Smart Structures and Systems, *Vol. 25, No. 1* (*2020*) *47-56*
DOI: https://doi.org/10.12989/sss.2020.25.1.047

Feasibility study on model-based damage detection in shear frames using pseudo modal strain energy

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(*Received August 27, 2018, Revised August 7, 2019, Accepted Sepetember 2, 2019*)

Abstract. This paper proposes a model-based approach for structural damage identification and quantification. Using pseudo modal strain energy and mode shape vectors, a damage-sensitive objective function is introduced which is suitable for damage estimation and quantification in shear frames. Whale optimization algorithm (WOA) is used to solve the problem and report the optimal solution as damage detection results. To illustrate the capability of the proposed method, a numerical example of a shear frame under different damage patterns is studied in both ideal and noisy cases. Furthermore, the performance of the WOA is compared with particle swarm optimization algorithm, as one the widely-used optimization techniques. The applicability of the method is also experimentally investigated by studying a six-story shear frame tested on a shake table. Based on the obtained results, the proposed method is able to assess the health of the shear building structures with high level of accuracy.

Keywords: damage detection; shear frame; pseudo modal strain energy; mode shape; whale optimization algorithm

1. Introduction

Engineering structures may be affected by different levels of local damage throughout their lifespan. Early detection of these damages not only reduces the risk of structural collapse, but also can help the engineers to design suitable rehabilitation plans. Generally, damage causes some changes in physical properties of the structures. Damage detection techniques employ the existing relationships between these changes and structural feedback (under an external excitation) to identify the location and severity of damage (Fan and Qiao 2012). Although utilizing classical non-destructive tests (such as visual or liquid inspections) can detect imperfections in the structural systems, they require long-term and expensive procedure. On the other hand, such methods are classified as *local inspections*, which means a priori information of damage is needed to identify its exact location (Fan and Qiao 2012). Vibration characteristics (like modal data), however, have high level of sensitivity to structural damage and can assess the health of the structure in a *global* scale. As a result, there is no need to priori information of the damage location if vibration characteristics are used for structural condition assessment, and the structural damage in local (element) level can be identified based on the theoretical relationship between vibration characteristics of the structure in global scale and physical properties of the structural elements in local scale. This is one of the promising aspects of the vibration-based damage detection methods which has absorbed the attention of the engineers in the field of mechanical, civil and aerospace engineering.

In a general view, vibration-based methods can be divided into two groups: *index* and *model updating* methods. In index methods, a damage-sensitive index is used for damage localization (Koo *et al*. 2010, Homaei *et al*. 2014, Sung *et al*. 2014, Ghodrati Amiri *et al*. 2015, Capecchi *et al*. 2016, Wei *et al*. 2016, Li *et al*. 2018, Ciambella *et al*. 2019) or quantification (Yang 2009, Sung *et al*. 2012, Ghodrati Amiri *et al*. 2013). These methods rely on forward problem definition to formulate the damage detection problem as one stage non-iterative model-based or reference-free approaches.

The second type of vibration-based methods is model updating methods, in which the damage detection problem is defined as an inverse problem (Alkayem *et al*. 2018). In these methods, the physical properties of a numerical model of the monitored system are tuned in a way that a function representing error between the numerical model and the tested structure is minimized. Different methods have been developed in this regard to solve the presented problem by the optimization algorithms (Ghodrati Amiri *et al*. 2011, Kaveh and Maniat 2015, Seyedpoor and Montazer 2016, Dinh-Cong *et al*. 2019, Ding *et al*. 2019). Generally, model updating problem is an ill-posed problem, and robust objective functions as well as suitable optimization

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http://www.techno-press.org/?journal=sss&subpage=7
ISSN: 1738-1584 (Print), 1738-1991 (Online)

techniques are needed to find the global optimal solution as the damage detection results. In the field of vibration-based model updating, different objective functions have been utilized to represent damage detection problem. Free vibration equilibrium (Ghodrati Amiri *et al*. 2011), generalized modal residual force (Zare Hosseinzadeh *et al*. 2019a), and weighted combination of modal data (Ding *et al*. 2019) are some the concepts used in this regard. Moreover, different optimization algorithms –like Charged System Search Algorithm (Tabrizian *et al*. 2014), Magnetic Charged System Search (Kaveh and Maniat 2015), Multi-swarm fruit fly Optimization Algorithm (Li and Lu 2015), Jaya Algorithm (Du *et al*. 2018), Grey Wolf Optimization (Zare Hosseinzadeh *et al*. 2019a), and Lightning Attachment Procedure Optimization (Dinh-Cong *et al*. 2019)– have been employed to solve the problem.

This paper proposes new objective function which is based on a generalized version of modal strain energy (MSE). MSE is a parameter that have been widely used for damage localization and/or quantification (Li *et al*. 2006, Nobahari and Seyedpoor 2013, Guo and Li 2013, Seyedpoor and Yazdanpanah 2014, Cha and Buyukozturk 2015, Li *et al*. 2016, Nguyen *et al*. 2016). Li *et al*. (2018) proposed a new damage index based on the total modal energy, indicating that total modal energy (which is calculated by means of both frequencies and mode shapes) can perform better than MSE (which is a mode shape-based parameter). On the other hand, MSE is a single-mode parameter and it cannot internally combine the information of the several first modes. To tackle the listed drawbacks of the MSE, this paper introduces a pseudo MSE which is based on calculating static displacements of the structural system under unit force using the modal data of the first several modes. Then, using linear combination of the employed mode shape vectors, a new parameter is derived from the calculated pseudo MSE which can uniquely represent the structural system by only one scalar. Finally, using this parameter, a new objective function is proposed to formulate damage detection problem. The objective function is solved be means of a recently-developed optimization technique, named Whale Optimization Algorithm (WOA). WOA is based on swarm intelligence and shows promising performance in comparison with evolutionary algorithms (Mirjalili and Lewis 2016). The applicability of the proposed method is investigated by numerical and experimental studies on shear frames. Moreover, the performance of the WOA is assessed by comparative studies.

2. Whale Optimization Algorithm (WOA)

Mirjalili and Lewis (2016) recently presented a new optimization algorithm called Whale Optimization Algorithm (WOA), which has shown successful performance in solving optimization problems. WOA is a swarm-based optimization technique which emulates the hunting behavior of the humpback whales, named *bubble-net foraging*. In this hunting behavior, the humpback whales select school of krill or small fishes (preferably close to the surface of ocean) as their prey and approach them by creating distinctive bubbles along a circle or ‘9’-shaped path. They swim around the prey with a shrinking circular movement and on a spiral-shaped path, simultaneously. Mathematical model of this procedure results in an optimization algorithm. In the following, different stages of this algorithm are briefly explained.

In WOA, whales update their position following the bubble-net hunting behavior to reach to the location of prey, which is the optimal solution of the problem. Similar to other meta-heuristic optimization algorithms, WOA starts with a set of random solutions representing the initial location of the agents (whales) as the candidate solutions. A point ($\mathbf{X}^*$) in the search domain is selected as the location of the target prey and the agents update their position ($\mathbf{X}$) towards $\mathbf{X}^*$. In terms of shrinking circular movement, this update is done as the follows

$$\boldsymbol{X}_{t+1} = \boldsymbol{X}_t^* - (\boldsymbol{A} \otimes \boldsymbol{D}) \tag{1}$$

$$\boldsymbol{D} = |(\boldsymbol{C} \otimes \boldsymbol{X}_t^*) - \boldsymbol{X}_t| \tag{2}$$

in which, t denotes the current iteration, $\otimes$ represents element-by-element multiplication, and |.| returns absolute value of its argument. $\mathbf{A}$ and $\mathbf{C}$ are defined as

$$\boldsymbol{A} = 2(\boldsymbol{a} \otimes \boldsymbol{r}) - \boldsymbol{a} \tag{3}$$

$$\boldsymbol{C} = 2\boldsymbol{r} \tag{4}$$

where, $\mathbf{a}$ is linearly decreased from 2 to 0 as the iteration goes forward, and $\mathbf{r}$ is a random vector and its entries are randomly generated within interval [0,1]. If $|\mathbf{A}| < 1$, the best agent (with minimum fitness value) is selected as the target $\mathbf{X}^*$. However, if $|\mathbf{A}| \geq 1$, a random point in the search space is selected as $\mathbf{X}^*$. The updating procedure for the case that whales swim towards the prey in a spiral-shaped path is done as

$$\boldsymbol{X}_{t+1} = \boldsymbol{X}_t^* + e^{bl} cos(2\pi l)\, \boldsymbol{D}' \tag{5}$$

where $\mathbf{D}'$ denotes the distance between whale and the prey (best solution up to now), b is a constant to define the shape of the logarithmic spiral, and l is a random scalar in the range of [–1,1].

It is assumed that the probability of selecting shrinking circular movement or spiral model is 50%. To consider this assumption in the mathematical model of the algorithm, a variable is defined which is randomly selected during the optimization procedure. If this variable is less than 0.5, the circular movement (described by Eq. (1)) is used to update the location of the agents. Otherwise, the spiral movement-based location updating (Eq. (5)) is followed. The WOA is terminated if the termination criteria are satisfied. Reaching to the maximum iteration is one of these criteria. For more details, see Mirjalili and Lewis (2016).

3. Methodology

3.1 Pseudo modal strain energy

Modal Strain Energy (MSE) is one of the well-known concepts which has been widely used in the field of tructural damage localization and quantification (Wang and Xu 2019). Consider a structural system with N_e elements and N degrees of freedom (DOFs). MSE for the eth element using the modal data of the ith mode is defined as

$$MSE_i^e = \frac{1}{2}\boldsymbol{\varphi}_i^T \boldsymbol{K}^e \boldsymbol{\varphi}_i \tag{6}$$

in which, $\boldsymbol{\varphi}_i$ and $\mathbf{K}^e$ are the ith mode shape vector and the stiffness matrix of the eth element, respectively. As it can be seen, only one mode's data is needed to calculate MSE, which is beneficial considering its simplicity from computational viewpoint. However, this can be problematic in terms of sensitivity to different damage scenarios, since some damages affect several modes in different levels and it is more preferred that a combination of several modes' data is used for damage assessment. In the present paper, a generalized version of the MSE –called pseudo MSE– is introduced as a multi-mode parameter.

Pseudo MSE is defined using the static displacement of the structure under unit force calculated by modal data of the first several modes. As a result, not only the first several mode shapes, but also the associated modal frequencies are used in the calculations. Following Hooke's law, the relationship between the static displacement ($\boldsymbol{\delta}$) and stiffness matrix of the structural system ($\mathbf{K}$) under external force $\mathbf{F}$ is presented as

$$\boldsymbol{\delta} = \boldsymbol{K}^{-1}\boldsymbol{F} \tag{7}$$

Although $\boldsymbol{\delta}$ can be easily calculated from Eq. (7), the modal data of all the modes are needed to estimate the stiffness matrix. To overcome this issue, modal flexibility concept can be used (Zare Hosseinzadeh *et al*. 2014). Considering the modal information of the first p modes, static displacement of the system under external force $\mathbf{F}$ is given by

$$\boldsymbol{\delta}_p = \boldsymbol{G}_p\boldsymbol{F} \tag{8}$$

in which, $\mathbf{G}_p$ is the flexibility matrix which is computed as

$$\boldsymbol{G}_p = \boldsymbol{\Psi}_p \boldsymbol{\lambda}_p^{-1} \boldsymbol{\Psi}_p^T \tag{9}$$

where, $\boldsymbol{\Psi}$ is matrix of the mode shape vectors and $\boldsymbol{\lambda}$ is a diagonal matrix of the square of natural frequencies. Note that in Eqs. (8) and (9), the subscript p is used to emphasize that the modal data of the first p modes (i.e., natural frequencies and the associated mode shape vectors) are used in the calculation. Employing Eq. (8), the pseudo MSE of the eth element ($PMSE^{(e)}$) is defined as

$$PMSE^{(e)} = \frac{1}{2}\boldsymbol{\delta}_p^T \boldsymbol{K}^e \boldsymbol{\delta}_p \tag{10}$$

The normalized $PMSE$ for the eth element ($\overline{PMSE}^{(e)}$) is calculated as

$$\overline{PMSE}^{(e)} = \frac{PMSE^{(e)}}{\sum_{j=1}^{N_e} PMSE^{(j)}}, \qquad e = 1,2,\ldots,N_e \tag{11}$$

Consequently, the vector of the normalized $PMSE$ is formed using the element-wise calculated $\overline{PMSE}^{(e)}$s as follows

$$\overline{\boldsymbol{PMSE}} = \left\{\overline{PMSE}^{(1)} \quad \overline{PMSE}^{(2)} \quad \cdots \quad \overline{PMSE}^{(N_e)}\right\}^T \tag{12}$$

3.2 The proposed method

In section 3.1 the normalized pseudo MSE was introduced. In this section, the proposed method for structural damage detection is described.

In this paper a data fitting-based updating approach is utilized to formulate damage detection problem as a model-based inverse problem. To do so, an analytical model of the monitored structure (with unknown variables representing damage in element level) is formed. Damage is defined as some reduction in the stiffness matrix of the damaged elements as below

$$\boldsymbol{K}_d^e = (1-\alpha_e)\boldsymbol{K}_u^e, 0 \le \alpha_e \le 1, e = 1,2,\ldots,N_e \tag{13}$$

in which, d and u are notations referring to the damaged and undamaged cases, respectively. Moreover, α_e is the variable represents damage severity in the eth element. Healthy and fully damaged elements are returned by $\alpha = 0$ and $\alpha = 1$, respectively. As a result, the unknown variables of the damage detection problem can be defined as vector $\boldsymbol{\alpha} = \{\alpha_1, \alpha_2, \ldots, \alpha_{Ne}\}^T$. Note that damage may also cause changes is the mass of the damaged elements; however, the impacts of mass changes on the modal data of the structure in negligible for light and moderate damages (Saada *et al*. 2013, Zare Hosseinzadeh *et al*. 2019b).

In the next step, the unknown variables are guessed in a way that the error between the behavior of the monitored structure and its analytical model is minimized. This paper proposes a new error (objective) function using normalized pseudo MSE as

$$f(\alpha_1, \alpha_2, \ldots, \alpha_{N_e}) = \left|\overline{\boldsymbol{PMSE}}^a(\alpha_1, \alpha_2, \ldots, \alpha_{N_e}).(\boldsymbol{D}^a)^T - \overline{\boldsymbol{PMSE}}^d.(\boldsymbol{D}^d)^T\right| \tag{14}$$

where, |.| returns the absolute value of its argument. In addition, $\mathbf{D}^a$ and $\mathbf{D}^d$ are the accumulative unweighted dimensionless displacements in modal coordinates using the mode shape vectors of the first p modes for the analytical and monitored (damaged) structures, respectively; defined as follows

$$\boldsymbol{D}^a = \sum_{j=1}^{p} \boldsymbol{\varphi}_j^a \tag{15}$$

$$\boldsymbol{D}^d = \sum_{j=1}^{p} \boldsymbol{\varphi}_j^d \tag{16}$$

In this paper, $\mathbf{D}$s are calculated by a simple linear summation; however, weighted summation can be also used to emphasize on the contribution of the predominant mode(s) on the dimensionless displacements in the modal coordinates. Note that employing **D** not only can strengthen the searching procedure (because of adding an internal constraint on the minimization problem), but also can add more simplicity on the problem when it is used for shear frames. The latter is because of the special property of the shear frames –in shear frames, the number of the DOFs is equal to the number of the elements (stories). Therefore, the two terms mentioned in the right hand side of Eq. (14) will be scalars and this considerably simplifies the evaluation procedure during the iterations.

Finally, the optimal solution of the inverse problem introduced by Eq. (14) is found using WOA. This solution will be the damage detection results. In the next sections, the method is evaluated by numerical and experimental studies.

Table 1 Physical properties of the numerical example

Story number	Mass (kg)	Stiffness (kN/m)
1	350	6.5
2	350	5.5
3	550	5.5
4	450	3
5	550	3
6	350	4.5
7	500	5
8	400	3.5
9	550	4
10	450	4

4. Numerical study

In this example, a ten-story shear frame under single and multiple damage patterns is studied to evaluate the performance of the proposed method in structural damage localization and quantification. Table 1 describes the physical properties of this structure. The structure is irregular in terms of both mass and stiffness distributions. Three damage patterns, as explained in Table 2, are considered. The first damage scenario is a single damage case. However, damage patterns II and III consist of multiple damaged stories with light, moderate and severe damages.

Table 2 Details of the simulated damage patterns in the numerical example

Damage pattern I		Damage pattern II		Damage pattern III	
Story number	Damage (%)	Story number	Damage (%)	Story number	Damage (%)
4	10	2	5	1	10
		7	15	3	15
				6	20
				9	25

In real cases, there are different sources of uncertainties which may adversely influence the accuracy of the acquired data. In this paper, the uncertainties in the recorded structural feedback by the sensors –known as *measurement errors*– are numerically simulated to evaluate the applicability of the method in such a condition. For this purpose, the natural frequencies and mode shape vectors are contaminated with noise as

$$\omega_i^n = \omega_i + \mu(\omega_i \times rand) \tag{17}$$

$$\boldsymbol{\varphi}_i^n = \boldsymbol{\varphi}_i + \varepsilon(\boldsymbol{\varphi}_i \otimes \boldsymbol{rand}) \tag{18}$$

in which, ω_i is the ith natural frequency without noise, μ and ε are the noise levels (in %) used to pollute the natural frequency and mode shape vector by unit-magnitude random number (*rand*) and vector (**rand**), respectively. Moreover, $\otimes$ shows element-by-element multiplication and superscript “*n*” denotes the parameter in the noisy state. In the present section, the modal information of the damaged structure in both noise-free and noisy states are fed to the method to study its performance and robustness not only in the ideal case, but also in the presence of the measurement errors. Noisy state is simulated by contaminating the natural frequencies and mode shape vectors with 3% and 5% noise levels, respectively.

Using finite element modelling, each damage pattern was simulated in the workspace of MATLAB and the modal data were extracted by the modal analysis. Then, the proposed method was used to solve the problem. To consider the effects of the number of the utilized modal data (p), two cases were investigated: p = 1 and p = 3. Moreover, the population size and the maximum number of iterations for the WOA were selected as 100 and 200, respectively. Since WOA is a stochastic optimization algorithm, it is possible that different solutions are reported as the optimal solution in different runs of a unique problem. To consider this issue, the problem was solved ten times for each case and the mean value of the obtained results was reported as the damage detection results. Figs. 1, 2 and 3 show the damage detection results for the simulated damage patterns. To check the distribution of the solutions in ten different runs for each case, the Standard Deviation (SD) of the reported damages was computed. For noise-free case, SD is equal to zero, since all the runs return the same solution. For the noisy state, however, the minimum and maximum SDs were 0.15% and 0.91%, respectively. Therefore, it is concluded that in general, WOA reaches to a unique solution in different runs of a problem.

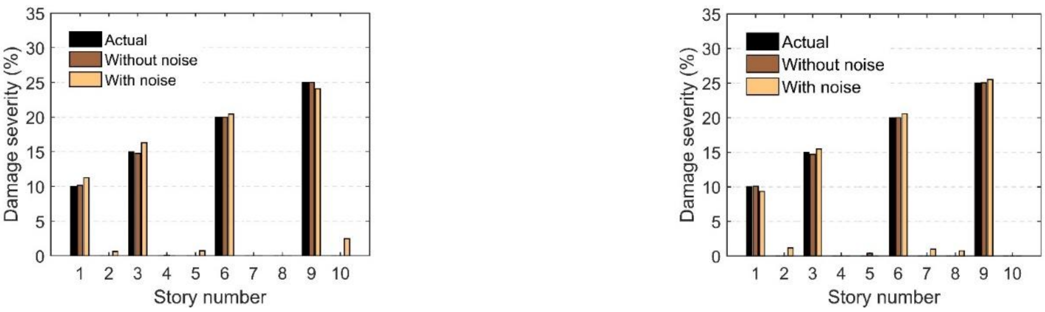
Generally, the proposed method identifies all the damage patterns with high level of accuracy in both noise-free and noisy states. In the latter state, however, there are some differences between the obtained results and the simulated patterns. Moreover, some of the healthy stories are detected as damaged stories (with low level of damage). Note that by increasing the number of the modes utilized for damage detection, the number and/or the amount of false alarms decrease (for example, see Fig. 1 and compare the results related to noisy state for p = 1 and p = 3). This can be justified if the presented modifications in the original

(a) p = 1 (b) p = 3

Fig. 1 Damage detection results for the first damage pattern of the numerical study

(a) p = 1 (b) p = 3

Fig. 2 Damage detection results for the second damage pattern of the numerical study



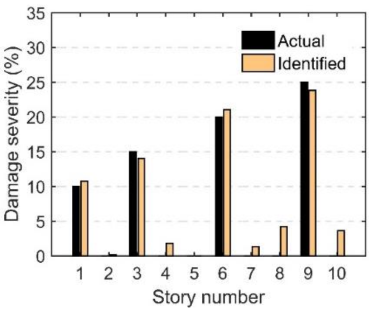
(a) p = 1 (b) p = 3

Fig. 3 Damage detection results for the third damage pattern of the numerical study

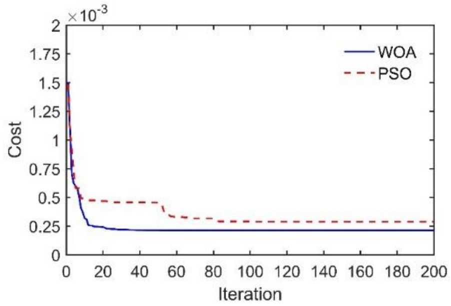
MSE is considered. Based on section 3.1, two modifications have been applied to the original MSE: including frequencies in the index (because of using **δ**) and adding the effects of the first p modes in the procedure. When $p > 1$, damage effects on the higher modes are also reflected in pseudo MSE. Besides, **D** in the proposed objective function (Eq. (14)), which is a linear summation of the nodal displacements in modal coordinate (see Eqs. (15) and (16)), can add more supporting details which help to reach the global optimal solution of the problem by suppressing the false alarms. It should be mentioned that although false alarms are reduced by increasing p, the accuracy of the detected damages in the damaged elements is slightly changed which is because of the noise effects.

To assess the performance of WOA in solving the proposed objective function, a comparative study was conducted. For this purpose, damage pattern III in noisy state and p = 3 was solved using Particle Swarm Optimization (PSO) algorithm. The parameters of PSO were selected by trial and error; however, the number of tot al iterations were selected 200 (similar to the number selected for WOA) to provide a suitable field to compare its performance with WOA. Fig. 4(a) shows the obtained results. As it can be seen, some of healthy elements have been detected as damaged elements (similar to the case that WOA was used). However, the reported damage severity by PSO for the healthy stories is bigger than the case in which WOA was employed (for instance, see the reported damage severity in the 8th story, which is greater than 4.5% when PSO is used). Moreover, the accuracy of the predicted damage severities in the damaged stories are less than the case in which WOA is employed.

As another factor to compare the performance of WOA and PSO, the convergence curves of the optimization



(a) Damage detection results using PSO



(b) Convergence curves of WOA and PSO

Fig. 4 Results for the third damage pattern of the numerical study when p = 3 (noisy state)

(a) Intact structure

(b) Damaged structure based on damage pattern III

Fig. 5 Experimental setup

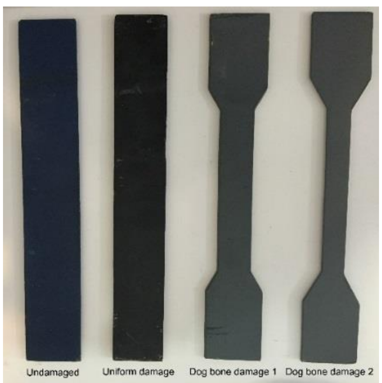


Fig. 6 Shape of the columns used in the experimental study

algorithms for the damage pattern III (in noisy state with p = 3) are studied (Fig. 4(b)). Based on this figure, WOA converges after almost 25 iterations. But, PSO converges after 80 iterations. Furthermore, WOA reaches a final cost which is lower than the minimum cost returned by PSO in the last iteration. This means that WOA performs better than PSO in terms of seeking the solution domain of the problem even though the noisy state is considered.

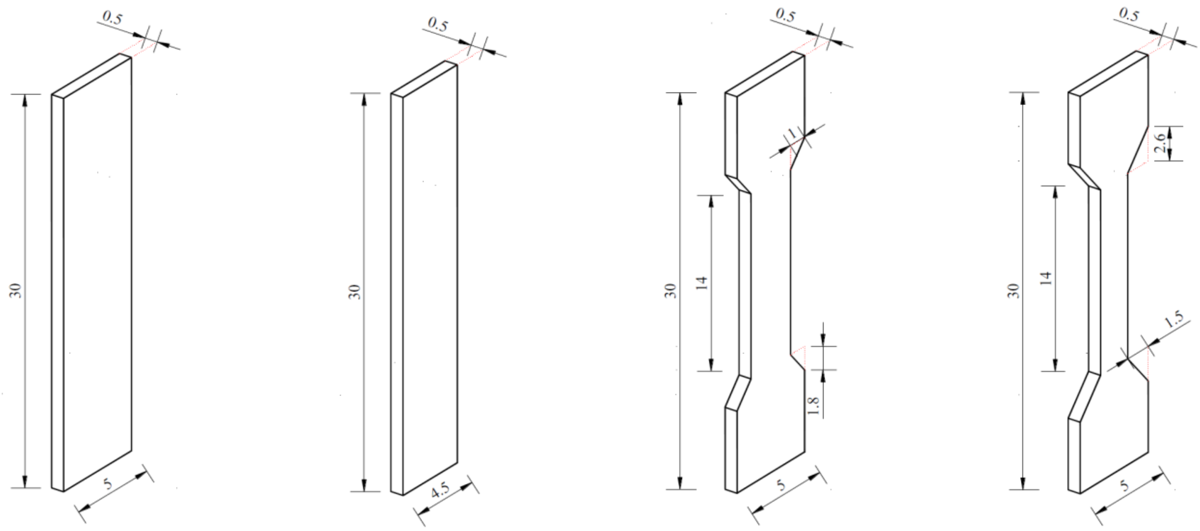
5. Experimental validation

In this section, the proposed method is used to detect damage in a lab-scale six-story steel structure tested on a shake table (see Fig. 5). The structure is a shear-type frame and the mass, stiffness and total length of each story are equal to 19.54 kg, 362.77 kN/m and 30 cm, respectively. To form rigid connections, the plates and columns were properly bolted to each other. Moreover, the base plate was firmly bolted to the shake table to produce fixed support for the structure. The El Centro earthquake (with 56 sec duration) was sent to the table to excite the structure in Y direction (Fig. 5). Also, six ARF-A accelerometers were attached to the structure (one accelerometer to each story) to acquire the structural response with a sampling frequency of 300 Hz. Two configurations were used to simulate damage by cutting the columns (see Fig. 6):

- *Configuration* 1, in which the width of columns associated with the damaged story was shortened equally from both sides. This configuration represents "*uniform damage*," and
- *Configuration* 2, in which the columns of the damaged story were cut in a symmetric (but non-uniform) shape. This configuration represents "*dog bone damage*."

In this study, one uniform and two dog bone configurations were considered. Figs. 6 and 7 show the details of these damage configurations as well as the details of the columns in the healthy (undamaged) state.

Since the proposed method defines the elemental damage by a number (α), each configuration should be converted to a number indicates the damage percentage in the story. To do so, an equivalent configuration (with symmetric, uniform shape) was generated for each damage



(a) Undamaged state (b) Uniform damage (configuration 1) (c) Dog bone damage 1 (configuration 2) (d) Dog bone damage 2 (configuration 2)

Fig. 7 Details of the column shapes used in the experimental study

configuration. Then, the stiffness of a typical story with the equivalent configuration was compared with the story stiffness of the undamaged configuration. Note that each story of this structure has four columns which are rigidly fixed to the upper and lower plates to guarantee shear behavior. Therefore, the stiffness of each story is equal to $4\times(12EI/h^3)$, where E, I and h are the elasticity modulus, moment of inertia for each column and effective length of the story, respectively. Following this strategy, the damage associated with the uniform damage, dog bone damage 1 and dog bone damage 2 are 10%, 10% and 20%, respectively. Considering the introduced damage configurations, three damage patterns were simulated. Table 3 describes details of the damage patterns. Fig. 5(b) shows the damaged structure (based on damage pattern III) on the shake table.

The recorded structural responses were analyzed using ARTeMIS Modal (v4.0.0.6, Structural Vibration Solutions A/S, Denmark) to extract frequencies and the corresponding mode shapes. The structural system was assembled as a lumped-mass system and Frequency Domain Decomposition (FDD) method (Brincker *et al*. 2001) was applied to the acceleration responses. The first three frequencies were identified with high level of accuracy. Note that in this study the structure was excited by simulating El Centro earthquake to investigate a case in which the exciting signal is ambient and unfiltered. If broadband white noise signal is used for excitation, higher modes can also be identified by the operational modal analysis. Table 4 summarizes the obtained frequencies for the healthy and damaged structures. In general, the frequencies decrease because of damage occurrence. Severe damage patterns cause large decrease. Moreover, if the entries of the pseudo MSE of the structure in the damaged state is compared with the undamaged state, it can be concluded that the tested structure has been damaged. However, no other conclusion is drawn on the location or severity of the damage(s).

In the following, the proposed method is employed to assess the health of the structure in undamaged and three damaged states. For undamaged case, it was assumed that p = 1, 2, 3. However, the damaged cases were solved employing the modal data of the first one and three modes (i.e., p = 1, 3). The parameters of the optimization algorithm were selected similar to the numerical example. Moreover, each case was solved ten times and the average of the obtained results were reported as the damage detection results. Fig. 8 shows the obtained results for the undamaged structure. As it can be seen, the predicted damage severities are close enough to zero, as it is expected. Damage detection results of the introduced damage patterns I, II and III are shown in Figs. 9, 10 and 11, respectively. The results have good accordance with the simulated patterns. Some differences between the patterns and the obtained results can be seen which are justifiable considering the measurement errors related to data acquisition by the sensors.

Table 3 Details of the damage patterns in the experimental study

Damage pattern I		Damage pattern II		Damage pattern III	
Story #	Damage config.	Story #	Damage config.	Story #	Damage config.
1	Dog bone 1 (10%)*	1	Uniform (10%)	1	Dog bone 1 (10%)
		3	Uniform (10%)	3	Dog bone 1 (10%)
				5	Dog bone 2 (20%)

*Damage severity corresponds to each configuration

Table 4 Frequencies of the tested structure (Hz)

State	1st mode	2nd mode	3rd mode
Undamaged	5.33	15.68	25.15
Damage pattern I	5.24	15.44	24.89
Damage pattern II	5.18	15.41	24.48
Damage pattern III	5.15	14.88	24.05

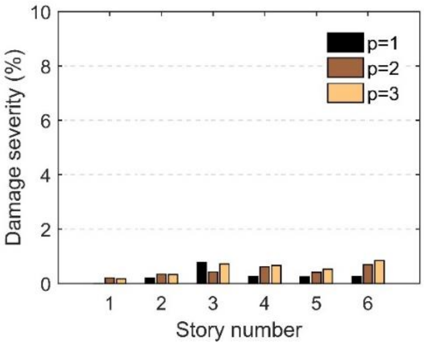


Fig. 8 Damage detection results for the tested structure in the intact state

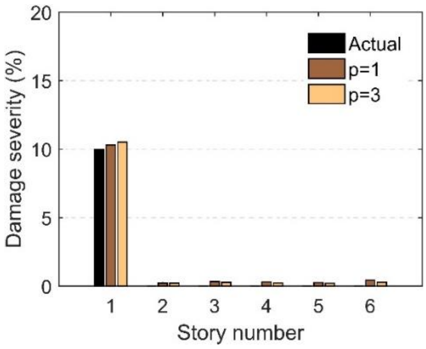


Fig. 9 Damage detection results for the tested structure in the damaged state (damage pattern I)

6. Conclusions

In this paper a new model-based damage detection method was proposed to identify and quantify damage in shear frames. Using pseudo modal strain energy and mode shape vectors, a new objective function was introduced which employs the sensitivity of both frequencies and mode shape vectors to identify structural damage. The problem was solved by means of the WOA, a meta-heuristic swarm-based optimization algorithm inspired by the hunting behavior of the humpback whales. The applicability of the method was demonstrated by numerical and experimental studies on shear frames. In the numerical investigations, challenges like the effects of the measurement noise as well as the number of the modes utilized for damage detection were studied. Comparative study with PSO algorithm was carried out to evaluate the performance of the WOA in solving the introduced inverse problem. Besides, in the experimental study, a six-story shear frame on a shake table was tested by introducing single and multiple damage

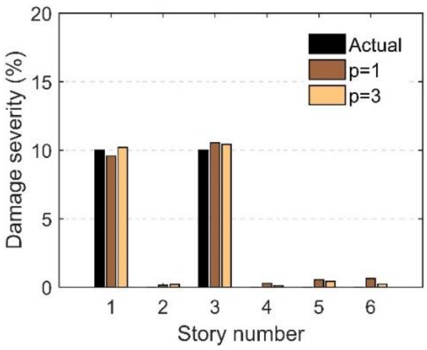


Fig. 10 Damage detection results for the tested structure in the damaged state (damage pattern II)

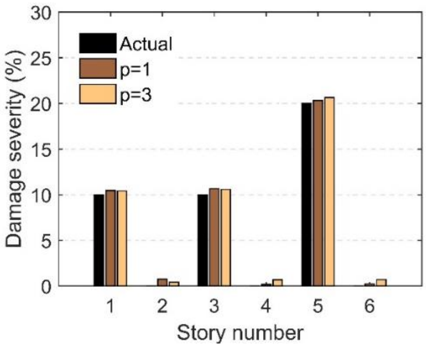


Fig. 11 Damage detection results for the tested structure in the damaged state (damage pattern III)

scenarios using uniform and non-uniform (dog bone shape) damage configurations. All the obtained results indicate good performance of the proposed method for health assessment of the shear building structures.

Acknowledgments

The experiments were conducted in the International Institute of Earthquake Engineering and Seismology (IIEES), Tehran, Iran. The assistance of the lab staff in preparing and testing the structural system is appreciated.

References

Alkayem, N.F., Cao, M., Zhang, Y., Mahmoud Bayat, M. and Su, Z. (2018), "Structural damage detection using finite element model updating with evolutionary algorithms: a survey", *Neural Comput. Appl.*, **30**(2), 389-411. https://doi.org/10.1007/s00521-017-3284-1

Brincker, R., Zhang, L. and Andersen, P. (2001), "Modal identification of output-only systems using frequency domain decomposition", *Smart Mater. Struct.*, **10**, 441-445. https://doi.org/10.1088/0964-1726/10/3/303

Capecchi, D., Ciambella, J., Pau, A. and Vestroni, F. (2016), "Damage identification in a parabolic arch by means of natural frequencies, modal shapes and curvatures", *Meccanica*, **51**, 2847-2859. https://doi.org/10.1007/s11012-016-0510-3

Cha, Y.J. and Buyukozturk, O. (2015), "Structural Damage Detection Using Modal Strain Energy and Hybrid Multiobjective

Optimization", *Comput.-Aided Civil Infrastruct. Eng.*, **30**(5), 347-358. https://doi.org/10.1111/mice.12122
Ciambella, J., Pau, A. and Vestroni, F. (2019), "Modal curvature-based damage localization in weakly damaged continuous beams", *Mech. Syst. Signal Process.*, **121**, 171-182. https://doi.org/10.1016/j.ymssp.2018.11.012
Ding, Z., Li, J., Hao, H. and Lu, Z.R. (2019), "Structural damage identification with uncertain modelling error and measurement noise by clustering based tree seeds algorithm", *Eng. Struct.*, **185**, 301-314. https://doi.org/10.1080/15732479.2019.1624785
Dinh-Cong, D., Pham-Toan, T., Nguyen-Thai, D. and Nguyen-Thoi, T. (2019), "Structural damage assessment with incomplete and noisy modal data using model reduction technique and LAPO algorithm", *Struct. Infrastruct. Eng.* https://doi.org/10.1080/15732479.2019.1624785
Du, D.C., Vinh, H.H., Trung, V.D., Hong Quyen, N.T. and Trung, N.T. (2018), "Efficiency of Jaya algorithm for solving the optimization-based structural damage identification problem based on a hybrid objective function", *Eng. Optimiz.*, **50**(8), 1233-1251. https://doi.org/10.1080/0305215X.2017.1367392
Fan, W. and Qiao, P. (2012), "Vibration-based damage identification methods: a review and comparative study", *Struct. Health Monitor.*, **10**(1), 83-111. https://doi.org/10.1177/1475921710365419
Ghodrati Amiri, G., Seyed Razzaghi, S.A. and Bagheri, A. (2011), "Damage detection in plates based on pattern search and Genetic algorithms", *Smar_ref*
t Struct. Syst., *Int. J.*, **7**(2), 117-132. https://doi.org/10.12989/sss.2011.7.2.117
Ghodrati Amiri, G., Zare Hosseinzadeh, A., Bagheri, A. and Koo, K.Y. (2013), "Damage prognosis by meansof modal residual force and static deflections obtained by modal flexibility based on the diagonalization method", *Smart Mater. Struct.*, **22**, 075032. https://doi.org/10.1088/0964-1726/22/7/075032
Ghodrati Amiri, G., Jalalinia, M., Zare Hosseinzadeh, A. and Nasrollahi, A. (2015), "Multiple crack identification in Euler beams by means of B-spline wavelet", *Arch. Appl. Mech.*, **85**(4), 503-515. https://doi.org/10.1007/s00419-014-0925-z
Gomes, G.F., Mendez, Y.A.D., Alexandrino, P.S.L., da Cunha, S.S. and Ancelotti, A.C. (2018), "A Review of Vibration Based Inverse Methods for Damage Detection and Identification in Mechanical Structures Using Optimization Algorithms and ANN", *Arch. Computat. Methods Eng.*, 1-15. https://doi.org/10.1007/s11831-018-9273-4
Guo, H.Y. and Li, Z.L. (2013), "Structural Multi-Damage Identification Based on Modal Strain Energy Equivalence Index Method", *Int. J. Struct. Stabil. Dyn.*, **14**(7), 1450028. https://doi.org/10.1142/S021945541450028X
Homaei, F., Shojaee, S. and Ghodrati Amiri, G. (2014), "A direct damage detection method using Multiple Damage Localization Index Based on Mode Shapes criterion", *Struct. Eng. Mech., Int. J.*, **49**(2), 183-202. https://doi.org/10.12989/sem.2014.49.2.183
Kaveh, A. and Maniat, M. (2015), "Damage detection based on MCSS and PSO using modal data", *Smart Struct. Syst., Int. J.*, **15**(5), 1253-1270. https://doi.org/10.12989/sss.2015.15.5.1253
Koo, K.Y., Sung, S.H., Park, J.W. and Jung, H.J. (2010), "Damage detection of shear buildings using deflections obtained by modal flexibility", *Smart Mater. Struct.*, **19**, 115026. https://doi.org/10.1088/0964-1726/19/11/115026
Li, S. and Lu, Z.R. (2015), "Multi-swarm fruit fly optimization algorithm for structural damage identification", *Struct. Eng. Mech., Int. J.*, **56**(3), 409-422. https://doi.org/10.12989/sem.2015.56.3.409
Li, H., Yang, H. and Hu, S.L.J. (2006), "Modal Strain Energy Decomposition Method for Damage Localization in 3D Frame Structures", *J. Eng. Mech.*, **132**(9), 941-951. https://doi.org/10.1061/(ASCE)0733-9399(2006)132:9(941)
Li, Y., Wang, S., Zhang, M. and Zheng, C. (2016), "An Improved Modal Strain Energy Method for Damage Detection in Offshore Platform Structures", *J. Marine Sci. Appl.*, **15**(2), 182-192. https://doi.org/10.1007/s11804-016-1350-1
Li, Y., Zhang, M. and Yang, W. (2018), "Numerical and experimental investigation of modal-energy-based damage localization for offshore wind turbine structures", *Adv. Struct. Eng.*, **21**(10), 1510-1525. https://doi.org/10.1177/1369433217750725
Mirjalili, S. and Lewis, A. (2016), "The Whale Optimization Algorithm", *Adv. Eng. Software*, **95**, 51-67. https://doi.org/10.1016/j.advengsoft.2016.01.008
Nguyen, K.D., Chan, T.H. and Thambiratnam, D.P. (2016), "Structural damage identification based onchange in geometric modal strain energy eigenvalue ratio", *Smart Mater. Struct.*, **25**, 075032. https://doi.org/10.1088/0964-1726/25/7/075032
Nobahari, M. and Seyedpoor, S.M. (2013), "An efficient method for structural damage localization based on the concepts of flexibility matrix and strain energy of a structure", *Struct. Eng. Mech., Int. J.*, **46**(2), 231-244. https://doi.org/10.12989/sem.2013.46.2.231
Saada, M.M., Arafa, M.H. and Nassef, A.O. (2013), "Finite element model updating approach to damage identification in beams using particle swarm optimization", *Eng. Optimiz.*, **45**(6), 677-696. https://doi.org/10.1080/0305215X.2012.704026
Seyedpoor, S.M. and Montazer, M. (2016), "A two-stage damage detection method for truss structures using a modal residual vector based indicator and differential evolution algorithm", *Smart Struct. Syst., Int. J.*, **7**(2), 347-361. https://doi.org/10.12989/sss.2016.17.2.347
Seyedpoor, S.M. and Yazdanpanah, O. (2014), "An efficient indicator for structural damage localization using the change of strain energy based on static noisy data", *Appl. Math. Model.*, **38**(9-10), 2661-2672. https://doi.org/10.1016/j.apm.2013.10.072
Sung, S.H., Koo, K.Y., Jung, H.Y. and Jung, H.J. (2012), "Damage-induced deflection approach for damage localization and quantification of shear buildings: validation on a full-scale shear building", *Smart Mater. Struct.*, **21**, 115013. https://doi.org/10.1088/0964-1726/21/11/115013
Sung, S.H., Koo, K.Y. and Jung, H.J. (2014), "Modal flexibility-based damage detection of cantilever beam-type structures using baseline modification", *J. Sound Vib.*, **333**(18), 4123-4138. https://doi.org/10.1016/j.jsv.2014.04.056
Tabrizian, Z., Ghodrati Amiri, G. and Hossein Ali Beigy, M. (2014), "Charged System Search Algorithm Utilized for Structural Damage Detection", *Shock Vib.*, 194753. https://doi.org/10.1155/2014/194753
Wang, S. and Xu, M. (2019), "Modal Strain Energy-based Structural Damage Identification: A Review and Comparative Study", *Struct. Eng. Int.*, **29**(2), 234-248. https://doi.org/10.1080/10168664.2018.1507607
Wei, Z.T., Liu, J.K. and Lu, Z.R. (2016), "Damage identification in plates based on the ratio of modal strain energy change and sensitivity analysis", *Inverse Problems Sci. Eng.*, **24**(2), 265-283. https://doi.org/10.1080/17415977.2015.1017489
Yang, Q.W. (2009), "A numerical technique for structural damage detection", *Appl. Math. Computat.*, **215**(7), 2775-2780. https://doi.org/10.1016/j.amc.2009.08.039
Yang, Q.W. (2010), "Damage Detection Method Based on Element Modal Strain Energy Sensitivity", *Adv. Struct. Eng.*, **13**(6), 1075-1088. https://doi.org/10.1260/1369-4332.13.6.1075
Zare Hosseinzadeh, A., Bagheri, A., Ghodrati Amiri, G. and Koo, K.Y. (2014), "A flexibility-based method via the iterated improved reduction system and the cuckoo optimization algorithm for damage quantification with limited sensors", *Smart Mater. Struct.*, **23**, 045019.

ttps://doi.org/10.1088/0964-1726/23/4/045019

Zare Hosseinzadeh, A., Ghodrati Amiri, G., Jafarian Abyaneh, M., Seyed Razzaghi, S.A. and Ghadimi Hamzehkolaei, A. (2019a), "Baseline updating method for structural damage identification using modal residual force and grey wolf optimization", *Eng. Optimiz.* https://doi.org/10.1080/0305215X.2019.1593400

Zare Hosseinzadeh, A., Seyed Razzaghi, S.A. and Ghodrati Amiri, G. (2019b), "An iterated IRS technique for cross-sectional damage modelling and identification in beams using limited sensors measurement", *Inverse Problems Sci. Eng.*, **27**(8), 1145-1169. https://doi.org/10.1080/17415977.2018.1503259

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