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STRUCTURAL DAMAGE DETECTION OF SYMMETRIC AND ASYMMETRIC STRUTURES USING DIFFERENT OBJECTIVE FUNCTIONS AND MULTIVERSE OPTIMIZER

M. Mohamadinasab[1],G. Ghodarti Amiri[2,*, †] and M. Mohamadi Dehcheshmeh[3]
[1]*School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran*
[2]*Natural Disasters Prevention Research Center, School of Civil Engineering, Iran University of Science & Technology, Tehran, Iran*
[3]*Department of Civil Engineering, Shahrekord Branch, Islamic Azad University, Shahrekord, Iran*

ABSTRACT

Most structures are asymmetric due to functionality requirements and limitations. This study investigates the effect of asymmetry on damage detection. For this purpose, the asymmetry has been applied to models by considering different spans' length and also different geometry properties for the section of members. Two types of structures comprising symmetric and asymmetric truss and frame have been modeled considering multiple damage scenarios and noise-contaminated data. Three objective functions based on flexibility matrix, natural frequency and modal frequency are proposed. These objective functions are optimized utilizing multiverse optimizer (MVO). For the symmetric models using limited modal data, flexibility-based objective function has the most accurate results, while by increasing the number of mode shapes, its accuracy reduced. Among asymmetric models of truss, damage detection results of the model is more accurate than those of its symmetric pair. Between asymmetric models of frame, the results obtained from frames which have only different spans' length are more precise than those of the symmetric model. This is while frequency-based objective functions have their least accurate results for the frame model having asymmetry only in the section properties of its elements.

Keywords: structural health monitoring, asymmetric structures, flexibility matrix, natural frequencies, multiverse optimizer.

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[*]Corresponding author: Iran University of Science and Technology, Narmak, Tehran, Iran, PO BOX 16765-163.
[†]E-mail address: ghodrati@iust.ac.ir (G. Ghodrati Amiri)

1. INTRODUCTION

Structural health monitoring (SHM) is an essential task for structural systems since they are prone to different kinds of damage during their life span. Early damage identification can prevent loss of life, destruction of structures and heavy financial losses to a large extent. The need to monitor the damage process in structures and infrastructures has led to the development of different damage identification methods.

SHM can be implemented using destructive and non-destructive methods [1]. One of the non-destructive methods is vibration-based structural damage detection (VBSDD) that has attracted increasing attention in recent years. The principle behind VBSDD is that any change in physical parameters of the structure like the stiffness, mass or damping matrix results in a shift in modal characteristic of the system (i.e., natural frequency and mode shapes) [2]. These damage-induced alterations in modal parameters can be investigated to identify the location and extent of damage using model-based and non-model-based techniques [3].

Model-based methods utilize an analytical finite element (FE) model of the structure to simulate the dynamic response of the actual damaged monitored structure [4]. This can be done using optimization-based inverse approach to minimize an objective function which can be formulated by calculating the differences between the modal parameters of the monitored structure and its analytical FE model [5,6]. Once the best accordance is gained, the unknown variables of the optimization problem that were meant to be found during optimization process, are taken as the damage factors for each element [7,8]. Natural frequencies and mode shapes are dynamic parameters that have been mostly used as damage indicators [9]. Since natural frequencies can be simply measured, many researchers have tried to identify the damage using changes in natural frequencies [10]. For instance, Yang and Wang [11] proposed a natural frequency vector assurance criterion for damage detection of numerical and experimental frames. However, natural frequencies are merely sensitive to severe damages, and small local damages cannot be accurately estimated by natural frequencies [12]. Therefore, some researchers have investigated changes in mode shapes which is inherently a local feature of the structures [13]. For instance, Mousavi and Gandomi [14] utilized the incomplete mode shapes and corresponding natural frequencies for damage identification in 2D and 3D frames.

Some researchers also preferred to use a combination of modal parameters in order to provide more precise results for damage localization and quantification. For example, Zare Hosseinzadeh *et al*. [15] proposed an objective function based on modal assurance criterion (MAC) and flexibility matrix for damage diagnosis in numerical and experimental structures using democratic particle swarm optimization algorithm. Mohamadi Dehcheshmeh *et al.* [16] suggested a pseudo modal strain energy (MSE)-based objective function which is highly effective for identifying damage in shear frames. Zare Hosseinzadeh *et al.* [17] in another study, examined the robustness of modal residual force vector in damage diagnosis of different numerical structures using grey wolf optimizer. Kaveh *et al*. [18] proposed a boundary strategy for damage detection using shuffled shepherd optimization algorithm which reduces the number of false detections and increases the accuracy of detected elements and convergence speed of the metaheuristic algorithms. Khatir *et al*. [19] suggested a new flexibility-based damage index to identify the location and severity of damage in

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different 3D structures using atom search algorithm and salp swarm optimization algorithm. A powerful approach for damage detection of full-scale structures was suggested by Dinh-Cong *et al*. [20] that implements a two-way link between MATLAB and SAP2000 to model large-scale structures. They utilized the flexibility matrix and mode shapes to identify the damage via enhanced symbiotic organisms search. Ghannadi and Kourehli [21] compared the performance of different optimization algorithm for structural damage identification through an objective function based on modified total modal assurance criterion. Huang *et al*. [22] introduced a modal frequency MSE parameter to improve the performance of MSE for locating the damaged elements. They examined their method on two laboratory structures including a simply-supported beam and a 3-story shear frame using enhanced moth-flame optimization algorithm. Wang *et al*. [23] proposed a modified MSE by decomposing MSE to its vertical and lateral components to derive an effective damage index for damage detection in numerical and experimental 3D asymmetric buildings.

The mentioned studies have examined their method on both symmetric and asymmetric structures. However, the effect of symmetry and asymmetry on the results of damage detection have been less independently studied in previous articles. Hence, this paper is devoted to investigating the influence of asymmetry in structures on the results of damage identification. To do so, the effect of asymmetry is modeled via applying the asymmetry in both geometry of structures (different lengths for spans) and geometry of members (different section properties). Moreover, three different objective functions have been proposed based on natural frequencies, flexibility matrix and modal frequencies of the structure. In order to effectively study the effect of asymmetry, four different symmetric and asymmetric trusses, and six examples for frames including the symmetric models and their asymmetric pairs were simulated under multiple damage scenario. Additionally, the impact of noisy input data on the estimated damage severities is included. A recently population-based metaheuristic algorithm called Multiverse optimizer (MVO) [24] has been taken as the optimization algorithm of this study to minimize the above-mentioned objective functions. MVO is chosen since its effectiveness for solving optimization problems has been proved in previous studies [25].

2. METHODOLOGY

2.1 The problem definition

For a structure with nd degrees of freedom, natural frequencies and their corresponding mode shapes can be extracted from the eigenvalue problem defined as follows:

$$\left[[K]-\omega_i^2[M]\right]\{\varphi_i\}=0 \qquad i=1,2,\dots,nd \tag{1}$$

in which M and K are the mass and stiffness matrix of the structure. ω_i and φ_i are ith natural frequency and mode shape of the system, respectively. Assuming that damage occurrence has negligible impact on the mass matrix, the damage can be defined by applying a reduction factor to the stiffness matrix of the structure as below:

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$$k_j^d = (1-\alpha_j)k_j^h \qquad j = 1,2,\dots,ne \tag{2}$$

where superscripts d and h denote the damaged and healthy state of the structure, ne is the total number of elements, and α_j is the stiffness reduction factor applied to the stiffness matrix of jth element. The global stiffness matrix of the structure can be obtained by assembling the stiffness matrices of all elements as follows:

$$[K^d] = \cup_{j=1}^{ne} [k_j^d] \tag{3}$$

2.2. Objective functions

A damage-sensitive objective function plays a significant role for accurately estimating the location and severity of damage. As mentioned before, natural frequencies, modal frequency, and flexibility matrix are some modal parameters that have been proved in previous studies to reflect the impact of damage. The mentioned modal parameters are functions of physical properties of the structure. Therefore, the asymmetry and symmetry of the structure will be indicative in its modal features. The reason behind implementing the three objective functions is to investigate the damage detection results of these objective functions and compare them in both symmetric and asymmetric structures to find the most accurate one for each case. Hence, the first objective function of this study is defined based on the differences take place in natural frequencies of the structure due to damage. It is known that natural frequencies are a global characteristic of the structure, which decrease as an outcome of damage. Therefore, by inspecting the changes between natural frequencies of the monitored damaged structure and its healthy model, one can identify the damage. The first objective function ($F1$) is defined as follows:

$$F1 = \sum_{i=1}^{nm} \left(\frac{\omega_i^d - \omega_i^u}{\omega_i^u} - \frac{\omega_i^m - \omega_i^u}{\omega_i^u} \right)^2 \tag{4}$$

where superscripts u and m refer to undamaged and analytical model of the structure, respectively. nm denotes the number of considered mode shapes for damage detection.

The second objective function is based on flexibility matrix which is the inverse of stiffness matrix of the structure. The flexibility matrix can be calculated as follows:

$$FM = \Phi_{nm} \Lambda_{nm}^{-1} \Phi_{nm}^T \tag{5}$$

where Φ_{nm} is the matrix of mass-normalized mode shapes for the first nm modes, Λ_{nm} is the diagonal matrix of eigenvalues of the first nm modes, and superscript T denotes the transpose of the matrix. When damage occurs to a structure, its stiffness matrix decreases, resulting in an increase in the flexibility matrix. Computing the stiffness matrix of a structure requires the information of whole modes, however, flexibility matrix can be precisely estimated using only a few first modal data as seen from Eq. (5). Flexibility matrix has an inverse relationship with the square of natural frequencies, therefore, natural frequencies of higher modes have less impact on estimating the flexibility matrix [26].

Regarding these advantages, the second objective function of this study is defined as follows:

$$F2 = \frac{1}{nd}\sum_{i=1}^{nd}\left\| FM_i^d - FM_i^m \right\| \tag{6}$$

where FM_i^d and FM_i^m represents the ith column of the flexibility matrix of the actual monitored structure and its analytical FE model. The second objective functions compute the Frobenius norm of differences between each column of flexibility matrix of damaged structure and its analytical model.

The third objective function is defined based on the difference between modal frequency of damaged structure and its analytical FE model as below:

$$F3 = \sqrt{\frac{\sum_{i=1}^{nm}(f_i^d - f_i^m)^2}{nm}} \tag{7}$$

where f_i refers to the ith modal frequency of the structure which can be obtained using natural frequencies as follows:

$$f_i = \frac{\omega_i}{2\pi} \tag{8}$$

Since modal frequencies are the function of natural frequencies of the structure, the damage-induced changes in them can reveal valuable information about the location and severity of damage.

3. MULTIVERSE OPTIMIZER (MVO)

The big bang is a renowned physics theory explaining that our universe originated from a massive explosion. It suggests that there was nothing prior to this event, marking the beginning of existence. Multiverse can be marked as another interesting concept for physicists, which posits the existence of multiple big bangs, each giving rise to a distinct universe. Essentially, this implies the presence of parallel universes alongside our own [24]. MVO is a recently developed optimization algorithm that draws inspiration from three key concepts found in multiverse theory: white holes, black holes, and wormholes [24]. According to physicists, the big bang can be viewed as a white hole, possibly serving as a crucial factor in the creation of a universe. Although white holes have not been directly observed in our universe, black holes, which exhibit contrasting characteristics, are frequently observed. Black holes possess immensely powerful gravitational forces and attract all matter and energy. Wormholes, on the other hand, perform as tunnels that connect different regions of a universe, allowing for travel through space or time.

In the model of MVO, white hole and black hole are responsible for the exploration

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phase of the algorithm, while wormhole is used to improve the quality of solutions (the exploitation phase) [24]. The following principles are behind the formulation of MVO:

(i) A universe is considered as a solution and the objects of the universe represent variables of the solution.

(ii) With respect to the fitness function value of each solution, an inflation rate is assigned to the solution.

(iii) Since the term time is a more consistent term with the theory of multiverse, it is used in the algorithm instead of iteration.

For the optimization process, some rules are utilized which is defined below [24]:

Rule 1: With higher inflation rate, it is more probable to have white holes.

Rule 2: With higher inflation rate, it is less likely to have black holes.

Rule 3: Universes with higher inflation rate desire to send objects through white holes.

Rule 4: Universes with lower inflation rate desire to receive more objects thorough black holes.

Rule 5: Regardless of the inflation rate, objects in all universes may experience random motions towards the best universe via wormholes.

The mathematical model of the components of MVO can be formulated using roulette wheel mechanism [24]. Regarding the inflation rate, universes are sorted at each iteration and one of them is selected by means of roulette wheel mechanism to be the white hole. This procedure is defined below:

$$U = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^d \end{bmatrix} \tag{9}$$

where *d* and *n* denote the number of variables and universes, respectively.

$$x_i^j = \begin{Bmatrix} x_k^j & r1 < NI(Ui) \\ x_i^j & r1 \geq NI(Ui) \end{Bmatrix} \tag{10}$$

where x_i^j represents the jth parameter of ith universe, Ui refers to the ith universe, NI denotes the normalized inflation rate, and $r1$ is a random number within $[0,1]$. x_k^j is the jth parameter of kth universe chosen via roulette wheel mechanism.

In order to have more probability of enhancing the inflation rate utilizing wormholes, and to consider local changes for each universe, wormholes is assumed to be formed between a universe and the best universe established so far [24]. This process is explained as follows:

$$x_i^j = \begin{Bmatrix} \begin{Bmatrix} X_j + TDR \times \left(\left(ub_j - lb_j\right) \times r4 + lb_j\right) & r3 < 0.5 \\ X_j - TDR \times \left(\left(ub_j - lb_j\right) \times r4 + lb_j\right) & r3 \geq 0.5 \end{Bmatrix} & r2 < WEP \\ x_i^j & r2 \geq WEP \end{Bmatrix} \tag{11}$$

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where X_j denotes the jth parameter of the best universe created so far, and lb and ub are the lower and upper bounds of the variables. x_i^j shows the jth variable of the ith universe, and $r2$, $r3$, and $r4$ are random values in $[0,1]$. Wormhole existence probability (WEP) and traveling distance rate (TDR) can be defined as follows:

$$WEP = min + l \times \left(\frac{max - min}{L}\right) \tag{12}$$

where *max* denotes a maximum number considered for this algorithm (equals to 1 in this study), and *min* is a minimum number (equals to 0.2 in this study).

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}} \tag{13}$$

where p describes the accuracy of exploitation over iterations.

4. NUMERICAL EXAMPLES AND THEIR RESULTS

To evaluate the performance of proposed objective functions and to compare the damage detection results of symmetric and asymmetric structures, two types of structures including truss and frame models have been studied. For the truss structures, firstly, a 21-bar planar symmetric truss is modeled using FE method. Then, by applying changes on cross-section area of some elements, and geometry of the structure, three asymmetric trusses have been modeled. For the frame model, firstly, a 27-element planar symmetric frame was modeled. Then, the changes in both geometry of the structure, and geometric properties of some elements (i.e., cross-section area and moment of inertia) have been applied on the symmetric model to produce four asymmetric frames. The detail of these changes will be provided for each type of numerical examples in the next section.

In order to provide meaningful statistical results, each model was run five times independently due to stochastic nature of optimization algorithm. The population size was set to be 100 for all numerical examples. For trusses, the maximum number of iterations was 1000, and for frame model was set to be 1500. The said values were obtained by means of trial-and-error. For simulating the real situation of SHM, the effect random noise should be considered on the modal data. Therefore, both natural frequencies and mode shapes have been polluted by noise as follows:

$$\eta_{noise} = \eta + \eta(2rand - 1)\beta \tag{14}$$

where η is the natural frequency or mode shape, η_{noise} is the noise-contaminated modal data, $rand$ denotes a random value in $[0,1]$, and β is the noise level. In this paper, both natural frequencies and mode shapes were contaminated by 3% noise.

An error function is also utilized to provide more detail about the precision of objective functions and to compare the damage identification results of the symmetric model to those of its asymmetric ones. The error function is defined as follows:

$$E1 = \sum_{i=1}^{m} \left| \frac{AD_i - ED_i}{AD_i} \right| \times 100 \tag{15}$$

$$E2 = \sum_{j=1}^{ne-m} ED_j \tag{16}$$

In Eq. (15), AD_i is the actual damage severity of ith damaged elements, and ED_i denotes the estimated damage severity for the ith damaged element. In Eq. (16), ED_j is the amount of false detection obtained for the jth healthy element. It can be seen that $E1$ computes the total normalized error for damaged elements, while $E2$ is the summation of errors reported for healthy ones. Theses error indexes are computed using mean results of damage detection over five runs for each structure.

To have a well-organized comparison, the truss and frame examples and their results will be provided in section 4.2 and 4.3. Then, in section 5, we will discuss the results obtained for each case to elaborate the effect of asymmetry on the damage detection. It should be mentioned that because in real application of SHM, the modal data is contaminated by noise, the results are provided only for the noisy state to have a realistic comparison. Moreover, it is obvious that by increasing the number of damaged elements, the damage identification via model updating method becomes more challenging, because there are more variables (damaged elements) that the optimization algorithm is supposed to identify. Therefore, one multiple damage scenario in which four elements of each structure are assumed to be damaged, have been considered to execute the proposed method.

4.1. The 21-bar planar truss

This section is devoted to investigating a 21-planar symmetric truss and its asymmetric models. Figs. 1 and 2 illustrate the symmetric truss and the asymmetric one which is produced by applying asymmetry on geometry of the structure. The other two types of asymmetric truss are modeled by changing the area of members. The modulus of elasticity and mass density for all members in all trusses are 200GPa and 7800 kg/m^3, respectively. The detail of members' area is explained in Table 1 for each truss, and the damage scenario is shown in Table 2. To study the effect of asymmetry on higher modes, the damage identification for trusses was carried out using firstly 15 first modes, and then the total modes of each truss.

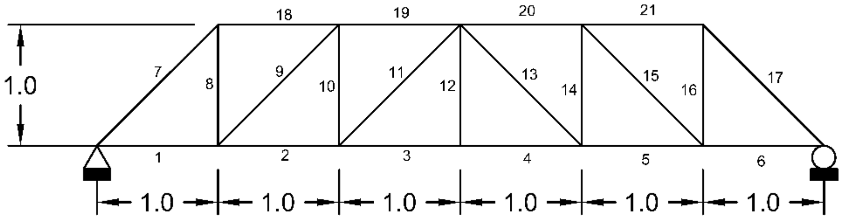

Figure 1. FE model of the symmetric truss

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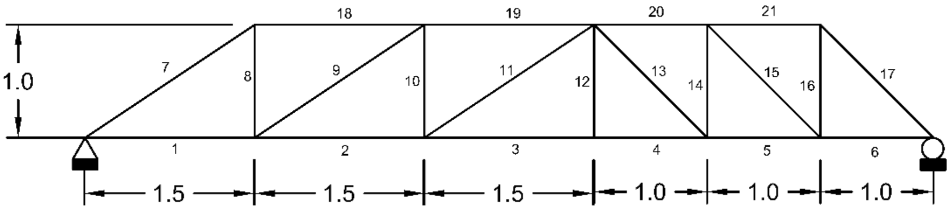

Figure 2. FE model of the geometrically-asymmetric truss

Table 1: The detail of cross-section area for elements of the truss models

Truss number	Element number	Area (m^2)
1 (Fig. 1), and 2 (Fig. 2)	All elements	0.01
3 (Fig. 1), and 4 (Fig. 2)	1-3	0.0165
	4-6	0.015
	7,9,11	0.0088
	8,10	0.011
	12	0.0115
	13,15,17	0.008
	14,16	0.01
	18,19	0.0055
	20,21	0.005

Table 2: The damage scenario of the truss models

Element number	Damage severity (%)
3	20
8	15
15	25
20	10

With respect to Table 1, it is seen that the first truss is the symmetric one, truss 2 is geometrically asymmetric, truss 3 has asymmetry in the geometry of its members (their areas), and truss 4 is geometrically asymmetric and also has members with asymmetric areas. Therefore, all combinations asymmetry is considered in these trusses. The damage detection results for each truss and objective functions are provided in bar figures for these trusses and depicted in Figs. 3-6. Table 3 reports the values obtained for error functions *E1* and *E2* for each objective function and truss.

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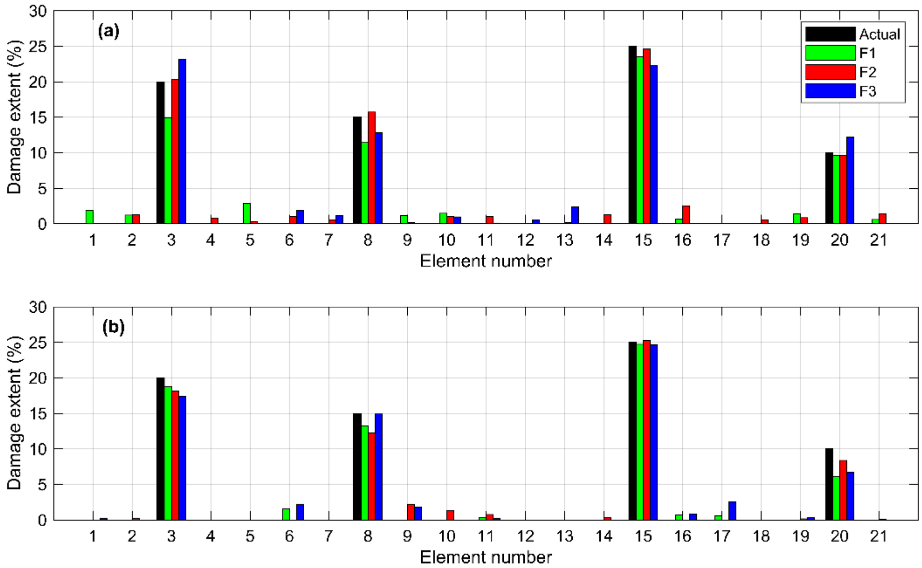

Figure 3. Damage detection results for the first truss in the noisy situation using (a) the first 15 modes and (b) all modes

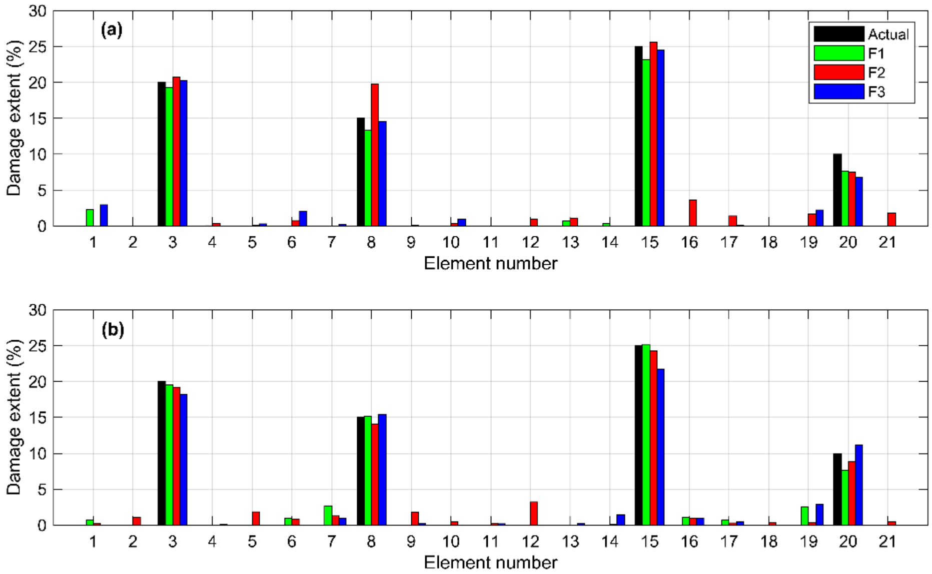

Figure 4. Damage detection results for the second truss in the noisy situation using (a) the first 15 modes and (b) all modes

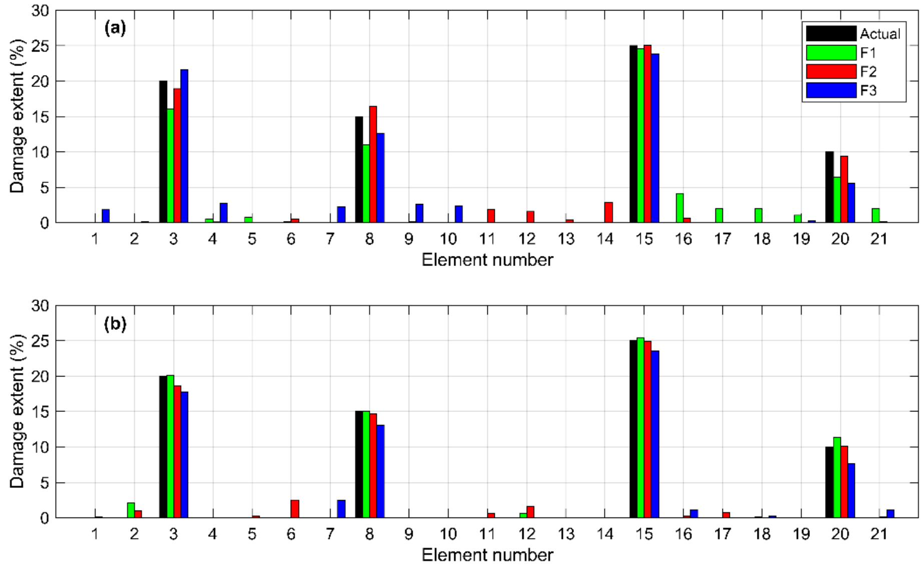

Figure 5. Damage detection results for the third truss in the noisy situation using (a) the first 15 modes and (b) all modes

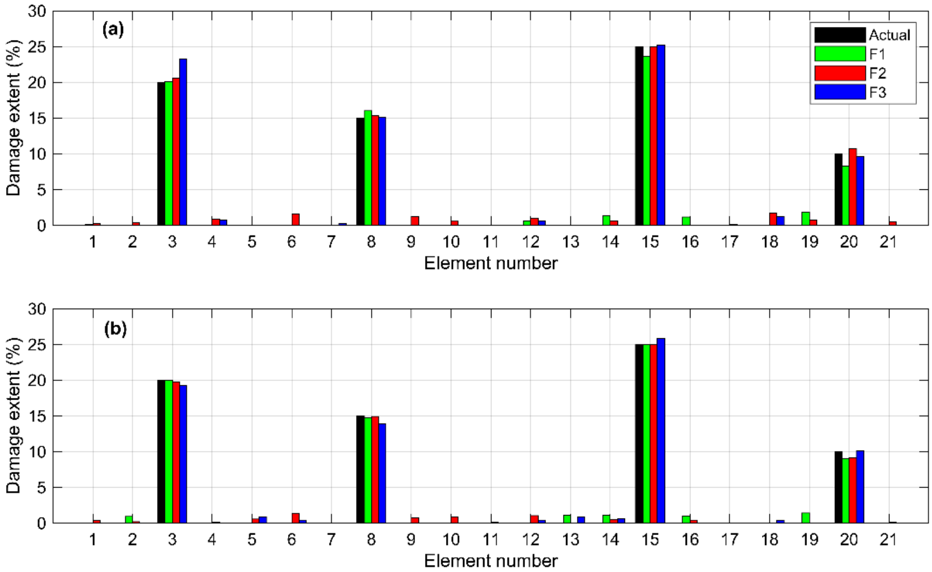

Figure 6. Damage detection results for the fourth truss in the noisy situation using (a) the first 15 modes and (b) all modes

Table 3. Errors percent for each truss and objective function

Truss number	Number of modes	F1	F2	F3
		$E1+E2$	$E1+E2$	$E1+E2$
1	15	58.6+11.3	11.8+13.0	63.3+7.0
	All modes	57.7+3.2	44.7+5.1	47.8+8.1
2	15	46.1+3.3	63.0+12.0	36.8+8.6

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	All modes	28.3+8.6	24.7+13.4	36.6+7.4
3	15	83.7+12.7	21.0+8.3	72.5+12.2
	All modes	15.7+2.9	10.4+7.3	53.2+5.1
4	15	29.2+5.1	12.2+9.6	21.4+2.8
	All modes	12.1+5.4	11.0+6.5	15.2+3.6

4.2. The 27-member planar frame

In this section, the effect of symmetry and asymmetry will be studied using six frame models. Firstly, the FE model of a 27-element symmetric frame is simulated. Then, by applying changes on geometry of the frame and geometry of members (i.e., moment of inertia and area), four asymmetric frames are modeled. Regarding that the geometry properties of beams and columns of the first symmetric model is identical; another symmetric model is also produced in which area and moment of inertia of beams are different from those of columns in order to realize whether this issue affects the results of damage detection. The cross-section area and moment of inertia for the elements of each frame is detailed in Table 4. It should be noted that for all frame models, modulus of elasticity and mass density are equal to 200 GPa and 7850 kg/m^3, respectively. Furthermore, the damage scenario defined in Table 5 is implemented for all frame models. Figs. 7 and 8 depict the FE model of the symmetric and asymmetric frame examples.

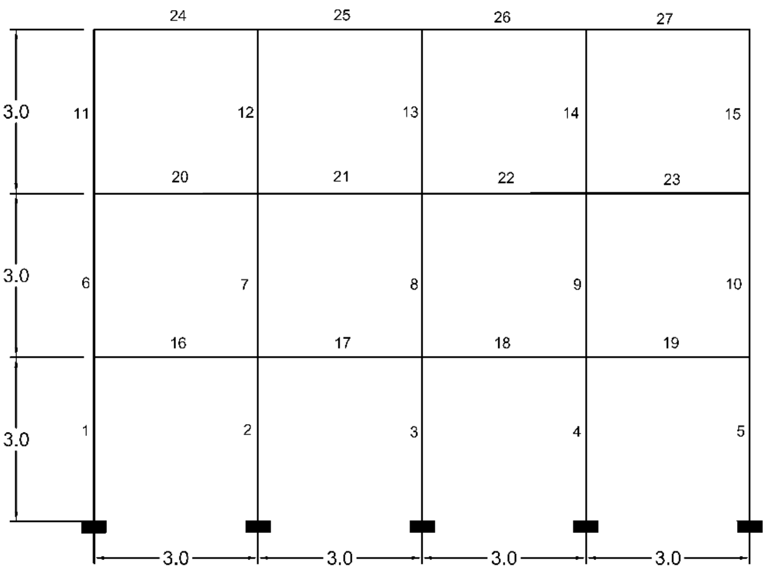

Figure 7. FE model of the symmetric frame

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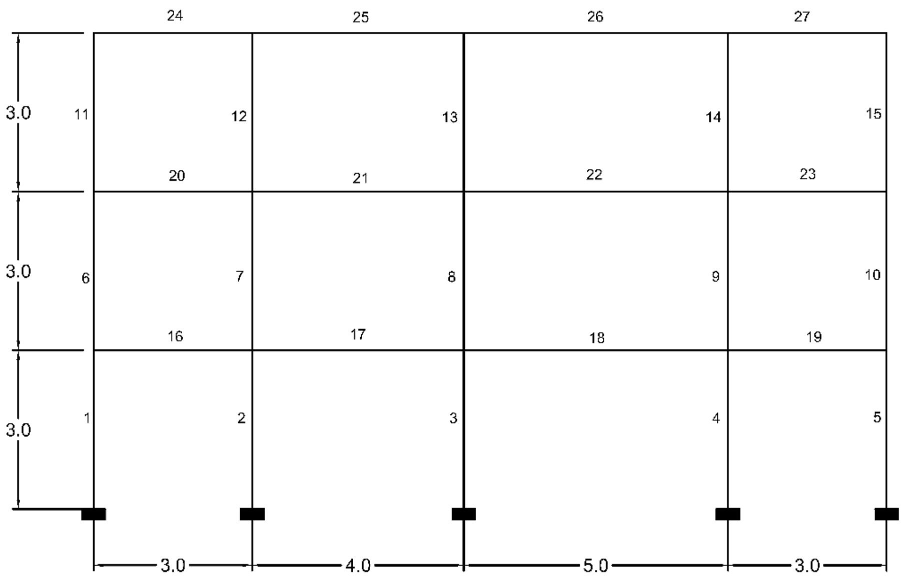

Figure 8. FE model of the geometrically-asymmetric frame

Table 4. The detail of cross-section area for elements of the frame models

Frame number	Element number	Area (m^2)	Moment of inertia (m^4)
1 (Fig. 7), and 2 (Fig. 8)	All elements	0.016	0.00035
3 (Fig. 7), and 4 (Fig. 8)	Beams	0.0162	0.000385
	Columns	0.016	0.00035
5(Fig. 7), and 6 (Fig. 8)	1,2,6,7,11,12,16,17,20,21,24,25	0.0176	0.000385
	3,8,13	0.016	0.00035
	4,5,9,10,15,15,18,19,22,23,26,27	0.0184	0.0004025

Table 5. The damage scenario of the frame models

Element number	Damage severity (%)
2	25
9	10
18	15
24	20

With respect to Table 4, two symmetric models and four asymmetric ones are considered. All combinations of asymmetry including asymmetry in geometry of the structure, and asymmetry in both geometry of the structure and geometry of members are considered. The damage identification results obtained from each objective function for all cases are demonstrated in Figs. 9-14. Moreover, Table 6 reports the errors percentage computed for each model using the three objective functions.

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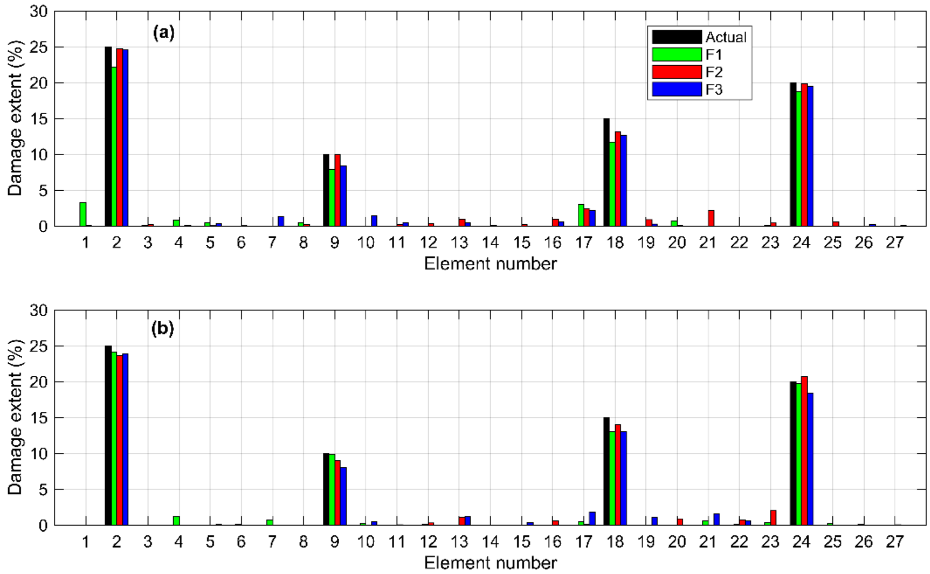

Figure 9. Damage detection results for the first frame in the noisy situation using (a) the first 35 modes and (b) all modes

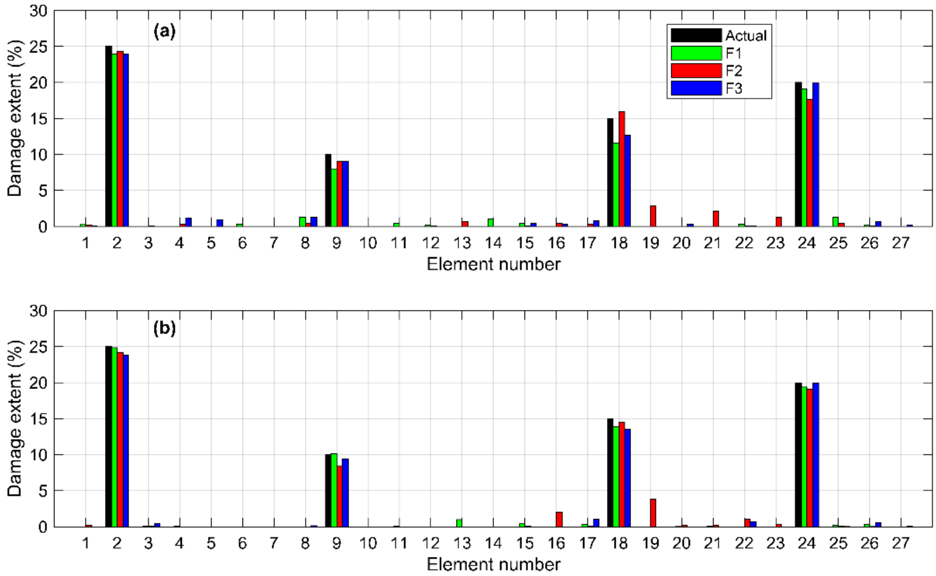

Figure 10. Damage detection results for the second frame in the noisy situation using (a) the first 35 modes and (b) all modes

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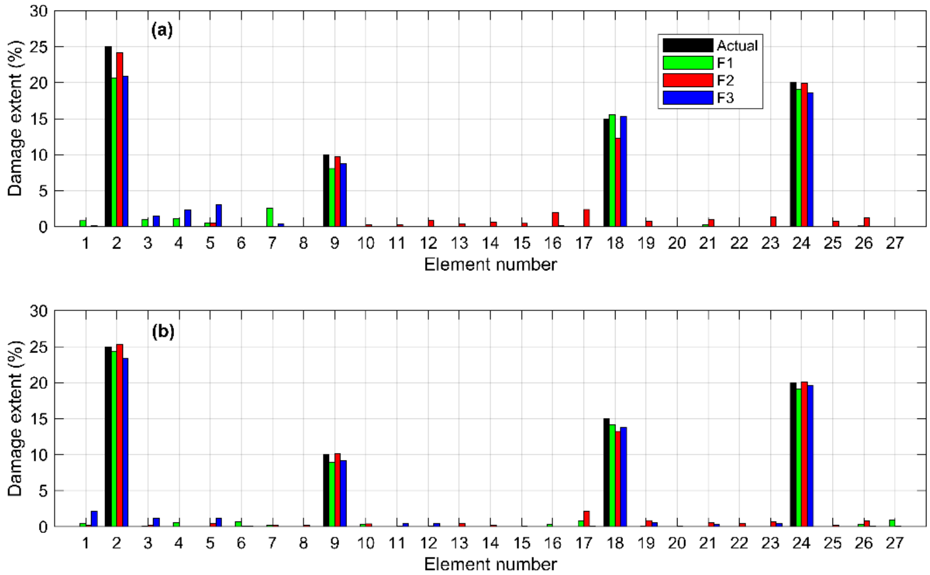

Figure 11. Damage detection results for the third frame in the noisy situation using (a) the first 35 modes and (b) all modes

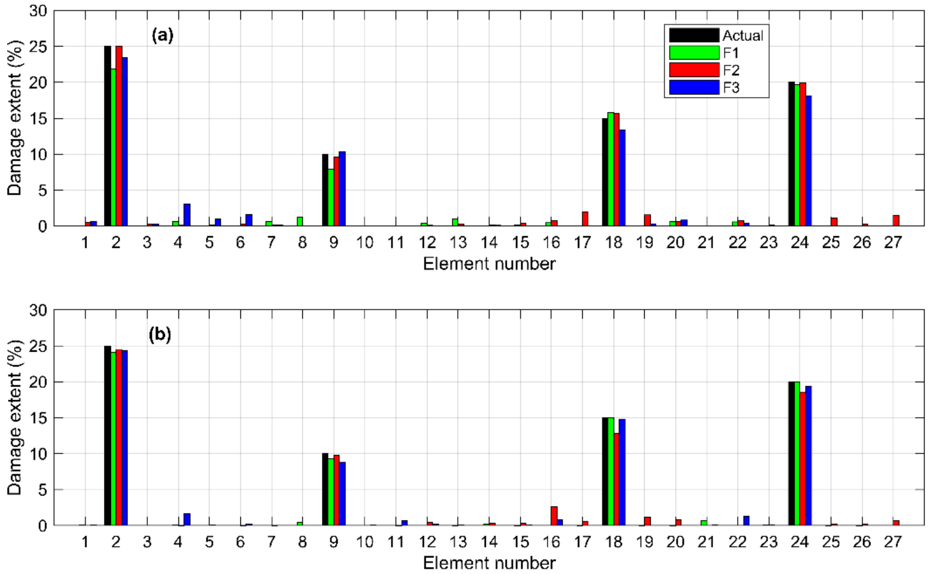

Figure 12. Damage detection results for the fourth frame in the noisy situation using (a) the first 35 modes and (b) all modes

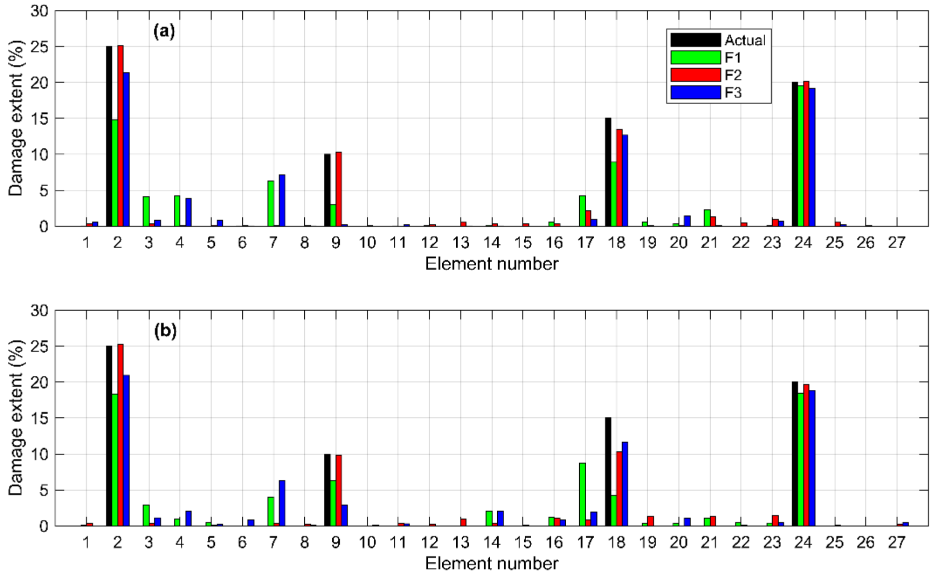

Figure 13. Damage detection results for the fifth frame in the noisy situation using (a) the first 35 modes and (b) all modes

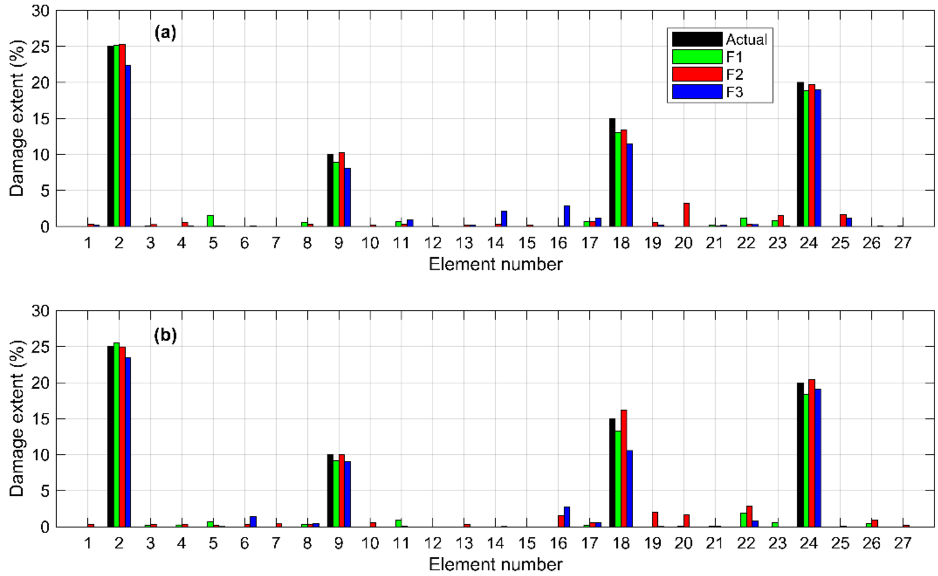

Figure 14. Damage detection results for the sixth frame in the noisy situation using (a) the first 35 modes and (b) all modes

Table 6. Errors percent for each frame and objective function

Frame number	Number of modes	F1	F2	F3
		$E1+E2$	$E1+E2$	$E1+E2$
1	35	60.6+9.1	14.4+10.1	36.4+7.6
	All modes	18.3+4.4	25.7+6.0	45.3+7.4
2	35	51.8+5.7	31.1+9.4	29.6+6.2

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	All modes	11.7+2.4	27.3+8.1	2.9+2.9
3	35	44.5+6.5	25.2+12.8	37.8+7.6
	All modes	22.7+4.9	15.5+8.7	24.7+7.0
4	35	40.5+5.7	8.7+11.0	29.8+8.3
	All modes	10.4+1.6	25.8+7.9	19.6+5.2
5	35	153.4+23.0	13.9+8.8	131.9+16.8
	All modes	143.2+23.0	35.4+9.8	115.6+18.0
6	35	30.1+5.7	16.1+10.9	58.4+9.5
	All modes	30.0+5.5	9.9+13.1	49.6+5.9

5. DISCUSSION

In this section, we discuss the performance of objective functions and compare the results of symmetric models to those of their asymmetric ones. Subsections 5.1 and 5.2 are devoted to explaining the results of trusses and frames, respectively.

5.1. Discussion of trusses' damage detection results

For the first truss which is the symmetric model, F2 has the superior performance with the most accurate results in comparison with the results of F1 and F3. This is because flexibility matrix is more sensitive to damage since it is a local damage feature. Moreover, using only natural frequencies for damage detection of symmetric structures yields in non-uniqueness of answers since the same natural frequencies can be obtained by identifying wrong elements as the damaged ones [27]. This issue can be overcome using the frequencies of higher modes as the results of Table 3 for truss 1 indicate that the accuracy of F1 and F3 has been improved using all modes of the structure. However, the accuracy of F2 has been declined using all modes because the mode shapes of higher modes are more prone to be affected by noise. It means in the symmetric truss, choosing the number of modes is dependent on the type of modal parameter used to identify the damage.

For the second truss which has asymmetry in its geometry, F3 gives the most accurate results when using the first 15 modes. However, when using all modes, F2 is more precise than the other objective functions which means the effect of damage is more indicative in flexibility matrix when using higher modal data in geometrically-asymmetric truss. It should be noted that all the three objective functions have performed more accurately using all modes in this case.

For the third truss in which the geometry properties of elements are asymmetric, when using 15 modes, F2 ranked first in accurately identifying both damaged and healthy elements. When using all modes, F2 maintains its superior and precise performance in comparison with the results of other objective functions. Furthermore, the results of F1 and F3 have improved when using all modes with fewer false detections. Also, F1 has superior performance over F3 using all modes, which means that formulating the objective function based on investigating changes between the natural frequencies of healthy and damaged structure leads to more accurate results than merely minimizing the alterations between monitored structure and its analytical model.

For the fourth truss which is geometrically-asymmetric and also has asymmetry

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concerning the area of members, all objective functions have satisfying results with a slight superiority of F2 when using information of 15 modes. When using all modes, the accuracy of all objective functions has enhanced in terms of both identifying the damaged elements and having minor false alarms. All objective functions have almost similar performance meaning that the influence of damage is more reflected in both natural frequencies and mode shapes in this type of asymmetry for truss using the modal information of all modes.

5.2. Discussion of frames' damage detection results

In the first symmetric frame, when using 35 modes, F2 ranked first in terms of accurately identifying damaged elements and avoiding false identifications. However, the precision of F2 was reduced using all modes while the results of F1 and F3 have become more accurate and the damage detections obtained via F1 are the most accurate ones in this condition. Like the symmetric truss, it can be concluded that using the mode shapes of higher modes does not always improve the precision of results especially when utilizing flexibility matrix which is a mode shape-based parameter.

For the second frame with different lengths in its spans, F2 and F3 have more accurate results compared to those of F1 when using 35 modes with a slight superiority of F3. When using all modes, the performance of all the three objective functions has improved, but the performance of F3 was significantly enhanced and ranked first in identifying damaged elements with the least false identification in comparison with other objective functions. This means that when using all modes, modal frequencies have more reliable damage identification results.

For the third frame which is a symmetric model but with different properties for beams and columns (compared to the first frame), F2 ranked first among the three objective functions with the most accurate results for both healthy and damaged elements using 35 modes. When using all modes, the errors obtained by all objective functions have decreased while F1 maintains its superior performance. Unlike the first frame in which using all modes resulted in decreasing the accuracy of F2; in the third frame in which beams have different geometry properties from those of columns, using all modes have no negative impact on the performance of F2.

For the fourth frame, F2 has the most precise damage diagnosis results compared to results of F1 and F3 using 35 modes. When utilizing all modes, the accuracy of F2 declined while the results of F1 and F3 have improved. F1 has the superior performance over two other objective functions in this case as seen from Table 6.

For the fifth frame which is geometrically symmetric but its members have different geometry properties, when using 35 modes, F1 and F3 gives considerably error values for identifying damaged elements with significant false detections, whereas F2 has the most accurate results with fewer false alarms. By using all modes, although the accuracy of F1 and F3 has improved, their performance is still inaccurate and unreliable with high error values, whereas F2 maintains its precise results.

For the last frame which has different spans' length and members with different geometry in their cross-sections, when using 15 modes, all objective functions have acceptable damage detection results with insignificant false identifications, and F2 ranked first as the most accurate one. When using all modes, unlike the first frame, the performance of F2 has improved, while no significant decrease can be seen in the error values of F1 and F3.

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6. CONCLUSIONS

In this study, we aim to investigate the effect of asymmetry in structures on results of damage identification. To do so, the asymmetry has been modeled via changing the span length of the structure, and also by considering members with different cross-section properties. Two types of structures including frame and truss examples have been studied. For these examples, symmetric structures along with their asymmetric models were investigated under multiple damage scenario and noisy situation. To inspect the effect of higher modes on damage detection of asymmetric models, the truss examples were simulated using the first 15 modal data and all modes, and frame models were studied utilizing the first 35 modes and all modes. Moreover, three objective functions have been defined to compare the performance of damage sensitive features in damage detection of different cases. Moreover, MVO algorithm was chosen as the optimization tool to minimize the objective functions. Based on the obtained results, the following conclusions can be highlighted:

F2 has the most accurate performance for the symmetric truss using 15 modes, although, this accuracy has decreased via implementing the modal data of all modes. The similar performance has been seen for the first frame which was a symmetric model with same beams and columns (identical sections). This means in symmetric model of truss and frame structures, increasing the number of considered mode shapes has an adverse influence of the accuracy of flexibility-based objective function. In contrast, using all modes leads to improving the precision of frequency-based objective function.

Among the asymmetric models of truss, the one in which the asymmetry has been modeled by changing both spans’ length and section of members, yields the most accurate damage detection results by means of all objective function using both limited modal data and total modes. Also, F2 ranked first as the most accurate objective function that means in this type of asymmetry, increasing the number used modal data has no negative impact on F2’s performance.

Among asymmetric models of frame, considering the results of F2, the damage detection of the fourth frame which has only different spans’ length is the most accurate results. However, regarding the error values of F3, the second frame yields the most accurate results. F1 and F3 have their worst performance for the fifth frame where the asymmetry was modeled via merely considering different sections for members. Overall, it can be said that the effect of damage is more reflected in asymmetric frames which has only different spans than the one having only different elements’ section properties.

When the asymmetry is applied in both spans’ length and section properties of members, via using all modes, the error values obtained for all objective functions decreased compared to the case when limited modal data was utilized. This means that this type of asymmetry affects the modal of higher modes, especially when using flexibility-based objective function; because F2 had shown higher error values in the symmetric models of truss and frame using total modes.

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