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Cyclical Parthenogenesis Algorithm for guided modal strain energy based structural damage detection

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ABSTRACT

In this paper, a newly developed multi-agent meta-heuristic method, named Cyclical Parthenogenesis Algorithm (CPA), is incorporated into a guided modal strain energy based structural damage detection technique. A modal strain energy based index is used to guide the structural damage identification process, which is formulated as an inverse optimization problem. Generalized Flexibility Matrix (GFM) of the structure is used to define the objective function of the optimization problem. Three numerical examples are provided in order to examine the viability of the proposed method. The results indicate that the proposed method is capable of locating and quantifying structural damage using only the first few modes of the structure. The results are also compared with those of three other meta-heuristic algorithms in order to show the efficiency of CPA in solving the problem.

1. Introduction

Different events might induce localized damage to the elements of a structural system during its lifespan changing the performance of the structure. Therefore, it is important to find the location and severity of damage in the structural elements in order to evaluate the condition of the structure and to propose necessary rehabilitation plans. Many different methods have been proposed for identification, localization, and severity assessment of damage in structural systems.

Local structural damage can be considered as a reduction in the stiffness of the corresponding structural element. As a result, the stiffness of the entire structure decreases, which changes its dynamic characteristics such as natural frequencies and mode shapes. Examination of these changes in the dynamic characteristics of the structure is the basic idea of the vibration-based damage detection methods [1].

Various vibration-based structural damage detection methods have been proposed in recent years by different researchers [2–13]. These methods identify the location and, in some cases, the extent of induced damage in structural elements. Model updating or inverse problems are a particular class of vibration-based structural identification techniques, where the basic idea is to compare the response characteristics of the actual damaged structure with those of an analytical finite element model. The locations and severities of damages in structural members are considered as variables of the analytical model. The aim is to find the optimal values of these variables, which result in the same dynamic response for the monitored structure and the analytical model. The resulting optimization problem should be solved by a competent optimization algorithm. Such an approach has received considerable attention by different researchers in recent years [14–24].

In practice measuring the modal data of higher modes is difficult while the measured data usually includes more noise and therefore, it is preferable to reduce the required amount of data. Attempts have been made in order to reduce the effect of incomplete modal data [9,25].

In addition to the global dynamic characteristics of the structure, which are used to define the objective functions of the inverse optimization problems, some auxiliary element-based indices, such as modal strain energy, might be defined in order to reduce the size of the problem by distinguishing healthy and damaged structural elements resulting in two-stage damage detection methods [6,18,26,27]. In these methods the location of damage is determined using the element-based index. Then an inverse optimization problem with few variables is solved in order to evaluate the extent of damage. Other applications of dynamic response parameters for structural damage detection could be found in refs [28–32]

During the last few decadesmeta-heuristic algorithms have attracted a great deal of attention as powerful optimization tech-

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niques. These nature-inspired methods do not require any gradient information of the involved functions and are generally independent of the starting points. Thanks to their global search capabilities, these methods are suitable for complex, nonlinear and non-convex search spaces, especially when near-global optimum solutions are sought after using limited computational effort. Some of the examples ofmeta-heuristic algorithms include Genetic Algorithms (GA) by Holland [33], Particle Swarm Optimization (PSO) by Eberhart and Kennedy [34], Ant Colony Optimization (ACO) by Dorigo et al. [35], Harmony Search (HS) by Geem et al. [36], Big Bang-Big Crunch (BB-BC) by Erol and Eksin [37], Charged System Search (CSS) by Kaveh and Talatahari [38], Firefly Algorithm (FA) by Yang [39], Ray Optimization (RO) by Kaveh and Khayatazad [40], Dolphin Echolocation (DE) by Kaveh and Farhoudi [41], Democratic PSO (DPSO) by Kaveh and Zolghadr [42], Colliding Bodies Optimization (CBO) by Kaveh and Mahdavi [43], Water Cycle, Mine Blast and Improved Mine Blast algorithms (WC-MB-IMB) by Sadollah et al. [44], Search Group Algorithm (SGA) by Gonçalves et al. [45], the Ant Lion Optimizer (ALO) by Mirjalali [46], and Tug of War Optimization (TWO) by Kaveh and Zolghadr [47]. Recent advances inmeta-heuristic algorithms in optimal design of structures could be found in, Kaveh [48].

CPA is a newly developed population-basedmeta-heuristic optimization method introduced by Kaveh and Zolghadr [49]. The main rules of the algorithm are derived from the reproduction behavior of some zoological species like aphids, which can alternate between sexual and asexual reproduction systems. In this paper, the abovementioned inverse optimization problem is solved by incorporating CPA into a guided modal strain energy based structural damage identification approach presented by the authors. The guided approach utilizes a modal strain energy based index in order to reduce the number of involved optimization variables in a probabilistic manner. The presented method is capable of capturing damage scenarios which might be missed by two-stage methods e.g. scenarios with drastically different damage extents (e.g. 75 percent in one element and 5 percent in another). The diagonal and anti-diagonal entries of the Generalized Flexibility Matrix are utilized to form a damage sensitive objective function, which only utilizes the first few lower modes as proposed by Ghodrati Amiri et al. [9].

The remainder of this paper is organized as follows: In Section 2, the main rules of CPA are briefly reviewed. The guided structural damage identification approach is then introduced in Section 3. Three numerical examples with different damage cases are examined in Section 4 in order to show the viability of the proposed method. For the first numerical example, results of three othermeta-heuristic optimization algorithm are also included and compared. Finally, some concluding remarks are presented in Section 5.

2. Cyclical Parthenogenesis Algorithm

In this section the newly developed Cyclical Parthenogenesis Algorithm [49] is briefly reviewed. The basic rules of CPA are inspired from the reproduction behavior of aphids as one of the highly successful organisms. Here, these rules are explained using some key aspects of the lives of aphids, especially their ability to reproduce both sexually and asexually (cyclical parthenogenesis), which seem to be interesting from an optimization point of view.

2.1. Aphids and cyclical parthenogenesis

Aphids are small sap-sucking insects and members of the superfamily Aphidoidea [50]. As one of the most destructive insect pests on cultivated plants in temperate regions, aphids have fascinated and frustrated man for a very long time. This is mainly because of their intricate life cycles, close association with their host plants, and ability to reproduce both asexually and sexually [51]. Fig. 1 shows a group of aphids on a host plant.

Fig. 1. A group of aphids on a host plant.

Aphids are capable of reproducing offspring both sexually and asexually. In asexual reproduction the offspring arise from the female parent and inherit the genes of that parent only. This form of reproduction is chosen by female aphids in suitable and stable environments and allows them to rapidly grow a population of genetically similar aphids, which can exploit the favorable circumstances. Sexual reproduction on the other hand, offers a net advantage by allowing more rapid generation of genetic diversity, allowing adaptation to changing environments [52].

Since the habitat occupied by an aphid species is not uniform but consists of a spatial-temporal mosaic of many different patches, each with its own complement of organisms and resources [51], aphids employ sexual reproduction in order to maintain the genetic diversity required for increasing the chance of including the fittest genotype for a particular patch. This is the basis of the lottery model proposed by Williams [53] for explaining the role of sexual reproduction in evolution.

Some aphid species produce winged offspring in response to poor conditions on the host plant or when the population on the plant becomes too large. These winged offspring, which are called alates can disperse to other food sources [50]. Flying aphids have little control over the direction of their flight because of their low speed. However, once within the layer of relatively still air around vegetation, aphids can control their landing on plants and respond to either olfactory or visual cues, or both. Dispersal in aphids can be viewed as a series of trials in which they land on plants at random and after probing decide whether to fly or stay on the plant. After settling, an aphid recognizes a potential host by the structure and chemistry of its surface and internal tissues and starts to colonize the plant [51].

2.2. Description of cyclical parthenogenesis algorithm (CPA)

CPA is a population-basedmeta-heuristic optimization algorithm inspired from social and reproduction behavior of aphids. It starts with a population of randomly generated candidate solutions metaphorized as aphids. The qualities of the candidate solutions are then improved using some simplified rules inspired from the life cycle of aphids [49].

Naturally, CPA does not attempt to represent an exact model of the life cycle of aphids, which is neither possible nor necessary. Instead, it encompasses certain features of their behavior to construct a global optimization algorithm.

Like many other population-basedmeta-heuristic algorithms, CPA starts with a population of N_a candidate solutions randomly generated in the search space. These candidate solutions, which are considered as aphids, are grouped into N_c colonies, each inhabiting a host plant. These aphids reproduce offspring through sexual and asexual reproduction mechanisms. Like real aphids, in general larger (fitter) individuals within a colony have a greater reproductive potential than smaller ones. Some of the aphids prefer to leave their current host plant and search for better conditions. In CPA it is assumed that these flying aphids cannot fly much further due to their weak wings and end up on a plant occupied by another colony nearby. Like real aphids, the agents of the algorithm can reproduce for multiple generations. However, the life span of aphids is naturally limited and less fit ones are more likely to be dead in adverse circumstances. The main steps of CPA can be stated as follows:

2.3. Step 1: initialization

A population of N_a initial solutions is generated randomly:

$$x_{ij}^0 = x_{j,\min} + rand(x_{j,\max} - x_{j,\min}) \qquad j = 1, 2, \ldots, n \tag{1}$$

where x_{ij}^0 is the initial value of the jth variable of the ith candidate solution; $x_{j,\max}$ and $x_{j,\min}$ are the maximum and minimum permissible values for the jth variable, respectively; *rand* is a random number from a uniform distribution in the interval [0,1]; n is the number of optimization variables. The candidate solutions are then grouped into N_c colonies, each inhabiting a host plant. The number of aphids in all colonies N_m is equal.

2.3.1. Step 2: evaluation, reproduction, and flying

The objective function values for the candidate solutions are evaluated. The aphids on each plant are sorted in the ascending order of their objective function values and saved in a Female Memory (***FM***). Each of the members of the female memory is capable of asexually reproducing a genetically identical clone in the next iteration.

In each iteration, N_m new candidate solutions are generated in each of the colonies in addition to identical clones. These new solutions can be reproduced either sexually or asexually. A ratio F_r of the best of these new solutions in each colony are considered as female aphids, the rest are considered as male aphids.

2.3.2. Asexually generated new solutions

A female parent is selected randomly from the population of all female parents of the colony (identical clones and newly produced females). Then, this female parent reproduces a new offspring asexually by the following expression:

$$x_{ij}^{k+1} = F_j^k + \alpha_1 \times \frac{randn}{k} \times (x_{j,\max} - x_{j,\min}) \qquad j = 1, 2, \ldots, n \tag{2}$$

where x_{ij}^{k+1} is the value of the jth variable of the ith candidate solution in the $(k+1)$th iteration; F_j^k is the value of the corresponding variable of the female parent in the kth iteration; *randn* is a random number drawn from a normal distribution and α_1 is a scaling parameter.

2.3.3. Sexually generated new solutions

Each of the male aphids selects a female randomly in order to produce an offspring sexually:

$$x_{ij}^{k+1} = M_j^k + \alpha_2 \times rand \times (F_j^k - M_j^k) \qquad j = 1, 2, \ldots, n \tag{3}$$

where M_j^k is the value of the jth variable of the male solution in the kth iteration and α_2 is a scaling factor. It can be seen that in a sexual reproduction, two different solutions share information, while in an asexual reproduction the new solution is generated using merely the information of one single parent solution. As a result of both sexual and asexual production mechanisms N_m new candidate solutions are generated in each of the colonies in the new iteration.

2.3.4. Death and flight

When all of the new solutions of all colonies are generated, flying occurs with a probability of P_f where two of the colonies are selected randomly and a winged aphid asexually reproduced by and identical to the best female of *Colony1* flies to *Colony2*. In order to keep the number of members of each colony constant, it is assumed that the worst member of *Colony2* dies.

2.3.5. Step 3: updating the colonies

The objective function values of the newly generated candidate solutions are evaluated and the female memories are updated.

2.3.6. Step 4: termination

Steps 2 and 3 are repeated until a termination criterion is satisfied. The pseudo code of CPA is presented in Table 1.

3. Guided structural damage detection method

Relatively simple structural damage identification techniques could be defined using the modal data of a structure such as the natural frequencies and mode shapes. Occurrence of damage in a structural element changes mass, stiffness, and damping characteristics of the structure, which in turn affect its dynamic response. Therefore, one way to locate and quantify the extent of damage in structural members is to compare the modal data of the healthy and the damaged structures. Localization and quantification of damage could be carried out either simultaneously or separately. When the location and extent of damage identified simultaneously the damage detection technique may be called a one-stage method. In the two-stage methods on the other hand, the damaged elements are identified in the first stage (localization). Then, the extent of damage in each of the damaged elements is evaluated in the second stage (quantification). In other words some of the elements of the structure are considered as healthy in the first stage and are excluded from the second stage [6]. Two-stage damage detection techniques offer the advantage of limiting the number of optimization variables. However, as it will be shown in the following, there is a chance of excluding some of the damaged elements in the first stage in some damage scenarios. This is especially the case when scenarios with drastically different damage extents are to be identified (e.g. 75 percent in one element and 5 percent in another).

In this paper a third probabilistic option is presented in which, while none of the elements are excluded, some of them are considered to be less likely to be damaged. Therefore, the proposed method manages to limit the number of optimization variables without taking the risk of excluding damaged elements. The advantages of such a probabilistic approach will be discussed in detail in the upcoming sections.

3.1. Damage sensitive objective function using Generalized Flexibility Matrix

Natural frequencies and mode shapes of a structure can be derived using modal analysis, which can be stated as:

$$K\phi_i = \omega_i^2 M\phi_i \quad \mathrm{i} = 1, 2, \cdots, \mathrm{ndf} \tag{4}$$

in which ω_i and ϕ_i are the ith natural frequency and mode shape of the structure, respectively. *ndf* is the number of degrees of freedom.

Table 1
Pseudo-code of the CPA algorithm.

```
procedure Cyclical Parthenogenesis Algorithm
begin
   Initialize parameters;
   Initialize a population of Na random candidate solutions;
   Group the candidate solutions in Nc colonies with each with Nm members;
   Evaluate and Sort the candidate solutions of each colony and save the best Nm ones in
Female Memory

   while (termination condition not met) do
      for m: 1 to Nc
            Reproduce an identical solution by each of the solutions of Female Memory
            Divide the newly generated offspring into male and female considering Fr
            for i: 1 to Fr×Nm
            Generate new solution i asexually using Eq. (2)
            end for
            for i: Fr×Nm+1 to Nm
            Generate new solution i sexually using Eq. (3)
            end for
            if rand<Pf
            Select two colonies randomly
            Generate an winged identical offspring from the best solution of Colony1
            Eliminate the worst solution of Colony2 and move winged aphid to Colony2
            end if
      Evaluate the objective function values of new aphids
      Update the Female Memory
      end for
   end while
end
```

Since the mode shape vectors are normalized with respect to the mass matrix, the following relationships hold:

$$M = \left(\Phi^{-1}\right)^T \Phi^{-1} \tag{5}$$

$$K = \left(\Phi^{-1}\right)^T \Lambda \Phi^{-1} \tag{6}$$

in which Φ is the mode shape matrix with the ith mode shape as its ith column; operator $\left(\Phi^{-1}\right)^T$ transposes the matrix; and Λ is a diagonal matrix with ω_i^2 on its ith diagonal entry. In the following the objective function and the modal strain energy based index utilized in this study are presented.

A damage sensitive objective function based on geometrical correlation measurement via Modal Assurance Criterion (MAC) as

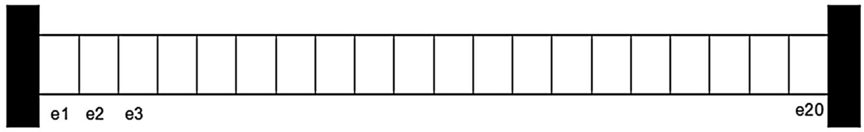


Fig. 2. Finite element model of the clamped-clamped beam.

introduced by Ghodrati Amiri et al. [9] is utilized in this paper. The objective function could be stated as:

$$f(d_1, d_2, \ldots, d_{Ne}) = \sqrt{\left(\frac{1-e_1}{e_1}\right)^2 + \left(\frac{1-e_2}{e_2}\right)^2} \quad , \quad 0 \le d_i \le 1 \quad (7)$$

where:

$$e_1 = MAC_1 \times MAC_3 \quad (8)$$

$$e_2 = MAC_2 \times MAC_4 \quad (9)$$

in which *MAC* stands for Modal Assurance Criterion and defines the amount of correlation between two sets of vectors (a_1, a_2, a_3, and a_4) and (a_1^d, a_2^d, a_3^d, and a_4^d):

$$MAC_i(a_i, a_i^d) = \frac{|(a_i)^T \cdot \left(a_i^d\right)|^2}{\left((a_i)^T \cdot (a_i)\right)\left(\left(a_i^d\right)^T \cdot \left(a_i^d\right)\right)} \quad , \quad i = 1, 2, 3, 4 \quad (10)$$

Vectors $\boldsymbol{a}_1$ and $\boldsymbol{a}_2$ could be defined using the diagonal and anti-diagonal entries of the first order of GFM for the damaged structure:

$$a_1 = \left\{F_m^{g(1)}(1{,}1) \quad F_m^{g(1)}(2{,}2) \quad \cdots \quad F_m^{g(1)}(\text{ndf,ndf})\right\}^T \quad (11)$$

$$a_2 = \left\{F_m^{g(1)}(1{,}\text{ndf}) \quad F_m^{g(1)}(2{,}\text{ndf-1}) \quad \cdots \quad F_m^{g(1)}(\text{ndf},1)\right\}^T \quad (12)$$

where $F_m^{g(1)}$ is the first order of GFM as proposed by Li et al. [25]:

$$F_m^{g(1)} = \Phi_m \Lambda^{-2} \Phi_m^T \quad (13)$$

If we denote the first order of GFM using the m first modes for the undamaged structure as $F_m^{g(l),u}$, the difference between the generalized flexibility matrices of the damaged and undamaged structures can be written as:

$$\Delta F = F_m^{g(1)} - F_m^{g(1),u} \quad (14)$$

The diagonal and anti-diagonal entries of ΔF can be used to define the following vectors:

$$a_3 = \left\{\Delta F(1{,}1) \quad \Delta F(2{,}2) \quad \cdots \quad \Delta F(\text{ndf,ndf})\right\}^T \quad (15)$$

$$a_4 = \left\{\Delta F(1{,}\text{ndf}) \quad \Delta F(2{,}\text{ndf-1}) \quad \cdots \quad \Delta F(\text{ndf},1)\right\}^T \quad (16)$$

By using the GFM of the analytical model of the damaged structure ($F_m^{g(1),d}$), which is to be updated during the inverse optimization process, instead of $F_m^{g(1)}$ vectors a_1^d, a_2^d, a_3^d, and a_4^d can be constructed using Eqs. (11), (12), (15), and (16), respectively. For the analytical model damage occurrence is consider as a decrease in the stiffness matrix. Therefore, when the ith element is damaged its stiffness matrix can be considered as:

$$k_i^d = (1 - \mathrm{d}_i)k_i^u \quad (17)$$

in which k_i^u and k_i^d are the stiffness matrices of the *ith* element in the undamaged and damaged states, respectively; d_i is the damage ratio occurred in *ith* element. Obviously, the values of $\mathrm{d_i}$ are 0 and 1 for an undamaged and fully damage element, respectively.

The goal of the inverse optimization problem addressed in this paper is to minimize the value of the objective function of Eq. (7). In order to accomplish this goal the damage ratios d_i should be selected properly by the damage detection technique such that the dynamic response of the damaged structure and the analytical model become as similar as possible.

3.2. Modal strain energy based index

The mode shape vectors represent the nodal displacements of a vibrating structure. Therefore, the strain energy stored in the elements associated with these displacements can be defined as modal strain energy (MSE). Modal strain energy of the ith element in jth mode could be formulated as:

$$MSE_j^i = \frac{1}{2}\phi_j^{iT} k^i \phi_j^i \quad (18)$$

where k^i is the stiffness matrix of the ith element and ϕ_j^i is the vector of nodal displacements corresponding to the ith element in jth mode of vibration. The summation of elemental modal strain energies results in the total modal strain energy of the structure in mode j:

$$MSE_j = \sum_{i=1}^{Ne} MSE_j^i \quad (19)$$

For computational purpose, it is better to normalize the MSE of elements with respect to the total MSE of the structure:

$$nMSE_j^i = \frac{MSE_j^i}{MSE_j} \quad (20)$$

The mean of normalized MSE values over the first m modes of vibration can be used as an efficient parameter for structural damage localization [6]:

$$mnMSE^i = \frac{\sum_{i=1}^{m} mnMSE_j^i}{m} \quad (21)$$

Occurrence of damage in a structural member results in a decrease in its stiffness and the corresponding modal displacements are expected to increase. Therefore, the defined *mnMSE* parameter increases in comparison to the undamaged state and this can be utilized as a means to identify damaged elements. By defining the following modal strain energy based index (*MSEBI*), Seyedpoor [6] formulates a two-stage structural damage detection method:

$$MSEBI^i = \max\left[0, \; \frac{\left(mnMSE^i\right)^d - \left(mnMSE^i\right)^h}{\left(mnMSE^i\right)^h}\right] \quad (22)$$

in which superscripts d and h stand for the damaged and healthy structures, respectively. The two-stage approach is based on the assumption that the values of *MSEBI* are positive for probable damaged elements and zero for undamaged ones. Although the above assumption is correct in most cases, as it will be discussed in the next section, problems might arise when the damage extents in elements are significantly different. As it will be seen, in these cases the values of MSE for the slightly damaged members might be negative and therefore the assumption of the two-stage damage detection

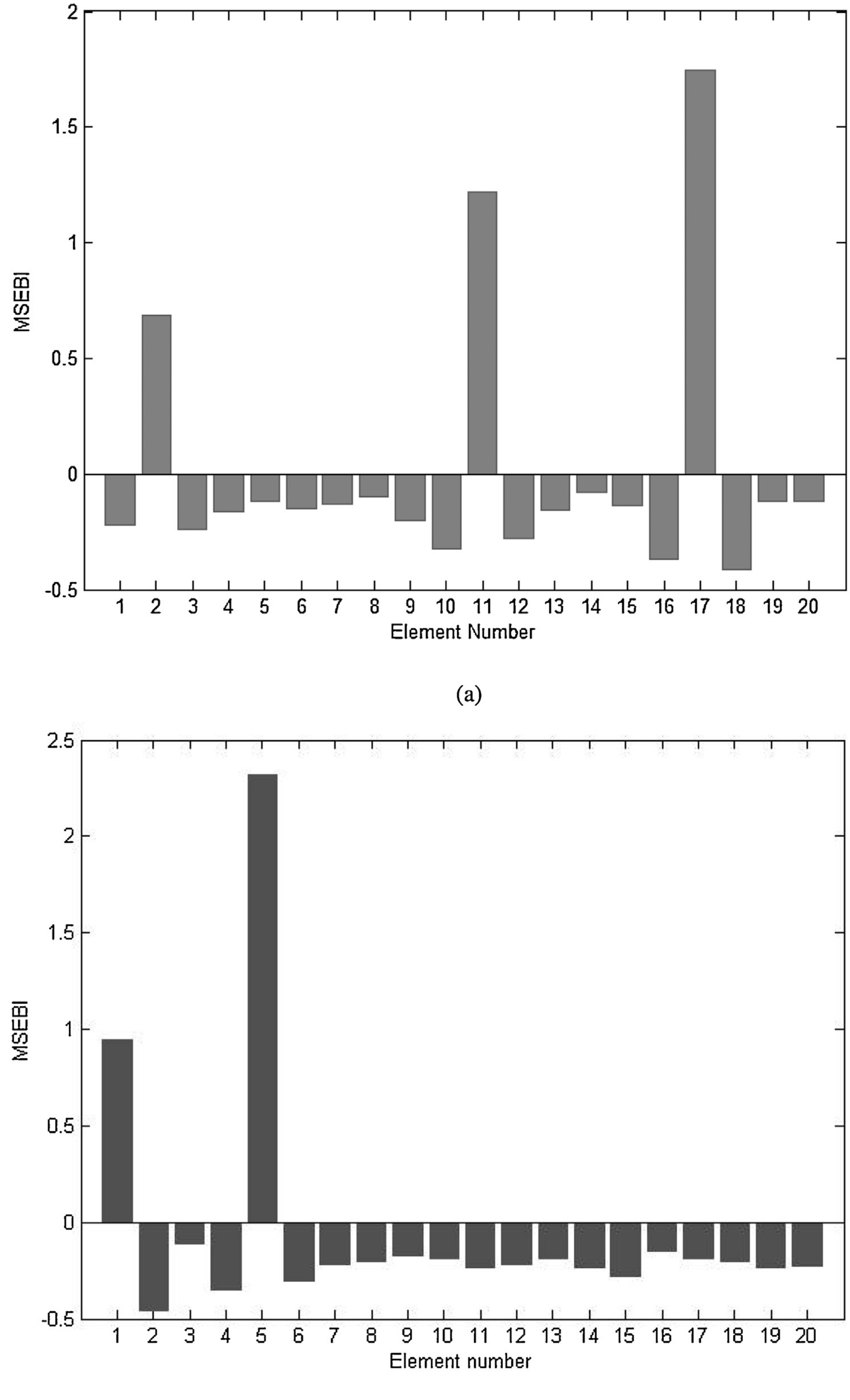


Fig. 3. MSEBI values for the cantilever beam a) Case 0, b) Case 1.

method might be incorrect. As a result the two-stage method might fail to capture some damage scenarios.

In this paper, modal strain energy is utilized to guide the search process without any of the structural elements being excluded from the search space. Therefore, damage scenarios where slightly damaged elements are present together with largely damaged ones could be captured.

It should be noted that since the location and severity of damage are not previously known, stiffness matrices of healthy elements are used for calculating *MSE*s of the damaged structures.

3.3. Guided modal strain energy based structural damage detection

The guided modal strain energy based structural damage detection approach is presented in this section. The method uses the modal strain energy data of the members of the structure to direct the search process. The details of the method are discussed here with the aid of a clamped-clamped beam structure as shown in Fig. 2. The structure will be further discussed as a numerical example in the next section.

In the first step of the proposed method mean normalized modal strain energy values of all elements are calculated for both the healthy and damaged structures. Then the MSEBI for the ith member is calculated as follows:

$$MSEBI^i = \frac{\left(mnMSE^i\right)^d - \left(mnMSE^i\right)^h}{\left(mnMSE^i\right)^h} \tag{23}$$

The definition of the MSEBI is slightly changed in the proposed method in order to make the negative values of MSEBI for the damaged elements in some cases visible. When the extent of induced damage in different members of the structure is relatively close, the values of MSEBI are usually positive for all damaged members. This case is shown in Fig. 3(a), where elements 2, 11, and 17 are 35, 45 and 55 percent damaged (Case 0), respectively. In such cases it is practical to reduce the size of the optimization problem by excluding all of the elements for which the values of MSEBI are negative. However, when the extent of damage is drastically different in the elements of the structure, MSEBI values for some damaged members might be negative. This case is shown in Fig. 3(b), where elements 1, 5, and 16 are 60, 60, and 5 percent damaged (Case1), respectively. It can be seen that MSEBI value for element 16 is negative, which means that if one excludes members with negative MSEBI values to perform a two-stage damage detection, this element would not be captured as a damaged element. It should be noted that the values of MSEBI for more severely damaged elements are still positive. These observations form the basis for the proposed guided damage detection method.

After evaluating MSEBI values, the members are divided into two groups. The first group includes members with positive MSEBI values. It is assumed that all of the extensively damaged members are in this group (Naturally, some undamaged members might also exhibit positive MSEBI values). Therefore, for the elements of this group d_i can vary between zero and one. The second group consists of members with negative MSEBI values. It is assumed that these members are either undamaged or very slightly damaged. Hence, for these elements d_i varies between zero and $\varepsilon < 1$. Moreover, in the optimization process these members could only be present as variables with a probability of stoch; otherwise their *di* is taken as zero. The inverse optimization problem is solved using CPA.

4. Numerical examples

Three numerical examples are solved in order to examine the viability of the proposed method using CPA; a 20-element clamped-clamped beam, a 37-bar planar truss, and a 56-element concrete portal frame. For each structure multiple damage scenarios are considered with drastically different damage extents. For all cases 32 agents and 300 iterations are considered and the first five vibrating modes are used. Parameters ε and *stoch* are taken as 0.1 and 0.6 respectively for all cases. The CPA parameters are taken as

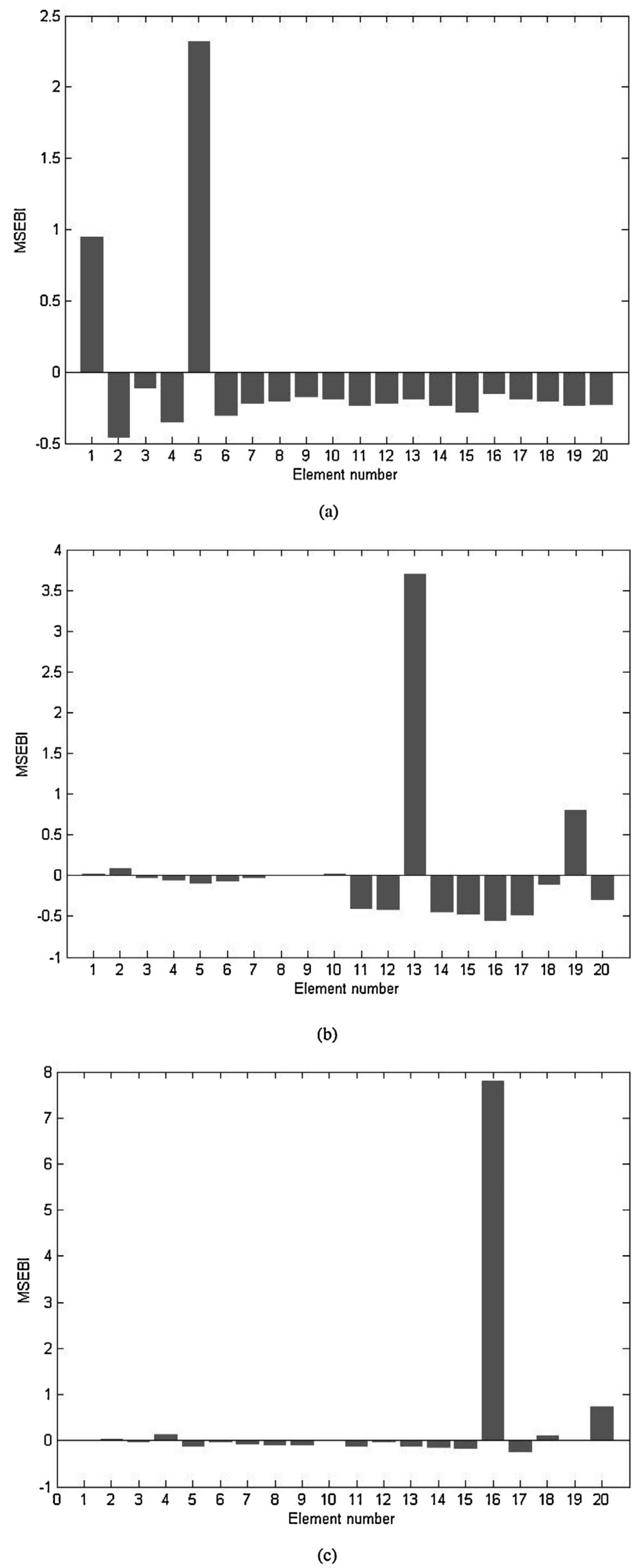


Fig. 4. MSEBI values for the 20-element cantilever beam a) Case 1, b) Case 2, c) Case 3.

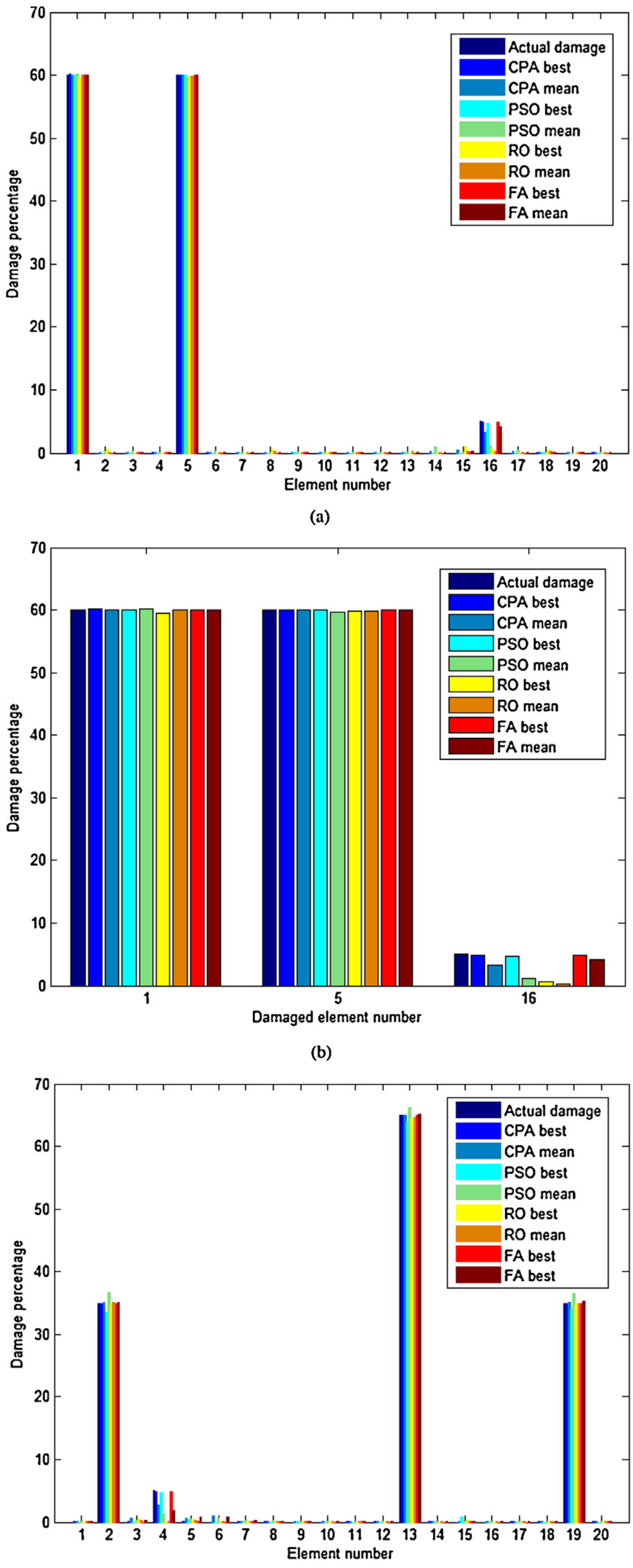


Fig. 5. Performance of the proposed method on the 20-element clamped-clamped beam a) Case 1 (all elements), b) Case 1 (damaged elements only), c) Case 2 (all elements), d) Case 2 (damaged elements only), e) Case 3 (all elements), f) Case 3 (damaged elements only).

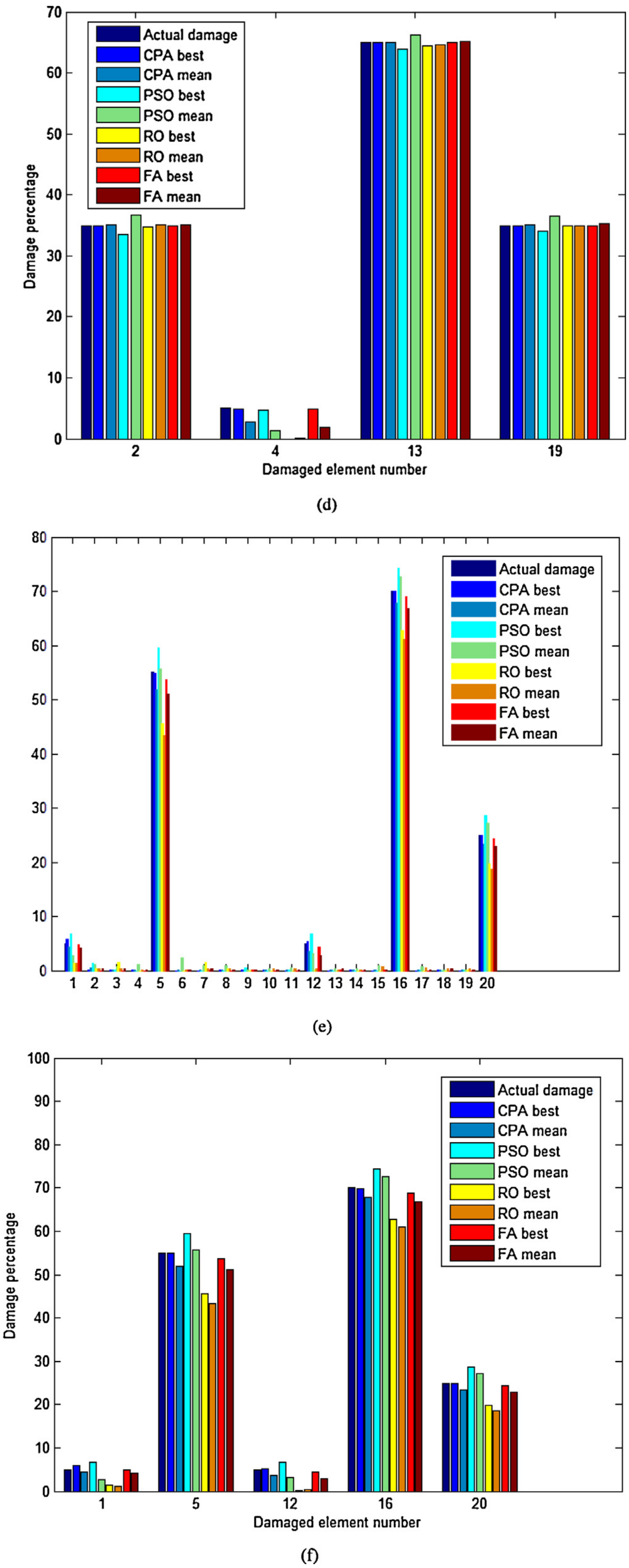


Fig. 5. (*Continued*)

Table 2
Different damage cases for the 20-bar cantilever beam.

Case 1		Case 2		Case 3	
Element number	Induced damage percentage	Element number	Induced damage percentage	Element number	Induced damage percentage
1	60	2	35	1	5
5	60	4	5	5	55
16	5	13	65	12	5
–	–	19	35	16	70
–	–	–	–	20	25

Table 3
Identified damaged extents in damaged elements by different algorithms for the 20-bar clamped-clamped beam.

	Damaged element number	Actual damage extent	CPA		PSO [34]		RO [40]		FA [39]	
			Best	Mean	Best	Mean	Best	Mean	Best	Mean
Case 1	1	60	60.13	59.98	59.95	60.16	59.55	59.95	60.00	60.00
	5	60	59.97	59.95	60.05	59.73	59.77	59.80	59.96	59.97
	16	5	4.85	3.32	4.69	1.20	0.53	0.27	4.89	4.23
Case 2	2	35	35.02	35.14	33.42	36.75	34.81	35.15	34.84	35.17
	4	5	4.99	2.68	4.70	1.26	0.00	0.11	5.11	1.83
	13	65	64.99	65.00	63.90	66.23	64.49	64.69	64.98	65.08
	19	35	34.97	35.12	34.09	36.47	34.82	34.95	35.03	35.19
Case 3	1	5	5.84	4.36	6.72	2.65	1.34	1.24	4.83	4.12
	5	55	54.89	51.84	59.42	55.67	45.58	43.31	53.61	51.10
	12	5	5.29	3.62	6.80	3.03	0.16	0.28	4.37	2.80
	16	70	69.94	67.72	74.33	72.68	62.70	61.08	68.93	66.87
	20	25	24.86	23.29	28.64	27.23	19.71	18.64	24.32	22.96

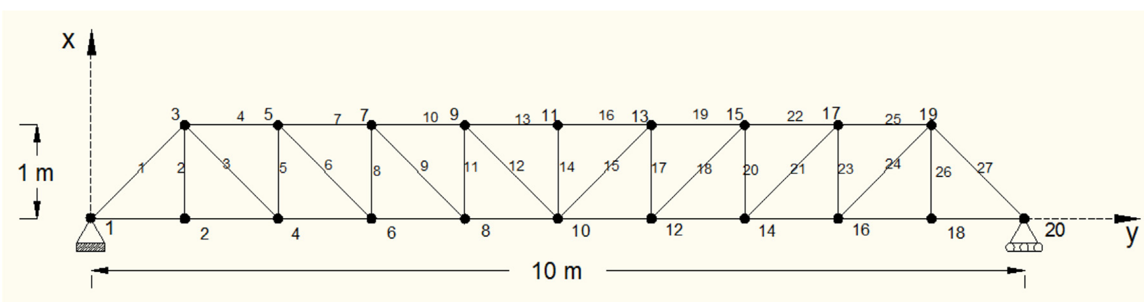


Fig. 6. A 37-bar simply supported truss bridge.

Table 4
Different damage cases for the 37-bar simply supported truss bridge together with identified damages by CPA.

Case 1				Case 2				Case 3			
Element number	Induced damage percentage	Identified damage		Element number	Induced damage percentage	Identified damage		Element number	Induced damage percentage	Identified damage	
		Best	Mean			Best	Mean			Best	Mean
4	50	50.00	50.02	8	15	15.00	15.00	3	10	10.00	9.86
16	50	50.00	50.02	17	30	30.00	30.00	14	55	54.99	55.32
23	5	4.99	5.01	22	5	5.00	5.00	17	5	5.02	3.25
–	–			36	70	70.00	70.00	26	65	65.00	64.92
–	–			–	–			35	40	40.00	39.82

$N_a = 32$, $N_c = 4$, $F_r = 0.4$, $\alpha_1 = 1$ and $\alpha_2 = 2$. A linear function increasing from 0 to 1 is considered for P_f.

4.1. A 20-element clamped-clamped beam

A clamped-clamped beam as shown in Fig. 2 is considered as the first numerical example. The length, height and width of the beam are 2m, 0.15m, and 0.15m, respectively. The beam is divided into 20 equal elements as shown in the figure. The modulus of elasticity and mass density are 68.9 GPa and 2770 kg/m^3, respectively. Three different damage cases as summarized in Table 2 are considered.

The values of MSEBI for the members of the structure in the different damage cases are depicted in Fig. 4. Comparisons presented in Table 2 and Fig. 4 reveal that MSEBI values for the severely damaged elements are positive and relatively high, while they might be negative for slightly damaged elements. In order to compare the performance of CPA with othermeta-heuristic optimization methods this example is also solved with PSO [34], RO [40], and FA [39]. The results are shown in Fig. 5. In order to make more details visible, only the damaged elements are depicted in Figs. 5.b, 5.d, and 5.f. Each damage case is solved 10 times independently in order to

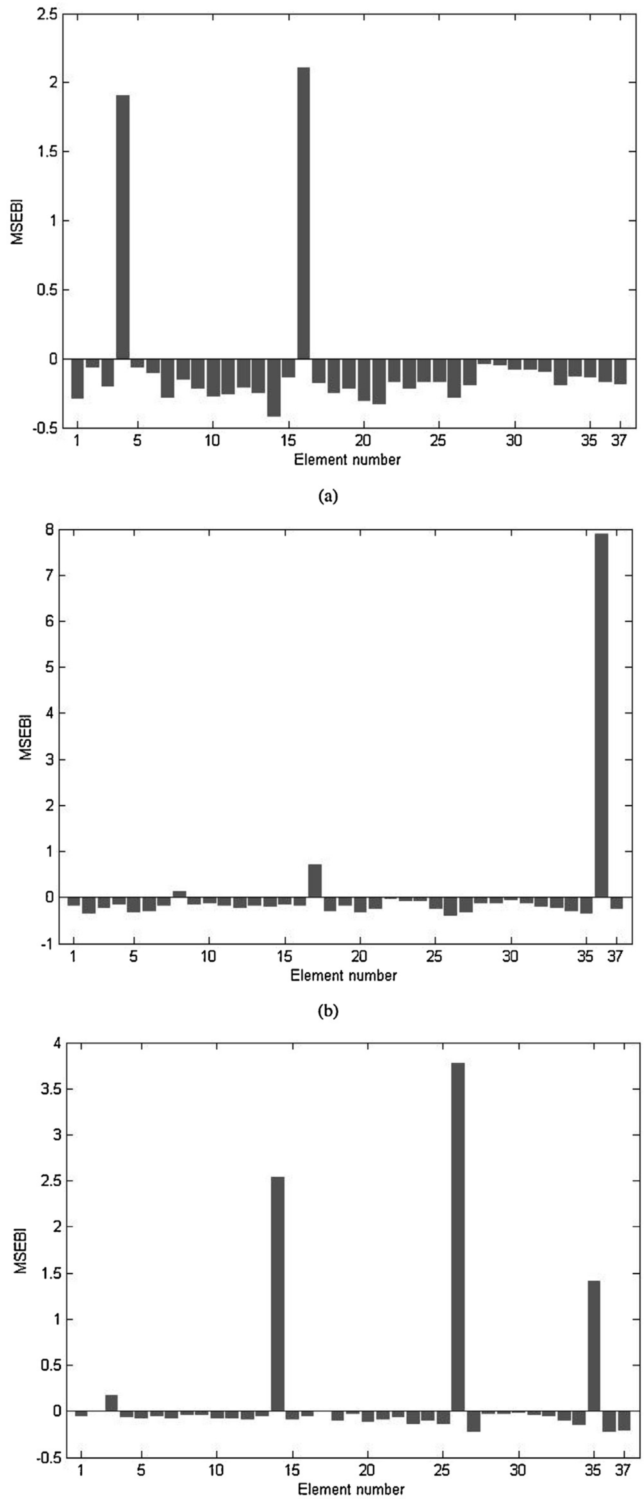
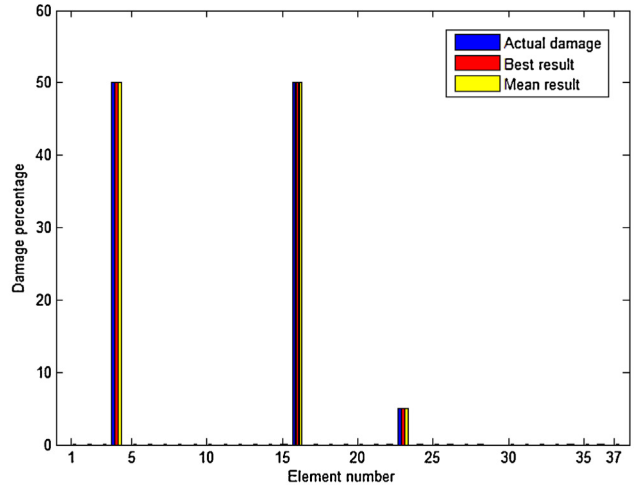
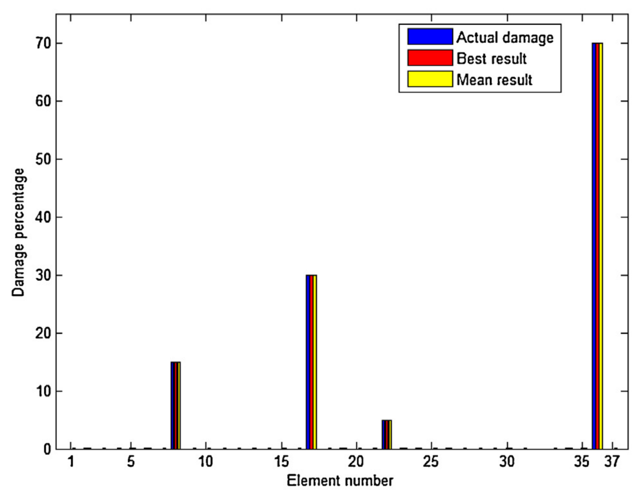


Fig. 7. MSEBI values for the 37-bar simply supported truss bridge a) Case 1, b) Case 2, c) Case 3.

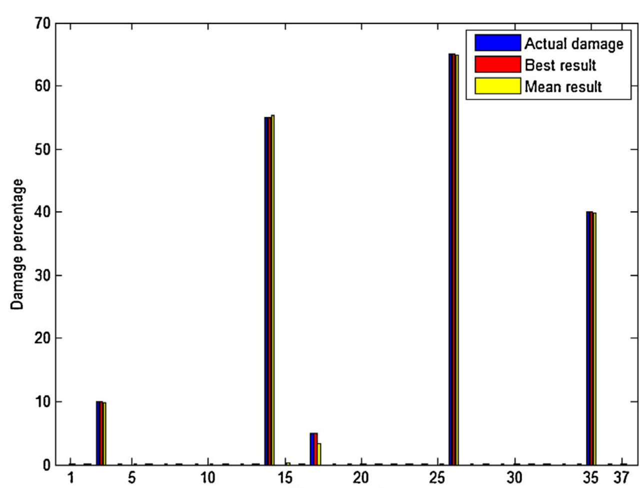
account for the probabilistic nature ofmeta-heuristic algorithms, and the mean results are also included. The best result corresponds to the smallest value of the objective function, while the mean result shows the average of the identified damage extents in an element in all runs. It can be seen that the problem at hand is a challenging one and competent optimization methods should be used to address it. It can be seen from the table that as the number of damaged elements increases the damage scenario gets more complex and the efficiency of CPA in finding the location and extent of damage becomes more evident. In Cases 1 and 2 where the number of damaged elements are smaller, all algorithms can identify the members with larger damage extents with acceptable approximation. However, in case 3 the damage extents found by PSO and RO are relatively less accurate in these elements compared to those of



(a)



(b)



(c)

Fig. 8. Performance of the proposed method on the 37-bar simply supported truss bridge a) Case 1, b) Case 2, c) Case 3.

FA and CPA. It should be noted that, for slightly damaged elements the difference is even more visible. These elements are difficult to find for PSO and RO even in cases 1 and 2. CPA and FA obtain the best results in all cases with small differences. It can be seen that the mean performance of FA is better than CPA in case 1, while CPA performs better in cases 2 and 3. The damage extents found in the damaged elements by the four algorithms are summarized in Table 3.

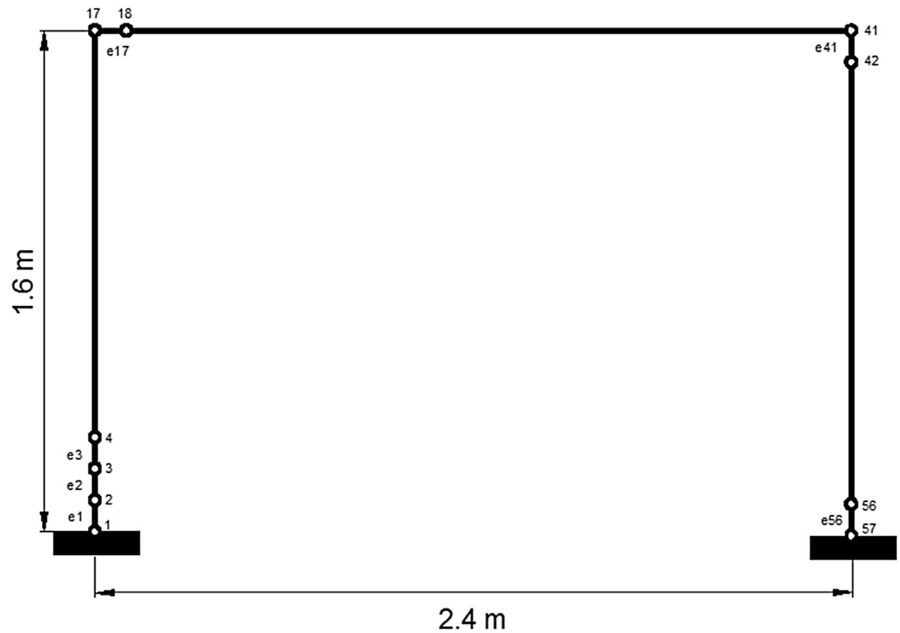


Fig. 9. A 56-element concrete portal frame.

Table 5
Different damage cases for the 56-element concrete portal frame together with identified damages by CPA.

Case 1				Case 2				Case 3			
Element number	Induced damage percentage	Identified damage		Element number	Induced damage percentage	Identified damage		Element number	Induced damage percentage	Identified damage	
		Best	Mean			Best	Mean			Best	Mean
15	45	44.91	44.99	7	45	44.97	44.81	4	55	55.00	54.97
38	70	69.87	69.93	21	5	4.88	4.67	16	25	25.02	24.95
49	5	4.06	1.52	34	65	64.97	64.83	39	5	4.95	4.20
–	–	–	–	–	–	–	–	54	65	65.01	64.95

4.2. A 37-bar simply supported truss bridge

A 37-bar simply supported truss bridge as shown in Fig. 6 is considered as the second numerical example. All of the members are assumed to be rectangular bars with 0.01 m^2 cross-sectional area. The modulus of elasticity and mass density are 210 GPa and 7800 kg/m^3, respectively. Induced damage scenarios for this example are listed in Table 4. Fig. 7 depicts the values of MSEBI for all cases.

Negative MSEBI values for damaged elements could again be observed in Fig. 7. Damage locations and extents found by the proposed method are provided in Fig. 8 and Table 4. It can be seen that the proposed method was capable of finding different damage cases with acceptable precision. It can also be seen than the extent of damage predicted by the algorithm for the undamaged members are negligible. It can be seen that the severity of damage is more accurately detected in elements with large damage extents. In the best run the proposed method detects the location and extent of damages almost accurately, while the mean performance shows some difference especially in case 3. This is predictable and could be attributed to the random nature ofmeta-heuristic algorithms.

4.3. A 56-element concrete portal frame

For the last numerical example a concrete portal frame is considered [54]. Fig. 9 shows the finite element model for this structure, where for the sake of clarity not all nodes and members are shown. The cross-section of the beam is assumed to be rectangular with constant width and height of 0.14 m and 0.24m, respectively. The modulus of elasticity and mass density are 25 GPa and 2500 kg/m^3, respectively. Two-dimensional frame elements with 3° of freedom at each node are used to model the structure. Three different damage cases as shown in Table 5 are considered for this example.

Fig. 10 shows the MSEBI values for all elements in different damage cases. Again, it can be seen that slightly damaged elements might have negative MSEBI values. These elements could be neglected in a two-stage damage detection method, which only considers elements with positive MSEBI values. However, in the proposed method these elements can still be detected since the size of the search space is decreased in a probabilistic manner and no element is left out. Locations and extents of damages found by the proposed method are depicted in Fig. 11. It can be seen that the method has successfully found the damage states with acceptable precision. Largely damaged elements and their damage extents are identified very accurately by the proposed method both in the best and the mean performance in all cases. In case of the slightly damaged elements the method is still capable of finding the location and severity in the best run. However, as it is expected, the mean performance shows some differences due to the probabilistic nature ofmeta-heuristic algorithms.

5. Concluding remarks

In this paper, a recent nature-inspired population-basedmeta-heuristic algorithm namely Cyclical Parthenogenesis Algorithm

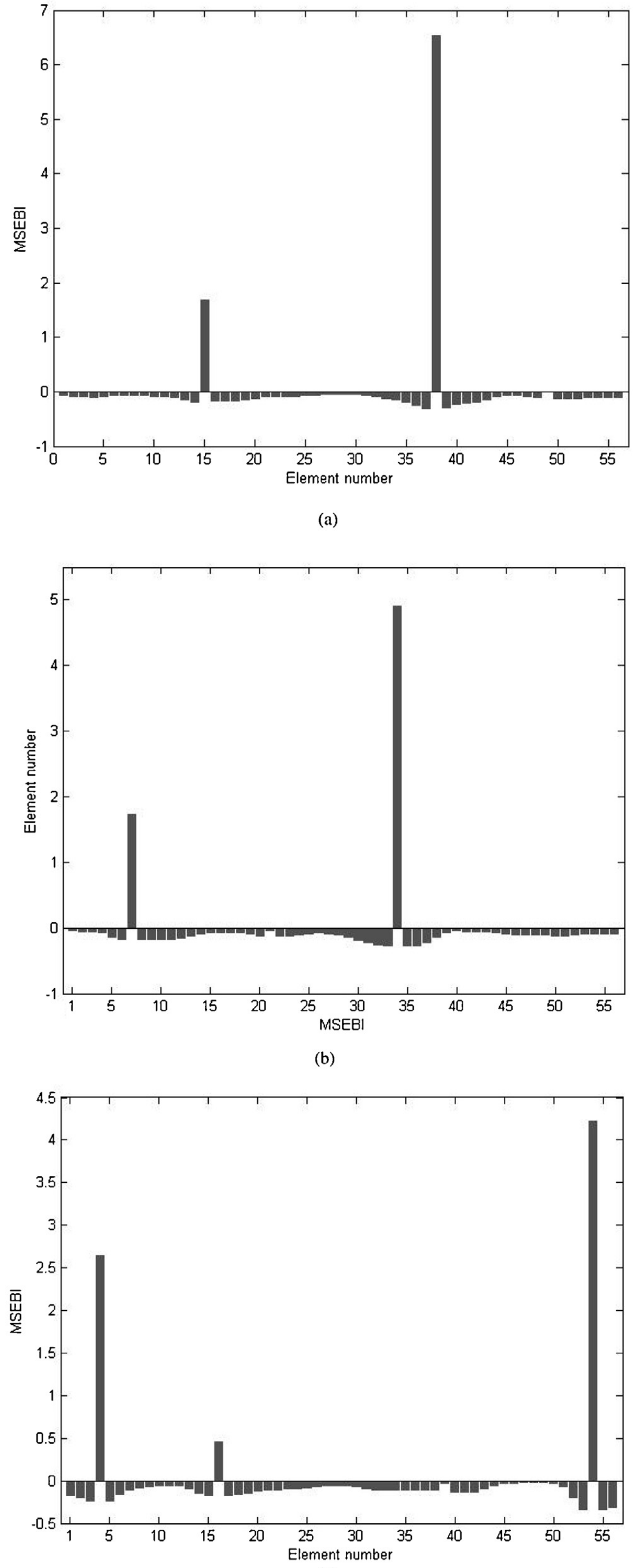


Fig. 10. MSEBI values for the 56-element concrete portal frame a) Case 1, b) Case 2, c) Case 3.

(CPA) is incorporated into a guided modal strain energy based structural damage identification method. The method uses a localized index in order to guide the search process in a structural damage detection procedure, which is formulated as an inverse optimization problem. A damage sensitive objective function based on the generalized flexibility matrix of the structure is utilized.

The proposed method uses a modal strain energy based index in order to divide the members of the structure into two groups and

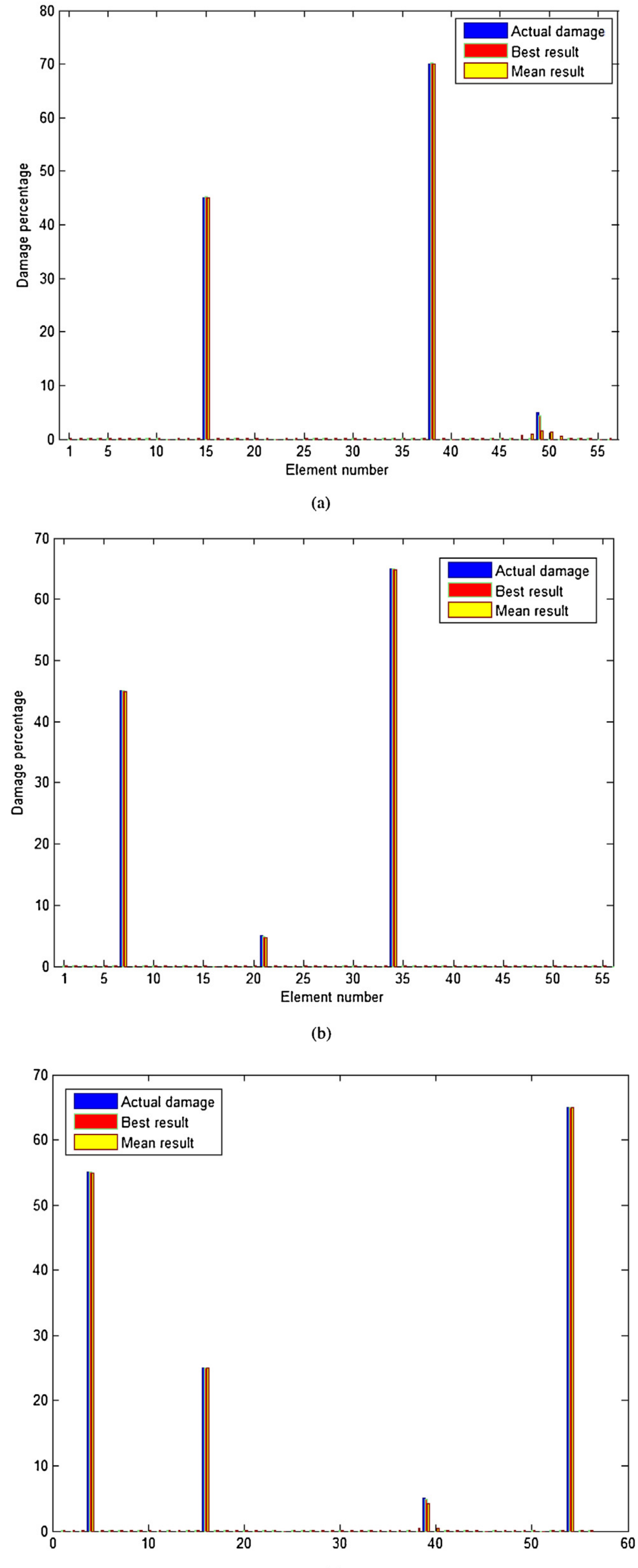


Fig. 11. Performance of the proposed method on the 56-element concrete portal frame a) Case 1, b) Case 2, c) Case 3.

probabilistically reduce the size of the optimization problem. As shown using the numerical examples, this helps the algorithm solve damage detection of large structural systems using only the first few modes. Moreover, identification of slightly damaged elements, which is not possible in two stage damage detection methods, could easily be carried out using the proposed method. Three numerical examples are presented in order to examine the applicability of the proposed method.

The performance of CPA is compared with three othermeta-heuristic algorithms, namely PSO, RO, and FA, in the first numerical example in order to clarify the efficiency of CPA. The mean and best performances of these algorithms are compared on three different damage scenarios. It can be seen that as the number of damaged elements increases the damage scenario becomes more involved and the difference between the performances of CPA and FA compared to PSO and RO becomes more evident. For slightly damaged elements PSO and RO have problems finding the extent of damage even in simpler cases.

In order to further investigate the performance of CPA, two additional numerical examples are also studied. The results indicate that the proposed method manages to identify the location and extent of multiple damaged members in beams, trusses, and frames.

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