Transmissibility Function Analysis for Boundary Damage Identification of a Two-Storey Framed Structure using Artificial Neural Networks

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ABSTRACT:
This paper presents a damage identification technique that uses output-only scalar transmissibility measurements of a structure to identify boundary conditions. A damage index is formulated based on output-only acceleration response measurements from ambient floor vibration. The damage index is analysed by a system of artificial neural networks (ANNs) to predict boundary condition changes of the structure. Using the data compression and noise filtering capabilities of principal component analysis (PCA), the size of the damage index is reduced in order to obtain suitable patterns for ANN training. To test the proposed method, it is applied to different models of a numerical two-storey framed structure with varying boundary conditions. Boundary damage is simulated by changing the condition of individual joint elements of the structure from fixed to pinned. The results of the investigation show that the proposed method is effective in identifying boundary damage in structures based on output-only response measurements.

1 INTRODUCTION

Large-scale civil structures, such as bridges or multi-storey buildings, continuously accumulate damage during their operational life spans. In order to ensure safety and reliability of these structures and to prevent catastrophic failures, early and reliable damage detection and health assessment is critically important. The concept of structural health monitoring was adopted in the 1960s and typically implies local and off-line assessments, such as visual inspection, ultrasounds, eddy-current and X- and Gamma-rays. These techniques, however, may involve high costs and intermittent exploration. During the last two decades, the focus of the investigations has been global and on-line evaluation with non-destructive techniques such as vibration analysis and imaging processing. One of the main objectives of using such techniques is to reach less costs and continuous monitoring of the structures (Maia et al. 2011). As such, vibration-based techniques received much attention for its effectiveness and practicality. Typical vibration-based parameters for structural health monitoring are natural frequencies, mode shapes, frequency response functions (FRFs) and time-history data. While most developed vibration-based techniques require knowledge of the excitation force during modal testing, ambient vibration based methods can operate solely on output-only response signals of the structure and thus making them very attractive for automated online health monitoring. Here, the structure is typically excited naturally by ambient loading from sources such as traffic, wind, or micro-earthquakes (Peeters, Maeck & De Roeck 2001). The advantage of using ambient sources is that once a monitoring system is installed, it continuously measures the structural response and records data without the need for interrupting operations such as traffic flow. A disadvantage of using ambient vibration excitation for structural health monitoring and damage detection is, however, that the excitation force can usually not be measured and therefore traditional methods of identifying the modal characteristics of a structure, which require knowledge of the excitation force, cannot be applied. In recent years, transmissibility function analysis attracted considerable interest due to its effectiveness in damage detection, as well as the fact that the analysis does not require input force measurements. Different aspects of transmissibility function analysis, such as the linearity of structures (Johnson et al. 2004), the nature of the input force (Devriendt et al. 2009), and the effect of operational and environmental variability (Kess & Adams 2007), have been explored (Yi et al. 2010).

This paper explores the feasibility of using natural ambient vibration loading, such as wind excitation, for the detection of boundary damage in a multi-storey building based on scalar transmissibility measurements in conjunction with principal component analysis (PCA) and artificial neural network (ANN) techniques. In a previous study conducted by the authors, a new damage detection algorithm based on FRFs, PCA and ANNs, was successfully applied to a numerical and experimental two-storey framed structure under forced impact excitation. From this investigation, it was found that the proposed damage detection algorithm was capable of accurately and reliably detecting damage using only measured floor vibration responses from impact loading (Dackermann, Li & Samali 2010) and (Samali, Dackermann & Li 2012). In this study, the method is now extended to ambient vibration excitation to allow for continuous online health monitoring. The focus of this investigation is to use output-only vibration measurements from floor members of a structure to detect damage. The reason for only using floor measurements is that in practice, it is usually more convenient to measure the floor vibration responses of multi-storey structures compared to measuring wall vibrations, especially under ambient excitation. To identify damage, it is proposed to use damage patterns embedded in scalar transmissibility functions obtained by relating various response output measurements captured along the floor members of the structure. To enhance damage patterns in the transmissibility functions, residual transmissibilities, which are differences in transmissibility functions between the undamaged structure and the damaged structure, are calculated. Neural networks are then trained to correlate the damage patterns in the residual transmissibilities to the damage characteristics. To obtain suitable input data for network training, the residual transmissibilities are compressed to a few principal components adopting PCA techniques. Besides data compression, PCA transformation has further the advantage of filtering noise. The most dominant PCs are then fed to ANNs for damage identification. In order to analyse various correlations of transmissibility relationships between different output measurements obtained from different locations, a hierarchal system of neural network ensembles is trained to evaluate damage patterns in PCA-compressed residual transmissibilities.

The proposed method is verified by numerical models of a two-storey framed structure. Various types of boundary damage are simulated by changing the condition of individual joint elements of the structure from fixed to pinned. In total, ten different types of boundary damage are investigated, i.e. four single and six multiple joint changes. To consider real life applications and to investigate the robustness of the method to noise, the ambient vibration responses obtained from the numerical model are polluted with various levels of white Gaussian noise.

2 BACKGROUND ON TRANSMISSIBILITY FUNCTION ANALYSIS

The governing equations of motion for an n-degree-of-freedom (n-DOF) finite-dimensional linear structure are given by:

$$\mathbf{M}\ddot{\mathbf{x}}(t)+\mathbf{C}\dot{\mathbf{x}}(t)+\mathbf{K}\mathbf{x}(t)=\mathbf{f}(t) \tag{1}$$

where $\mathbf{x}(t)$ is the n×1 displacement response, $\mathbf{M}$ is the n×n mass matrix, $\mathbf{C}$ is the n×n viscous damping matrix, $\mathbf{K}$ is the n×n stiffness matrix, and $\mathbf{f}(t)$ is the n×1 external force vector. If the external force is applied to only the k-th DOF, then $\mathbf{f}(t) = \{0_1, 0_2, \ldots, f_k(t), \ldots, 0_n\}^T$ has only one non-zero entry.

After Fourier transformation, Eq. (1) is given in the frequency domain by:

$$\mathbf{X}(\omega)=\mathbf{H}(\omega)\mathbf{F}(\omega) \tag{2}$$

where $\mathbf{H}(\omega)$ is the n×n frequency response function (FRF) matrix. Assuming the external force is applied to only the k-th DOF, the Fourier transform of the input force vector $\mathbf{f}(t)$ is defined as:

$$\mathbf{F}(\omega)=\left\{0_{\mathbf{1}}, 0_{\mathbf{2}}, \ldots, \mathbf{F}_{\mathbf{k}}(\omega), \ldots, 0_{\mathbf{n}}\right\}^{\mathbf{T}} \tag{3}$$

The acceleration vector in the frequency domain can be calculated from Eq. (2) as:

$$\mathbf{A}(\omega)=-\omega^2\mathbf{H}(\omega)\mathbf{F}(\omega) \tag{4}$$

The scalar transmissibility function $T_{ij}(\omega)$ between the output DOF i and reference-output DOF j is defined as the ratio between two frequency spectra $A_i(\omega)$ and $A_j(\omega)$. With $h_i(\omega)$ being the i-th row of $\mathbf{H}(\omega)$, the scalar transmissibility function $T_{ij}(\omega)$ is given as:

$$T_{ij}(\omega)=\frac{A_i(\omega)}{A_j(\omega)}=\frac{-\omega^2\mathbf{h}_i(\omega)\mathbf{F}(\omega)}{-\omega^2\mathbf{h}_j(\omega)\mathbf{F}(\omega)}=\frac{\mathbf{h}_i(\omega)\mathbf{F}(\omega)}{\mathbf{h}_j(\omega)\mathbf{F}(\omega)} \tag{5}$$

By substituting Eq. (3) into Eq. (5) $T_{ij}(\omega)$ is reduced to:

$$T_{ij}(\omega)=\frac{H_{ik}(\omega)}{H_{jk}(\omega)} \tag{6}$$

where $H_{ik}(\omega)$ and $H_{jk}(\omega)$ are entries of the FRF.

The damage index defined in this paper is termed “residual transmissibility function” and is defined as differences between scalar transmissibility functions of the damaged structure and scalar transmissibility functions of the undamaged structure given as:

$$ResT_{ij}(\omega)=T_{ij}^{d}(\omega)-T_{ij}^{ud}(\omega) \tag{7}$$

where $T_{ij}^{d}(\omega)$ is the scalar transmissibility function from the damaged structure and $T_{ij}^{ud}(\omega)$ the scalar transmissibility function from the undamaged structure.

3 THE TEST STRUCTURE

To validate the proposed damage identification method, it was tested on a numerical two-storey framed structure (the counterpart of an experimental structure, see (Dackermann, Li & Samali 2010)). The finite element model was created with ANSYS Workbench (ANSYS Inc 2007b) and consisted of two columns, two cross-beams and four interchangeable joint elements (see Figure 1). The two columns were connected to the ground through a fixed base connection. They had a cross-section of 65 mm × 5.5 mm and a height of 1600 mm. The crossbeams consisted of a box section of 150 mm × 50 mm and were located at a height of 700 mm and 1400 mm above the base connection, respectively. The structure was modelled in steel with a density of 7,850 kg/m^3, a Poisson's ratio of 0.3 and a modulus of elasticity of 200,000×10^6 N/m^2.

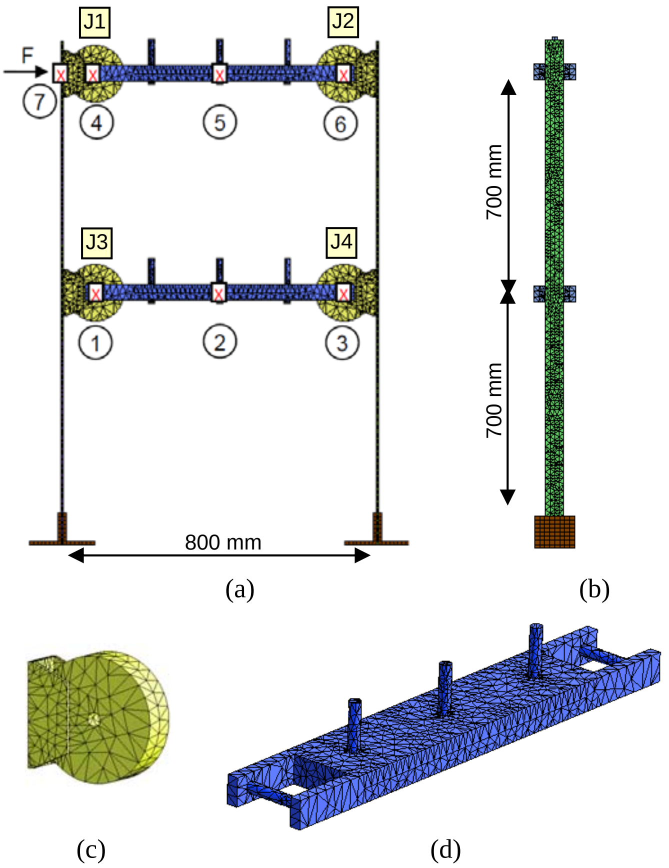

Figure 1. Numerical two-storey framed structure (a) front view, (b) side view, (c) joint element and (d) crossbeam.

To simulate boundary damage, the conditions of the joint elements were modified. In practice, boundary changes are generally caused by environmental or ageing decay such as corrosion or loosening of connections and are a common and serious issue in aged civil engineering structure. In this numerical study, boundary damage was simulated by changing the conditions of the four joint elements (J1 to J4, see Figure 1) that connect the crossbeams with the columns from fixed to pinned joints. For the modelling of a fixed joint element (undamaged boundary condition), the contact region between crossbeam and joint element was made rigid. For the pinned connection (damaged boundary condition), the horizontal shaft of the crossbeam was deleted and replaced by a revolute joint connection. The revolute joint was constrained in five local degrees of freedom (UX, UY, UZ, ROTX, ROTY) and free in ROTZ, which allows free rotation around the longitudinal axis of the deleted horizontal shaft. For the undamaged state of the structure, fixed connections were modelled for all four joints (termed FFFF). Four scenarios of single joint changes were studied by changing one of the four fixed joints with a pinned joint at a time. In addition, six multiple joint alterations with two joints changed each from fixed to pinned were also investigated. All boundary changes are listed in Table 1.

Table 1 Boundary damage scenarios.

Boundary case	Boundary scenario	Joint conditions J1	J2	J3	J4
1	PFFF	P	F	F	F
2	FPFF	F	P	F	F
3	FFPF	F	F	P	F
4	FFFP	F	F	F	P
5	PPFF	P	P	F	F
6	FFPP	F	F	P	P
7	FPFP	F	P	F	P
8	PFPF	P	F	P	F
9	FPPF	F	P	P	F
10	PFFP	P	F	F	P

Note: F indicates a fixed joint and P a pinned joint

To identify the dynamic properties, the undamaged and damaged models were subjected to ambient vibration loading using transient analysis in ANSYS Classic (ANSYS Inc 2007a). To simulate ambient vibration, such as excitation caused by wind loading, a random load 'F' of Gaussian distribution, with a mean of 0 and a standard deviation of 1, was applied in horizontal direction at the upper end of the potentially damaged column indicated with an arrow in Figure 1 (a) at location '7'. The ambient loading was applied for 16.385 s with integration time steps of 0.001 s. For the duration of the ambient loading, the displacement time history responses of the structure were recorded at the cross-beams at measurement locations '1' to '6' (in vertical direction).

To simulate real testing conditions, the recorded time history data were polluted with white Gaussian noise to simulate measurement noise interferences experienced during experimental testing. Noise of four intensities (1 %, 2 %, 5 % and 10 % noise-to-signal-ratio) was added to the input impact force signal and the response time histories using the 'awgn' function in Matlab (The MathWorks 2009). For each level of noise, five sets of noise-contaminated data were generated to simulate five repeated tests.

4 DAMAGE IDENTIFICATION PROCEDURE

4.1 *Residual transmissibility functions*

For the derivation of the residual transmissibility functions (to be used as damage fingerprints for boundary damage identifications), first, different scalar transmissibility functions $T_{ij}(\omega)$ of the undamaged and all damaged models were determined by cross-correlating various frequency-domain response output measurements of locations ‘1’ to ‘6’. Therefore, first, the noise-contaminated acceleration response time history data obtained from locations ‘1’ to ‘6’ were transformed into the frequency domain by estimating the power spectral density using Welch’s method. In Welch's method, the time history data is first split into overlapping segments and modified periodograms are computed. The resulting periodograms are then averaged to produce the power spectral density $A(\omega)$. Second, to calculate the scalar transmissibility functions $T_{ij}(\omega)=A_i(\omega)/A_j(\omega)$, the frequency spectra $A(\omega)$ of all measurement locations ‘1’ to ‘6’ were cross-correlated with each other resulting in a total of 30 scalar transmissibility functions according to Table 2. The calculated scalar transmissibilities capture a frequency range of 0 to 500 Hz with 8,192 spectral lines for a frequency resolution of 0.061 Hz per data point.

Table 2 Scalar transmissibility functions $T_{ij}(\omega)$

		Output Frequency Spectra $A_i(\omega)$					
		A_1	A_2	A_3	A_4	A_5	A_6
Reference-Output Frequency Spectra $A_j(\omega)$	A_1	×	T_{2-1}	T_{3-1}	T_{4-1}	T_{5-1}	T_{6-1}
	A_2	T_{1-2}	×	T_{3-2}	T_{4-2}	T_{5-2}	T_{6-2}
	A_3	T_{1-3}	T_{2-3}	×	T_{4-3}	T_{5-3}	T_{6-3}
	A_4	T_{1-4}	T_{2-4}	T_{3-4}	×	T_{5-4}	T_{6-4}
	A_5	T_{1-5}	T_{2-5}	T_{3-5}	T_{4-5}	×	T_{6-5}
	A_6	T_{1-6}	T_{2-6}	T_{3-6}	T_{4-6}	T_{5-6}	×

For a frequency range from 0 to 150 Hz, the derived scalar transmissibilities $T_{2-3}(\omega)$ of output measurements at location ‘2’ with reference-outputs of location ‘3’ are depicted in Figure 2 for various boundary damage cases. From the figure, clear changes in the scalar transmissibilities related to the different boundary damage condition can be observed, i.e. changes in amplitude, shape and position of the frequency peaks. These changes in the transmissibility functions form the basis of the damage identification approach.

Next, to enhance the damage fingerprints embedded in the transmissibilities, residual transmissibility functions were determined by calculating the differences between the scalar transmissibility functions of the undamaged and the various damaged models of the structure following Eq. 7. These residual transmissibility functions form the damage index used subsequently by ANNs for pattern recognition and boundary damage identification.

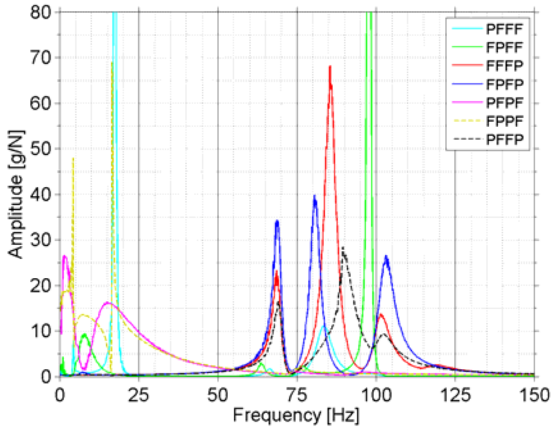

Figure 2. Scalar transmissibilities $T_{2-3}(\omega)$ of various boundary damage cases of 1 % noise pollution.

4.2 *Data compression with PCA*

Using full-size residual transmissibility functions as inputs for ANN training is not efficient and can also lead to convergence problems due to the large data size. A full-size residual transmissibility function generated from ambient vibration analysis contains 8,192 spectral lines and covers a frequency range of 0 to 500 Hz. This corresponds to 8,192 input nodes in the neural network, which would cause severe problems in training convergence in addition to computational inefficiency. Even a reduced size residual FRF, which covers a frequency range from 0 to 150 Hz still contains 2,458 spectral lines. Therefore, Principal Component Analysis (PCA) is proposed in this study to reduce the size of the residual transmissibility functions. PCA was developed by Pearson (Pearson 1901) and is one of the most powerful statistical multivariate data analysis techniques for achieving dimensionality reduction. Besides the benefit of data reduction, PCA is also a powerful tool for disregarding unwanted measurement noise. In this investigation, the MATLAB function ‘princomp’ was used to reduce the size of the residual transmissibility functions. Therefore, for each of the 30 derived transmissibility correlations, the reduced residual transmissibility functions $ResT_{ij}(\omega)$ of all investigated boundary damage cases and all noise pollution levels were combined to form 30 different PCA matrices. While the columns of the matrices were formed of the 2,458 spectral lines of the reduced residual transmissibility functions, the rows comprised 1000 captured samples (10 boundary condition scenarios × 5 boundary damage data sets × 5 undamaged data sets × 4 levels of noise pollution). After PCA transformation, the 2,458 spectral lines of the reduced residual transmissibility functions were projected onto their 2,458 PCs. To compress the size of the PCA transformed reduced residual transmissibility functions, the most dominant PCs that contain sufficient enough information to allow the identification of damage had to be determined. Therefore, the PCs of higher power were plotted in graphs for visual evaluation. As example, Figure 3 displays the first 18 PCs of reduced residual transmissibility functions of various boundary damage cases of 1 % noise pollution of data derived from transmissibility correlation $T_{2\text{-}3}(\omega)$. For each depicted scenario, three different data sets are displayed, each generated from different sets of noise pollution. From the figure, it can be seen that the first 10 PCs show clear distinguishable patterns for the different boundary damage cases. The PC values of the 11th component onwards are small, indicating their insignificant contribution for the investigated cases. Further, the three data sets of each scenario group together, and thus they are represented by the same/similar PCs. Such clustering behaviour and the distinct PC patterns of the different boundary conditions are ideal conditions for neural network based pattern recognition. From these findings it was concluded that it was sufficient to use the first 10 PCs as input parameters for the ANN training.

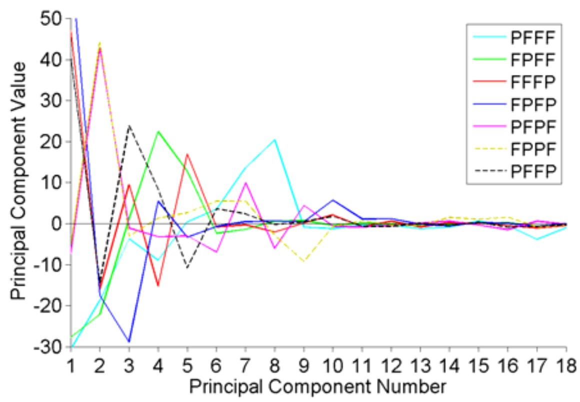

Figure 3. The first 18 PCs of reduced residual transmissibility functions of various boundary damage cases for transmissibility correlation $T_{2\text{-}3}(\omega)$ of 1 % noise pollution.

4.3 *Artificial neural network design*

To extract the damage patterns in the derived PCA transformed reduced residual transmissibility functions, a number of multi-layer back propagation neural networks were created. The design and operation of all neural networks was performed with the software Alyuda NeuroIntelligence version 2.2 from Alyuda Research Inc (Alyuda Research Inc 2006). In total 30 individual networks and one network ensemble (fusing the outcomes of the individual networks) were designed. The individual networks were trained with the first ten PCs of the reduced residual transmissibility functions obtained from the 30 different transmissibility correlations. The network ensemble was trained with the outcomes of the 30 individual networks. The results of the individual networks were then compared against the results of the neural network ensemble to demonstrate the advantage of the network ensemble. For the network outcomes, the networks were designed to categorise the conditions of the four joint elements as either fixed or pinned in a winner-takes-all fashion. As such, the network outputs comprised four output nodes. As example, the desired network output for boundary condition PFFF was {1,0,0,0}. To avoid over fitting, the input data were separated into training, validation and testing sets. While the network was trained with the training samples, its performance was supervised utilising the validation set to avoid over fitting. Therefore, for each of the 30 different transmissibility correlations, the 1000 available samples were divided into three sets of 600 samples for training, and 200 samples each for validation and testing.

5 RESULTS AND DISCUSSIONS

The testing set outcomes of the 30 individual neural networks are shown in Figure 4. The outcomes are given in mean correct classification rate error (MCCRE), which is defined as the error of the number of correctly predicted boundary condition cases normalised by the total number of cases.

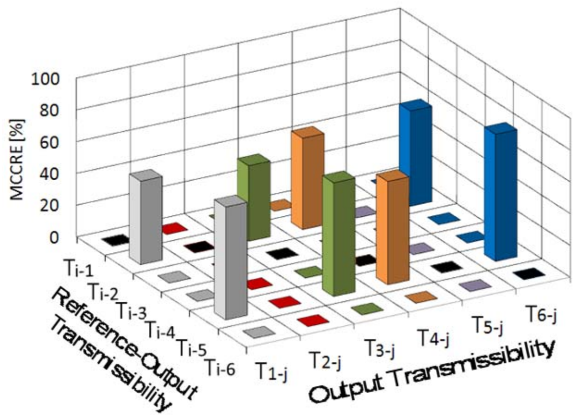

Figure 4. Testing set outcomes (in MCCRE) of the 30 trained individual networks.

From the figure, it can be observed that the networks trained with data from transmissibilities of reference-outputs from locations ‘1’, ‘3’, ‘4’ and ‘6’ correctly identify all boundary damage cases, while some networks of reference-outputs from locations ‘2’ and ‘5’ give error values of around 50 %. The reason for this phenomenon is that locations ‘2’ and ‘5’ are located on the symmetry axis of the two-storey framed structure and are therefore less sensitive to transmissibility function changes due to symmetric boundary condition modifications. The final boundary identification results of the network ensemble, that fuses the outcomes of the 30 individual networks, give precise boundary damage classifications with 0 % MCCRE for all investigated boundary scenarios and all noise pollution levels. These outcomes demonstrated that network training in a hierarchical network ensemble is highly efficient in filtering poor results from underperforming networks and in delivering results that are at least as good as the best outcomes of any of the individual networks. The outcomes further show that it is feasible to identify boundary damage in a multi-storey building/structure based on ambient floor/cross-beam measurements. This has great benefits for practical applications as it is usually very challenging to install measurement equipment at wall elements of multi-storey buildings, while measurements of ambient floor vibrations are easier to obtain.

6 CONCLUSIONS

This paper presented an output-only damage identification method that uses scalar transmissibility functions obtained from ambient floor vibration measurements to identify boundary damage in a multi-storey framed structure. In the proposed method, embedded damage patterns in scalar transmissibility functions are extracted using a hierarchical system of network ensembles to identify different boundary condition scenarios in a numerical two-storey framed structure. In the network ensemble, first, a number of individual networks were trained with data separated by various transmissibility correlations and then, the outcomes of the individual networks were fused in the network ensemble to give final damage predictions. PCA techniques were adopted to extract damage features from residual transmissibility functions and to compress large-size FRF data to make them suitable for neural network training. White Gaussian noise of up to 10% noise-to-signal-ratio was added to data of the numerical structure to simulate field-testing conditions. The results showed that the proposed method is capable of accurately and reliably identifying boundary damage in complex multi-storey structures based on output-only ambient floor vibration measurements. The final damage identification outcomes obtained from the network ensembles precisely estimated the boundary conditions of all investigated damage cases. These positive outcomes demonstrated the efficiency of the proposed hierarchical network ensemble approach. Further, the presented study showed that the proposed damage identification approach, which uses scalar transmissibility function data from only vertical ambient floor vibration response measurements combined with PCA and ANN techniques, has great potential to be used for online structural health monitoring.

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