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Damage detection of skeletal structures using particle swarm optimizer with passive congregation (PSOPC) algorithm via incomplete modal data

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Abstract

This paper uses a PSOPC model based non-destructive damage identification procedure using frequency and modal data. The objective function formulation for the minimization problem is based on the frequency changes. The method is demonstrated by using a cantilever beam, four-bay plane truss and two-bay two-story plane frame with different scenarios. In this study, the modal data are provided numerically using the finite element method. The effectiveness of using frequencies as the data for quantification of damage severity and location are checked. The effects of noisy incomplete data on the accuracy of damage detection with PSOPC algorithm are also discussed.

Keywords: Damage identification; Finite element method; Modal data, PSOPC algorithm.

1. Introduction

Bridges and buildings as civil engineering structures are important assets to a nation. Structural systems are susceptible to structural damage over their lives due to various reasons. Undetected damage may cause catastrophic failure leading to loss of lives and structural properties. It is important to obtain information on the occurrence, the geometric place and the severity of the damage at the as earlier as possible.

In recent years numerous damage identification methods have been developed. Damage detection methods of structural systems based on changes in their modal characteristics have been widely used during the last two decades.

Methods of damage detection by using dynamic responses can be classified into two large groups: the experimental methods based on signals and the methods based on models [1,2].

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One of the signal-based methods is the technique of Novelty Detection in a changing environment: regression and interpolation approaches [3], X-ray, electron scanning, ultrasound, magnetic resonance imagery, coin tapping; dye penetration, thermal field, visual inspection and Eddy's currents technique [4] are some Examples of non-destructive damage identification. Mentioned methods tend to be time consuming and costly, often requiring priori knowledge of the damage location and the guarantee of access to any part of the structure.

Moreover these limitations, the signal-based methods can only identify damage in near the structure surface.

However, these methods work relatively well in small structures and are inefficient when applied to large structural systems. Conversely, the methods based on models allow determining the damage location and severity by the simultaneous use of mathematical models of the structure and vibration data [5].

Modal vibration test data, such as structural natural frequencies and mode shapes, characterize the state of a structure [6]. Generally showing, existing methods include those based on examination of changes in frequencies; mode shapes or mode shape curvatures, those based on vibration parameters and those based on updating structural model parameters, etc. [7]

The damage detection can be defined as a non-linear inverse problem [8]. As mentioned the experimental data are usually limited, but multiple solutions that satisfy the formulation of the inverse problem can be obtained. To succeed in this difficulty, evolutionary computational techniques, like Artificial Neural Networks (ANNs) [9], Genetic Algorithms (GAs) [10], particle swarm optimization [11], have been used to damage detection.

The other related works is mentioned in follow. A multi-stage particle swarm optimization (MSPSO) for structural damage detection introduced [12]. A hybrid particle swarm optimization–simplex algorithm (PSOS) for structural damage identification using frequency domain data has been presented [13].

A Particle Swarm Optimization (PSO) algorithm is examined to solve the inverse problem in structural health monitoring and is compared to the Alternating Projection method in estimating damage using a simulated cantilever beam model [14].

In other work application of particle swarm optimization and genetic algorithms to multi-objective damage identification inverse problems with modelling errors is studied [15]. The accuracy comparison of Hybrid of particle swarm and genetic algorithm for structural damage detection has been discussed [16].

To examine the effectiveness of using modal parameters for quantification of damage severity, only frequencies data have been used. The used method is applied to non-damping cantilever beam; four bay plane trusses and a two-span-story plane frame multiple damage locations with free vibration. The effects of incomplete and complete modal data on the accuracy of damage detection are also discussed.

2. Damage detection method

2.1. A particle swarm optimizer with passive congregation

The particle swarm optimizer (PSO) is an algorithm for determining the optimum solution that is based on population and was invented by Kennedy and Eberhart [17]. This method is inspired by the social behavior of animals such as bird flocking. Similar to other population-based algorithms, such as evolutionary algorithms, PSO can solve a variety of difficult optimization problems but has shown a faster convergence rate than other evolutionary algorithms on some problems [18]. In standard PSO algorithm, population (swarm) is initialized with random solutions (particles) in search space. Each particle repetitive moves

across the search space and is attracted to the position of the best fitness (evaluation of the objective function) historically reached by the particle itself (local best) and by the best among the neighbors of the particle (global best). Basically, each particle continuously focuses and refocuses the try to its search according to local and global best.
Additional change on velocity V_i^{k+1} update the move of a particle to the current position X_i^k as follows:

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

Three contributing factors of velocity is: (1) previous velocity V_i^k, (2) movement in the direction of the best previous position P_i^k, and (3) movement in the direction of the best solution that the swarm has found so far P_g^k. The mathematical formulation can be expressed as:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \tag{2}$$

where ω is an inertia weight to control the influence of the previous velocity, r_1 and r_2 are two random numbers uniformly distributed in the range of (0,1), and c_1 and c_2 are two acceleration constants.

Adding the passive congregation model to the standard PSO may increase its performance [19]. Passive aggregation is a passive grouping by physical processes. Passive congregation is an attraction of an individual to other group members but where there is no display of social behavior. By introducing passive congregation to PSO, information can be transferred among individuals of the swarm that will help individuals to avoid misjudging information and becoming trapped by poor local minima. The new position of particles in hybrid PSO with passive congregation is calculated as following [19]:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) + c_3 r_3 (R_i^k - X_i^k) \tag{3}$$

where r_3 is a uniform random sequence in the range (0,1); R_i is a particle selected randomly from the swarm, c_3 is the passive congregation coefficient.
Since the new positions of particles can violate from allowable boundaries, it is therefore necessary to limit their values in order to keep them in the search space.

2.2. Objective function

The parameter vector used for evaluating the correlation coefficients, that consists of the ratios of the first n_f natural frequency changes ΔF due to structural damage:

$$\Delta F = \frac{F_h - F_d}{F_h} \tag{4}$$

where F_h and F_d denote the natural frequency vectors of the undamaged and damaged structures. Similarly, the parameter vector predicted from an analytical model can be defined correspondingly as

$$\delta F(X) = \frac{F_h - F(X)}{F_h} \tag{5}$$

where $F(X)$ is a natural frequency vector that can be predicted from an analytic model and $X = [x^1, x^2, \ . \ . \ . \ , x^n]$ represents a damage variable vector containing the damage severity of all *n* structural elements,

Given a pair of parameter vectors, one can estimate the level of correlation in several ways. An efficient way is to evaluate a correlation-based index, termed the multiples damage location assurance criterion (MDLAC), and covered in the form of equation (6) [20]:

$$MDLAC(X) = \frac{\left|\Delta F^T . \delta F(X)\right|^2}{\left(\Delta F^T . \Delta F\right)\left(\delta F^T(X) . \delta F(X)\right)} \quad : \quad 0 < MDLAC < 1 \tag{6}$$

Two frequency change vectors are compared with MDLAC that one calculated from the structural parameters that considered and the other from a structural model analysis. When the vector of analytical frequencies becomes the same to the frequency vector of the damaged structure, MDLAC will be maximal. That is, $F(X) = F$ so considering this theory can be used to find a set of damage variables maximizing the MDLAC using an optimization algorithm:
Find:

$$X = [x_i, x_2, \ . \ . \ . \ , x_n] \qquad \text{To maximize: } w(X) = MDLAC(X) \tag{7}$$

The damage severity can take values only from the set that given from $[0 \ 1]$ set of continuous values. Moreover, the objective function that should be maximized is w. As mentioned the damage occurrence in a structural element, decreases the element stiffness. Thus, one of the methods for the damage identification problem, is simulation damage by decreasing one of the stiffness parameters of the element such as the modulus of elasticity (E), cross-sectional area (A), inertia moment (I), and ... . In this study, the damage variables are defined via a relative reduction of the elasticity modulus of an element as,

$$K_i^d = (1 - x_i) K_i^h \tag{8}$$

K_i^d = stiffness matrix of damaged element i

K_i^h = stiffness matrix of healthy element i

where E is the primary modulus of elasticity and E_i is the final modulus of elasticity of the *i*th element. In this study, an initial study was prepared on the performance of the MDLAC as an objective function, and then equation (7) solved by an optimization method. The MDLAC as an objective function for the optimization algorithm is more sensitive to damaged elements than undamaged elements. It means, this method can find the true place of the damaged elements but it may find an undamaged element as a damaged one. Therefore, in this study a function and new optimization algorithm is discussed, the used function is as below [21]:

$$obj(X) = \frac{1}{n_f} \sum_{i=1}^{n_f} \frac{\min(f_{xi}, f_{di})}{\max(f_{xi}, f_{di})} \tag{9}$$

where f_{xi} and f_{di} are the *i*th components of vectors *F(X)* and F_d, correspondingly. The obj(X) function can rapidly find the locations of healthy elements when compared to the MDLAC; however, it is very probable that it finds a damaged element as a healthy one. Therefore, in this study, a combinational function of equations (6) and (9), called here the efficient correlation-based index (ECBI), is used as[21],

$$ECBI(X)=\frac{1}{2}\left[\frac{\left|\Delta F^{T}.\delta F(X)\right|^{2}}{\left(\Delta F^{T}.\Delta F\right)\left(\delta F^{T}(X).\delta F(X)\right)}+\frac{1}{n_f}\sum_{i=1}^{n_f}\frac{\min(f_{xi},f_{di})}{\max(f_{xi},f_{di})}\right] \quad (10)$$

If damage detection by this algorithm equals to the exact value, $ECBI$ value equals to 1. So by defining the objective function as equation (11) and minimizing objective function, the exact solution will be achieved.

$$Objective\ function = 1 - ECBI \quad (11)$$

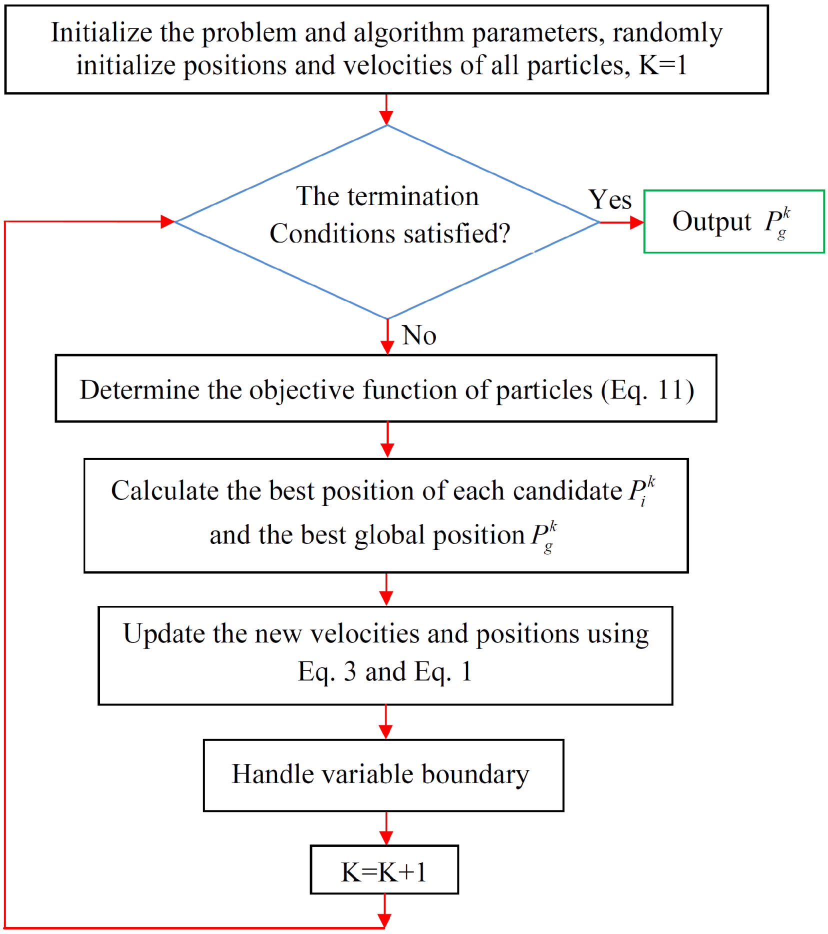

Figure 1. Flowchart of PSOPC algorithm.

3. Examples of damage detection

To evaluate the efficiency of this method, numerical simulations are done by using modal data, which may be complete or incomplete. A cantilever beam, four bay plane trusses and a two-span-story plane frame are chosen for this purpose. In the study, for numerical simulating the modal data an FE model were used. Up to the first 15 modes are utilized in cantilever beam and truss damage detection and 20, 30 and 40 first modes are used for two-span-story plane frame damage detection. Complete and incomplete modal data sets comprising only the translational DOFs in truss and the translational and rotational DOFs in beam and frame.

Population size of algorithms used was set in 100 and the acceleration constants in PSOPC, c_1 and c_2 considered equal to 0.5. The inertia weight for PSOPC started at 0.9 and ended at 0.7. Passive congregation coefficient c3 (linearly increasing) was started at 0.4 and ended at 0.6. For maximum iterations fixed number (50) was applied as stoppage criterion.

3.1. Cantilever beam damage detection

Damage was detected in a cantilever beam with Specifications as follow:
A cantilever beam which contains 10 elements, 11 nodes and 20 nodal DOFs. The cantilever beam is a *W12 × 65* with an area of $A = 0.0123\, m^2$ and second moment of inertia $I = 2.218 \times 10^{-4}\, m^4 (533\, in^4)$, $E = 207 \times 10^9\, N/m^2$, $\rho = 7780\, kg/m^3$ and $L=7.62\ m\ (25ft)$.

A cantilever steel beam is shown in Figure 2. For the reason of modal analyzing the beam was divided in to 10 one-dimensional beam elements.
Different locations and severity of damage (damage scenarios) were subjected to the beam. modal responses of the beam before and after damage were measured in each scenario. In inverse procedure instead of experimental measurements, numerically generated measurements are used. To detect the damage place and extension different scenarios were presented. Especially, for the cantiliver beam damage detection, three different simulated damage scenarios were considered:
Scenario (1): a simple damage- the stiffness of element 3 was reduced by 40 percent.
Scenario (2): a multiple damage- the stiffness of elements 2 and 7 were reduced by 70 and 30 percent respectively.
Scenario (3): a multiple damage- the stiffness of elements 1, 6 and 10 were reduced by 80, 50 and 60 percent respectively.
Damage by complete and incomplete Modal data sets comprising, 5, 10 and 15 first modes were detected.

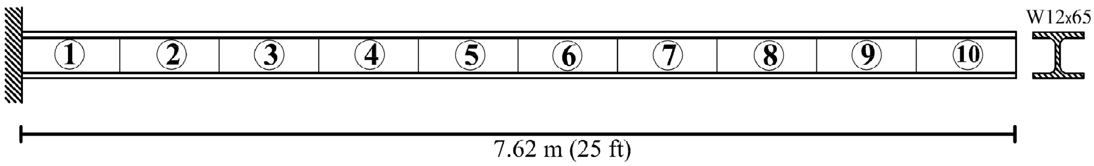

Figure 2. The finite element model of a cantilevered beam having 10 elements.

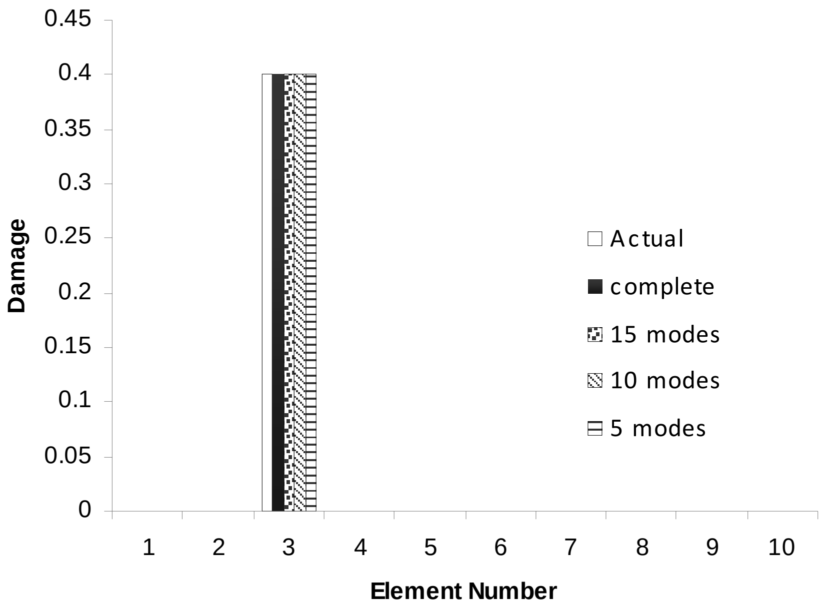

Figure 3. Cantilever beam with damage at Element 3: effect of incompleteness of mode shape data on damage detection data in Scenario 1.

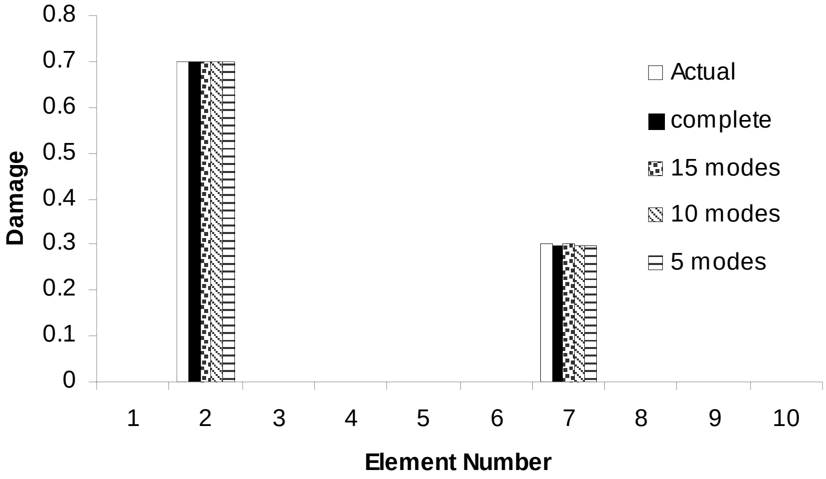

Figure 4. Cantilever beam with damage at Elements 2 and 7: effect of incompleteness of mode shape data on damage detection data in Scenario 2.

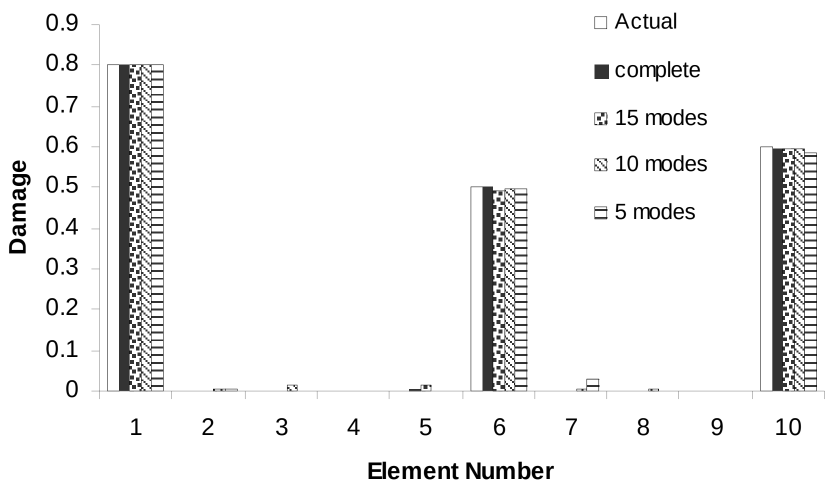

Figure 5. Cantilever beam with damage at Elements 1, 6 and 10: effect of incompleteness of mode shape data on damage detection data in Scenario 3.

As these results show significant accuracy of the results even in incomplete data considering only first 5 modes by PSOPC algorithm. Bar diagrams in Figure 3 to 5 illustrates little difference between actual and detected damage.

3.2. Truss damage detection

A four bay plane truss is next considered. Each bay is equal to 2 m and all other parameters of the truss are listed below.

$A = 18\,cm^2$

$E = 207 \times 10^9\ N/m^2$

$\rho = 7860\ Kg/m^3$

The modal data for the study are simulated using an FE model with 13 elements (with length as shown in Figure 6) numbering sequentially from the extreme left end to the right.

To evaluate the efficiency of this method as described above, the three scenarios as listed in below were used:
Scenario (1): a simple damage- the stiffness of element 3 was reduced by 30 percent.
Scenario (2): a multiple damage- the stiffness of elements 3 and 9 were reduced by 20 and 60 percent respectively.
Scenario (3): a multiple damage- the stiffness of elements 4, 11 and 16 were reduced by 50 percent.

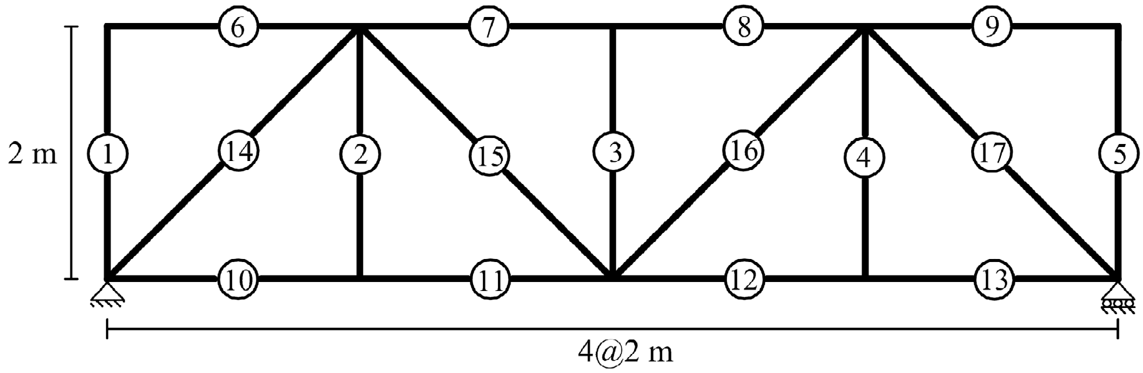

Figure 6. The finite element model of a truss having 13 elements.

The results show the efficiency of the PSOPC algorithm, even in incomplete data. Figure 7 to 9 illustrates the accuracy of this method of damage detection.

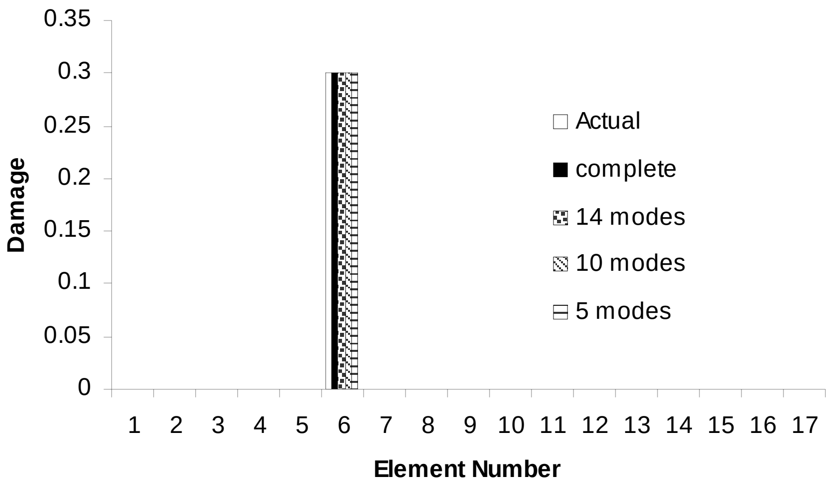

Figure 7. Truss with damage at Element 6: effect of incompleteness of mode shape data on damage detection data in Scenario 1.

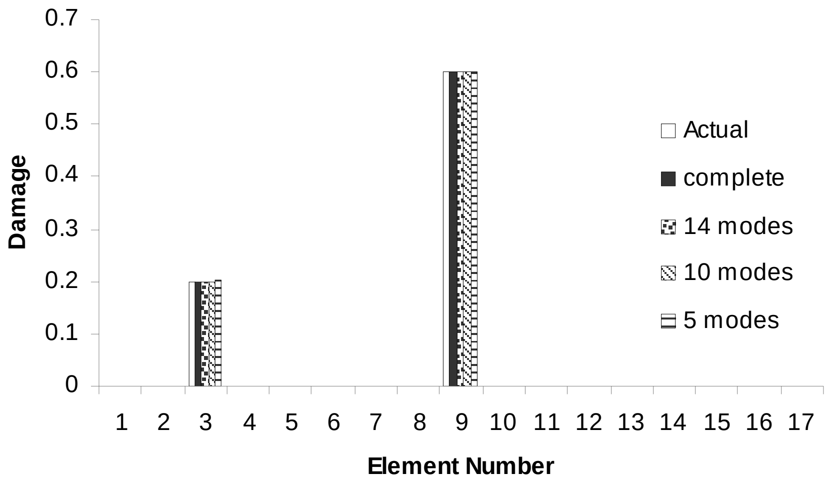

Figure 8. Truss with damage at Elements 3 and 9: effect of incompleteness of mode shape data on damage detection data in Scenario 2.

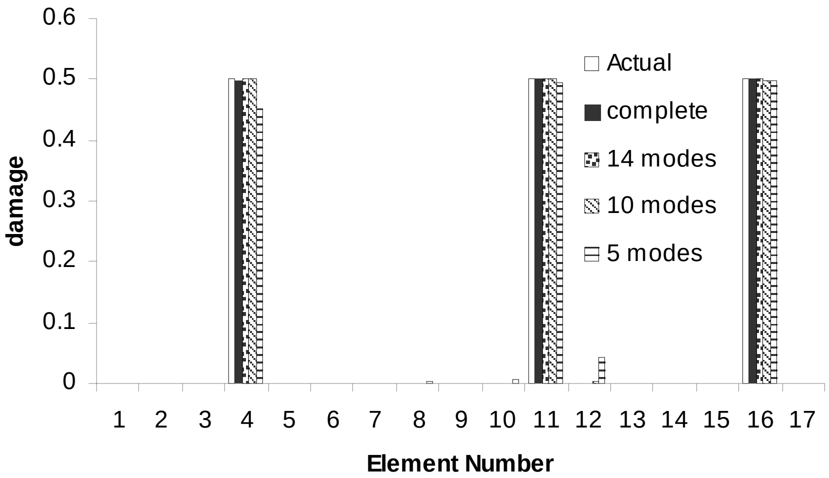

Figure 9. Truss with damage at Elements 4, 11 and 16: effect of incompleteness of mode shape data on damage detection data in Scenario 3.

3.3. Plane frame damage detection

A numerical simulation was performed to examine the used PSOPC procedure. Two-span-story plane frame considered with parameters that are listed below:

$$A = 0.025\ m^2$$
$$E = 207 \times 10^9\ N/m^2$$
$$\rho = 7780\ Kg/m^3$$
$$I = 6.368 \times 10^{-4}\ m^4$$

As the more studied frame has been divided in to 24 elements, 24 unknown parameters are to be identified using the PSOPC, (i.e. all 24 damage indexes). By considering three scenarios damage detection on frame have done.

Scenario (1): a simple damage- the stiffness of element 3 was reduced by 50 percent.

Scenario (2): a multiple damage- the stiffness of elements 6 and 13 were reduced by 20 and 70 percent respectively.

Scenario (3): a multiple damage- the stiffness of elements 1, 10, 21 and 24 were reduced by 60 percent.

In order to study the effect of input error on the estimated parameters, the k_{th} component of the noisy measured vector of frequency can be computed the k_{th} simulated noise free as equation (12) :

$$F_k^n = F_k^0 (1 + \eta \times rand(-1,1)) \tag{12}$$

where η is the relative magnitude of the error ($\eta = 3\%$ is considered).
Completeness and incompleteness of mode shape data noise was considered.

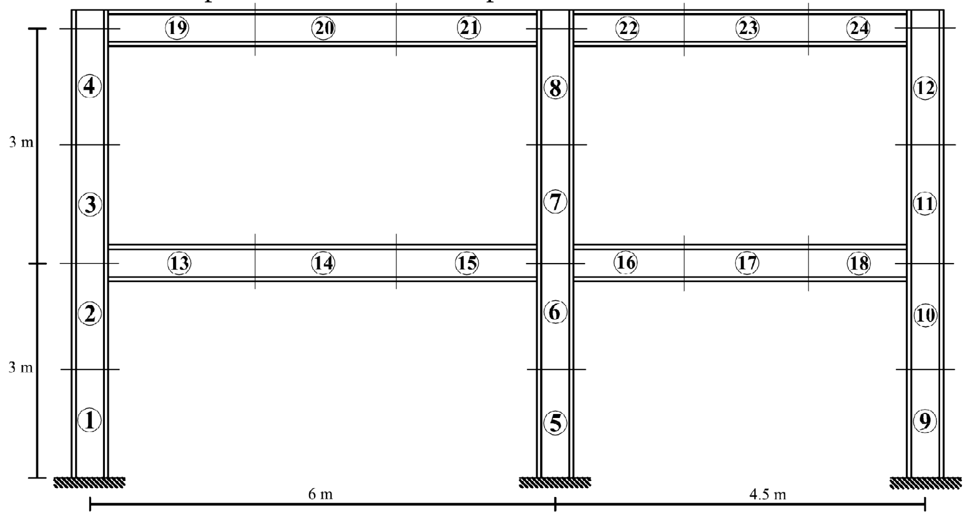

Figure 10. The finite element model of a plane frame with 24 elements.

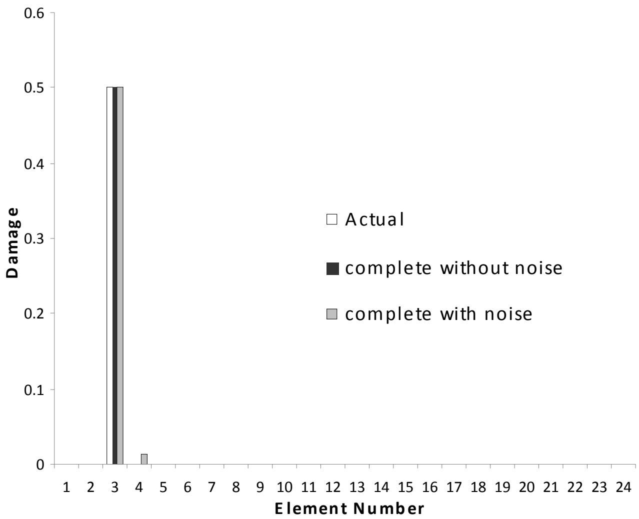

Figure 11. Frame with damage at Element 3: effect of noise on damage detection data in Scenario 1.

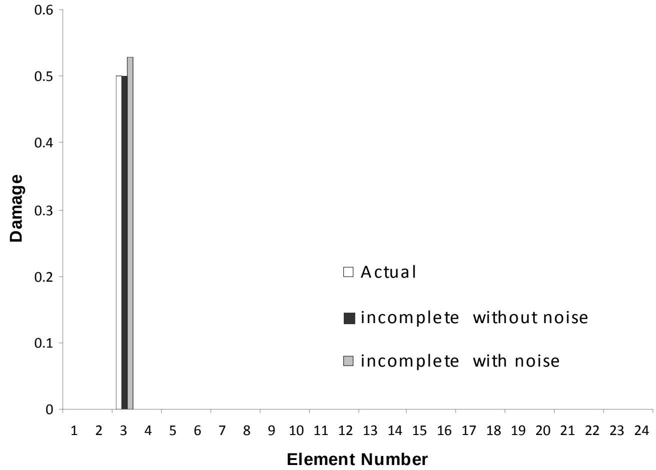

Figure 12. Frame with damage at Element 3: effect of incompleteness of mode shape data on damage detection data in Scenario 1(with noise).

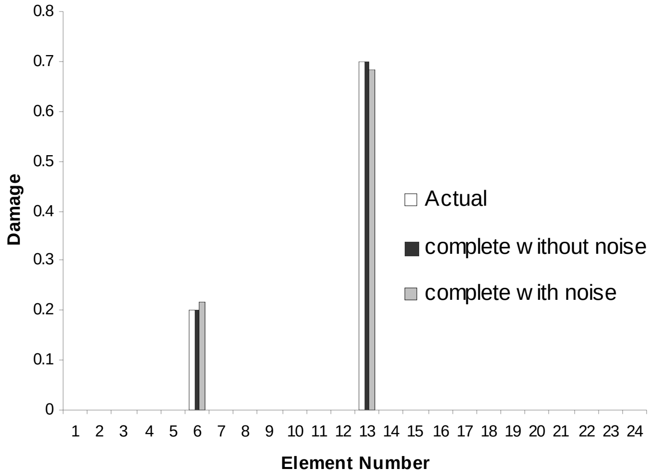

Figure 13. Frame with damage at Elements 6 and 13: effect of noise on damage detection data in Scenario 2.

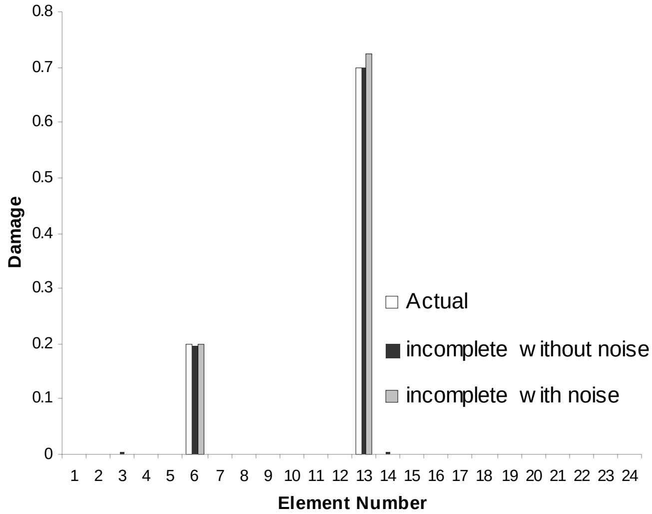

Figure 14. Frame with damage at Elements 6 and 13: effect of incompleteness of mode shape data on damage detection data in Scenario 2 (with noise).

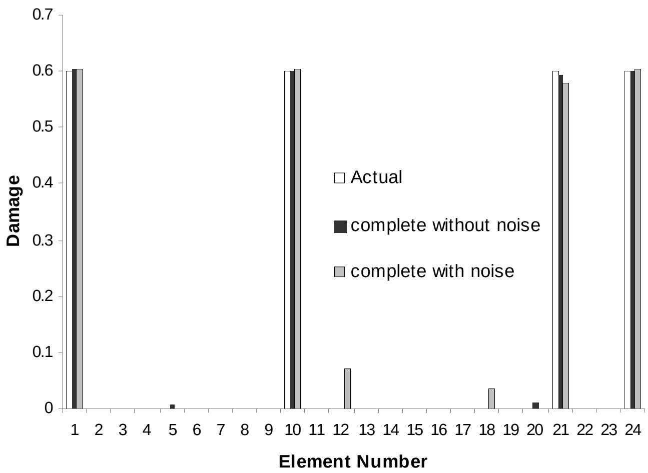

Figure 15. Frame with damage at Elements 1, 10, 21 and 24: effect of noise on damage detection data in Scenario 3.

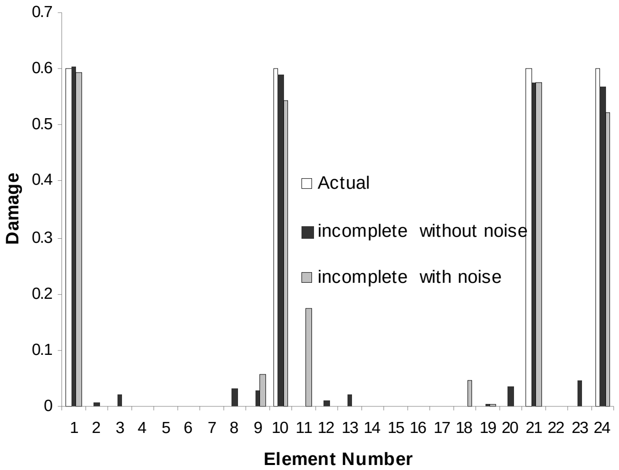

Figure 16. Frame with damage at Elements 1, 10, 21 and 24: effect of incompleteness of mode shape data on damage detection data in Scenario 3 (with noise).

The results in bar diagrams (Figure 11 to 16) show the significant accuracy between actual and detected damage even in noisy incomplete data.

4. Conclusion

A particle swarm optimizer with passive congregation (PSOPC) method for structural damage detection was presented. For structural damage detection, this methodology has no special requirements regarding the number and location of output measurements from the structure; even when large number of properties are unknown, the used strategy can still converge to accurate results, as illustrated by the numerical study. In order to show the robustness of the used method, three examples are used. In each example three different scenarios with incompletion of damaged structural dynamic data are considered. Noisy data considered in plane frame damage detection which has more elements. Finally the results are illustrated the capability of PSOPC algorithm to identify the damage severity and location even with noisy data.

References

[1] Y. Zou, L. Tong, P. Steven, Vibration-based model-dependent damage (delamination) identification and health monitoring for composite structures: a review, *Journal of Sound and Vibration*, Vol. 230 (2000) 357–378.

[2] X. Fang, H. Luo, J. Tang, Structural damage detection using neural network with learning rate improvement, *Computers and Structures*, Vol. 83 (2005) 2150–2161.

[3] K. Worden, H. Sohn, CR. Farrar, Novelty detection in a changing environment: regression and interpolation approaches, *Journal of Sound and Vibration*, Vol. 258, 4 (2002) 741–761.

[4] G. Goch, B. Schmitz, B. Karpuschewski, J. Geerkens, M. Reigl, P. Sprongl, et al., Review of non-destructive measuring methods for the assessment of surface integrity: a survey of new measuring methods for coatings, layered structures and processed surfaces, *Precision Engineering*, Vol. 23 (1999) 9–33.

[5] K .Worden, J.M. Dulieu-Barton, An overview of intelligent fault detection in systems and structures, *Structural Health Monitoring*, Vol. 3, 1 (2004) 85–98.

[6] D.J. Ewins, *Modal testing: Theory and practice*, Wiley, New York, 1984.

[7] S.W. Doebling, C.R. Farrar, M.B. Prime, A summary review of vibration-based, damage identification methods, *The Shock and Vibration Digest*, Vol. 30, 2 (1998) 91-105.

[8] G.M.L. Gladwell, Inverse problems in vibration - II, *Applied Mechanics Reviews*, Vol. 49 (1996) 525–534.

[9] M. Mehrjoo, N. Khaji, H. Moharrami, A. Bahreininejad, Damage detection of truss bridge joints using Artificial Neural Networks, *Expert Systems with Applications*, Vol. 35 (2008) 1122–1131.

[10] R. Perera, R. Torres, Structural Damage Detection via Modal Data with Genetic Algorithms, *Journal of Structural Engineering*, ASCE, Vol. 132, 9 (2006), 1491-1501.

[11] S. Xue, H. Tang, J. Zhou, Identification of Structural Systems Using Particle Swarm Optimization, *Journal of Asian Architecture and Building Engineering*, Vol. 8, 2 (2009) 517-524.

[12] S.M. Seyedpoor, Structural damage detection using a multi-stage particle swarm optimization, *Advances in Structural Engineering*, Vol. 14, 3 (2011) 533-549.

[13] O. Begambre, J.E. Laier, A hybrid particle swarm optimization–simplex algorithm (PSOS) for structural damage identification, *Advances in Engineering Software*, Vol. 40 (2009) 883–891.

[14] M.O. Abdalla, Particle swarm optimization (PSO) for structural damage detection, *ASMCSS'09 Proceedings of the 3rd International Conference on Applied Mathematics, Simulation, Modelling, Circuits, Systems and Signals*, Vouliagmeni, Athens, Greece (Dec. 29-31, 2009) 43-48.

[15] R. Perera, S.-E. Fang, A. Ruiz, Application of particle swarm optimization and genetic algorithm to multiobjective damage identification inverse problems with modeling errors, *Meccanica*, Vol. 45 (2010) 723-734.

[16] S. Sandesh, K. Shankar, Application of a hybrid of particle swarm and genetic algorithm for structural damage detection, *Inverse Problems in Science and Engineering*, Vol. 18, 7 (2010) 997-1021.

[17] J. Kennedy, R. Eberhart, Particle swarm optimization, *IEEE International Conference on Neural Networks, vol. IV*, Piscataway, NJ, United States (1995).

[18] J. Kennedy, R.C. Eberhart, *Swarm Intelligence*. Morgan Kaufmann Publishers, 2001.

[19] S. He, Q.H. Wu, J.Y. Wen, J.R. Saunders, R.C. Paton, A particle swarm optimizer with passive congregation, *BioSystems*, Vol. 78 (2004) 135–147.

[20] J. M. Ndambi, J. Vantomme, K. Harri, Damage assessment in reinforced concrete beams using eigenfrequencies and mode shape derivatives, *Engineering Structures*, Vol. 24 (2002) 501–515.

[21] M. Nobahari, S. M. Seyedpoor, Structural damage detection using an efficient correlation-based index and a modified genetic algorithm, *Mathematical and Computer Modeling*, Vol. 53 (2011) 1798–1809.