ASIAN JOURNAL OF CIVIL ENGINEERING (BHRC) VOL. 15, NO. 1 (2014)
PAGES 95-106

DAMAGE ASSESSMENT VIA MODAL DATA WITH A MIXED PARTICLE SWARM STRATEGY, RAY OPTIMIZER, AND HARMONY SEARCH

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Received: 10 January 2013; **Accepted:** 20 July 2013

ABSTRACT

A mixed particle swarm-ray optimization together with harmony search (HRPSO) is applied to detect damage in structures. In fact, PSO acts as the main engine of the algorithm, RO boost the movement vector of the particles, and HS is used to enhance the local search for better exploitation. The objective functions for damage detection are based on modal characteristics in both frame and truss. In addition, a hybrid double stage approach incorporates the advantages of both modal parameters and Modified Total Modal Assurance Criterion has been used. Numerical analysis is performed for skeletal structures under different damage scenarios with incomplete data. The results have shown the efficiency of the hybrid objective function in identifying damage by using HRPSO.

Keywords: Damage detection; dynamic parameters; particle swarm optimization; ray optimization.

1. INTRODUCTION

Structural damage assessment has been developed in the last few decades. Detecting real damages in a structure due to impact load, earthquake, corrosion or other events that cause severe faults in the structure, can provide vital information about the operating state and structural reliability. Traditional methods of damage identification are either visual or localized experimental methods require that the vicinity of the damage is known and accessible. Subjected to these deficiencies, the requirement for applicable techniques to global damage detection in complex structures is tangible [1].

It is well known that damage in a structure changes the structural characteristics, such as

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stiffness, and mass which effect on dynamic properties, therefore numerous vibration-based damage detection methods have been developed in the literature. Some of these damage detection methods minimize an objective function, which is defined in terms of the discrepancies between the vibration data identified by modal testing and those computed from the analytical model [2]. Adams et al. [3] used ratios of the reduction in measured natural frequencies to locate the damage by correlating it with the results of a finite element model of plates with holes. Mottershead and Friswell [4] summarized vibration response based finite element model updating methods, Hassiotis and Jeong [5] detect the reduction in stiffness by observing the sensitivity of the natural frequencies to local stiffness reduction. Salawu [6] used the natural frequencies as a parameter in structural assessment procedure. Shi et al. [7] proposed a sensitivity-based method to identify damage using incomplete measured modes shapes and natural frequencies. Kosmatka and Ricles [8] developed a sensitivity method based on residual forces and used this technique to detect damage on an experimental space truss structure. An and Ou [9] used four cost functions by model updating method for experimental and numerical damage identification in steel-truss bridge. Sholeh et al [10] utilized an algorithm of the least square estimation with the use of adaptive tracking for identification of breathing crack in structures. Catbas et al. [11] employed modal flexibility for damage detection and assessment of two real life bridge for certification.

Moreover, in the recent years investigation about optimization techniques and computational intelligence approaches have been widely applied to damage detection, Hao and Xia [12] concluded that conventional optimization methods are gradient based and usually lead to a local minimum.

Friswell et al. [13] used the genetic algorithm to optimize the discrete damage location variables. He and Hwang [14] combined an adaptive real-parameter genetic algorithm with simulated annealing to detect damage occurrence in beam-type structures. Yun et al. [15] proposed a two-stage damage detection method in which, in the first stage, the subset selection method is applied for the identification of the multiple damage locations and in the second stage, the damage severities of the identified damaged elements are determined applying SSGA to solve the optimization problem. Jaishi and Ren [16] used the strain energy residual and updated the finite element models of a simulated beam and a real bridge by means of multi objective optimization technique. Recently, Kang et al. [2] proposed an immunity enhanced particle swarm optimization (IEPSO) algorithm, which combines particle swarm optimization (PSO) with the artificial immune system for damage detection of structures, Fallahian and Seyedpoor [17] proposed a two stage method for structural damage identification using an adaptive neuro–fuzzy inference system and particle swarm optimization, and Kaveh and Zolghadr [18,19] used a charged system search [20] for structural damage identification in beams and frames using changes in natural frequencies.

In the present work, a new hybrid HRPSO algorithm is used for identifying multi damage scenarios using incomplete data with noise. A comparison between some objective functions based on modal parameters is conducted. In addition, a hybrid double stage approach incorporates the advantages of both modal characteristics and Modified Total Modal Assurance Criterion (MTMAC) are utilized. This method is verified by two numerical examples including a five-story and four-span frame and a 52-bar space truss.

2. DAMAGE DETECTION AS AN OPTIMIZATION PROBLEM

The lack of clear objective function in complex structures causes many researchers to innovate new methods, or to hybridize some former objective functions to improve the ability of damage identification. An objective function represents the error between the measured and numerical modal data. In this paper, different methods are utilized in order to localize and quantify damages in complex structures. These methods are stated as follows:

2.1 Algorithm A

Evaluation of changes in the flexibility matrix of a structure is presented as a candidate method for damage identification. In practice, the measured flexibility matrix is not computed for the full DOF set, because only a limited number of measurements are available [21]. It has been shown that the flexibility matrix can be accurately estimated from a few of the lower frequency modes of vibration of the structure, which can easily be measured [22].

The difference between the measured and analytical modal flexibility matrices has been defined as follows [20]:

$$Error = \left\| [\phi_A][\Lambda_A]^{-1}[\phi_A]^T - [\phi_E][\Lambda_E]^{-1}[\phi_E]^T \right\| \tag{1}$$

Where ϕ_E and ϕ_A are experimental and analytical eigenvector matrix, respectively, which must be properly scaled; Λ is the eigenvalue matrix.

2.2 Algorithm B

The effect of high frequency components in flexibility matrix will rapidly decrease with the increase of natural frequency [23]. Damage is a local phenomenon and may not significantly influence mode shapes of the lower modes that are usually measured from vibration tests of large structures [24]. In order to magnificent the effect of the higher modes, cost function is defined as follows:

$$Error = \left\| [\phi_A][\Lambda_A][\phi_A]^T - [\phi_E][\Lambda_E][\phi_E]^T \right\| \tag{2}$$

2.3 Algorithm C

In this method, algorithm B and Modified Total Modal Assurance Criterion (MTMAC) [25] create a two stage method. Modal assurance criterion (MAC) and MTMAC are defined as follows:

2.3.1 Modal assurance criterion

The function of the modal assurance criterion (MAC) is to provide a measure of consistency between estimates of a modal vector. This provides an additional confidence factor in the evaluation of a modal vector from different excitation locations [26]. MAC for two arbitrary vectors, {x} and {y}, is defined as follows [27]:

$$MAC = \frac{\left|\{x\}^T \{y\}\right|^2}{\left(\{x\}^T \{x\}\right)\left(\{y\}^T \{y\}\right)} \tag{3}$$

2.3.2 Modified Total Modal Assurance Criterion

Modified version of MAC was adapted by Perera et al. [25] which defined the error as follows:

$$Error = 1 - MTMAC = 1 - \prod_{i=1}^{r} MTMAC_i \tag{4}$$

Where *r* refers to the number of measured modes and $MTMAC_i$ is:

$$MTMAC_i = \frac{MAC\left(\{\phi_i^A\},\{\phi_i^E\}\right)}{1 + \left|\dfrac{\Lambda_i^A - \Lambda_i^E}{\Lambda_i^A + \Lambda_i^E}\right|} \tag{5}$$

2.3.3 Double stage method

In this method, at the first stage, algorithm B is used to identify the damage in a structure and then in the second stage the candidate solution of the first stage is utilized as an initial solution for the optimization procedure by MTMAC function.

3. MIXED PARTICLE SWARM, RAY OPTIMIZATION, AND HARMONY SEARCH ALGORITHM

Compared to other algorithms, the PSO has a versatility to hybridize with other metaheuristics and it is simple to implement. However, the standard PSO has some infirmity, Shi and Eberhart [28] introduced a parameter known as the inertia weight into the original particle swarm optimizer, to decrease the computational time and improve ability in finding the global optimum. Conceptually, PSO seems to lie somewhere between genetic algorithm and evolutionary programming [29]. In this algorithm, in each iteration, the swarm is updated by the following equations ([28],[30]):

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \tag{6}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{7}$$

Where P_i is the best previous position of the ith particle and P_g is the best position of the particles which ever found. Here, ω is an inertia weight to control the influence of the previous velocity, c_1 and c_2 are two acceleration constants and r_1 and r_2 are two random numbers uniformly distributed in the range of (0,1). Therefore in the PSO there are parameters such as c_1 and c_2 with each of them having an important role on performance of the algorithm.

On the other hand Ray optimization algorithm has an origin making part which has an important role in this algorithm. In the RO first the point to which each particle moves must be determined. This point is named origin and it is specified by:

$$O_i^k = \frac{(ite+k).GB+(ite-k).LB_i}{2.ite} \tag{8}$$

Where O_i^k is the origin of the ith agent or particle for the kth iteration, ite is the total number of iterations of the optimization process, GB and LB_i are the global best and local best of the ith agent, respectively [31]. In HRPSO ray origin making is used to update the positions of the particles by the following equations:

$$V_i^{k+1} = \omega V_i^k + rand.O_i^k \tag{9}$$

Thus in this algorithm, parameters such as c_1 and c_2 in the standard PSO substitute with origin making relation which is independent from parameter tuning. In this equation, the inertia weight is considered as a decreasing function of time which gradually decreases from 1 by each iteration and $rand$ is a random number between 0 and 1.

On the other hand for enhancing the exploitation, the HS introduces a parameter named pitch adjustment which helps the algorithm to find locally improved solutions [32], The value (1−PAR) sets the rate of doing nothing, If the pitch adjustment decision for x_i is yes then

$$x_i' \square\, x_i' + bw.u\,(-1,1)$$

Where bw is an arbitrary distance bandwidth for the continuous design variable and u (−1, 1) is a uniform distribution between −1 and 1.

By these techniques, there is no dependency on the parameters like as c_1 and c_2 in the PSO. The flowchart of the HRPSO is shown in figure 1.

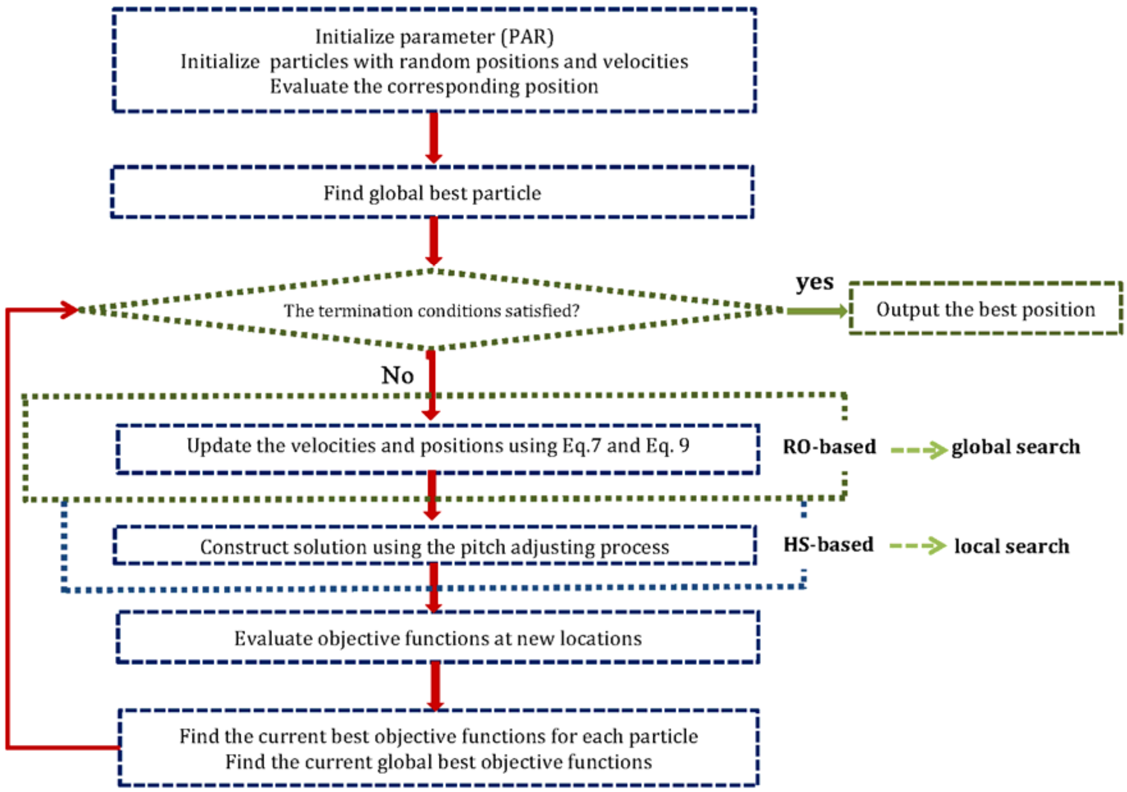

Figure 1. The flowchart of the HRPSO.

4. NUMERICAL TESTS

To demonstrate the efficiency of the proposed algorithm for detecting damage, two types of structures are numerically tested. Most of the dynamic identification algorithms assume, unavoidably, that there is no damping and the damage will not cause the variation in mass [33]. In both examples, it is assumed that damage causes a change in the stiffness of the structure.

In a real dynamic test it is impossible to avoid the presence of noise. The measurement accuracy of structural vibration mode is lower than that of the natural frequency [23], hence in the numerical examples all of the data perturbed by noise on natural frequencies and mode shapes. In these examples, algorithm A and B have same iteration but algorithm C has the half of this iteration for each stage. Due to the measured vibration modes are often not complete, the number of measured modes for both examples is considered as ten.

4.1 A five-story and four-span frame

A five-story and four-span frame as depicted in figure 2 is considered as the first example. The sections used for the beams and columns are (W12×87) and (W14×145), respectively. The modulus of elasticity is 210 GPa and the material density is 7780 kg/m^3. Different damage scenarios are considered as shown in Table 1. The performances of these methods have been shown in figure 3, figure 4 and figure 5, respectively. Results are demonstrated that HRPSO successfully find correct locations and severity of the damages. It is worth mentioning that in the frame structure, the second stage of algorithm C could not improve the first stage.

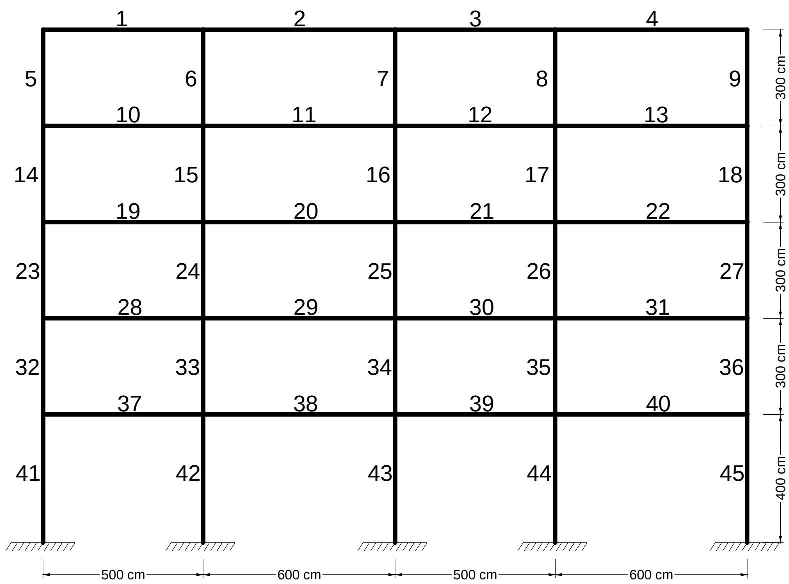

Figure 2. A four-span five-story frame

Table 1: Different damage scenarios for planar frame

Scenario 1		Scenario 2		Scenario 3	
Element	Damage %	Element	Damage %	Element	Damage %
10	25	14	35	9	30
30	20	28	30	18	20
40	25	38	35	36	25

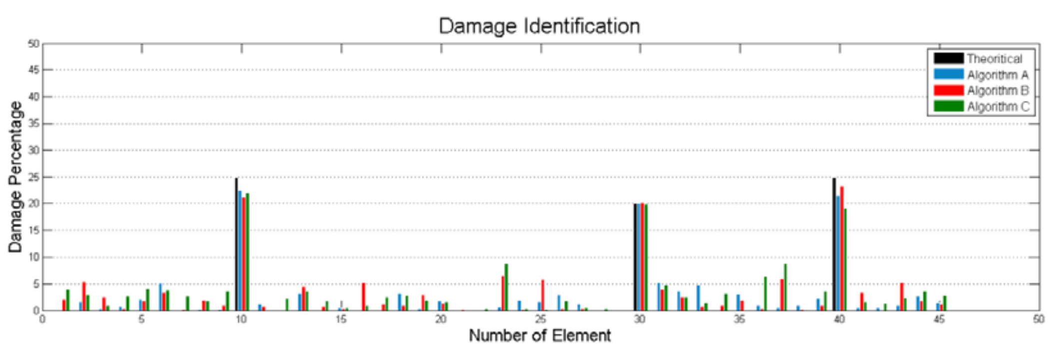

Figure 3. Results of the algorithms for 1% noise for both natural frequencies and mode shapes, and incomplete data for scenario 1.

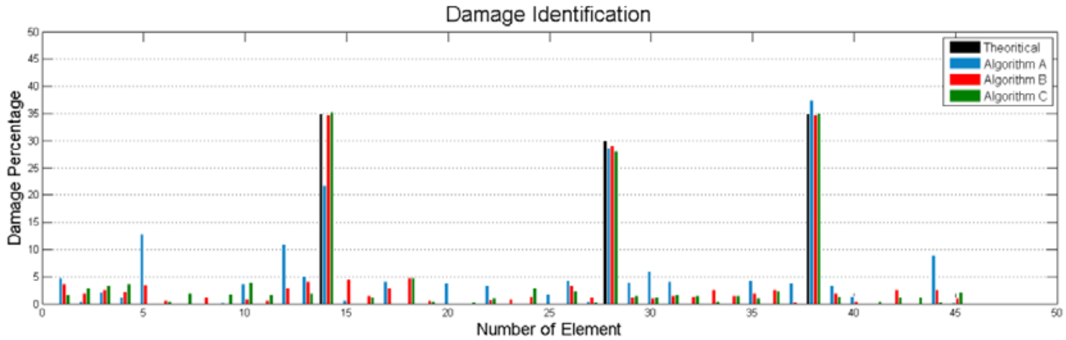

Figure 4. Results of the algorithms for 1% noise for both natural frequencies and mode shapes, and incomplete data for scenario 2.

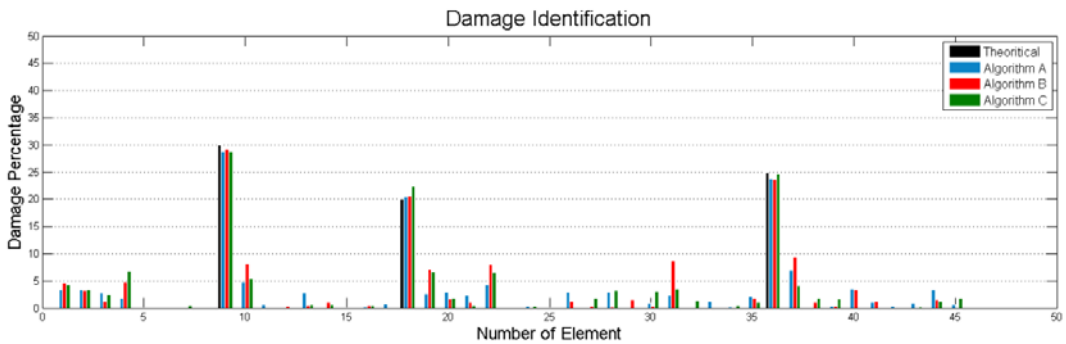

Figure 5. Results of the algorithms for 1% noise for both natural frequencies and mode shapes, and incomplete data for scenario 3.

4.2 A 52-bar space truss

A 52-member steel dome structure depicted in figure 6 is considered. The elastic modulus and material density of elements are 210 GPa and 7800 kg/m^3, respectively. Four different damage scenario with different level of noise are considered as shown in Table 2. Results have been shown in figure 7-12. In this truss structure the first two algorithms have not enough precision whereas algorithm C behaves as a stable function in a low percentage of damage and high level of noise. For the sake of clearity and better judgment, the first two methods are depicted just in figure 7 and figure 9 and in the other cases algorithm C depicted solitarily.

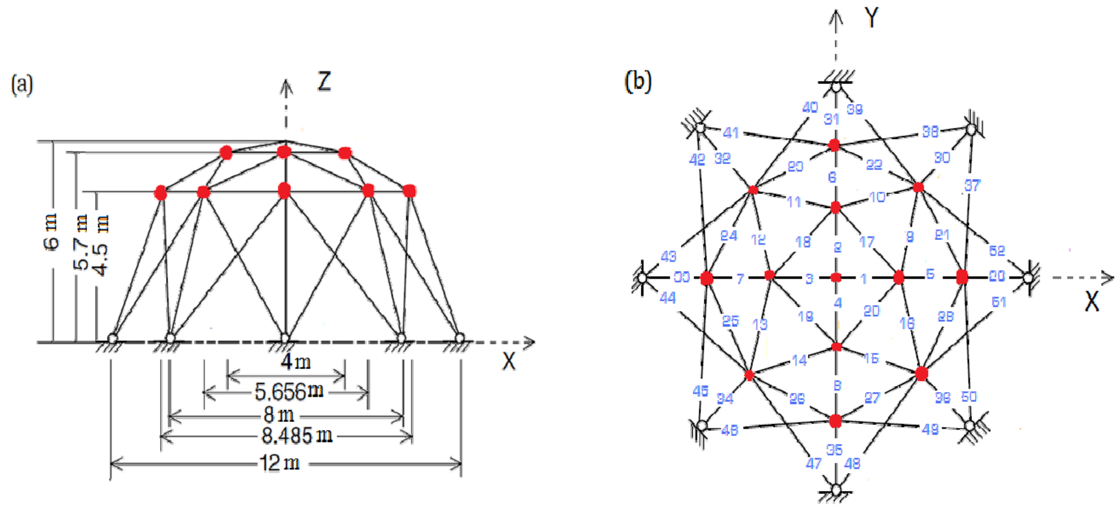

Figure 6. A 52-bar space truss

Table 2: Different damage scenarios for the 52-element dome

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Element number	Damage %	Element number	Damage %	Element number	Damage %	Element number	Damage %
10	30	28	25	13	20	12	30
14	40	42	20	21	20	28	20
52	30			39	20	43	25
						49	20

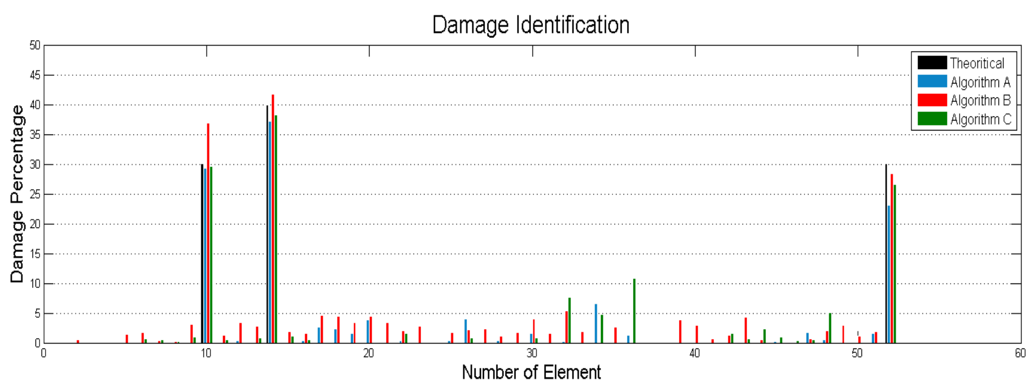

Figure 7. Results of the algorithms for 1% noise for natural frequencies and 3% for mode shapes, and incomplete data for scenario 1.

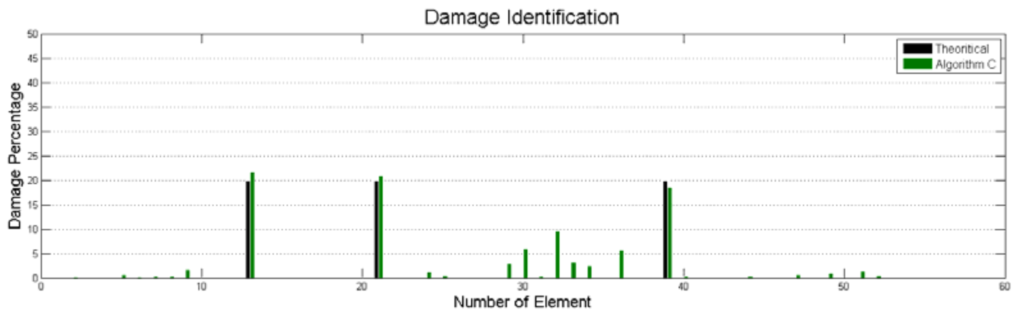

Figure 10. Results of the algorithm for 1% noise for natural frequencies and 3% for mode shapes, and incomplete data for scenario 3.

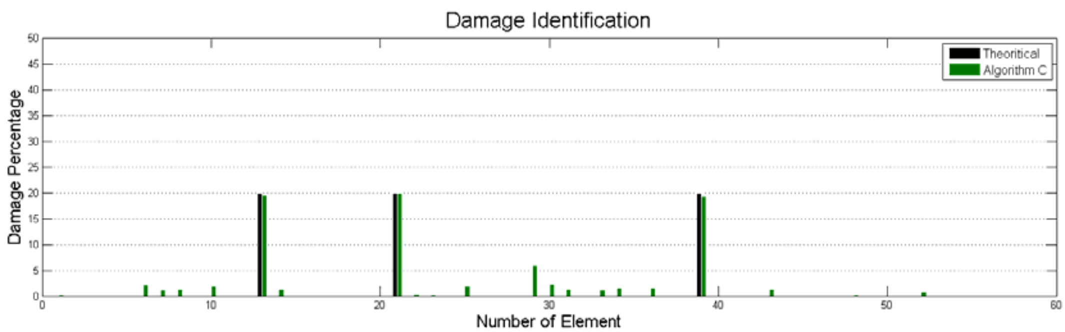

Figure 11. Results of the algorithm for 2% noise for natural frequencies and 5% for mode shapes, and incomplete data for scenario 3.

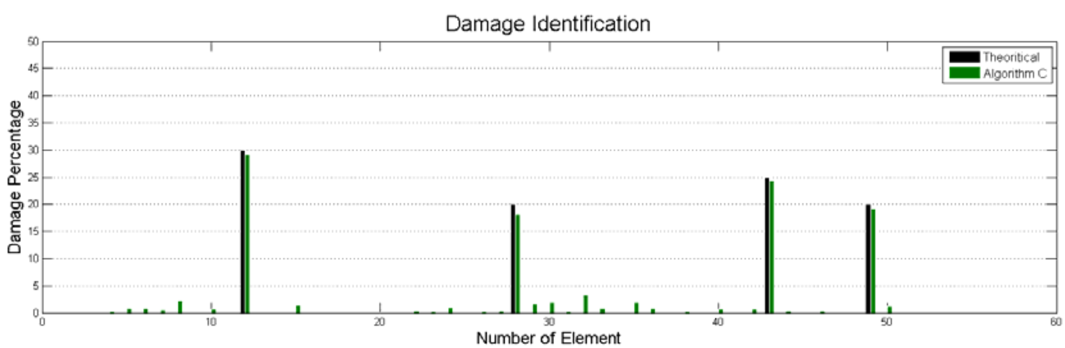

Figure 12. Results of the algorithm for 1% noise for natural frequencies and 3% for mode shapes, and incomplete data for scenario 4.

5. CONCLUDING REMARKS

Hybrid methods for detection damage in skeletal structures are proposed which use a HRPSO algorithm. HRPSO is an efficient hybrid algorithm in which PSO acts as a skeleton of the algorithm, RO enhanced the movement vector, and HS is used to enhance the local search for better exploitation. Damage identification is performed on two numerical examples utilizing three methods, in addition multiple damage scenarios are considered with different levels of noise. Results show the efficiency and robustness of hybrid algorithm C compared to other functions which are considered in this paper particularly in the dome truss.

REFERENCES

1. Doebling SW, Farrar CR, Prime MB. A summary review of vibration-based damage identification methods, *Shock and Vibration Digest*, **30**(1998) 91-105.
2. Kang F, Li JJ, Xu Q. Damage detection based on improved particle swarm optimization using vibration data, *Applied Soft Computing*, **12**(2012) 2329-35.
3. Adams, RD, Cawley P, Pye CJ, Stone BJ. A vibration technique for non-destructively assessing the integrity of structures, *Journal of Mechanical Engineering Science*, **20**(1978) 93-100.
4. Mottershead J, Friswell M. Model updating in structural dynamics: a survey, *Journal of Sound and Vibration*, **167**(1993) 347-75.
5. Hassiotis S, Jeong GD. Identification of stiffness reductions using natural frequencies, *Journal of Engineering Mechanics*, **121**(1995) 1106-13.
6. Salawu O. Detection of structural damage through changes in frequency: a review, *Engineering Structures*, **19**(1997) 718-23.
7. Shi ZY, Law SS, Zhang LM. Damage localization by directly using incomplete mode shapes, *Journal of Engineering Mechanics*, **126**(2000) 656-60.
8. Kosmatka JB, Ricles JM. Damage detection in structures by modal vibration characterization, *Journal of Structural Engineering*, **125**(1999) 1384-92.
9. An Y, Ou J. Experimental and numerical studies on model updating method of damage severity identification utilizing four cost functions, *Structural Control and Health Monitoring*, **20**(2013) 107-20.
10. Sholeh K, Vafai A, Kaveh A. Online detection of the breathing crack using an adaptive tracking technique, *Acta Mechanica*, **188**(2007) 139-54.
11. Catbas FN, Brown DL, Aktan AE. Use of modal flexibility for damage detection and condition assessment: case studies and demonstrations on large structures, *Journal of Structural Engineering*, **132**(2006) 1699-1712.
12. Hao H, Xia Y. Vibration-based damage detection of structures by genetic algorithm, *Journal of Computing in Civil Engineering*, **16**(2002) 222-9.
13. Friswell MI, Penny JET, Garvey SD. A combined genetic and eigensensitivity algorithm for the location of damage in structures, *Computers and Structures*, **69**(1998) 547-56.
14. He RS, Hwang SF. Damage detection by an adaptive real-parameter simulated annealing genetic algorithm, *Computers and Structures*, **84**(2006) 2231-2243.
15. Yun GJ, Ogorzalek KA, Dyke SJ, Song W. A two-stage damage detection approach based on subset selection and genetic algorithms, *Smart Structures and Systems*, **5**(2009) 1-21.
16. Jaishi B, Ren WX. Finite element model updating based on eigenvalue and strain energy residuals using multiobjective optimisation technique, *Mechanical Systems and*

Signal Processing, **21**(2007) 2295-2317.
17. Fallahian S, Seyedpoor SM. A two stage method for structural damage identification using an adaptive neuro-fuzzy inference system and particle swarm optimization, *Asian Journal of Civil Engineering (Building and Housing)*, **11**(2010) 795-808.
18. Kaveh A, Zolghadr A. An improved charged system search for structural damage identification in beams and frames using changes in natural frequencies, *International Journal of Optimization in Civil Engineering*, **2**(2012) 321-39.
19. Kaveh A, Zolghadr A. Damage Detection of Truss Structures using an Improved Charged System Search Algorithm, in B.H.V. Topping, (Editor), *Proceedings of the Eleventh International Conference on Computational Structures Technology*, Civil-Comp Press, Stirlingshire, UK, Paper 82, 2012. doi:10.4203/ccp.99.82.
20. Kaveh A, Talatahari S. A novel heuristic optimization method: charged system search, *Acta Mechanica*, **213**(2010) 267-89.
21. Jaishi B, Ren WX. Damage detection by finite element model updating using modal flexibility residual, *Journal of Sound and Vibration*, **290**(2006) 369-87.
22. Pandey A, Biswas M. Damage detection in structures using changes in flexibility, *Journal of Sound and Vibration*, **169**(1994) 3-17.
23. Yan YJ, Cheng L, Wu ZY, Yam LH. Development in vibration-based structural damage detection technique, *Mechanical Systems and Signal Processing*, **21**(2007) 2198-2211.
24. Kim JT, Ryu YS, Cho HM, Stubbs N. Damage identification in beam-type structures: frequency-based method vs mode-shape-based method, *Engineering Structures*, **25**(2003) 57-67.
25. Perera R, Torres R. Structural damage detection via modal data with genetic algorithms, *Journal of Structural Engineering*, **132**(2006) 1491-1501.
26. Allemang RJ. The modal assurance criterion–twenty years of use and abuse, *Sound and Vibration*, **37**(2003) 14-23.
27. Allemang RJ, Brown DL. A correlation coefficient for modal vector analysis, *in Proceedings of the 1st International Modal Analysis Conference*, SEM, Orlando, vol. 1, 1982, pp. 110-16.
28. Shi Y, Eberhart R. A modified particle swarm optimizer, in Evolutionary Computation Proceedings, *IEEE World Congress on Computational Intelligence*, The 1998 IEEE International Conference on, IEEE, 1998, pp. 69-73.
29. Eberhart R, Kennedy J. A new optimizer using particle swarm theory. in Micro Machine and Human Science, MHS'95, *Proceedings of the Sixth International Symposium on, IEEE*, 1995, pp. 39-43.
30. Kennedy J, Eberhart R. Particle swarm optimization, Proceedings, *IEEE International Conference on Neural Networks, IEEE*, 1995.
31. Kaveh A, Khayatazad M. A new meta-heuristic method: Ray Optimization, *Computers and Structures*, **112**(2012) 283-94.
32. Lee KS, Geem ZW. A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice, *Computer Methods in Applied Mechanics and Engineering*, **194**(2005) 3902-33.
33. Wang X, Hu N, Fukunaga H, Yao ZH. Structural damage identification using static test data and changes in frequencies, *Engineering Structures*, **23**(2001) 610-21.