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Structural damage detection based on MAC flexibility and frequency using moth-flame algorithm

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Abstract. Vibration-based structural damage detection through optimization algorithms and minimization of objective function has recently become an interesting research topic. Application of various objective functions as well as optimization algorithms may affect damage diagnosis quality. This paper proposes a new damage identification method using Moth-Flame Optimization (MFO). MFO is a nature-inspired algorithm based on moth's ability to navigate in dark. Objective function consists of a term with modal assurance criterion flexibility and natural frequency. To show the performance of the said method, two numerical examples including truss and shear frame have been studied. Furthermore, Los Alamos National Laboratory test structure was used for validation purposes. Finite element model for both experimental and numerical examples was created by MATLAB software to extract modal properties of the structure. Mode shapes and natural frequencies were contaminated with noise in above mentioned numerical examples. In the meantime, one of the classical optimization algorithms called particle swarm optimization was compared with MFO. In short, results obtained from numerical and experimental examples showed that the presented method is efficient in damage identification.

Keywords: moth-flame optimization algorithm; flexibility; frequency

1. Introduction

Numerous factors including rain, storm, fire, fatigue, and corrosion may cause damage to structural elements. Disregarding these damages leads to disruption of the elements. Therefore, different methods of structural health monitoring have drawn researchers' attention. Modal properties including natural frequencies and mode shapes have been used in damage detection in the past three decades (Abdo 2002). Use of evolutionary algorithms and minimization of objective function as mechanisms of damage detection is widely spreading (Gordan *et al*. 2017). Mares and Surace (1996) published one of the earliest papers on application of Genetic Algorithm (GA) for detecting damage in two-dimensional truss structures and cantilever beam. Ruotolo and Surace (1997), Friswell *et al*. (1998), Hao *et al*. (2002), Perera and Torres (2006), Vakil-Baghmisheh *et al*. (2008) have also studied damage detection based on GA. Vaez and Fallah (2017) have presented one of the newest applications of GA for damage detection on thin plates. Tiachacht *et al*. (2018) have proposed a new damage detection and quantification method for two and three-dimensional structures, using GA and Modified Cornwell Indicator (MCI). MCI is thereby utilized as an objective function to compare between measured and calculated indicators.

A number of studies have been conducted based on incomplete modal data and optimization algorithms. For instance, Kourehli *et al*. (2013a, b) investigated damage detection in continuous and discretized structures, using reduced models (Guyan method was used for model reduction) and different optimization algorithms such as Pattern Search and Simulated Annealing. Another damage detection method based on incomplete modal data and Particle Swarm Optimization (PSO) was proposed by Rasouli *et al*. (2014). However, Dinh-Cong *et al*. (2018a) have introduced the newest method that uses reduced models (Neumann series expansion was used for model reduction) and a Teaching-Learning-Based optimization algorithm. Moreover, Ghannadi and Kourehli (2018) studied different Finite Element Model (FEM) reduction techniques. A laboratory example of crack detection in cantilever beams, using Hybrid Particle Swarm-Nelder-Mead optimization was presented by Vakil Baghmisheh *et al*. (2012). In a laboratory example, Moezi *et al*. (2018) have recently used Hybrid Cuckoo-Nelder-Mead optimization for crack detection. Following the line of utilizing optimization methods in crack detection, Fatahi *et al*. (2018) have studied a laboratory example of three-story frame by Swarm-based optimization method. Khatir *et al*. (2018) have also presented a method of detection and localization of open crack in beam-like structures using PSO and experimentally natural frequencies.

Charged System Search (CSS) is among optimization algorithms that has gained popularity in recent years (Kaveh and Talatahari 2010). Kaveh and Zolghadr (2015) have studied damage detection in truss structures using improved CSS and objective function consisted of natural frequencies and mode shapes. Hosseinlou *et al*. (2017) developed a new and effective damage detection strategy for offshore jacket structures by performing CSS for model updating. One

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other efficient study for model updating in large-scale steel truss bridge using PSO and GA was conducted by Tran-Ngoc *et al*. (2018). Giagopoulos *et al*. (2019) have presented a fatigue damage estimation method using vibration measurements and FEM updating.

Recently, Jaya optimization algorithm has been introduced (Rao 2016). Dinh-Cong *et al*. (2018b) used Jaya algorithm and hybrid objective function in order to detect damages. Thermal exchange optimization is another newly developed optimization algorithm (Kaveh and Dadras 2017). In their article, Kaveh and Dadras (2018) have indicated capabilities of this algorithm to detect damages in different structures. Wei *et al*. (2018) have performed a comparative study using improved PSO and GA for damage prediction. A number of other researchers have also proposed two-stage methods based on optimization algorithm and modal data. (Seyedpoor 2012, Rasouli *et al*. 2015, Seyedpoor and Montazer 2016). Fallah *et al*. (2018) have suggested a new two-stage method using Crow Search Algorithm and Damage Locating Vector for damage detection in structures with a large number of elements. They used an objective function based on Modal Assurance Criterion (MAC) flexibility.

Some of the structural damage detection methods have been recently introduced through Transmissibility Function. Transmissibility is derived from structural dynamic responses. Results of this approach indicated a good performance of damage detection (Zhou *et al*. 2017, Zhou *et al*. 2018). Gillich *et al*. (2019) have presented a method based on Multi-Modal Analysis, which enables damage assessment in beams subjected to axial forces caused by temperature variations. One other efficient study for damage localization under varying environmental conditions was conducted by Shokrani *et al*. (2018).

Online structural health monitoring methods have been recently developed. Eftekhar Azam *et al*. (2017) have proposed an approach based on Synergy of Proper Orthogonal Decomposition and Recursive Bayesian Filters for the online health monitoring of damaged structures. Following the line of developing online structural health monitoring methods, Eftekhar Azam and Mariani (2018) have presented a framework for the joint state tracking and parameter estimation of partially observed structural systems characterized by a relatively large number of Degrees Of Freedom (DOFs).

Minimization of different objective functions may affect the quality of damage diagnosis. Khatir *et al*. (2015) performed a comparative study to detect the location and severity of damage in a cantilever beam. It was found that minimization of objective function based on MAC and natural frequencies, was more accurate. Shabbir *et al*. (2017) used objective functions based on natural frequency, mode shape, modal flexibility and strain energy.

Gomes *et al*. (2018) presented a review paper comparing vibration-based inverse methods using optimization algorithms and Artificial Neural Networks (ANN). Elsewhere in their study, they have reviewed different objective functions.

Eftekhar Azam *et al*. (2019) developed an effective damage identification method for railway truss bridge by ANN and Proper Orthogonal Decomposition. Another damage detection approach based on output-only strain measurements and ANN was proposed by Rageh *et al*. (2018).

Moth-Flame is an optimization algorithm inspired by nature, formulated by Mirjalili (2015). Gholizadeh *et al*. (2017) used this algorithm for optimal design in frame structures. Another paper has studied damage detection for three-dimensional truss structures based on objective function consisted of natural frequencies and Hybrid Radial Basis Function. This study has evaluated several optimization algorithms such as Moth-Flame Optimization (MFO). Results showed that MFO failed to completely minimize the objective function, thus it did not demonstrate a successful function in damage detection. But Inverse Problem-Based Differential Evolution (IPB-DE) was partially effective. The said study was performed under conditions where no noise was applied to modal data (Bureerat and Pholdee 2018).

The present study introduces a new and robust damage detection method. The novelty of the present study is the using of the MFO algorithm and new objective function consisted of natural frequency and MAC flexibility to detect damage in structures. To show the performance of the proposed method, two numerical examples including truss and shear frame have been studied. Furthermore, Los Alamos National Laboratory (LANL) test structure was used for validation purposes. In the meantime, to show the performance of the MFO, PSO was compared with it. It is shown that MFO provides more accurate damage detection and localization than PSO.

2. Problem formulation

Structural damage is caused by various factors including erosion, corrosion, and reduced cross-section. Damage reduces structural elements' stiffness. The stiffness matrix of the damaged structure (Bureerat and Pholdee 2018) is formulated in Eq (1) as shown below.

$$\left[K_d\right] = \sum_{e=1}^{nel} \left(1 - d_e\right) \times \left[k_{element}\right] \tag{1}$$

Where, d_e is defining parameter of damage. This parameter ranges between 0 and 1, indicating undamaged and fractured structure, respectively. Also, $k_{element}$ represents element stiffness matrices. nel is the total number of elements.

In this study, the objective function introduced in Eq (2) was used to detect location and severity of damage.

Objective function is composed of two parts: natural frequency and MAC flexibility.

$$\begin{aligned} Minimize:\ f(x) &= \left(\frac{1}{n}\sum_{i=1}^{n}\left|\left(\omega_i^{ex} - \omega_i^{nu}\right)^2\right|\right)^{0.5} \\ &+ \left(\sum_{j=1}^{n}\left|\left(1 - MacFlex(F_j^{ex}, F_j^{nu})\right)^2\right|\right)^{0.5} \end{aligned} \tag{2}$$

$$Find: x = \left\{d_1, \ldots, d_{nel}\right\}^T \tag{3}$$

$$Bound: 0 \le d_e \le 1 \tag{4}$$

In Eq (2), ω_i^{ex} and ω_i^{nu} represent experimental natural frequency and numerical natural frequency of *i-th* mode, respectively. *n* is the sum of DOFs.

In order to minimize Eq (2), a vector in number of structural elements (according to Eq (3)) in 0 and 1 interval (according to Eq (4)) should be found. Furthermore, MACflex is obtained from Eq (5).

$$MACflex\left(F_j^{ex}, F_j^{nu}\right) = \frac{\left|\left\{F_j^{ex}\right\}^T \left\{F_j^{nu}\right\}\right|^2}{\left(\left\{F_j^{ex}\right\}^T \left\{F_j^{ex}\right\}\right)\left(\left\{F_j^{nu}\right\}^T \left\{F_j^{nu}\right\}\right)} \tag{5}$$

Where, $\{F_j^{nu}\}$ and $\{F_j^{ex}\}$ are numerical and experimental flexibility vectors, respectively.

Modal flexibility matrix is obtained from Eq (6).

$$[F] = [\varphi][\Lambda]^{-1}[\varphi]^T = \sum_{i=1}^{n} \frac{1}{\omega_i^2}\{\varphi_i\}\{\varphi_i\}^T \tag{6}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix} \tag{7}$$

$$\left(K - M\lambda_i\right)\varphi_i = 0 \tag{8}$$

Where, φ_i and λ_i are mode shape vector and square of natural frequency of *i-th* mode, respectively (Perera *et al*. 2009).

Natural frequency and mode shapes calculated by modal analysis are slightly different with those obtained from numerical calculations, due to different factors such as measurement conditions. In this study, noise-polluted natural frequencies have been obtained from Eq (9).

$$\bar{\omega}_i = \omega_i\left(1 + N^{level}.random[-1,1]\right) \tag{9}$$

In Eq (9), $\bar{\omega}_i$ is noise-polluted natural frequency and N^{level} represents noise level. Noise-polluted mode shapes have been obtained from Eq (10).

$$\bar{\varphi}_j = \varphi_j\left(1 + N^{level}.random[-1,1]\right) \tag{10}$$

In Eq (10), $\bar{\varphi}_j$ is mode shape vector polluted with noise (Kaveh and Dadras 2018).

3. MFO algorithm

MFO is a nature-inspired algorithm presented by Mirjalili (2015). Based on this algorithm, moth's ability to navigation in dark, is identified as transverse orientation.

Moths enjoy an efficient ability of flying along a straight line in long distances. In MFO, every moth is assumed to have a position in a D-dimensional solution space (Bozorg-Haddad 2018). Since MFO algorithm is population-based, the position of moths can be shown as:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \dots & \dots & m_{1,d} \\ m_{2,1} & m_{2,2} & \dots & \dots & m_{2,d} \\ . & . & . & . & . \\ . & . & . & . & . \\ m_{n,1} & m_{n,2} & \dots & \dots & m_{n,d} \end{bmatrix} \tag{11}$$

Where *n* is the number of moths and *d* is the number of dimensions. For every moth, the corresponding fitness values are sorted in an array as follows:

$$OM = \begin{bmatrix} OM\,1 \\ OM\,2 \\ . \\ . \\ OM_n \end{bmatrix} \tag{12}$$

The other important component of MFO is flames. The matrix of flames is considered as follows, similar with the matrix of moths:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \dots & \dots & F_{1,d} \\ F_{2,1} & F_{2,2} & \dots & \dots & F_{2,d} \\ . & . & . & . & . \\ . & . & . & . & . \\ F_{n,1} & F_{n,2} & \dots & \dots & F_{n,d} \end{bmatrix} \tag{13}$$

For every flame, the corresponding fitness values are sorted in an array as follows:

$$OF = \begin{bmatrix} OF1 \\ OF2 \\ . \\ . \\ OF_n \end{bmatrix} \tag{14}$$

In this algorithm, moths and flames are the solutions. Moth is search agent, while flame is the best position of moth. Flames are flags dropped by moth during the search and flying around the position, updated accordingly afterwards. By this account, the moths never lose the best solution (Mohanty 2018). The position of every moth is updated as follows:

$$M_{i,j} = S\left(M_i, F_j\right) \tag{15}$$

Where M_i denotes *i-th* moth, F_j denotes *j-th* flame, and *S* is the spiral function. The logarithmic spiral is determined for MFO algorithm as follows:

$$S\left(M_i, F_j\right) = D_i\, e^{bt}\cos\left(2\pi t\right) + F_j \tag{16}$$

Where b is a constant to define the shape of the logarithmic spiral, t is a random number between [-1,1], and D_i represents the distance between *i-th* moth and *j-th* flame.

$$D_i = \left| F_j - M_i \right| \tag{17}$$

To enhance exploitation of MFO algorithm, Eq. (18) is used to reduce the number of flames, therefore moths would only fly around the best solution.

$$flameNo = round\left(N - I * \frac{N-1}{T} \right) \tag{18}$$

Where I, T, N are number of iterations, maximum number of iterations, and maximum number of flames, respectively.

4. PSO algorithm

PSO is a population-based optimization algorithm presented by Eberhart and Kennedy (1995). The PSO algorithm was based on swarm intelligence and has been utilized extensively in recent years. The PSO algorithm is based on two equations. Eq. (19) updates the position of a particle and Eq. (20) updates the velocity of a particle (Tran-Ngoc *et al*. 2018).

$$x^i(t+1) = x^i(t) + v^i(t+1) \tag{19}$$

$$v^i(t+1) = wv^i + C_1 r_1 (p^i(t) - x^i(t)) + C_2 r_2 (G_{best} - x^i(t)) \tag{20}$$

Where $x^i(t)$, and $x^i(t+1)$ indicate the position vectors of particle i at time t and $t+1$, respectively. v is the velocity vector of particle, w represents the inertia weight parameter. C_1, C_2 indicate the cognition learning factor and the social learning factor, respectively, r_1 and r_2 are random numbers in the range of (0,1), $p^i(t)$ is the best position of each particle, and G_{best} is the best position of all particles. When the objective function is minimum, the G_{best} is achieved.

5. Examples

This paper studies numerical and experimental examples to show performance of the presented method in determining location and severity of the damage. Numerical examples include a truss with 29 elements and a 40-floor shear frame. The experimental example consists of a LANL test structure with three floors.

In practice, the measured signals are corrupted by noise and the uncertainty is propagated to the identified modal properties like frequencies and the mode shapes. In the present study, the efficiency of the proposed method has been investigated using noisy modal properties and noisy measured signals for the numerical and experimental examples, respectively.

The applied noise level is 1% and 10% for natural frequencies and mode shapes, respectively. Simple bar elements were used to model the truss structures. Each truss bar element consists of two nodes, each having two DOFs in X and Y directions. Additionally, boundary conditions were applied on support locations. In the shear frame, the mass of each floor was idealized to lump to the center of the mass. Stiffness matrix of the shear frame was assembled according to equivalent stiffness of each floor. For each numerical example, three scenarios including single and multiple damages were considered. Yet in the experimental example, some states including different damaged conditions were investigated. In total, during this study 12 runs of MFO have been performed.

Moreover, to show the performance of the MFO, PSO was compared with it. Table 1 shows parameters of MFO for each of the examples, while the flowchart in Fig. 1 illustrates a summary of damage detection steps.

All calculations were performed by MATLAB (2018) software.

Table 1 Parameters of MFO

Structure	Number of iterations	Number of search agents
29-bar truss	400	170
40-floor shear frame	400	150
LANL test structure	250	80

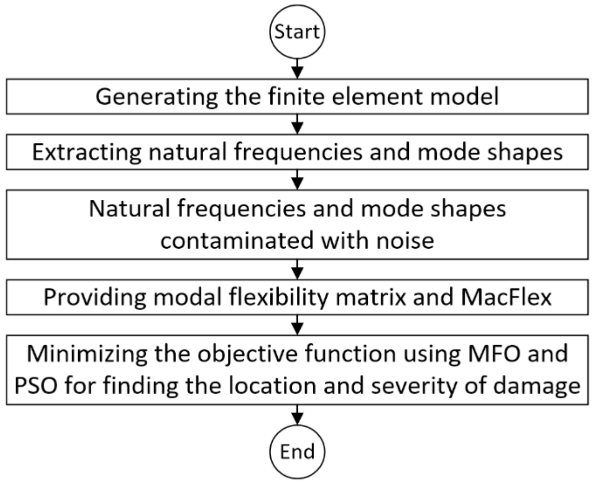

Fig. 1 Flowchart of the damage detection steps

Table 2 Material properties of 29-bar truss

Cross-section (m^2)	Mass density (kg/m^3)	Young's modulus (GPa)
A= 1.122×10^{-4}	ρ = 7830	E = 199.9

Table 3 Damage scenarios for 29-bar truss

Scenarios	Element(s)	Severity
1	8	0.2
2	6, 16	0.3
3	21, 25, 28	0.4

5.1 A 29-bar truss

The truss shown in Fig. 2 consists of 29 elements and 16 nodes. Length of horizontal and vertical elements is 0.4 m.

Table 2 represents material properties of this example. Additionally, Table 3 indicates damage scenarios. The predicted values of damage are shown in Figs. 3, 4, and 5.

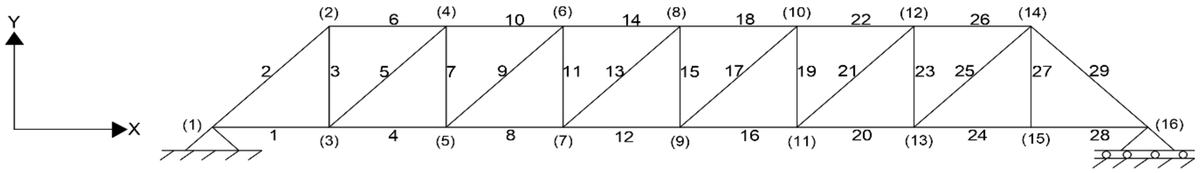

Fig. 2 A 29-bar truss

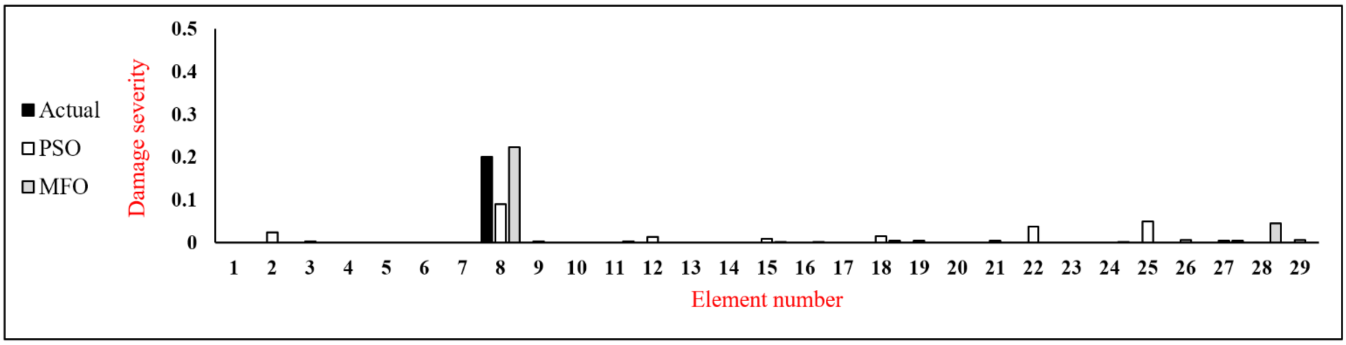

Fig. 3 Results of damage detection for 29-bar truss – Scenario 1

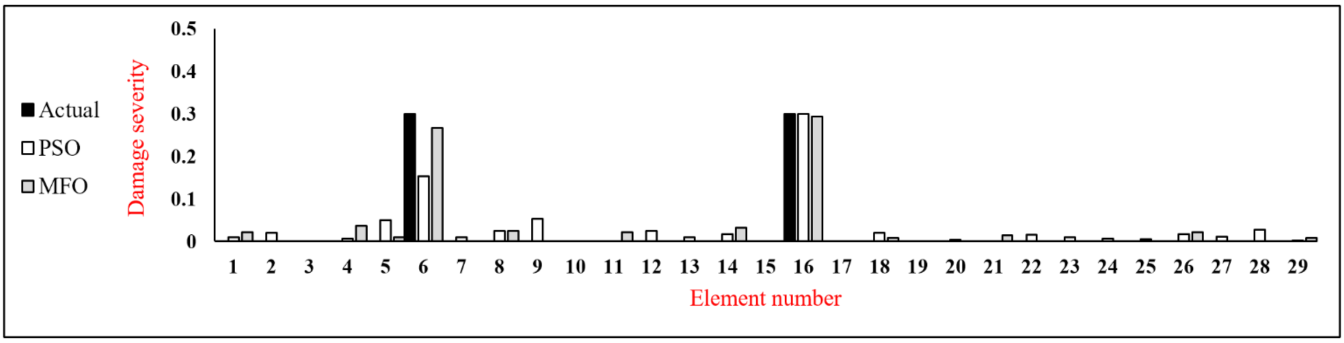

Fig. 4 Results of damage detection for 29-bar truss – Scenario 2

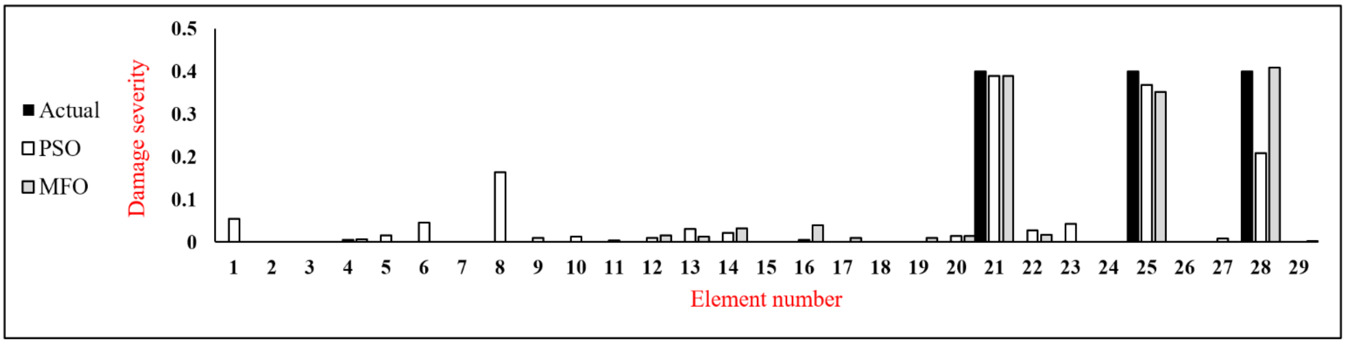

Fig. 5 Results of damage detection for 29-bar truss – Scenario 3

5.2 A 40-floor shear frame

The shear frame shown in Fig. 6 consists of 40 floors. Lateral stiffness and mass of the floors are assumed to be 250 kN/m and 200 kg, respectively. Table 4 indicates damage scenarios and Figs. 7, 8 and 9 demonstrate predicted damage values.

5.3 LANL test structure

The four-DOFs frame structure shown in Fig. 10 is used as a vibration-based damage detection test structure. The frame consists of aluminum columns and plates attached with bolted joints, moving on rails that enable movement in X direction. On every floor, four aluminum columns are connected to the top and bottom of aluminum plates forming a four-DOFs system. Dimensions of columns and plates are 17.7 × 2.5 × 0.6 cm, 30.5 × 30.5 × 2.5 cm, respectively.

An electrodynamic shaker imposes a lateral excitation to the base floor of the frame.

The frame and shaker are fixed together on an aluminum baseplate and the whole system rests on rigid foam.

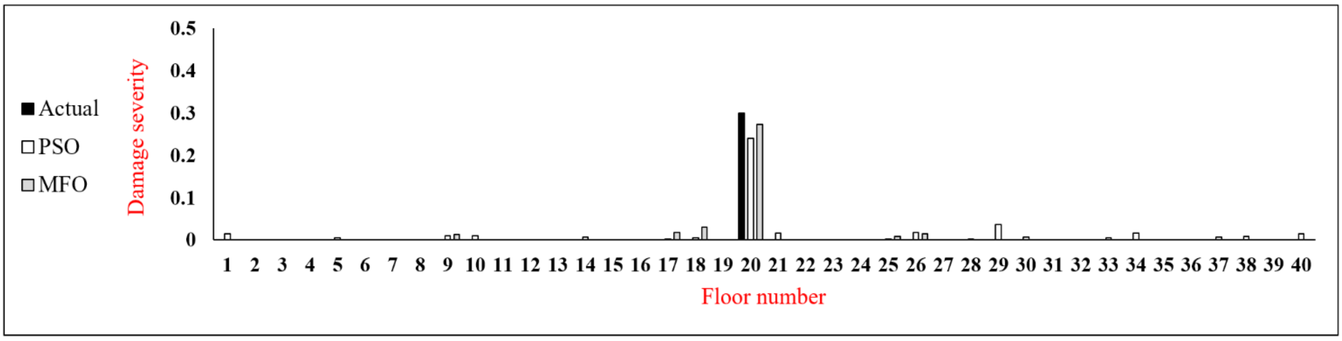

Fig. 7 Results of damage detection for 40-floor shear frame – Scenario 1

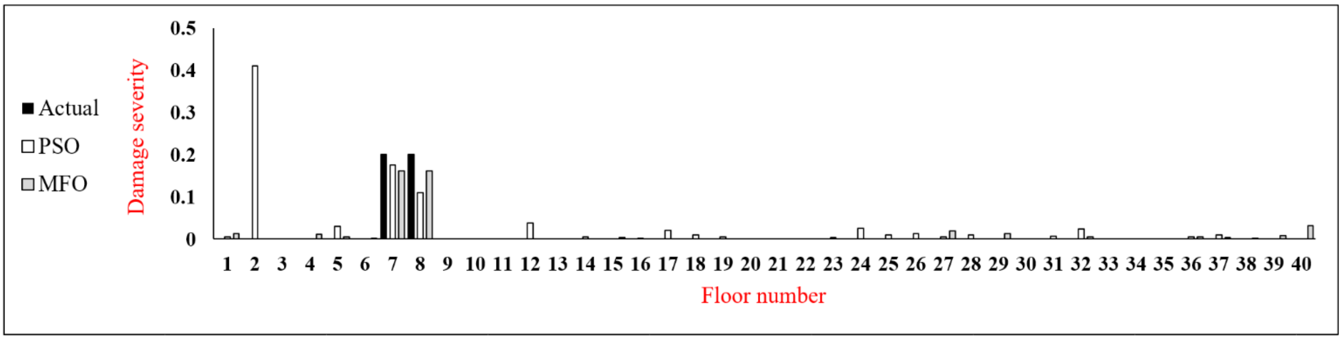

Fig. 8 Results of damage detection for 40-floor shear frame – Scenario 2

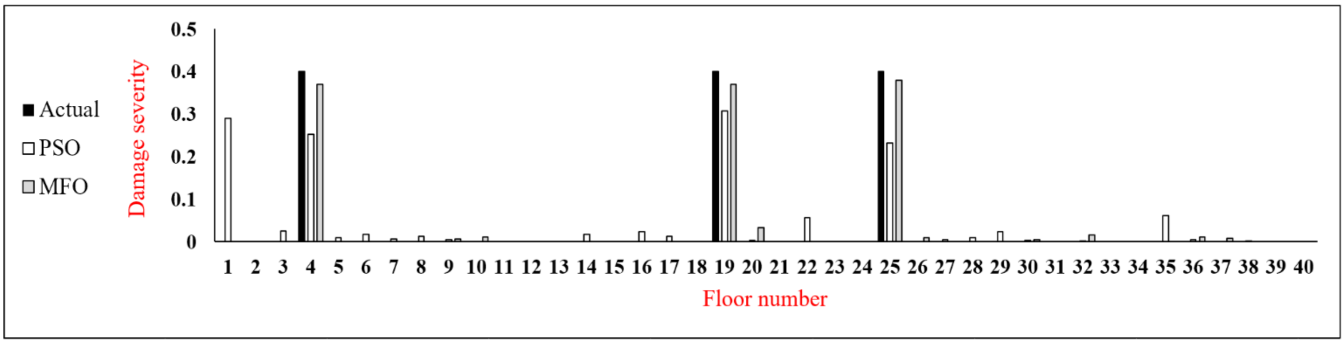

Fig. 9 Results of damage detection for 40-floor shear frame – Scenario 3

Table 4 Damage scenarios for 40-floor shear frame

Scenarios	Floor(s)	Severity
1	20	0.3
2	7, 8	0.2
3	4, 19, 25	0.4

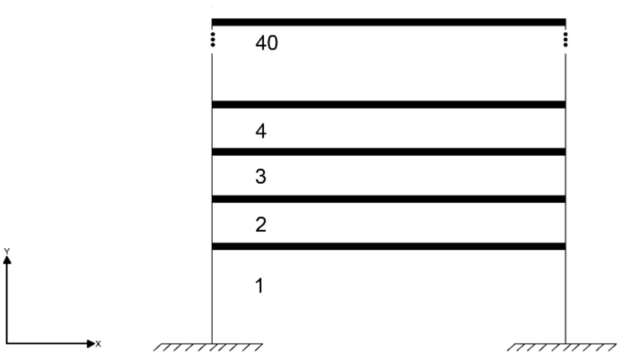

Fig. 6 A 40-floor shear frame

A load cell with a nominal sensitivity 2.2 mV/N was connected to the end of a stinger to measure the input force exerted from the shaker to the frame. Four accelerometers were connected to the center line of each floor on the reverse side of the excitation source to measure the structure response.

Nominal sensitivities of each accelerometer were 1000 mV/g. The accelerometers were installed to the centerline of all floors thus insensitive to torsional modes of the frame.

Dactron Spectrabook data acquisition system was used to collect and process the data.

Location of five sensor channels, and dimensions of theframe used in these experiments can be seen in Fig. 11.

During this experiment, 8192 data points were measured at 3.125 ms intervals. Also, the duration of time histories and sampling frequency are 25.6 s and 320 Hz, respectively (Figueiredo *et al*. 2009). In order to transform these data into frequency domain, MATLAB Signal Processing Toolbox was used. Figs. 12 and 13 show the force-time

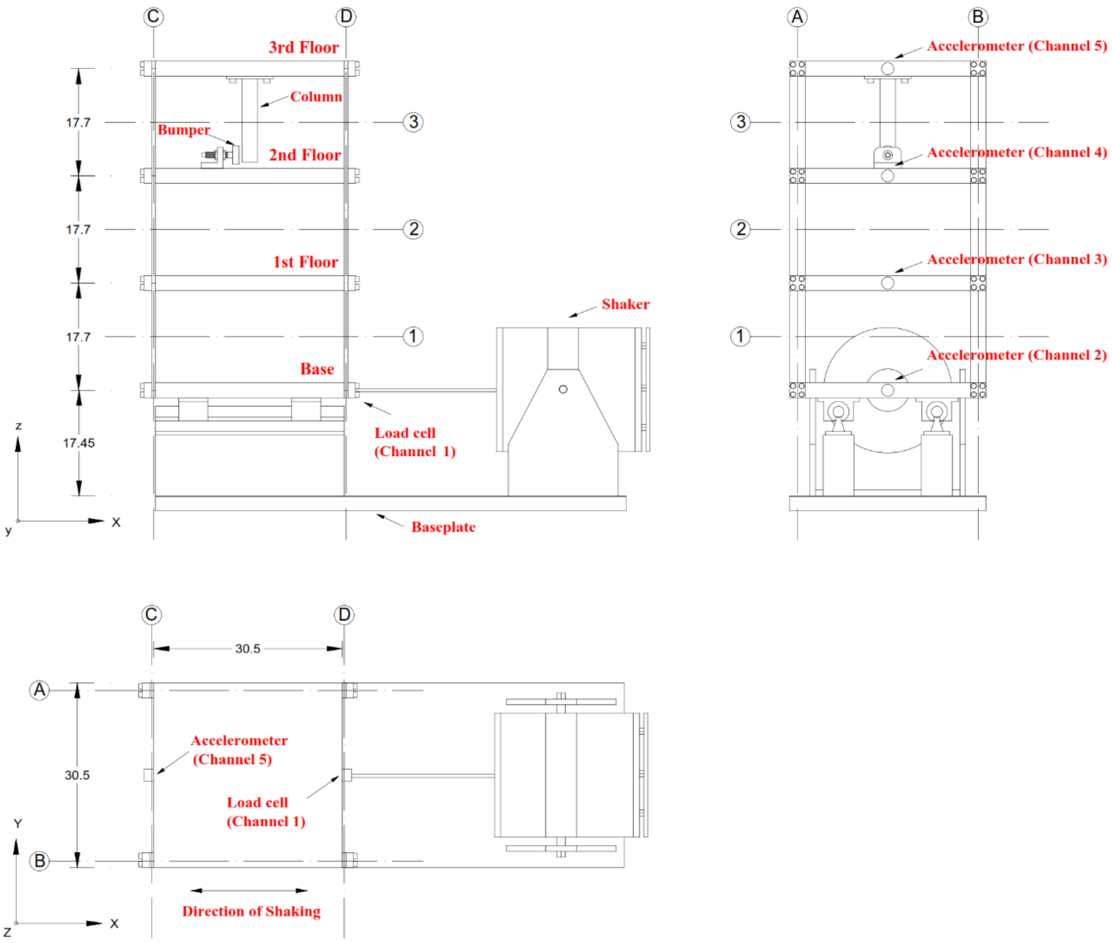

Fig. 11 Location of the sensor channels and dimensions of the LANL test structure (Figueiredo *et al*. 2009)

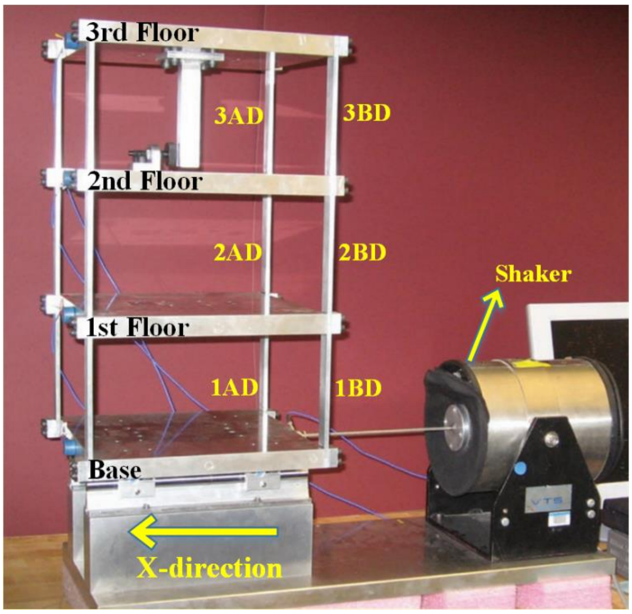

Fig. 10 LANL test structure (Figueiredo *et al*. 2009)

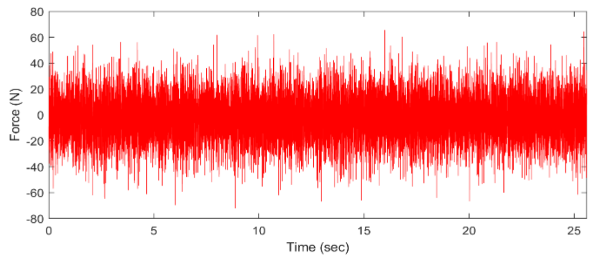

Fig. 12 Force-time history from Channel 1 of State #1

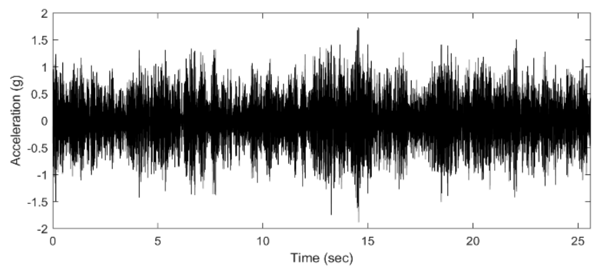

Fig. 13 Acceleration-time history from Channel 4 of State #1

history from channel 1 and acceleration-time history from Channel 4, respectively.

Experimental and numerical mode shapes from state #1 were illustrated in Fig. 14. Conditions of different states of LANL test structure are collected in Table 5. Table 6 presents experimental and numerical natural frequencies for different states. Predicted values of damage are shown in Figs. 15 to 20.

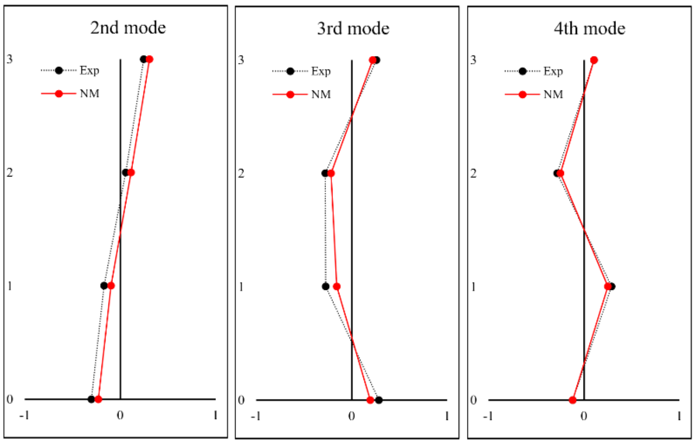

Fig. 14 Numerical (NM) and experimental (Exp) mode shapes of the state #1

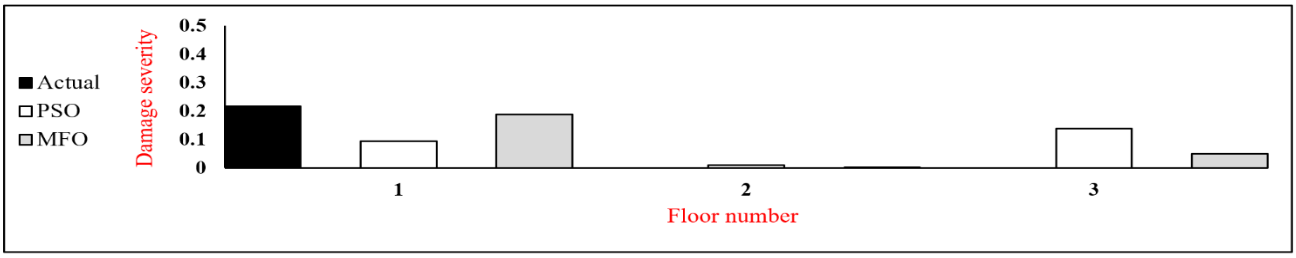

Fig. 15 Results of damage detection for LANL test structure – State #2

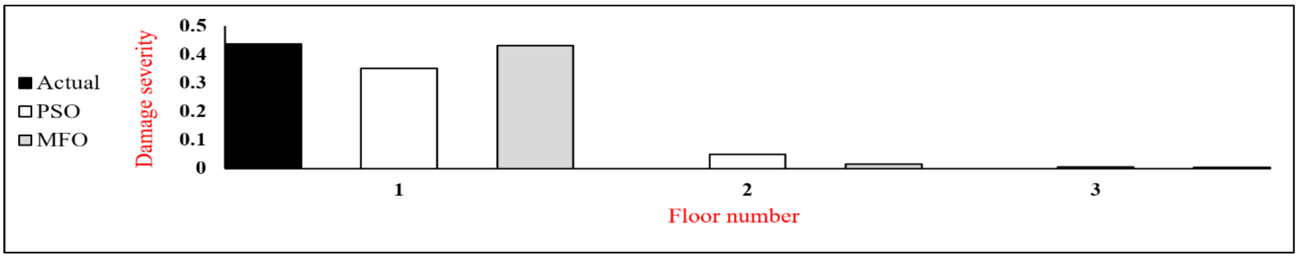

Fig. 16 Results of damage detection for LANL test structure – State #3

Table 5 LANL test structure state conditions

State	Condition	Description
#1	Baseline	Undamaged
#2	87.5% stiffness reduction in column 1BD	21.8% 1st-floor stiffness reduction
#3	87.5% stiffness reduction in column 1AD and 1BD	43.7 % 1st-floor stiffness reduction
#4	87.5% stiffness reduction in column 2BD	21.8% 2nd-floor stiffness reduction
#5	87.5% stiffness reduction in column 2AD and 2BD	43.7 % 2nd-floor stiffness reduction
#6	87.5% stiffness reduction in column 3BD	21.8% 3rd-floor stiffness reduction
#7	87.5 % stiffness reduction in column 3AD and 3BD	43.7 % 3rd-floor stiffness reduction

$$Difference = \frac{(f_{NM} - f_{Exp})}{f_{Exp}} \times 100 \tag{21}$$

Differences between experimental and numerical frequencies are calculated by Eq (21), where f_{NM} and f_{Exp} indicate numerical and experimental frequencies, respectively.

6. Conclusion

The present study introduces a vibration-based method of damage detection in truss structures and shear frame. Moreover, the presented method of damage detection is validated by LANL test structure. In numerical examples, natural frequencies and mode shapes were contaminated with 1% and 10% levels of noise, respectively. To find location and severity of damage, a new objective function composed of a term with MAC flexibility and natural frequency was minimized. To minimize objective function, a new optimization algorithm called moth-flame was applied. Results indicated that the proposed method is efficient and accurate in detecting damage as an inverse problem.

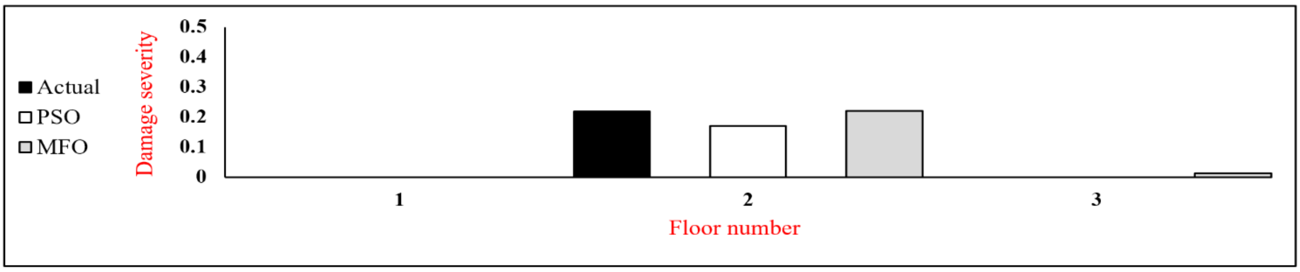

Fig. 17 Results of damage detection for LANL test structure – State #4

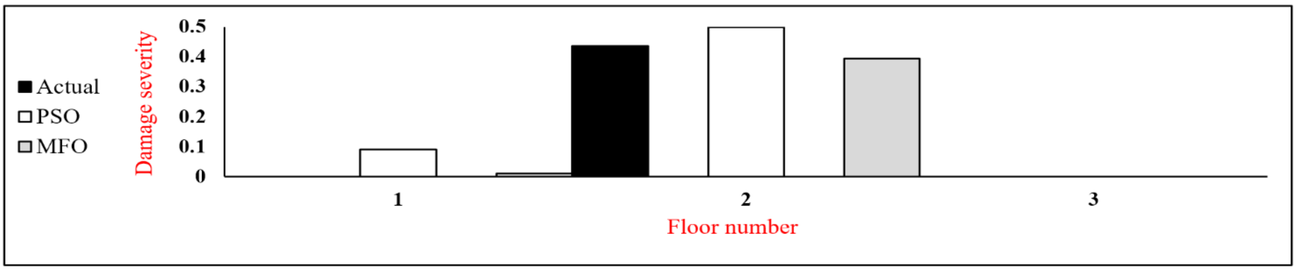

Fig. 18 Results of damage detection for LANL test structure – State #5

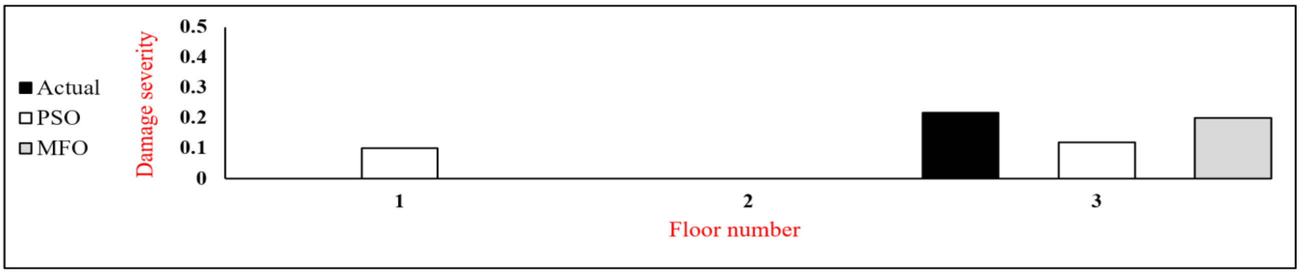

Fig. 19 Results of damage detection for LANL test structure – State #6

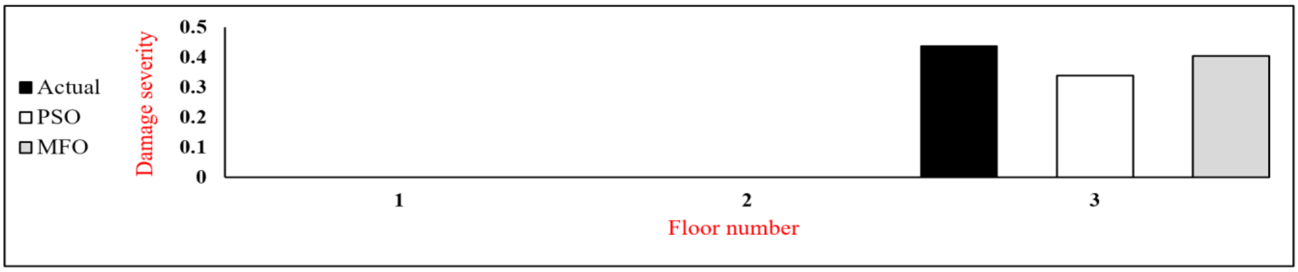

Fig. 20 Results of damage detection for LANL test structure – State #7

Table 6 Experimental and numerical natural frequencies of LANL test structure

State	**Frequency (Hz)**						**Difference (%)**		
	Experimental			Numerical					
	2nd	3rd	4th	2nd	3rd	4th	2nd	3rd	4th
#1	30.7	54.2	70.7	31.3	55.4	72.7	2.0	2.2	2.8
#2	30.9	51.2	69.2	30.4	52.0	70.7	-1.6	1.6	2.2
#3	30.3	47.0	67.8	28.6	47.8	69.2	-5.6	1.7	2.1
#4	29.7	53.9	65.8	29.4	55.3	68.7	-1.0	2.6	4.4
#5	28.6	54.2	62.2	26.5	55.1	64.8	-7.3	1.7	4.2
#6	30.2	51.1	69.3	30.0	52.1	71.5	-0.7	2.0	3.2
#7	28.9	47.4	68.0	27.7	48.5	70.6	-4.2	2.3	3.8

References

Abdo, M.A.B. (2002), "A numerical study of structural damage detection using changes in the rotation of mode shapes", *J. Sound Vib.*, **251**(2), 227-239.

Bureerat, S. and Pholdee, N. (2018), "Inverse problem based differential evolution for efficient structural health monitoring of trusses", *Appl. Soft Comput.*, **66**, 462-472. https://doi.org/10.1016/j.asoc.2018.02.046.

Bozorg-Haddad, O. (2018), *Advanced Optimization by Nature-Inspired Algorithms*, Springer, Singapore. http://doi.org/10.1007/978-981-10-5221-7.

Dinh-Cong, D., Vo-Duy, T. and Nguyen-Thoi, T. (2018a), "Damage assessment in truss structures with limited sensors using a two- stage method and model reduction", *Appl. Soft Comput.*, **66**, 264-277. https://doi.org/10.1016/j.asoc.2018.02.028.

Dinh-Cong, D., Ho-Huu, V., Vo-Duy, T., Ngo-Thi, H.Q., Nguyen Thoi, T. (2018b), "Efficiency of Jaya algorithm for solving the optimization-based structural damage identification problem based on a hybrid objective function", *Eng. Opt.*, **50**(8), 1233-1251.

Eftekhar Azam, S., Mariani, S. and Attari, N. K. A. (2017), "Online damage detection via a synergy of proper orthogonal decomposition and recursive Bayesian filters", *Nonlinear Dynam.*, **89**(2), 1489-1511.

Eftekhar Azam, S. and Mariani, S. (2018), "Online damage detection in structural systems via dynamic inverse analysis: A recursive Bayesian approach", *Eng. Struct.*, **159**, 28-45. https://doi.org/10.1016/j.engstruct.2017.12.031.

Eftekhar Azam, S., Rageh, A. and Linzell, D. (2019), "Damage detection in structural systems utilizing artificial neural networks and proper orthogonal decomposition", *Struct. Control Health Monitor.*, **26**(2), https://doi.org/10.1002/stc.2288.

Eberhart, R. and Kennedy, J. (1995), "A new optimizer using particle swarm theory", *Proceedings of the Sixth International Symposium*, Nagoya, Japan, 4–6 October.

Friswell, M., Penny, J. and Garvey, J. (1998), "A combined genetic and eigensensitivity algorithm for the location of damage in structures", *Comput. Struct.*, **69**(5), 547-556.

Fatahi, L. and Moradi, S. (2018), "Multiple crack identification in frame structures using a hybrid Bayesian model class selection and swarm-based optimization methods", *Struct. Health Monitor.*, **17**(1), 39-58.

Fallah, N., Vaez, SRH. and Mohammadzadeh, A. (2018), "Multi-damage identification of large-scale truss structures using a two-step approach", *J. Build Eng.*, https://doi.org/10.1016/j.jobe.2018.06.007.

Figueiredo, E., Park, G., Figueiras, J., Farrar, C. and Worden, K. (2009), "Structural health monitoring algorithm comparisons using standard data sets", Report No. LA-14393; Los Alamos National Laboratory, Los Alamos.

Gordan, M., Razak, H.A., Ismail, Z. and Ghaedi, k. (2017), "Recent Developments in Damage Identification of Structures Using Data Mining", *Latin American J. Solid Struct.*, **14**(13), 2373-2401.

Gomes, G.F., Mendez, Y.A.D., Alexandrino P.D.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. Comput. Method Eng.*, 1-15. https://doi.org/10.1007/s11831-018-9273-4.

Gholizadeh, S., Davoudi, H. and Fattahi, F. (2017), "Design of steel frames by an enhanced moth-flame optimization algorithm", *Steel Compos Struct.*, **24**(1), 129-140.

Ghannadi, P. and Kourehli, S.S. (2018), "Investigation of the accuracy of different finite element model reduction techniques", *Struct. Monitor Maintenance.*, **5**(3), 417-428.

Gillich, G.R., Furdui, H., Wahab, M.A. and Korka, Z.I. (2019), "A robust damage detection method based on multi-modal analysis in variable temperature conditions", *Mech. Syst. Signal Process.*, **115**, 361-379. https://doi.org/10.1016/j.ymssp.2018.05.037

Giagopoulos, D., Arailopoulos, A., Dertimanis, V., Papadimitriou, C., Chatzi, E. and Grompanopoulos, K. (2019), "Structural health monitoring and fatigue damage estimation using vibration measurements and finite element model updating", *Struct. Health Monitor.* https://doi.org/10.1177/1475921718790188

Hao, H. and Xia, Y. (2002), "Vibration-based damage detection of structures by genetic algorithm", *J. Comput. Civil Eng.*, **16**(3), 222-229.

Hosseinlou, F., Mojtahedi, A. and Yaghin, MAL. (2017), "Developing a SIM strategy for offshore jacket platforms based on the FE model updating and a novel simplified method", *Ocean Eng.*, **145**, 158-176. https://doi.org/10.1016/j.oceaneng.2017.08.013

Khatir, S., Belaidi, I., Serra, R., Benaissa, B. and Saada, A. A. (2015), "Genetic algorithm based objective functions comparative study for damage detection and localization in beam structures", *J. Physics: Conference Series*. http://doi.org/10.1088/1742-6596/628/1/012035

Khatir, S., Dekemele, K., Loccufier, M., Khatir, T. and Wahab, M. A. (2018), "Crack identification method in beam-like structures using changes in experimentally measured frequencies and Particle Swarm Optimization", *Comptes Rendus Mécanique.*, **346**(2), 110-120.

Kourehli, S.S., Amiri, G.G., Ghafory-Ashtiany, M. and Bagheri, A. (2013a), "Structural damage detection based on incomplete modal data using pattern search algorithm", *J. Vib. Control.*, **19**(6), 821-833.

Kourehli, S.S., Bagheri, A., Amiri, G.G. and Ashtiany, M.G. (2013b), "Structural damage detection using incomplete modal data and incomplete static response", *KSCE J. Civil Eng.*, **17**(1), 216-223.

Kaveh, A. and Talatahari, S. (2010), "A novel heuristic optimization method: charged system search", *Acta Mechanica.*, **213**(3-4), 267-289. https://doi.org/10.1007/s00707-009-0270-4

Kaveh, A. and Zolghadr, A. (2015), "An improved CSS for damage detection of truss structures using changes in natural frequencies and mode shapes", *Adv. Eng. Software.*, **80**, 93-100. https://doi.org/10.1016/j.advengsoft.2014.09.010

Kaveh, A., Dadras, A. (2017), "A novel meta-heuristic optimization algorithm: thermal exchange optimization", *Adv. Eng. Software.*, **110**, 69-84. https://doi.org/10.1016/j.advengsoft.2017.03.014

Kaveh, A. and Dadras, A. (2018), "Structural damage identification using an enhanced thermal exchange optimization algorithm", *Eng. Opt.*, **50**(3), 430-451.

Mares, C. and Surace, C. (1996), "An application of genetic algorithms to identify damage in elastic structures", *J. Sound Vib.*, **195**(2), 195-215.

Moezi, S.A., Zakeri, E. and Zare, A. (2018), "Structural single and multiple crack detection in cantilever beams using a hybrid Cuckoo-Nelder-Mead optimization method", *Mech. Syst. Signal Process.*, **99**, 805-831. https://doi.org/10.1016/j.ymssp.2017.07.013

Mirjalili, S. (2015), "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm", *Knowledge-Based Syst.*, **89**, 228-249. https://doi.org/10.1016/j.knosys.2015.07.006

Mohanty, B. (2018), "Performance analysis of moth flame optimization algorithm for AGC system", *J. Model. Simul.*, 1-15. https://doi.org/10.1080/02286203.2018.1476799

MATLAB (2018), MATLAB Documentation.; MathWorks, Massachusetts, USA. https://www.mathworks.com/help/matlab

Perera, R. and Torres, R. (2006), "Structural damage detection via modal data with genetic algorithms", *J. Struct. Eng.*, **132**(9), 1491-1501.

Perera, R., Ruiz, A. and Manzano, C. (2009), "Performance assessment of multicriteria damage identification genetic algorithms", *Comput. Struct.*, **87**(1-2), 120-127.

Ruotolo, R. and Surace, C. (1997), "Damage assessment of multiple cracked beams: numerical results and experimental validation", *J. Sound Vib.*, **206**(4), 567-588.

Rasouli, A., Amiri, G.G., Kheyroddin, A., Ashtiany, G.M. and Kourehli, S.S (2014), "A new method for damage prognosis based on incomplete modal data via an evolutionary algorithm", *Europe. J. Environ. Civil Eng.*, **18**(3), 253-270.

Rao, R. (2016), "Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems", *J. Industrial Eng. Comput.*, **7**(1), 19-34.

Rasouli, A., Kourehli, S.S., Amiri, G.G. and Kheyroddin, A. (2015), "A two-stage method for structural damage prognosis in shear frames based on story displacement index and modal residual force", *Adv. Civil Eng*. http://dx.doi.org/10.1155/2015/527537

Rageh, A., Linzell, D. G. and Azam, S. E. (2018), "Automated, strain-based, output-only bridge damage detection", *J. Civil Struct. Health Monitor*., **8**(5), 833-846.

Seyedpoor, S. (2012), "A two stage method for structural damage detection using a modal strain energy based index and particle swarm optimization", *J. Non-Linear Mech.*, **47**(1), 1-8.

Seyedpoor, S.M., 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*., **17**(2), 347-361.

Shabbir, F., Khan, M.I., Ahmad. N., Tahir, M.F., Ejaz, N. and Hussain, J. (2017), "Structural Damage Detection with Different Objective Functions in Noisy Conditions Using an Evolutionary Algorithm", *Appl. Sci.*, **7**(12), 1-26.

Shokrani, Y., Dertimanis, V. K., Chatzi, E. N. and N. Savoia, M. (2018), "On the use of mode shape curvatures for damage localization under varying environmental conditions", *Struct. Control Health Monitor*., **25**(4), https://doi.org/10.1002/stc.2132.

Tiachacht, S., Bouazzouni, A., Khatir, S., Abdel Wahab, M., Behtani, A. and Capozucca, R. (2018), "Damage assessment in structures using combination of a modified Cornwell indicator and genetic algorithm", *Eng. Struct*., 177, 421-430. https://doi.org/10.1016/j.engstruct.2018.09.070

Tran-Ngoc, H., Khatir, S., De Roeck, G., Bui-Tien, T., Nguyen-Ngoc, L. and Abdel Wahab, M. (2018), "Model Updating for Nam O Bridge Using Particle Swarm Optimization Algorithm and Genetic Algorithm". *Sensors*., **18**(12), 4131.

Vakil Baghmisheh, M.T., Peimani, M., Sadeghi, M.H. and Ettefagh, M.M. (2008), "Crack detection in beam-like structures using genetic algorithms", *Appl. Soft Comput*., **8**(2), 1150-1160.

Vaez, S.R.H. and Fallah, N. (2017), "Damage detection of thin plates using GA-PSO algorithm based on modal data", *Arabian J. Sci. Eng.*, **42**(3), 1251-1263.

Vakil Baghmisheh, M.T., Peimani, M., Sadeghi, M.H. and Tabrizi, A.F. (2012), "A hybrid particle swarm–Nelder–Mead optimization method for crack detection in cantilever beams", *Appl. Soft Comput*., **12**(8), 2217-2226.

Wei, Z., Liu, J. and Lu, Z. (2018), "Structural damage detection using improved particle swarm optimization", *Inverse Problems Sci. Eng.*, **26**(6), 792-810.

Zhou, Y. L., Maia, N. M., Sampaio, R. P. and Abdel Wahab, M. (2017), "Structural damage detection using transmissibility together with hierarchical clustering analysis and similarity measure", *Struct. Health Monitor*., **16**(6), 711-731.

Zhou, Y. L., Maia, N. M. and Abdel Wahab, M. (2018), "Damage detection using transmissibility compressed by principal component analysis enhanced with distance measure", *J. Vib. Control*., **24**(10), 2001-2019.

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