truck is modeled as a moving load on the bridge.

By solving Eq. (1), we can calculate the bridge responses. These responses can be measured by attaching sensors to the bridge in field measurement as well as by numerical simulations. Displacement, acceleration response time-histories are collected based on the impact of the truck. The time-history of the response data is then transformed to the frequency domain using a fast-Fourier transform. The transmissibility $T_{i,j}$ is then calculated as the ratio between two locations as shown in Eq. (2)

$$T_{(i,j)}(\omega) = X_i(\omega)X_j^{-1}(\omega) \tag{2}$$

Where X_i and X_j are the response in the frequency domain at location *i* and *j*, respectively.

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

2.2 Artificial Neural network (ANN)

ANN is estimating a mapping function based on the knowledge of some example input-output pairs. This study intends to train the neural networks using the training set composed of pairs of values for the independent (input) and dependent (output) variables (Beale *et al.* 1992). In general, the neural network will be playing the role of *f(.)* as:

$$y = f(x) \tag{3}$$

Where *x* is vector of inputs and *y* is vector of outputs.

The network consists of many layers:

- One input layer that receives the indicator got from the transmissibility functions.
- One or more hidden layers that analyze the data.
- One output layer that provides the results of the analysis. In this work, the output is the location and the severity of the damage.

One layer has many neurons, which behave as functions. They transform an input signal into an output signal *f(x)*. The weights are incrementally adjusted to decrease the error, and this process is iterated until the error can no longer be minimized. The process can be expressed:

$$x_i^{(k)} = f\left(\sum_j \omega_{ij}\, x_j^{(k-1)}\right) \tag{4}$$

Where: $x_j^{(k-1)}$ is the signals from preceding layer *k*-1, passed through a nonlinear activation function *f* to emerge as the output of the node $x_i^{(k)}$ to the next layer.

During the training process, the value of the weights ω_{ij} are continuously adjusted to optimize network performance. The default performance function for feedforward networks is mean square error (*mse*), i.e. the average squared error between the network outputs *y* and the target outputs *t*. It is defined as follows:

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \tag{5}$$

There are many training algorithms available in Neural Network Toolbox software. The chosen training algorithm is the Levenberg-Marquardt backpropagation algorithm. This algorithm is fast and performs well on function fitting (nonlinear regression) problem (Demuth and Beale 2009).

2.2.1 Input for ANNs

The input parameters for ANNs are the most importance part for the algorithm, which reflect the characteristic of the structural. The indicator takes the sum of transmissibility along the specific frequency range that can be described as:

$$TI_k = \int_{f_{min}}^{f_{max}} T_{i,j}(\omega)\, df \tag{6}$$

Where f_{min} and f_{max} are the low and high boundaries for the integration area. The choice of f_{min} and f_{max} greatly influences results. This is usually done by using engineering's experience. The frequency range was chosen based on the regions of high similarities between different transmissibility function in a structure.

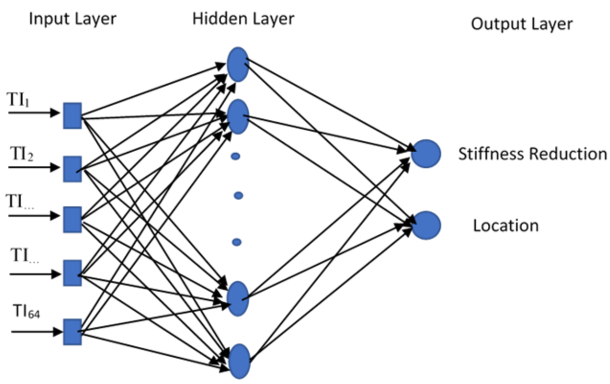


Fig. 1 A schematic structure of neural Networks model

2.2.2 Target for ANNs

In this paper, the location and the severity of damage is the target of the network. The severity of damage is shown by the percentage decrease of the stiffness of the damaged section. All input parameters for the network are calculated based on the damaged position and the severity of the damage, respectively. The network diagram is shown in Fig. 1.

3. Numerical verification

3.1 Description of Ca-Non Bridge

For the simulations, Ca-Non Bridge is used. The bridge is located at Km 359 + 724 of the Ho Chi Minh Road (West branch), in the A Luoi district, Thua Thien Hue province, and put into operation in 1979. Two pictures of the bridge are shown in Fig. 2.

The bridge consists of a simply supported span, composed of steel girders and concrete slab. The length of the bridge is 27.3 m (from the end of right abutment to the end of left abutment). The cross-section of the bridge consists of eight steel girders having the length of 18 m and height of 80 cm. The top and bottom flange are 270 mm wide and 20 mm thick, respectively, the web is 760 mm high and 13 mm thick. The distance between the two girders is 1000 mm. Fig. 3 shows a drawing of bridge cross section. The bridge has eight crossbeams including two beams at the abutments. Each cross beam is the combination of two C-shape; each C-shape steel is 205 mm

Fig. 2 Ca-Non Bridge

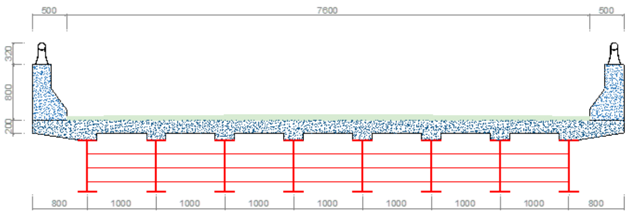


Fig. 3 The Ca-Non bridge cross section (dimensions in mm)

high and 60 mm wide. The cross beams are located equally along the girders. The width of the bridge is 8.6 m including 7.6 m for the traffic lane and two barriers having 0.5 m width each. The bridge deck is made of asphalt concrete, the two abutments are made of concrete, and the bearings are made of steel. The dimension of the bearing is 20 × 50 × 8.5 cm.

3.2 Finite element model

Finite element model of the Ca-Non Bridge is established in a CSiBridge FEM (CSI 2002), as shown in Fig. 4. The reinforced concrete slab is supported by eight I-shape steel girders, which are connected by eight cross beams in the transverse direction. Different types of finite elements have been used to model bridge superstructure. The bridge deck is modeled by shell elements. The girder is modeled using beam elements (Chung and Sotelino 2006). The composite action between the concrete deck and the

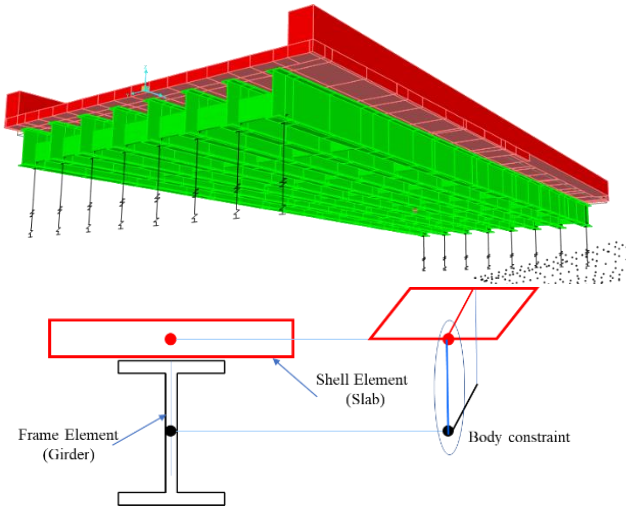
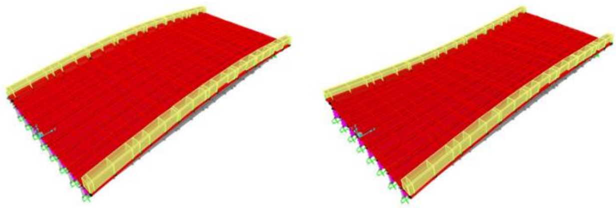


Fig. 4 The Ca-Non Bridge FE model



(a) Mode 1: 6.25 Hz (b) Mode 2: 9.9 Hz

Fig. 5 The two first mode shapes and the corresponding frequencies

Table 1 Material properties of Ca-Non Bridge

$E_{concrete}$	$\rho_{concrete}$	$\upsilon_{concrete}$	E_{steel}	ρ_{steel}	υ_{steel}
(GPa)	(kg/m^3)	-	(GPa)	(kg/m^3)	-
27	2400	0.2	190	7800	0.3

steel girders is modeled as in Fig. 4. Beams and shell elements are connected using rigid body constraint. Separated body constraints are used for each pair of connected nodes. The bridge model contains 735 elements, 813 nodes and 432 constraints. The mesh size is 0.2 × 0.2 m and 1 m for the deck and I girder, respectively. The barrier, deck surface was modeled as added mass. The material properties are summarized in Table 1.

The boundary conditions are simply supported at the two ends of the eight I-shape girders bearings. Rotations in all directions are allowed in order to simulate the simply supported structure. Vertical restraint is placed at the two bearings, while longitudinal and transverse restraints are assigned at one bearing. Mode frequency analysis is conducted for the calibration of the bridge model. The first two mode shapes of FEM are shown in Fig. 5, the numerical frequency is 6.25 Hz for mode 1 and 9.9 Hz for mode 2.

After obtaining the most appropriate numerical results for modal analysis, we introduced a truck passing through the bridge, then the displacement response of 72 nodes in the bridge is calculated (Fig. 6). The truck characteristics are listed in in Table 2.

Table 2 Truck characteristic

Distance between 2 axles in vertical direction	Distance between first axle and middle axle	Distance between middle axle and last axle	First axle load P_1	Middle axle load P_2	Last axle load P_3
(m)	(m)	(m)	(ton)	(ton)	(ton)
1.8	2.7	1.35	5.07	10.14	10.14

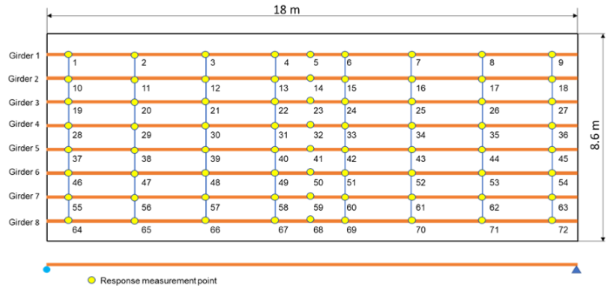


Fig. 6 Location of the considered nodes

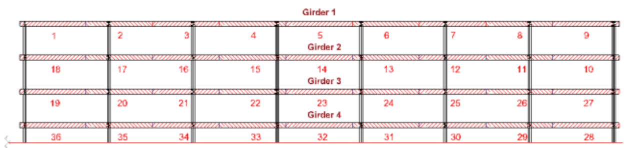


Fig. 7 Damage locations in Ca-Non Bridge

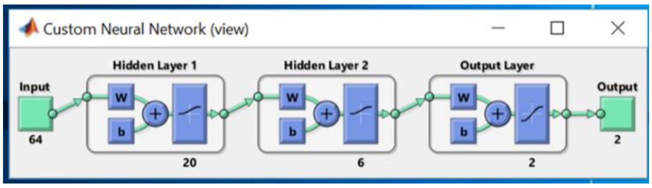


Fig. 8 The structure of neural network

3.3 Damage detection procedures

To detect damage in the Ca-Non bridge, the following steps are followed.

Step 1: Responses determination

Calculate the responses of 72 nodes in the bridge.

Step 2: ANNs targets

The targets of the networks in this paper are the locations and the severity of the damage in the bridge girders. The severity of damage is shown by the percentage of stiffness decrease in the damaged section. Each bridge girder is divided into 9 elements, with two meters in length for one element. Damages are introduced in half of the bridge in four girders. The 36 locations of damaged are presented and counted by number and shown in Fig. 7.

Step 3: Transmissibility evaluation

The transmissibility functions in each girder could be evaluated directly from the simulated measurements of the responses at 72 analyzing nodes using Eq. (1). The load excitation is the moving truck, run across the bridge with the constant velocity. The weight of the truck is assumed to be constant. An amount of 2% random Gaussian noise was added to the simulated responses.

In girder 1, we consider 9 nodes (from 1 to 9), using node 1 as the reference node, 8 transmissibility functions (from $T_{1,2}$ to $T_{1,9}$) and 8 indicators (from TI_1 to TI_8) are calculated using Eq. (2) and Eq. (6), respectively.

This procedure is repeated for all girders from 2 to 8. Sum up, we got 64 indicators to be used as input for ANNs, which are calculated based on 36 damaged locations. Each damage location has 26 scenarios of damage severity. The damage locations and damage severity are saved as the target of the ANNs corresponding with ANNs inputs.

Step 4: ANNs training and testing

All the ANNs data are divided into three part. One part is taken for ANNs training, one part for valid the network and one part is used for testing. The number of neurons is chosen and the value of the weights are adjusted to obtain the best performance networks.

Step 5: Result analysis

This step is to confirm that the trained ANNs can predict the location and the severity of the damage.

3.4 Results and Discussion

The general neural network design process has seven primary steps, namely collect data, create the network, configure the network, initialize the weights and biases, train the network, validate the network and use the network. As discussed above, we use simulated transmissibility functions to collect data. This step is critical to the success of the design network. To create the network, the most important is choosing the number of the hidden layers and number of the neurons in each layer. These may depend on some factors such as the complexity of function to be learned, the training algorithm, the number of neurons in the input layer, the output layer. Using too few neurons in the hidden layer will result in something called under fitting. There are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. Using too many neurons in the hidden layers can result in overfitting. The information contained in the training set is not enough to train all the neurons in the hidden layers. A large number of neurons in the hidden layers can increase the time it takes to train the network. By trial and error, the correct number of neurons to be used in the hidden layers can be selected. In this work, the network with two hidden layers, hidden layer 1 has 20 neurons and hidden layer 2 has 6 neurons are proposed (Fig. 8). This network then will be trained and validated using *mse* performance network, and Levenberg-Marquardt training algorithm. The results will be shown in the next section.

3.4.1 Intact bridge

For the intact girder, Fig. 10 shows the transmissibility of Girder 1. Fig. 9 show the $T_{1,3}$ before and after using GRNN function to approximate. Before approximating, the result shows oscillation because the numerical response being calculated every 0.005 s, instead of being a continuous variable. GRNN was suggested by D.F. Specht in 1991 (Specht 1991). GRNN is a single-pass associate memory feed-forward type ANNs and available in Matlab. Based on observations, the trend of both curves is similar,

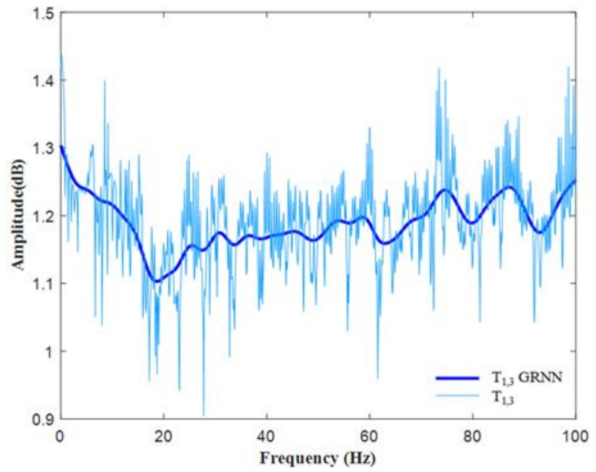


Fig. 9 $T_{1,3}$ transmissibility from numerical model and approximation function using GRNN

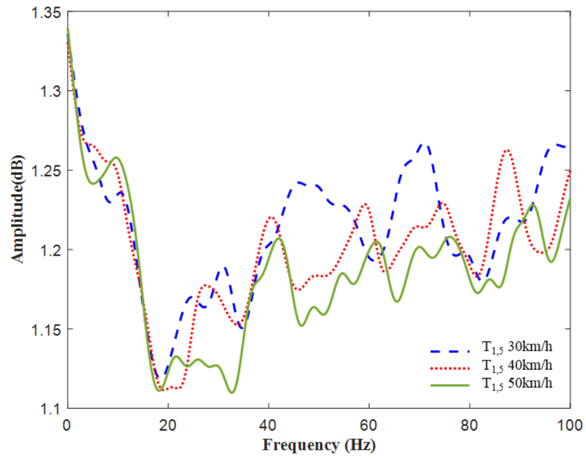


Fig. 11 $T_{1,5}$ with different velocity of truck -truck weight 25 ton

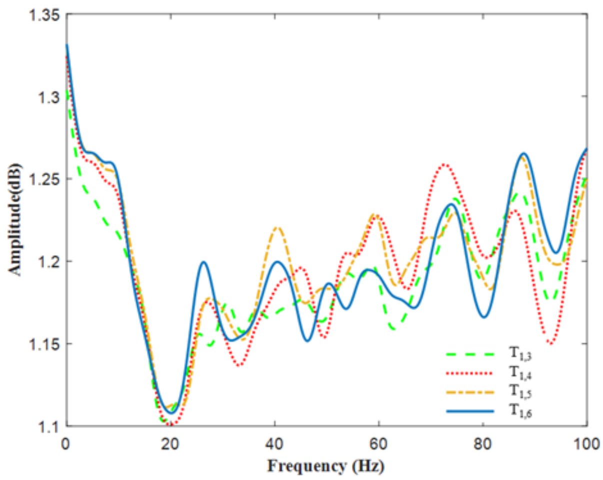


Fig. 10 Transmissibility of intact girder 1

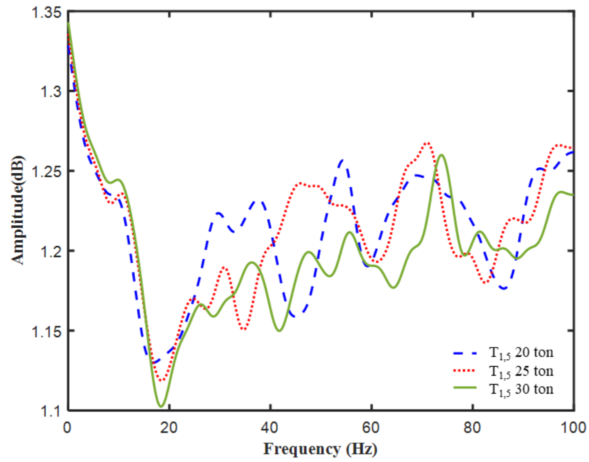


Fig. 12 $T_{1,5}$ with different weights of truck - truck velocity 30 km/h

as the peak and valley appear at the same frequencies. Using this method, we got the results for other transmissibility functions as shown in Fig. 10. The moving truck is 25 ton weight and runs with 30 km/h velocity on the bridge. Fig. 11 shows the transmissibility functions when we change the velocity of the truck. From Fig. 11, when the velocity of the truck changes, the transmissibility function between node 1 (near the bearing) and node 5 (in the middle span) changes, especially at high frequencies. We observe the same remarks when we compare the transmissibility in the same location, with the same velocity of the truck, but with diffeernt truck weight (Fig. 12).

3.4.2 Damaged bridge

The advantage of using steel in constructing a bridge is its high strength, easy to fabricate, fast construction time. The disadvantage is corrosion, which often appears in a part of a steel girder. The severity of the damage depends on the depth and the area of the corrosion. In this paper, we reduce the stiffness of each element to reflect the severity of damage in the girder. There are 36 locations of damage in 4 girders as discussed above and shown in Fig. 7. For each damage location, we have 26 scenarios. The stiffness in the damage element is reduced from 0% to 50% with an interval of 2%. Therefore, there will be 26 scenarios in each damage location, i.e. from D1 to D50 in addition to D0 for an intact case.

The transmissibility for damaged girder 1 and 2 are shown in Fig. 13 and Fig. 14. In girder 1, the location of damage is numbered as 1 and in girder 2 as 17. We observe that when the severity of the damage changes, the transmissibility function changes also, especially at high frequencies. This proved that transmissibility function is sensitive to local damage and can be used as a damage indicator. To calculate the input for ANNs, we use Eq. (6) frequency range from 9 Hz to 11 Hz. This frequency range covers the first frequency peak of all transmissibility functions.

As discussed above, 64 *TI* indicators calculated from 26 scenarios in 36 damage locations are used as input data for the ANNs network. Fig. 5 shows 8 of these indicators when the damage occurs at location 1. These indicators change according to the change of damage location and damage

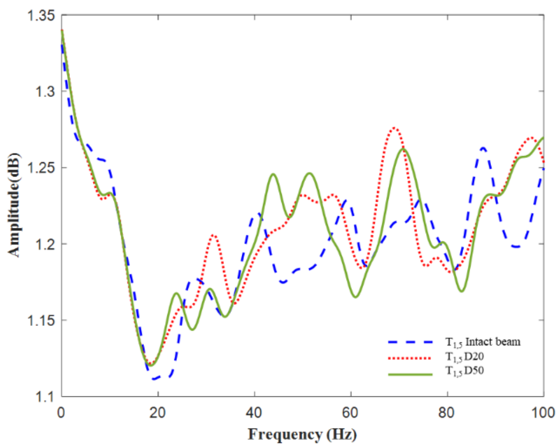


Fig. 13 $T_{1,5}$ transmissibility with different scenarios - damage at location 1

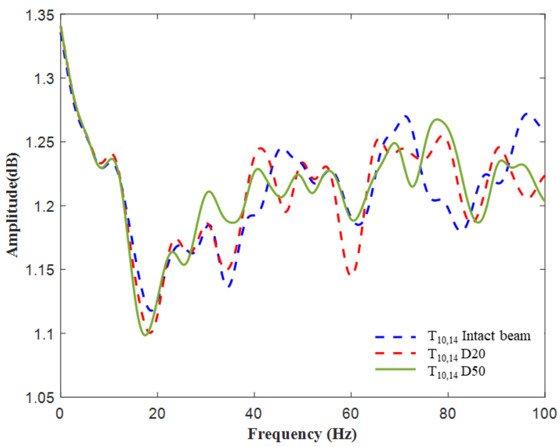


Fig. 14 $T_{10,14}$ transmissibility with different scenarios - damage at location 17

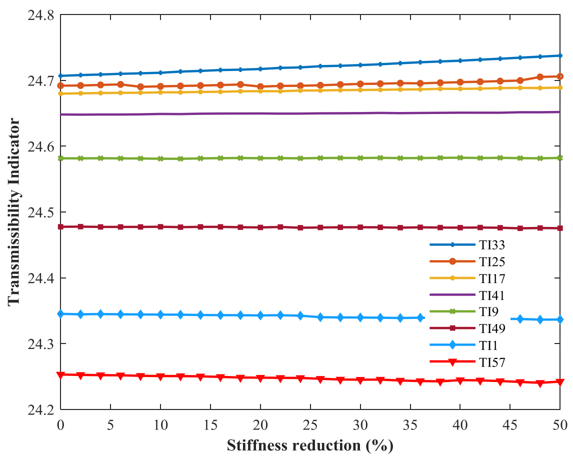


Fig. 15 Transmissibility Indicators - damage at location 1

severity. There are 936 simulated data in total. A sample of 70% of the data is used to train the network and a sample of 15% is used to measure the network generalization. A sample of 15% is used to test the network, which has no effect on training and therefore it provides an independent measure of network performance during and after training. The target of the networks is the location of the damage and its severity.

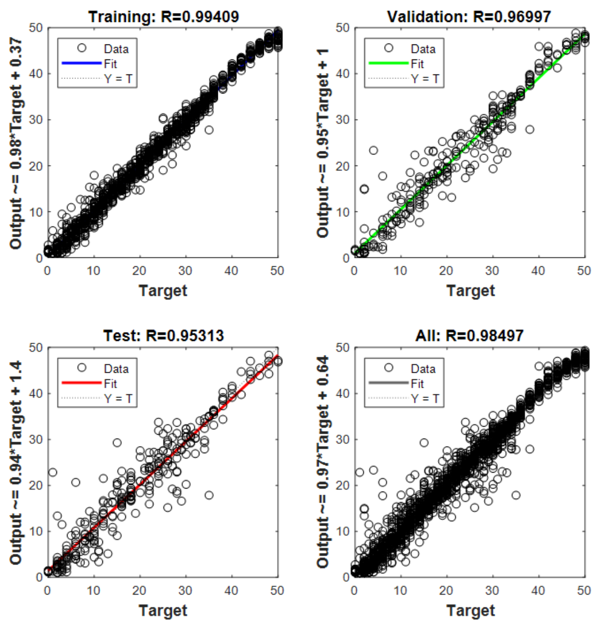


Fig. 16 Regression analyses of the considered scenarios

Table 3 Number of sensors and R-value of the network

Number of sensors	72	40	24
Number of neurons in Hidden Layer 1	20	10	6
Number of neurons in Hidden Layer 2	6	4	2
All: R-value	0.985	0.956	0.82

Fig. 16 shows a regression plot for relationship between the outputs of the network and the targets. There are four plots in Fig. 16. The first one shows the relationship between outputs of the network and the targets in training data sample. The second is for the validation of data sample, the third is for testing data sample and the last is for all data set. The dashed line in each plot presents the perfect line outputs= targets. The solid line represents the best fit linear regression line between outputs and targets. If R=1, this indicates that the network outputs are perfectly fit the targets and there is an exact linear relationship between outputs and targets. In our case, the four R-values are greater than 0.95 indicating a good fit. That means that the network, we proposed before, has successfully built a linear relationship between outputs and targets. After establishing the networks, they can be used for any new case. Therefore, by only using the displacement responses of a bridge, we can predict the location and severity of damage.

The number of considered points can be reduced based on the number of measurement heads. Table 3 shows the structure of the chosen ANNs and the R-value of each network, depending on the number of sensors. The more sensors are used, the bigger the R-value is, and the more neurons should be used in each hidden layer.

4. Conclusions

In this paper, a damage detection method is proposed using simulated transmissibility together with ANNs. Transmissibility is calculated from the simulated displacement responses of many points in the bridge. The feasibility of this method is assessed through a numerical model of Ca-Non Bridge. The results indicate that transmissibility together with ANNs could be used to find out the location and severity of the damage in a bridge with good precision. The use of ANNs provides a suitable methodology for damage detection.

Research has shown that with the collected data, the network after training was completely capable to identify damage. However, this method requires a large number of datasets to train and test the network. The most important is that we have a well calibrated FE model to reflect all the responses of the bridge. The proposed method utilized the displacement responses under a moving truck. The response of the bridge should be recorded at as many points as possible. The model vibration meter makes this method reliable. The life of a bridge can be extended if it is regularly inspected then repaired after damage detection.

The potential of this method for practical application is high. First, a well calibrated FE model is created. Then, the model is updated using the measured modal properties. The responses of some considered points are used to calculate the simulated transmissibility functions. The number of considered points in the bridge depends on the measurement points on site. The simulated truck is the same moving truck as in the experiment. If we want to use different trucks, the truck characteristics such as the axle weight, number of axles, the distance between two axels and the velocity of the truck could be added as input to the networks. The damage scenarios are introduced in the FE model and used to train the ANNs. The ANNs input parameters are obtained from the simulated transmissibility functions. The ANNs targets are the locations and the severity of the damage. In the second step, an experiment is carried out to measure the responses at all considered points due to a truck moving on the real damaged bridge. Then the measured transmissibility functions and transmissibility indicators are calculated. These parameters are put into the ANNs established before. The output of the created ANNs is the location and the severity of the damaged bridge.

In this research, we only consider that the bridge has only damage at one location. Multiple damages will be the subject of future research.

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