Transmissibility based damage assessment by intelligent algorithm

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ABSTRACT:

In civil engineering structural health monitoring has attracted increasing attention in damage identification under operational conditions during daily use, as it is quite difficult to control the loads. Hence, transmissibility, due to its dependence with output-only data and its sensitivity to local structural changes, has been of continuing interest to the scientific communities in recent years and became a relatively well-studied topic. In this paper, a new neural network-based damage assessment approach by using power spectrum density transmissibility (PSDT) is proposed and developed for assessing the damage severities directly from the forced vibration frequency-domain response. Above all, Latin Hypercube Sampling (LHS) method is used to generate different damage severities, then the transmissibility is calculated through finite element method via the vibration response after choosing a reference point; afterwards, transmissibility power mode shape is constructed and damage indicators are carried out. Hence, the undamaged structure data is settled as a baseline and the different damage severity data is also used as an input in the neural network. And the targets are the damage severities while the beam is divided into four parts. Continuously, the neural network is trained using a number of patterns. Finally, structural response based damage indicators are given to the well-trained neural network, which outputs the appropriate value for test patterns. A two sided-fixed beam example is included to demonstrate the feasibility and applicability of the proposed technique. Simulation results show promising use in real engineering use. The contribution of this paper is that the back propagation neural network is used in transmissibility based damage assessment under LHS method.

KEY WORDS: Transmissibility; damage assessment; intelligent algorithm; Latin Hypercube Sample (LHS).

1 INTRODUCTION

In civil engineering structural health monitoring has attracted increasing attention in damage identification under operational conditions during daily use, as it is quite difficult to control the influence from the operational environment. During last decades, researchers have devoted to proposing and developing new methods in damage identification, localization and quantification as well as structural remaining life assessment [1-5]. Pandey et al. proposed the mode shape curvature method and the flexibility matrix method [1,2]. Stubbs et al. proposed the strain energy method [3]. Fang and Perera [4] advised using power mode shape for early damage detection. However, vibration-based structural health monitoring methods normally need to extract vibration characteristics from operational vibration measurements. In recent years, transmissibility, which only depends on the vibration responses, is a relatively new research direction. Due to its dependence with output-only data and its sensitivity to local structural changes, transmissibility has been of continuing interest to the scientific communities in recent years and became a relatively well-studied topic. Q. Chen et al [6] firstly proposed transmissibility functions as potential features for damage detection. Afterwards, researchers developed a lot more transmissibility-based methods for monitoring the structural health in real engineering [6-11].

Artificial intelligence (AI) is a term that in its broadest sense would indicate the ability of a machine to perform the same kind of functions that characterize human thought [12]. And particularly Artificial Neural Networks (ANNs) are a part of artificial intelligence, which have been used in structural damage identification to improve the capacity in dealing with qualitative, uncertain and incomplete information. Modeling a linear or nonlinear structural system with neural networks has been increasingly recognized as one of the system identification paradigms (Masri et al., 1993). The neural networks firstly learn in training and store the knowledge in weights and biases. Normally the multi-layer neural networks are the first choice in structural identification use. ANNs could recognize damage patterns and determine the extent of damage in structural assessment due to their own pattern recognition capacity. ANNs have been used in a lot of parts of structural health monitoring by dealing with the engineering structural vibration response [13-14].

In this paper, a new neural network-based damage assessment approach by using power spectrum density transmissibility (PSDT) is proposed and developed for assessing the damage severities directly from the forced vibration frequency-domain response. Above all, a theoretical study has been done to find the damage indicators. And Latin Hypercube Sampling (LHS) method is used to generate different damage severities, then the transmissibility is calculated through finite element method via the vibration response after choosing a reference point; afterwards, the transmissibility power mode shape is constructed and damage indicators are carried out. Hence, the undamaged structure
data is settled as a baseline and the different damage severity data is also used as an input in the neural network. Continuously, the neural network will be trained using a number of training patterns. Finally, some structural response based damage indicators will be given to the well-trained neural network, which will output appropriate value for untrained patterns.

2 THEORETICAL DESCRIPTION

2.1 Transmissibility

Transmissibility measurement is an increasing widely used technique, and is very suitable for operational dynamic analysis in structural health monitoring. Here, the power spectrum density transmissibility (PSDT) function is defined as the ratio of two responses spectra by assuming a single force applied in an input degree of freedom. Normally, in real life several operational forces or even more complicated forces are exciting the structure, as this happens, it would be quite more sophisticated in calculation. In order to avoid this problem here using a reference response signal instead of an excitation signal to estimate the power spectrum density transmissibility.

As to power spectrum density, the transmissibility between the outputs $y_i(t)$ and $y_j(t)$ with reference to the output $y_p(t)$ is defined as the ratio between the power spectral densities responses $X_r^p(\omega)$ and $X_f^p(\omega)$:

$$T_{ij}^p(\omega) = \frac{X_r^f(\omega)}{X_f^f(\omega)}$$

(1)

where $\omega$ is the frequency.

Actually, in several ways transmissibility could be derived, one of the most common ways is the use of cross- and auto-power functions $G$ .

$$|T_{ij}^p(\omega)| = \left| \frac{X_r(\omega)X_f(\omega)}{X_f(\omega)X_r(\omega)} \right| = \left| \frac{G_{ij}(\omega)}{G_{rr}(\omega)} \right|$$

(2)

Furthermore, as has been proved \[15, 16\], when the Laplace variable approaches system's nth pole, denoted by $\lambda_n$, the following equation is verified as

$$\lim_{s \rightarrow \lambda_n} T_{ij}^p(s) = \frac{\phi_n}{\phi_j}$$

(3)

Therefore, if to choose two different reference points, $k$ and $l$, the subtraction of the two PSDTs satisfies

$$\lim_{s \rightarrow \lambda_k} (T_{ij}^k(s) - T_{ij}^l(s)) = \frac{\phi_k}{\phi_l} - \frac{\phi_l}{\phi_l} = 0$$

(4)

This means that the system's poles are zeros of the rational function

$$\Delta T_{ij}^k(s) = T_{ij}^k(s) - T_{ij}^l(s)$$

and its inverse which called inverse transmissibility subtraction function (ITSF) is

$$\Delta^{-1} T_{ij}^k(s) = 1$$

(5)

$$\Delta T_{ij}^k(s) = \frac{1}{\Delta^{-1} T_{ij}^k(s)} = \frac{1}{T_{ij}^k(s) - T_{ij}^l(s)}$$

(6)

The normalized inverse transmissibility subtraction function (NITSF), and the average normalized inverse transmissibility subtraction function (ANITSF) are as:

$$NITSF_{ij} = \frac{\Delta^{-1} T_{ij}^k(s) - \Delta^{-1} T_{ij}^l(s)}{\Delta^{-1} T_{ij}^k(s) - \Delta^{-1} T_{ij}^l(s)}$$

(7)

$$ANITSF = \frac{1}{N} \sum_{i=1}^{N} NITSF_{ij}$$

(8)

The above theoretical results conclude that transmissibility is feasible to establish a rational function $\Delta^{-1} T_{ij}^k(s)$, with poles equal to the system’s poles.

2.2 Damage indicators

The transmissibility at the system poles are coincident with values of the mode shape ratios, i.e. the values of the $T_{ij}$ at the system poles are directly related to the scalar operational mode-shape values $\phi_n$ and $\phi_n$. Therefore, once the resonant frequencies are identified by using ANITSF, it is also possible to identify the operational mode shape vectors from different PSDTs. By choosing a fixed reference DOF $j$ and giving $\phi_j$, a normalized value of unit, the full unscaled mode-shape (operational deflection) vector $(\phi_1, \phi_2, \ldots, \phi_K)$ ($K$ is the number of measured output DOFs) can be constructed from the PSDT vector $(T_{ij}, T_{ij}, \ldots, T_{ij})$ . Then, by analogy with the concept of power mode shape presented in [17], a new concept of transmissibility power mode shape (TPMS) might be defined from the PSDT in the following way:

$$TPMS_{ij}^v = \int_{\omega} T_{ij}^v(f) df$$

(9)

where $TPMS_{ij}^v$ is the $v$th component of the $i$th transmissibility power mode shape and $f_{ij} - f_{ii}$ is the integrated frequency bandwidth for the $i$th TPMS.

By assembling $TPMS_{ij}^v$ for all the measured points considered in the structure, a $i$th TPMS vector is generated:

$$\{TPMS_i\} = \{TPMS_i^1, TPMS_i^2, \ldots, \phi_{ij}, \ldots, \phi_{ij}^K\}$$

(10)

The same procedure should be repeated for each TPMS by choosing the appropriate bandwidth affecting each system’s pole $\nu$. In this way, any of the damage criteria based on mode shapes might be extended to include the transmissibility power mode shapes.

As to identify the structural damages, based on mode shape, the curvature is another parameter to detect and localize the damage which is defined as the second derivative of mode shape.

$$\phi_i = \phi_{i-1}^\nu - 2 \phi_i + \phi_{i+1}^\nu$$

(11)

The location of the existing damage is estimated by the absolute change in mode shape curvature of healthy and unhealthy structural states and expressed as
\[ MSC_i = \sum \left[ \phi_i^+ - \phi_i^- \right] \]  

As used here, the transmissibility power mode shape curvature change will be showed as

\[ \Delta TPMSC = [TPMSC_i^+ - TPMSC_i^-] \]

In order to show the real state of increase and decrease, in this paper the real subtraction value other than the absolute value will be used.

And a damage index method constructed by Stubbs, Kim and Farrar [18], which uses the pre-damage and post-damage modal curvature, has been proved to be feasible for localizing the damages. It is defined as

\[ \beta = \left( \frac{\int [\phi_i^+(x)]^2 dx + \int [\phi_i^-(x)]^2 dx}{\int [\phi_i^+(x)]^2 dx + \int [\phi_i^-(x)]^2 dx} \right)^2 \]

As to the discrete system, a more common damage localization index is indicated as

\[ \beta_y = \frac{\sum_{i=1}^{N} \phi_i^{+2} + \sum_{i=1}^{N} \phi_i^{-2}}{(\sum_{i=1}^{N} \phi_i^{+2} + \sum_{i=1}^{N} \phi_i^{-2})} \]

Considering the transmissibility power mode shape (TPMS) here, as to all the nodes and \( j \)th mode in the calculation, damage index in each element

\[ DI_j = \frac{(TPMS_j^{+2} + \sum_{i=1}^{N} TPMS_i^{+2}) \sum_{i=1}^{N} TPMS_i^{+2}}{(TPMS_j^{+2} + \sum_{i=1}^{N} TPMS_i^{+2}) \sum_{i=1}^{N} TPMS_i^{+2}} \]

And to more modes, the damage index to the \( i \)th node is

\[ ID_i = \sum_{m=1}^{M} (TPMS_i^{+2} + \sum_{j=1}^{N} TPMS_j^{+2}) \sum_{j=1}^{N} TPMS_j^{+2} \]

Then, to one node for all the measured modes, a normalized damage index is described as follows:

\[ NDI = \frac{DI_i - \min(DI_i)}{\max(DI_i) - \min(DI_i)} \]

2.3 Artificial neural networks


A typical three-layer BP network is shown in Figure 1. The input layer receives inputs from the outside environment, the output layer generates the predictions while the hidden layer works as a link between the input layer and the output layer, which extracts and remembers the main features of the input patterns to predict the outcome of the network. Hundreds of ANNs models have been proposed since McCulloch and Pitts (1943) made the first neural model. The type of activation function like sigmoid transfer function or Gaussian radial basis function used by the hidden layer neurons will make a big difference between different networks types. Meanwhile, the accepted values, the topology and the learning algorithms will also make a difference between the types of neural networks.

Among the different types of ANNs, the back propagation (BP) neural network, which means feed forward, multilayered and supervised neural network with the error back propagation, is the commonest neural network used due to its simplicity. The core point is that the errors for the units of the hidden layers are determined by back-propagating the errors of the units of the output layer. Before ANNs could be conducted in use, they need to be processed in learning or training from a training set. The BP training algorithm includes two periods: the first of which the data feed forward, output of each neuron is obtained by calculating the input information in each hidden layer. The second is error back propagation, the difference between actual output and target output could be calculated layer by layer in recursion and the weights will be altered in accordance to the difference until the demanded output is acquired in the out layer. BP algorithm is mostly used in a lot of ANNs in real engineering of structural health monitoring.

3 NUMERICAL SIMULATION

Numerical simulation is carried out with a two–sided fixed beam with length 0.6 m, which was adopted to examine the performance of the proposed damage indices. A schematic diagram of this beam with its geometric dimensions and material properties is shown in Figure 2. Different simulations were carried out considering a mesh of 20 beam elements. The beam was assumed to be lightly damped with a constant damping ratio of 0.5%. And the loading point is node 10 with a vertical force of 1000 from 0 to 2047 Hz. Transmissibility of node 5 to node 3 is shown in Figure 3.

![Figure 2. Two sided fixed beam model](image-url)
3.1 Single damage

Damage is introduced by stiffness reduction in this paper. In this part, firstly LHS method is used to generate a single damage among the twenty elements with 50 scenarios, and responses of these scenarios are calculated. Therefore, total 50 patterns are generated out of which 50 patterns are used to train the network and later those 50 patterns are also used for test. The input data is the damage indicator (DI) of each scenario, and as to the goal data, the beam is divided into four parts with each part 5 elements. The goal data of each part is the sum of the severities in its own part. This is the same in the multiple damages.

As shown in Figure 4, the transmissibility power mode shapes are quite similar to the mode shapes as demonstrated in Figure 5. Here the damage indicator will be estimated based on these transmissibility power mode shapes. And an example of damage indicator for transmissibility power mode shape of a beam is shown in Figure 6.

As in figure 7, it shows that the output data fits well to the goal data.
train the network and later those 50 patterns are also used for test.

Figure 8. Damage prediction results for part I.

Figure 9. Damage prediction for four parts

In figure 8 and figure 9, the horizontal axis is the scenario number, and the vertical axis is the damage severity. Figure 8 demonstrates that the damage prediction results in the beam part I where those dots with zero value mean that the single damage is not in part I, and those dots with values between 0 and 1 mean that the single is in part I. The value of the dot in vertical axis means the damage severity. The red dot is the test results of the trained network, and the x is the goal. When the red dot and blue x in the same position, it means that the test is successful in assess the damage severity as well as the location otherwise it means there is error in the test. In figure 9, it is the same. It shows that to each scenario, there is a dot with value between 0 and 1.

As in table 1, it shows the damage prediction result in each part of the beam. The results demonstrate that the network functions well in the test.

Table 1. Damage prediction in each part.

<table>
<thead>
<tr>
<th>Part</th>
<th>Success prediction rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part I</td>
<td>90.6863%</td>
</tr>
<tr>
<td>Part II</td>
<td>90.1961%</td>
</tr>
<tr>
<td>Part III</td>
<td>90.1961%</td>
</tr>
<tr>
<td>Part IV</td>
<td>91.6667%</td>
</tr>
</tbody>
</table>

3.2 Multiple damages

In this part, firstly LHS method is used to generate multiple damages among the twenty elements with 50 scenarios, and responses of these scenarios are calculated. Then, total 50 patterns are generated out of which 50 patterns are used to

Figure 10. Regression result

Figure 10 shows that the output data fits well to the goal data, and this is not as well as it in the single damage scenarios.

Figure 11. Damage prediction results for part I.

Figure 11 demonstrates that the damage prediction results in the beam part I where those dots with zero value mean that there is no damage in part I, the number of dots in each
scenario means the number of damages in beam part I. And the value of the dot means the damage severity. The red dot is the test results of the trained network, and the x is the goal. When the red dot and blue x in the same position, it means that the test is successful in assess the damage severity as well as the location otherwise it means there is error in the test. In figure 12, it is the same. It shows that to each scenario, there is some dots with value between 0 and 1. The figure 12 shows that the prediction result is good.

As in table 2, it shows the damage prediction result in each part of the beam. The results demonstrate that the network functions well in the test, which could assess the damage severities successfully more than 90%.

Table 2. Damage prediction in each part.

<table>
<thead>
<tr>
<th>Part</th>
<th>Success prediction rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part I</td>
<td>92.7885%</td>
</tr>
<tr>
<td>Part II</td>
<td>93.2692%</td>
</tr>
<tr>
<td>Part III</td>
<td>92.3077%</td>
</tr>
<tr>
<td>Part IV</td>
<td>91.3462%</td>
</tr>
</tbody>
</table>

4 CONCLUSIONS

The objective of this study is to implement a new method using neural network based on the transmissibility power mode shape (TPMS) to assess the structural damages. The proposed method upon the use of transmissibility power mode shape (TPMS) shows great promising future in damage localization. Above all, the proposed method only depends on the output response signals and has no demands for FRF, IRF and so on. Secondly, the method can be also used to localize and assess the damages for complex structures. One thing should be paid attention is that the loading point should be well chosen in order to achieve a better transmissibility power mode shape (TPMS) which can be fulfilled by the experience.

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