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COMPARISON OF EXISTING DAMAGE DETECTION ALGORITHMS ON STRUCTURAL HEALTH MONITORING

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Abstract

This paper presents an operational assessment of existing damage detection algorithms for structural health monitoring (SHM) of building structures. This project assumed the typical SHM scenario involving continuous structural vibration recording using accelerometers. This study compared six established stiffness based damage detection algorithms utilising the ASCE benchmark instrumented structure dataset. This will be one of the first studies comparing the effectiveness of current damage detection algorithms using the benchmark data. The analyses indicate that all six considered damage detection algorithms have no difficulty in detecting the existence of the damage. Additionally, the identified stiffnesses using PP, FDD, EFDD methods were the most accurate for identifying the damage severity. The AR-ARX model was the least accuracy in estimating the stiffness amongst the six methods. All six algorithms were sensitive to modelling errors, while ANN and AR-ARX model techniques were sensitive to loading condition.

Keywords: Structural Heath Monitoring; Damage Detection, ASCE Benchmark Structure

1. Introduction

Structural Health Monitoring (SHM) refers to the use of continuous sensor data to monitor the condition of structures, typically via tracking of building dynamic characteristics. The most common application is the continuous recording of building vibration using accelerometers. SHM has the potential to detect and quantify damage which is substantially helpful for decision making following an extreme event, such as earthquakes. It has potential to largely reduce loss of life and injuries, and reduce operation downtime following the disaster [1].

In general, structural damage detection can be classified into global damage detection and local damage detection. Local damage detection techniques refer to non-destructive testing (NDT), including the use of radiographs, ultrasonic and magnetic imaging. It is mainly used to detect local damage, determine the extent and locate damage in structures [2]. Research has shown that they can be very effective for small structures [3]. However, local damage detection methods are difficult to implement in large or complex structures as it requires extensive instrumentation and many areas of the structure may be difficult to access. Under this situation, the global damage detection is the only option. Global damage detection infers damage on the basis of changes in a structure's dynamic parameters (stiffness, mass and damping) [4].

At present, numerous global damage detection techniques exist for SHM. Examples include regression analysis using AR-ARX model [5], Natural Excitation Technique and Eigensystem Realization Algorithm (NExT and ERA) [6], Neural Network (NN) method [7] and etc. However, these various techniques have been applied to different numerical or experimental structures, which make it difficult to compare the effectiveness of the different methodologies. In order to provide a platform for the comparison of those techniques, a benchmark problem in structural health monitoring was established by the joint IASC–ASCE Task Group on Structural Health Monitoring. For the first phase of the benchmark problem, the selected structure is a four-storey, two-bay by two-bay steel-frame quarter-scale model structure, shown in Fig. 1. The section properties are given in Table 1. Analytic models of the structure were developed, and simulated responses for five damage cases were generated. The goal of phase I benchmark study is to identify the location the damage in the structure using only noisy acceleration measurements. Issues such as limited sensor data and modelling errors were also considered in phase I of this problem. The details of the benchmark problem can be found in Johnson et al. [8].

Fig. 1 – The benchmark structure [7]

Table 1 – Properties of Structural Members

Property	**Columns**	**Floor beams**	**Braces**
Section Type	B100×9	S75×11	L25×25×3
Cross-sectional area A (m^2)	1.133×10^{-3}	1.43×10^{-3}	0.141×10^{-3}
Moment of inertia (Strong direction), I_y [m^4]	1.97×10^{-6}	1.22×10^{-6}	0
Moment of inertia (Weak direction), I_z [m^4]	0.664×10^{-6}	0.249×10^{-6}	0
St. Venant torsion constant J [m^4]	8.01×10^{-9}	38.2×10^{-9}	0
Young's Modulus E (Pa)	2×10^{11}	2×10^{11}	2×10^{11}
Mass per unit length ρ [kg/m]	8.89	11.0	1.11

In this study, a total of six damage detection methods were considered in this paper. It included Peak Picking (PP) method, Frequency Domain Decomposition (FDD) method, Enhanced Frequency Domain Decomposition (EFDD) method, Eigen Realization Algorithm combined with the Natural Excitation Technique (NExT and ERA), AR-ARX model and Artificial Neural Network (ANN) method. First three of the five damage cases in the benchmark study were used to compare the effectiveness of the six damage detection methods.

2. Past Studies

Traditional methods of damage detection are predominately stiffness based and relied upon changes of structural vibration characteristics, including natural frequencies, damping ratios or mode shapes. These variations are used to determine the damage location and severity between undamaged and damaged structures. In 2000, Lee and Chung [9] presented a damage detection method using natural frequencies. They used three procedures to determine the location and size of damage First, the approximate crack location was identified using Armon's Rank-ordering method, in which the first four natural frequencies were used. Then, a corresponding Finite element (FE) model is established based on the results of the crack position range, and the crack size is obtained by the FE model. Finally, Gudmundson's equation was applied with the obtained crack size and the system's natural frequencies to determine the actual crack location. Curadelli et al. [10] proposed a damage detection technique using the instantaneous damping coefficient as a damage-sensitive parameter based on a wavelet transform. With examples using experimental and simulated results on structures subjected to seismic base excitation, it was shown that the damage detection technique using the instantaneous damping coefficient is useful to assess changes in the vibration characteristics due to incremental damage of nonlinear systems. Khoo et al. [11] demonstrated a damage detection method of locating damage by evaluating damage-sensitive parameters including mode shapes and resonant pole shifts in a wooden wall structure. The damaged location was determined using the visual comparison of the deformation mode shapes before and after damage.

In recent years, structural damage detection methods based on machine learning of measured response signal of structures in service have gained popularity amongst researchers. This type of damage detection method has the advantage of being easy to implement, lower cost and more accurate dynamic characteristic information of structures [12]. The methods include Neural Network, Factor Analysis, Wavelet Analysis, Genetic Algorithm, etc. In 2003, Kao and Huang [13] proposed a Neural Network based damage detection method, which included two steps. First, the neural system identification network was formulated to identify the undamaged and damaged states of the structure. Then, the trained neural system identification network was used to generate free vibrations responses with the same initial condition. Finally, the extent of the damage could be assessed by comparing the periods and amplitudes of the free vibration responses of the undamaged and damaged statuses. Kim and Melhem [14] classified wavelet-based damage detection methods into three categories, i) variation of wavelet coefficients, ii) local perturbation of wavelet coefficients in a space domain and iii) reflected wave caused by local damage. The first identified the existence and severity of damage. The second localized the damage in structures by detecting the irregularity of wavelet coefficients. The last identified the location and severity of damage.

This far, a complete comparison of the current damage detection methods using IASC-ASCE benchmark problem is not yet available. Caicedo et al. [6] applied NExT and ERA techniques to the benchmark study and showed that this method was effective for detecting damage in benchmark model. This was confirmed by the less than 1% errors in typical stiffness estimates and that the method was insensitive to noise. Lam et al. [15] also applied a statistical model updating approach in the benchmark study. The results indicated that this method slightly overestimated the damage extent for cases with modelling error, but was accurate in cases with zero modelling error. This highlighted the importance in selecting an appropriate model for successful damage detection. Shuichi et al. [16] used a vibration-based damage detection algorithm on the ASCE benchmark building model. This approach was limited to identifying structural damages that produced changes in the structural dynamic characteristics. Results showed the applied algorithm had a good accuracy in damage identification and was relatively insensitive to noise in the sensors. However, it could not be used to estimate the severity of the damage.

3. Damage detection methods

A total of 6 damage detection methods were considered in this paper. It included Pick Peaking (PP) method, Frequency Domain Decomposition (FDD) method, Enhanced Frequency Domain Decomposition (EFDD) method, Eigen Realization Algorithm combined with the Natural Excitation Technique (NExT and ERA), Auto-regressive and auto-regressive with exogenous inputs (AR-ARX) model and Artificial Neural Network (ANN) method.

The first four methods could be regarded as system identification approaches, which were used to extract modal parameters (frequency, damping ratio, mode shape etc.). Since the reduction of the story stiffness was considered as the damage indicator, these four method, combined with modal updating, could be used as damage detection methods to monitor the story stiffness change of the ASCE benchmark structure.

Pick Peaking (PP) method [17] is the simplest method for identifying the modal parameters of a structure. The PP method is achieved based on that the frequency response function (FRF) goes through an extreme value around the natural frequencies. The frequency at that extreme value can be taken as eigenfrequency. When under ambient vibration measurements, the FRF is replaced by the auto spectra of the ambient outputs. In this way, the natural frequencies are simply determined from the observation of the peaks on the graphs of the averaged normalised power spectral densities (ANPSDs).

Frequency Domain Decomposition (FDD) [18] is a frequency domain identification, which is based on decomposing the power spectral density function matrix using Singular Value Decomposition (SVD). Then, modes can be picked by locating the picks in SVD plots, but no modal damping is calculated The enhanced Frequency Domain Decomposition (EFDD) technique [19] is an extension to the FDD technique. Compared to FDD, EFDD gives an improved evaluation of both the natural frequencies and the mode shapes and also includes damping. Besides, in EFDD, the SDOF Power Spectral Density function, identified around a resonance peak, is calculated using the Inverse Discrete Fourier Transform (IDFT). The natural frequency is obtained by determining the number of zero-crossing as a function of time, and the damping by the logarithmic decrement of the corresponding SDOF normalized auto correlation function. The SDOF function is estimated using the shape determined by the previous FDD peak picking.

Natural Excitation Technique and Eigensystem Realization Algorithm (NExT and ERA) [20,21] includes two main stages: the first is to eliminate the effect of the unknown force from the governing equation of motion using the Natural Excitation Technique (NExT), and the second procedure is to extract the modal parameters of the homogeneous model using the Eigensystem Realization Algorithm (ERA). The fundamental principles of the NExT method is that the cross-correlation function between the response vector and the response of selected reference DOFs satisfies the homogeneous equation of motion, provided that the excitation and responses are weakly stationary random processes, which is normally the case for ambient vibration. Eigensystem Realization Algorithm (ERA) starts with formation of Hankel block data matrix. Then, Hankel block data matrix is factorized using SVD. Finally, the discrete-time state-space realization matrices for the structural model can be obtained.

Auto-regressive and auto-regressive with exogenous inputs (AR-ARX) model is a two-stage prediction model, which is proposed by Sohn and Farrar [22]. The model is constructed with selected and normalized acceleration signals obtained from the undamaged structure. The one-step-ahead error prediction is defined as a damage-sensitive index. If there is any damage in the structure, the previously obtained model using the reference signals will not be able to reproduce the new time series measured from the damaged structure.

Artificial Neural Network (ANN) method is one of pattern recognition approach, whose basic mechanism is first to calculate the pattern features of a selected list of possible damage scenarios by computer simulation, and then to match the measured pattern features from the possibly damaged structure with all the calculated pattern features one by one [23]. The damage scenario that corresponds to the “best fit” calculated pattern feature is then regarded as the “true” damage scenario for the structure. ANN is used for matching the measured pattern features to the calculated pattern features. The multi-layer feedforward type of ANN is adopted in this paper. It includes three layers: input layer, hidden layer and output layer. The unit in each layer is named neurons, which refer to the inputs and output data in the mathematical models. The design of the ANN involves the selection of 1) the number of hidden neuron in the hidden layer and 2) the activation function for all the neurons in the hidden layer. Further details could be found in Wu et al. [24].

4. Comparison of Different Methods using Benchmark Problem

This study adopts the same cases and damage patterns previously comprehensively described in Johnson et al. [8]. 1% equivalent viscous damping was assumed for all modes. Measurement noise was numerically simulated using a white noise signal with a root mean square (RMS) amplitude equaling to 10% of the RMS amplitude of the roof response. Forty seconds of data at 1,000 Hz sampling rate were used for the damage detection analyses.

Two finite element (FE) models were developed based on the benchmark structure. The first model assumes each floor is perfectly rigid with translation restricted to a plane parallel to the floor. Therefore, in this model, each floor has 3 degrees of freedom (DOF), for a total of 12 DOF in structural model. The second FE model has 120 DOFs, where floor nodes have the same horizontal translation and in-plane rotation but can have relative vertical translation. This model is considered to determine the effects of modelling errors in the identification process. The benchmark problem included 5 Cases, shown in Table 2. Case 1 was designed to be the computationally simplest to process, while Case 5 was considered the most complex. The case complication increased as the case number increased. In terms of Cases 1, 3, and 4, the simulated response data were generated using a 12-DOF shear building model, while in Cases 2 and 5, a 120-DOF model was used. The natural frequencies and horizontal storey stiffness of these two models could be found in Johnson et al. [8]. There were additionally six different Damage Patterns in this benchmark problem, shown in Table 3. It was assumed that a broken brace has zero stiffness contribution, but it would not affect the mass of the structure (mass matrix). Damage Pattern 0 represented the undamaged state. In Cases 1–3, only Damage Patterns 1 and 2 were studied. In this paper, only these three cases were considered.

Table 2 – Damage Cases considered in the benchmark study

Case Number	**Model used to generate simulated response**	**Damage Patterns**	**Excitation**	**Mass Distribution**
1	12 DOF	1,2	Ambient	Symmetric
2	120 DOF	1,2	Ambient	Symmetric
3	12 DOF	1,2	Shaker Diagonal on Roof	Symmetric
4	12 DOF	1,2,3,4,6	Shaker Diagonal on Roof	Asymmetric
5	120 DOF	1,2,3,4,5,6	Shaker Diagonal on Roof	Asymmetric

Table 3 – Damage patterns considered in the benchmark study

Damage Pattern	**Characteristics**
0	undamaged
1	All braces at the first floor are broken
2	All braces at the first and third floors are broken
3	One brace at the first floor is broken
4	Two braces are broken, one at the first floor and other at the third floor
5	Damage Pattern 4 plus on beam-column connection at the first floor is broken
6	One third stiffness reduction of one brace at the first floor

A total of 6 damage detection methods were considered in this paper. It included Pick Peaking (PP) method, Frequency Domain Decomposition (FDD) method, Enhanced Frequency Domain Decomposition (EFDD) method, Eigen Realization Algorithm combined with the Natural Excitation Technique (NExT and ERA), Auto-regressive and auto-regressive with exogenous inputs (AR-ARX) model and Artificial Neural Network (ANN) method. To effectively compare these methods, the horizontal stiffness in each storey was calculated and compared by each method.

For PP, FDD, EFDD and NExT and ERA methods, a 40-second length acceleration data with a sampling rate of 100 Hz was used. In general, damage detection based on AR-ARX model is a time series analysis using the residual error. Residual error being the difference between the actual acceleration measurement and the prediction obtained from the AR-ARX model. When the damage occurred in the structure, the increase in residual errors would be maximized at the sensors instrumented near the actual damage locations. To compare with other methods, a different way of AR-ARX model is used. In this paper, a 40-second length acceleration data was obtained for damage detection with a sampling rate of 100 Hz. The AR-ARX model was constructed only using the first half data both in undamaged and damage data. The second half data was used to calculate stiffness of the structure using the AR-ARX model constructed in the first half data. The order of AR-ARX model is selected as 15 by using AIC criterion. The parameters of AR-ARX model na=5, nb=5 and time delay was set to 1. The design of ANN is discussed as follows. The damaged-induced changes in the modal parameters of the first two modes are employed as the ANN input, the number of input neurons is ten. The number of output neurons is four, because of four possible damage locations in each direction. The hyperbolic tangent sigmoid (tansig) is selected as the activation function, with 17 hidden neurons. Since this selection gives the highest value of evidence.

4.1 Case 1

For Case 1, mass was distributed in the structure symmetrically in both the undamaged and damaged (Damage Patterns 1 and 2) states, and the response was restricted in the y direction. Therefore, a planar 4-DOF shear building model was considered sufficient as the identification model in this case.

Table 4 – Comparison of Horizontal Storey Stiffness – K (MN/m) using different methods for Case 1

Damage Pattern	Storey Stiffness, K (Benchmark Study)		PP		FDD		EFDD		NExT and ERA		AR-ARX		ANN	
			K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.
0	L1	67.90	67.76	-0.2%	67.76	-0.2%	67.76	-0.2%	68.62	1.1%	70.38	3.6%	68.77	1.3%
	L2	67.90	67.74	-0.2%	67.58	-0.5%	67.74	-0.2%	67.32	-0.9%	66.21	-2.5%	67.42	-0.7%
	L3	67.90	68.04	0.2%	67.94	0.1%	68.04	0.2%	67.83	-0.1%	69.63	2.6%	67.23	-1.0%
	L4	67.90	67.79	-0.2%	67.79	-0.2%	67.79	-0.2%	67.67	-0.3%	66.02	-2.8%	67.42	-0.7%
1	L1	19.67	19.61	-0.3%	19.61	-0.3%	19.61	-0.3%	19.36	-1.6%	19.11	-2.9%	21.06	**7.1%**
	L2	67.90	67.58	-0.5%	67.77	-0.2%	67.58	-0.5%	67.77	-0.2%	69.81	2.8%	67.90	0.0%
	L3	67.90	67.83	-0.1%	67.94	0.1%	67.83	-0.1%	67.68	-0.3%	66.17	-2.6%	66.28	-2.4%
	L4	67.90	67.79	-0.2%	67.87	0.0%	67.96	0.1%	67.70	-0.3%	69.41	2.2%	67.90	0.0%
2	L1	19.67	19.94	1.4%	19.94	1.4%	19.94	1.4%	19.87	1.0%	20.63	4.9%	19.63	-0.2%
	L2	67.90	67.90	0.0%	68.17	0.4%	67.90	0.0%	67.44	-0.7%	70.48	3.8%	67.13	-1.1%
	L3	19.67	19.75	0.4%	19.71	0.2%	19.75	0.4%	19.71	0.2%	20.30	3.2%	20.17	2.5%
	L4	67.90	68.00	0.1%	67.90	0.0%	68.00	0.1%	67.70	-0.3%	69.65	2.6%	66.47	-2.1%

Six methods were used in this Case and the horizontal storey stiffness calculated by different methods were summarized in Table 4. In the table, the differences between the used methods and the benchmark study results were also presented. Johnson et al. [8] reported exact stiffness values of the undamaged and damaged 12-DOF structure. For undamaged structure, the horizontal storey stiffness in y direction is 67.90 MN/m. However, the first storey stiffness is reduced to 19.67 MN/m in the damage pattern 1. For damage pattern 2, both the first storey stiffness and the third storey stiffness is reduced to 19.67 MN/m. In undamaged condition, the identified stiffness using PP, FDD, EFDD methods ranged from 67.58 to 68.04 MN/m, which were within 0.5% difference from the benchmark study value. For NExT and ERA method and ANN method, the difference increased to 1.1% and 1.3%, respectively. The AR-ARX model had the largest difference from benchmark study up to 3.6%. For damaged structure, differences between the all methods and the benchmark study results increased slightly and ANN method produced the largest difference (7.1%). Nevertheless, all these methods have no difficulty in detecting the existence of the damage, since a difference within 5% could be considered as being reduced for structural analysis purposes. Besides, only the identified stiffness at damaged location using ANN method was over 5% from benchmark study results.

4.2 Case 2

Case 2 is similar to Case 1 except it used a 120-DOF model to simulate the response measurements. Compared to 12-DOF model, the horizontal slab panels were assumed to only contribute to the in-plane stiffness, making the floor behave as rigid regarding in-plane motions only. Also, the remaining out-of-plane degrees of freedom, including vertical motion and rolling of the floor, were active. The inclusion of this Case is to evaluate the effect of modelling error in damage detection. In this case, only symmetric mass distribution was considered and the ambient vibration was imposed along the y direction as in Case 1. Thus, a planar 4-DOF shear building model was also employed as the identification analysis model in this case.

The identified horizontal storey stiffness are summarized in Table 5. In short, similar conclusions can be drawn as in Case 1. The PP, FDD, EFDD, NExT and ERA methods produced very similar stiffness to the benchmark study, and ANN method produced the largest differences compared to the other five methods. Furthermore, it can be seen that the differences amongst all the methods tend to be larger due to the modelling error. Especially for ANN method, the difference from the benchmark study results is increased to 10.7%. Also, most storey stiffness have lower values compared to Case 1. This is reasonable as the 120-DOF model had fewer constraints leading to a more flexible model.

Table 5 – Comparison of Horizontal Storey Stiffness (MN/m) using different methods for Case 2

Damage Pattern	Storey Stiffness, K (Benchmark Study)		PP		FDD		EFDD		NExT and ERA		AR-ARX		ANN	
			K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.
0	L1	61.62	61.91	0.5%	61.91	0.5%	60.90	-1.2%	62.48	1.4%	63.79	3.5%	62.34	1.2%
	L2	53.66	53.89	0.4%	53.89	0.4%	54.16	0.9%	53.43	-0.4%	51.94	-3.2%	54.12	0.9%
	L3	51.04	51.21	0.3%	51.10	0.1%	51.21	0.3%	51.10	0.1%	52.75	3.3%	50.54	-1.0%
	L4	49.16	49.33	0.3%	49.26	0.2%	49.20	0.1%	49.14	0.0%	47.64	-3.1%	48.80	-0.7%
1	L1	15.41	15.52	0.7%	15.52	0.7%	15.52	0.7%	15.75	2.2%	14.85	-3.6%	16.56	**7.5%**
	L2	46.57	47.05	1.0%	47.05	1.0%	47.05	1.0%	47.30	1.6%	48.13	3.3%	45.81	-1.6%
	L3	51.13	50.93	-0.4%	50.93	-0.4%	50.75	-0.7%	50.87	-0.5%	49.52	-3.1%	51.04	-0.2%
	L4	48.69	48.86	0.3%	48.86	0.3%	48.86	0.3%	48.77	0.2%	50.22	3.1%	49.16	1.0%
2	L1	15.54	15.79	1.6%	15.60	0.4%	15.79	1.6%	15.35	-1.2%	16.62	**7.0%**	17.21	**10.7%**
	L2	42.90	42.83	-0.2%	43.04	0.3%	42.83	-0.2%	42.90	0.0%	44.94	4.8%	42.19	-1.7%
	L3	12.25	12.25	0.0%	12.25	0.0%	12.25	0.0%	12.25	0.0%	12.71	3.8%	13.38	**-9.2%**
	L4	41.68	41.83	0.4%	41.90	0.5%	41.83	0.4%	41.79	0.3%	43.27	3.8%	41.68	0.0%

4.3 Case 3

The only difference between Cases 1 and 3 is that the loading in Case 3 stemmed from a single white noise input acting at the centre of the roof in the diagonal direction. This loading excited both x and y translational motions. In this case, the mass distribution of the structure was symmetric and there was no torsional motion. An 8-DOF shear building model was used to capture the motions excited in both x and y directions.

Table 6 summarizes the identified stiffness parameters in Case 3. Accordingly, this shows that the different excitation had not materially affected the stiffness estimation. The PP, FDD, EFDD, and NExT and ERA methods very accurately identified stiffness in the X direction. But the results in ANN method showed significant sensitivity to loading conditions and produced large stiffness variations (up to 34.7%) from actual values.

Table 6 – Comparison of Horizontal Storey Stiffness (MN/m) using different methods for Case 3

Damage Pattern	Dir.	Storey Stiffness, K (Benchmark Study)		PP		FDD		EFDD		NExT and ERA		AR-ARX		ANN	
				K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.	K	Diff.
0	X	L1	77.38	77.25	-0.2%	77.25	-0.2%	78.04	0.8%	76.73	-0.8%	74.00	-4.4%	75.42	-2.5%
		L2	57.38	57.27	-0.2%	57.27	-0.2%	57.27	-0.2%	57.27	-0.2%	55.32	-3.6%	56.31	-1.9%
		L3	54.88	55.06	0.3%	54.99	0.2%	54.93	0.1%	54.86	0.0%	56.68	3.3%	55.90	1.9%
		L4	52.85	53.33	0.9%	53.11	0.5%	53.11	0.5%	52.71	-0.3%	55.32	4.7%	53.87	1.9%
	Y	L1	61.62	62.28	1.1%	61.88	0.4%	61.49	-0.2%	62.94	2.1%	63.87	3.6%	62.54	1.5%
		L2	53.66	53.53	-0.2%	53.53	-0.2%	53.53	-0.2%	53.28	-0.7%	51.29	-4.4%	52.61	-1.9%
		L3	51.04	51.30	0.5%	51.22	0.4%	51.15	0.2%	51.01	-0.1%	52.82	3.5%	51.70	1.3%
		L4	49.16	49.71	1.1%	49.53	0.8%	49.59	0.9%	49.02	-0.3%	50.83	3.4%	49.84	1.4%
1	X	L1	35.21	35.49	0.8%	35.28	0.2%	35.07	-0.4%	35.07	-0.4%	33.53	-4.8%	43.78	**24.3%**
		L2	49.05	49.08	0.1%	49.19	0.3%	49.08	0.1%	49.36	0.6%	50.80	3.6%	49.05	0.0%
		L3	54.85	54.90	0.1%	54.83	0.0%	54.90	0.1%	54.69	-0.3%	57.43	4.7%	53.62	-2.2%
		L4	52.44	52.77	0.6%	52.61	0.3%	52.56	0.2%	52.28	-0.3%	54.63	4.2%	52.21	-0.4%
	Y	L1	15.41	15.36	-0.3%	15.36	-0.3%	15.36	-0.3%	15.02	-2.5%	14.68	-4.7%	18.49	**20.0%**
		L2	46.57	46.92	0.7%	46.92	0.7%	46.92	0.7%	46.61	0.1%	48.32	3.8%	46.57	0.0%
		L3	51.13	51.24	0.2%	51.16	0.1%	51.08	-0.1%	51.02	-0.2%	52.84	3.3%	51.04	-0.2%
		L4	48.69	49.24	1.1%	49.18	1.0%	49.24	1.1%	48.69	0.0%	51.12	**5.0%**	49.16	1.0%
2	X	L1	35.49	35.56	0.2%	35.56	0.2%	35.56	0.2%	35.56	0.2%	37.23	4.9%	42.57	**19.9%**
		L2	43.35	43.52	0.4%	43.42	0.2%	43.32	-0.1%	43.45	0.2%	45.64	5.3%	42.82	-1.2%
		L3	22.17	22.13	-0.2%	22.13	-0.2%	22.13	-0.2%	22.22	0.2%	21.46	-3.2%	29.86	**34.7%**
		L4	42.22	42.38	0.4%	42.33	0.3%	42.38	0.4%	42.19	-0.1%	43.46	2.9%	42.22	0.0%
	Y	L1	15.54	15.75	1.4%	15.75	1.4%	15.75	1.4%	15.70	1.0%	16.13	3.8%	17.20	**10.7%**
		L2	42.90	42.90	0.0%	43.07	0.4%	42.90	0.0%	42.61	-0.7%	44.82	4.5%	42.90	0.0%
		L3	12.25	12.30	0.4%	12.28	0.2%	12.30	0.4%	12.28	0.2%	12.83	4.8%	14.81	**20.9%**
		L4	41.68	41.74	0.1%	41.68	0.0%	41.74	0.1%	41.56	-0.3%	40.10	-3.8%	41.68	0.0%

5. Conclusion

The effectiveness of six damage detection methods was investigated utilising the IASC–ASCE benchmark structure. This study evaluated the effectiveness and accuracies of the methods subjected to various excitation scenarios, modelling complexity, structural regularity and damage patterns. The horizontal storey stiffness in each storey were identified and utilised as the metric for comparing the effectiveness of the methods, these were also compared against the benchmark results for verification of accuracy. The results show that all six damage detection methods have no difficulty in detecting the existence of the damage. However, the identified stiffness using PP, FDD, EFDD and NExT and ERA method methods were most reliable and accurate, which are less than 5% difference from benchmark study results. The results from AR-ARX model was less accurate, whose difference is up to 7.0%. Regarding ANN method, it has large error (up to 34.7%) when calculating the storey stiffness of the structure and there is damage occurred in this level. Furthermore, all six methods were sensitive to the modelling errors, while only ANN method were sensitive to excitation conditions.

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