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Structural Damage Identification Using a Multi-stage Gravitational Search Algorithm

Saeed Fallahian,[a] Seyed Mohammad Seyedpoor,[a,*] Eshagh Norouzi,[a] Sara Ghasemi[a]

[a] *Department of Civil Engineering, Shomal University, Amol, Iran*

ABSTRACT

A multi-stage gravitational search algorithm (MSGSA) is proposed here to solve the optimization-based damage detection of structural systems. Natural frequency changes of a structure are considered as a criterion for damage occurrence. Finite element method and structural dynamic principles are also employed to evaluate the required natural frequencies. The structural damage detection problem is first transformed into a standard optimization problem dealing with continuous variables, and then the MSGSA is utilized to solve the optimization problem for finding the site and severity of damage. In order to assess the performance of the proposed method for damage identification, an example with experimental data and two numerical examples with considering measurement noise are considered. All the results demonstrate the effectiveness of the proposed method for accurately determining the site and extent of multiple structural damage. Also, the performance of the MSGSA for damage detection compared to the standard gravitational search algorithm (GSA) is confirmed by examples.

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1. Introduction

Many structural systems may experience some local damage during their functional age. As the local damage is accurately detected and then rehabilitated within an appropriate time span, it will lead to increasing the total age of the system. Moreover, neglecting the local damage may cause to reduce the functional age of structural systems or even an overall failure of the structures. As a result, health monitoring and structural damage identification is a vital topic that has drawn wide attention from various engineering fields such as civil, mechanical, and aerospace engineering. The theoretical basis of damage detection lies in the fact that responses of a structure vary because of its inherent damage. This gives rise to the possibility of identifying the damage from the variation of structural responses before and after damage occurs. In particular, the damage detection formulates the relationship between the damage and modal parameter changes of a structure. A common practice is to obtain the fingerprint or baseline of modal parameters when a structure is in perfect health. Later, when the changes of these parameters occur, it is

* Corresponding author. Tel.: +981144203726; e-mail: s.m.seyedpour@shomal.ac.ir.

possible to investigate the structural damage which brings about the changes. During the last decades, many approaches have been introduced to determine the location and extent of eventual damage in the structural systems. One type of the methods employs the optimization algorithms for solving the damage detection problem.

Many successful applications of damage detection using an optimization algorithm have been reported in the literature. Mares and Surace used the genetic algorithm (GA) to maximize an objective function in order to identify macroscopic structural damage in elastic structures from measured natural frequencies and mode shapes [1]. A procedure for detecting the damage in beam-type structure based on a micro genetic algorithm using incomplete and noisy modal test data was proposed by Au et al. [2]. An application of GA for determining the damage site and extent of flexible bridge maximizing a correlation coefficient, named the multiple damage location assurance criterion (MDLAC) has been proposed by Koh and Dyke [3]. A fault diagnosis method in beam-like structures based on binary and continuous genetic algorithms and a model of the damaged structure has been proposed by Vakil-Baghmisheh et al. [4]. A two-stage method of determining the location and extent of multiple-beam-type structure damage by using the information fusion technique and micro-search genetic algorithm (MSGA) has been presented by Guo and Li [5]. Structural damage detection using an efficient correlation-based index (ECBI) and a modified genetic algorithm (MGA) has been introduced by Nobahari and Seyedpoor [6]. A self-adaptive multi-chromosome genetic algorithm (SAMGA) for localizing and quantifying the damage of truss structures was presented by Villalba and Laier [7]. An application of the bee algorithm (BA) to the problem of crack detection in beams was introduced by Moradi et al. [8]. A hybrid particle swarm optimization–simplex algorithm (PSOS) for structural damage identification using frequency domain data has been proposed by Begambre and Laier [9]. In order to find the location and extent of structural damage, a multi-stage particle swarm optimization (MSPSO) assuming a discrete nature for damage variables has been introduced by Seyedpoor [10]. Nouri Shirazi et al. used the modified particle swarm optimization (MPSO) to minimize an objective function (ECBI) in order to identify structural damage from changes of natural frequencies [11]. A mixed particle swarm-ray optimization together with harmony search (HRPSO) for localizing and quantifying the structural damage was presented by Kaveh et al. [12]. The differential evolution algorithm (DEA) for structural damage identification using natural frequencies has been proposed by Seyedpoor et al. [13]. The ant colony optimization (ACO) for structural damage identification has been proposed by Braunet al. [14]. An improved hybrid Pincus-Nelder-Mead optimization algorithm (IP-NMA) for structural damage identification using natural frequencies has been proposed by Nhamage et al. [15]. However, the performance of gravitational search algorithm (GSA) and its other versions for solving the damage detection problem have not been assessed seriously.

In this study, a multi-stage gravitational search algorithm (MSGSA) is introduced to identify multiple structural damage. For this, the problem of structural damage detection is first transformed into the standard form of an optimization problem dealing with real damage variables. The MSGSA is utilized as an optimization solver for finding the site and severity of damaged elements. Three illustrative test examples are considered to show the performance of the proposed method. The results show that the MSGSA can provide a robust tool for determining the site and extent of multiple damage precisely and quickly.

2. Optimization Based Damage Detection Method

Structural damage detection using non-destructive methods has received significant attention during the last years. The fundamental law is that damage will change the mass, stiffness, and damping properties of a structure. Such a change would lead to changes in the response data of the structure. This rule enables us to identify the damage by comparing the response data of the structure before and after damage. The damage detection problem can be interpreted to find a set of damage variables minimizing or maximizing a correlation index between response data of a structure before and after damage [1, 3-8, 10, 11, 13, 14]. Therefore, the problem can be transformed into an optimization problem as:

$$\begin{aligned} &\text{Find: } X^T = \{x_1, x_2, \dots, x_n\} \\ &\text{Minimize: } Obj\ (X) \\ &\text{Subject to: } X^l \le X \le X^u \end{aligned} \tag{1}$$

where $X^T = \{x_1, x_2, \dots, x_n\}$ is a damage variable vector containing the location and size of n unknown damages; X^l and X^u are the lower and upper bounds of the damage vector and $Obj\ (X)$ is an objective function that need to be minimized.

In many researches, various correlation indices were chosen as the objective function. In this study, an efficient correlation-based index (*ECBI*) introduced in [6] is used as the objective function for the optimization given by:

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

In the objective function, ΔF is the change of frequency vector of damaged structure with respect to the frequency vector of healthy structure. The ΔF can be defined as:

$$\Delta F = \left\{ \Delta f_i = \frac{f_{hi} - f_{di}}{f_{hi}} \right\}, i = 1,2,\ldots,n_f \quad (3)$$

where f_{hi} and f_{di} are the i_{th} component of healthy frequency vector F_h and damaged frequency vector F_d of the structure, respectively. The number of total frequencies considered for damage detection is denoted by n_f.

Also, $\delta F(X)$ is the change of frequency vector of an analytical model with respect to the frequency vector of healthy structure. The $\delta F(X)$ can be defined as:

$$\delta F(X) = \left\{ \Delta f_i(X) = \frac{f_{hi} - f_i(X)}{f_{hi}} \right\}, \ i = 1,2,\ldots,n_f \quad (4)$$

where $f_i(X)$ is the ith component of an analytical frequency vector $F(X)$ of the structure.

The *ECBI* varies from a minimum value −1 to a maximum value 0. It will be minimal when the vector of analytical frequencies becomes identical to the frequency vector of the damaged structure, that is, $F(X)= Fd$.

In this study, the damage variables for truss and frame structures are defined via a relative reduction of elasticity modulus of an element as:

$$x_i = \frac{E - E_i}{E}, \quad i = 1,2,\ldots,n \quad (5)$$

where E is the original modulus of elasticity and E_i is the final modulus of elasticity of ith element.

By solving the Eq. (1) using an optimization algorithm the damage variables can be determined. A non-zero value for the variable x_i represents that the ith element of the structure is damaged while a zero value denotes that the element is healthy.

3. The Proposed Optimization Algorithm

The selection of an efficient algorithm for solving the damage optimization problem is a critical issue, because the damage identification problem has many local solutions. In this study, a multi-stage gravitational search algorithm (MSGSA) is proposed to properly solve the damage detection problem. In the remaining part of this section, the original gravitational search algorithm (GSA) is briefly described at first and then the proposed MSGSA is discussed.

3.1. Gravitational Search Algorithm (GSA)

Gravitational search algorithm was introduced by Rashedi et al. [17] in 2009 to solve optimization problems. The population-based heuristic algorithm is based on the law of gravity and mass interactions. The algorithm is comprised of collection of searcher agents that interact with each other through the gravity force. The agents are considered as objects and their performance is measured by their masses. The gravity force causes a global movement where all objects move towards other objects with heavier masses. The agents are actually obeying the law of gravity as shown in Eq. (6) and the law of motion in Eq. (7).

$$F = G\left(\frac{M_1 M_2}{R^2}\right) \quad (6)$$

$$a = \frac{F}{M} \quad (7)$$

where F represents the magnitude of the gravitational force, G is gravitational constant, $M1$ and $M2$ are the mass of the first and second objects and R is the distance between the two objects. Eq. (6) shows that in the Newton law of gravity, the gravitational force between two objects is directly proportional to the product of their masses and inversely proportional to the square of the distance between the objects. Moreover, in Eq. (7), Newton's second law shows that when a force, F, is applied to an object, its acceleration, a, depends on the force and its mass, M.

In GSA, an agent has two parameters which are position and mass. The position of the agent represents the solution of the problem, while the mass of the agent is determined using a fitness function. Agents are attracted by the heaviest agent. Hence, the heaviest agent presents an optimum solution in the search space. The steps of GSA can be summarized as follows [17-19]:

Step 1) Agents initialization

The positions of the N number of agents are initialized randomly.

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n), \quad i = 1,2,\ldots,N \quad (8)$$

where x_i^d represents the positions of the ith agent in the dth dimension, while n is the dimension of the problem.

Step 2) Fitness evolution and best fitness computation

For minimization problems, the fitness evolution is performed by evaluating the best and worst fitness of all agents at each iteration.

$$best(t) = \min fit_j(t) \quad , \quad j \epsilon \{1,2,\ldots,N\} \quad (9)$$

$$worst(t) = \max fit_j(t) \quad , \quad j \epsilon \{1,2,\ldots,N\} \quad (10)$$

where $fit_j(t)$ represents the fitness value of the jth agent at iteration t, $best(t)$ and $worst(t)$ represents the best and worst fitness at iteration t.

Step 3) Gravitational constant computation

In the algorithm, gravitational constant G is reduced with iteration to control the search accuracy and it is computed at iteration t as [18, 19]:

$$G(t) = G_0 . e^{\left(-\frac{\alpha t}{T}\right)} \tag{11}$$

where $G_0 = 100$ and $\alpha = 20$ are initialized at the beginning of the algorithm [19]. Also, T is the total number of iterations.

Step 4) Calculation of masses of the agents

Mass for each agent is calculated at iteration t as:

$$M_i(t) = \frac{m_i(t)}{\sum_{i=1}^{N} m_i(t)} \tag{12}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{13}$$

where $m_i(t)$ represents the compatibility of the *ith* agent at iteration t and $M_i(t)$ the mass of the *ith* agent at iteration t.

Step 5) Calculation of accelerations of agents

Acceleration of the *ith* agent at iteration t is computed using Eq. (14):

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{14}$$

where $F_i^d(t)$ is the total force acting on *ith* agent calculated as:

$$F_i^d(t) = \sum_{j \epsilon Kbest, j \neq i} \text{rand}_j . F_{ij}^d(t) \tag{15}$$

in which, *Kbest* is the set of first K agents with the best fitness value and biggest mass. *Kbest* will decrease linearly with iteration and at the end there will be only one agent applying force to the others. Also, $F_{ij}^d(t)$ is computed using Eq. (16):

$$F_{ij}^d(t) = G(t). \frac{M_i(t). M_j(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{16}$$

where $F_{ij}^d(t)$) is the force acting on agent i from agent j at dth dimension and tth iteration, $R_{ij}(t)$ is the Euclidian distance between two agents i and j at iteration t, $G(t)$ is the computed gravitational constant at the same iteration while ε is a small constant.

Step 6) Updating velocity and positions of agents:

Velocity and the position of the agents at next iteration *(t+1)* are computed based on the following equations:

$$v_i^d(t+1) = \text{rand}_i \, v_i^d(t) + a_i^d(t) \tag{17}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{18}$$

where $V_i(t+1)$ represents the velocity of the ith agent at iteration $t+1$ and $X_i(t+1)$ indicates the mass of the ith agent at iteration $t+1$.

Step 7) Check the convergence

Steps 2 to 6 are repeated until the stop criteria are met. The best fitness value at the final iteration is considered as the global fitness while the position of the corresponding agent at specified dimensions is taken as the global solution of the problem. The flowchart of GSA can be simply shown in Fig. 1.

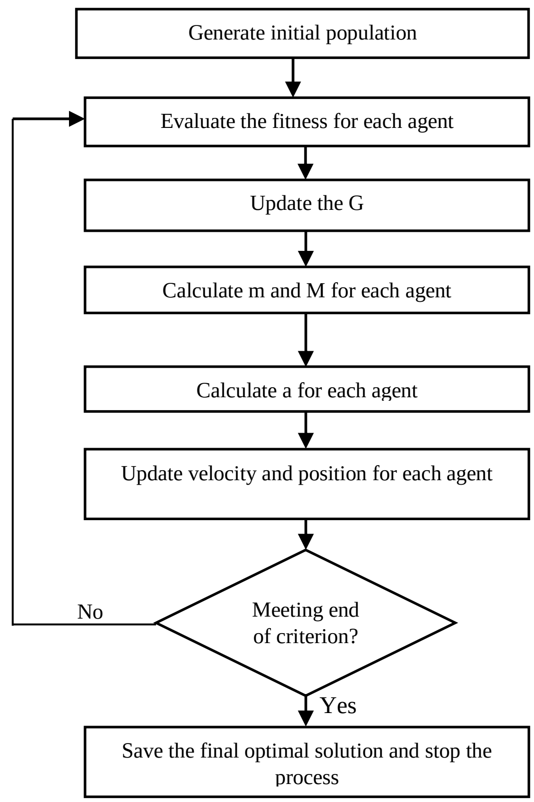

Figure 1. The flowchart of GSA

3.2. The multi-stage gravitational search algorithm (MSGSA)

A multi-stage gravitational search algorithm (MSGSA) is proposed here to accurately detect the multiple structural damages. Based on this algorithm, the location of damaged elements of a structure found in each optimization stage is imposed on the next optimization stage while the effects of healthy elements on the subsequent stage are neglected. By this approach, all healthy elements are successively eliminated during some stages and the algorithm converges to the correct locations and extents of flawed elements. During the optimization stages, the dimension of optimization problem are decreased gradually and this makes the time and total computational cost of the optimization reduce. The step by step summary of the multi-stage gravitational search algorithm (MSGSA) is as follows:

Step 1) Set the initial number of damage variables, n to the total number of structural elements. Randomly generate the initial position vectors of agents distributed throughout the design space bounded by the specific limits: $X^l \leq X_i \leq X^u$, $i = 1, \dots, N$.

Step 2) Employ the standard GSA to find the optimal solution, $X_{GSA}^T = \{x^1, x^2, \dots, x^n\}$

Step 3) Find the locations of healthy elements, that is, for all components of damage vector X_{GSA} find i: $x^i = 0$, and also determine the total number of healthy elements, m.

Step 4) Remove the healthy elements from the set of damage variables and reduce the dimension of optimization problem from n to *n-m*.

Step 5) Employ a new GSA stage to find the optimal solution of current stage, i.e. $X_{GSA}^T = \{x^1, x^2, \dots, x^{n-m}\}$.

Step 6) Check the convergence by comparing the optimal solutions of two sequential optimization stages. If two vectors are identical go to step 7, otherwise go to step 3.

Step 7) Save the final optimal solution and stop the optimization process. According to steps 1 to 7, the flowchart of the MSGSA can be simply shown in Fig. 2.

4. Test examples

In order to demonstrate the capabilities of the proposed approach for identifying the damage, three illustrative test examples selected from the literature are considered. The first example is a 16-element cantilevered beam with experimental data, the second example is a 47-bar planar truss and the last example is a 45-element frame (A five-story and four-span frame). In 47-bar planar truss and 45-element frame, the effect of measurement noise on the efficiency of the method is studied.

4.1. Sixteen-element cantilevered beam with experimental data

The proposed method is validated using experimental data obtained from test on the 16-element cantilevered beam by Sinha et al [16]. Table 1 gives details of the geometric and material properties of the beam. The modal test was conducted by Sinha et al. on the beam without any crack and also with a single crack at 275mm (element 5) with the crack depths 8 mm (damage extent 0.32) and 12 mm (damage extent 0.48). Table 2 gives the identified experimental natural frequencies.

A finite element model of the cantilever beam was constructed using Euler-Bernoulli beam elements including translational and rotational springs to simulate the boundary conditions at the clamped end of the beam. The finite element model, shown schematically in Fig. 3 has 16 elements and 34 degrees of freedom. The boundary stiffnesses, $k_t = 26.5\ MN/m$ and $k_\theta = 150\ kN.m/rad$, are required to simulate the translation and rotation flexibility of the clamped support [16].

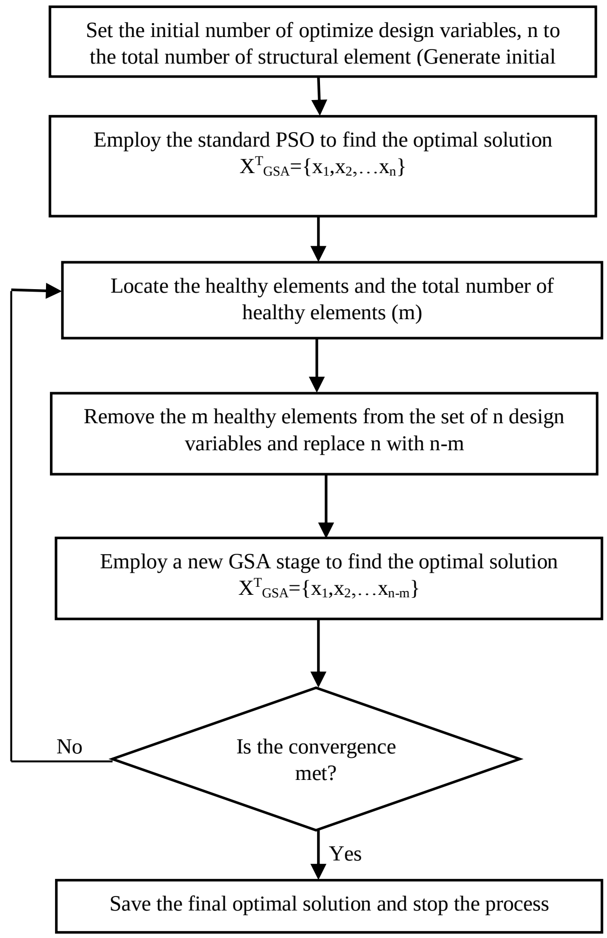

Figure 2. The flowchart of the MSGSA

For this example, two damage scenarios of experimental test [16], listed in Table 3, are studied and the first four natural frequencies are used for damage detection.

Table 1.
The properties of 16-element cantilevered beam

Boundary conditions	Cantilever
Material	Aluminum
Young's modulus (*E*)	69.79 GN/m^2
Mass density (*ρ*)	2600 kg/m^2
The Poisson Ratio (*ν*)	0.33
Beam length (*L*)	996 mm
Beam width (*w*)	50 mm
Beam depth (*d*)	25 mm
Boundary stiffnensses	$k_t = 26.5\ MN/m^2$ $k_\theta = 150\ kN.m/rad$

Table 2.
The natural frequencies of the beam without any crack and with one crack [16]

Mode	No crack	d_{c1}=8 mm x_1=275 mm	d_{c1}=12 mm x_1=275 mm
	Experimental natural frequencies (Hz)	Experimental natural frequencies (Hz)	Experimental natural frequencies (Hz)
1	20	19.75	19
2	124.5	124.063	123
3	342.188	336.875	326.563
4	664.375	662.313	660.313

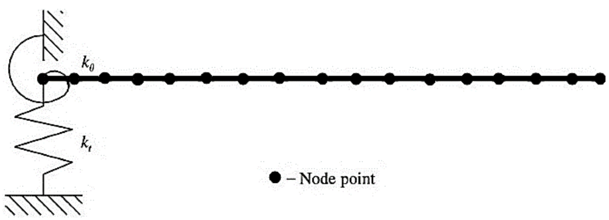

Figure 3. The finite element model for the 16-element cantilevered beam

Table 3.
Two different experimental damage scenarios induced in a 16-element beam

Scenario 1		Scenario 2	
Element number	Damage extent	Element number	Damage extent
5	0.32	5	0.48

The specifications of standard GSA and the proposed MSGSA for applying to the damage detection problem are also given in Table 4.

Table 4.
The specifications of GSA and MSGSA

Algorithm	Parameter	Description	Value
GSA	npop	The number of agents	50
	maxiter	The maximum number of iterations	1000
	G_0	The primal value of the gravitational constant	100
	α	The exponent coefficient of gravitational constant equation	20
MSGSA	npop	The number of GSA agents	40
	maxiter	The maximum iterations performing by GSA	100
	max_stage	The maximum number of optimization stages	2

The convergence of the GSA is met when the objective function does not considerably change after 150 successive iterations or the maximum number of iterations is attained. Also, the convergence of the MSGSA is met when the all optimization stages are attained. The reason why the convergence conditions are different in two algorithms is that each of the algorithms has been considered in the best possible conditions to achieve a completely correct answer with the most minimal number of analyses. In order to consider the stochastic nature of the optimization process using two algorithms, 10 independent sample runs are made for each damage scenario. The damage identification results of damage scenario 1 using two algorithms are given in Tables 5a and 5b, respectively. The average damage ratios for scenario 1 using two algorithms are also shown in Figs. 4a and 4b, respectively. The damage identification results of damage scenario 2 are given in Tables 6a and 6b, respectively. The average damage ratios for scenario 2 are also shown in Figures 5a and 5b, respectively.

Table 5a.
The damage detection results of 16-element beam for scenario 1 via GSA

Run numbers	Element numbers 1	...	5	...	11	12	...	16	Required modal analyses	*ECBI*
1	0		0.338		0.086	0.04		0	23850	-0.978
2	0		0.338		0.086	0.04		0	25200	-0.978
3	0		0.338		0.086	0.04		0	24050	-0.978
4	0		0.338		0.086	0.04		0	24650	-0.978
5	0		0.338		0.086	0.04		0	22850	-0.978
6	0		0.338		0.086	0.04		0	23600	-0.978
7	0		0.338		0.086	0.04		0	23800	-0.978
8	0		0.338		0.086	0.04		0	24600	-0.978
9	0		0.338		0.086	0.04		0	25800	-0.978
10	0		0.338		0.086	0.04		0	26000	-0.978
Average	0		0.338		0.086	0.04		0	24440	-0.978
Actual damage	0		0.32		0	0		0	-	-1

Table 5b.
The damage detection results of 16-element beam for scenario 1 via MSGSA

Run numbers	Element numbers 1	...	5	...	11	12	...	16	Required modal analyses	*ECBI*
1	0		0.348		0.057	0.06		0	8080	-0.978
2	0		0.429		0.065	0.054		0	8080	-0.978
3	0		0.348		0.042	0.079		0	8080	-0.978
4	0		0.442		0.073	0.065		0	8080	-0.978
5	0		0.359		0.044	0.074		0	8080	-0.978
6	0		0.383		0.064	0.062		0	8080	-0.978
7	0		0.373		0.052	0.061		0	8080	-0.978
8	0		0.351		0.061	0.058		0	8080	-0.978
9	0		0.386		0.072	0.055		0	8080	-0.978
10	0		0.361		0.043	0.063		0	8080	-0.978
Average	0		0.376		0.057	0.063		0	8080	-0.978
Actual damage	0		0.32		0	0		0	-	-1

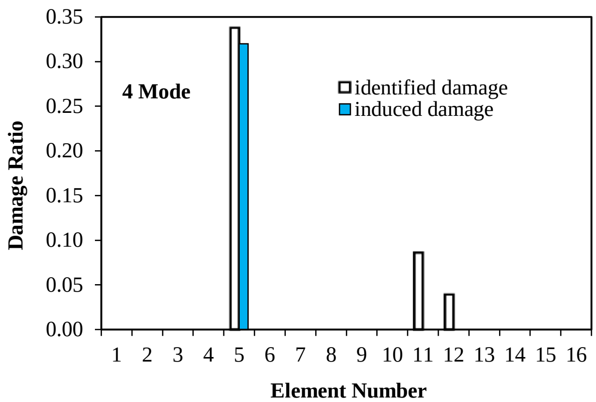

Figure 4a. Final damage ratios of the 16-element beam for scenario 1 via GSA

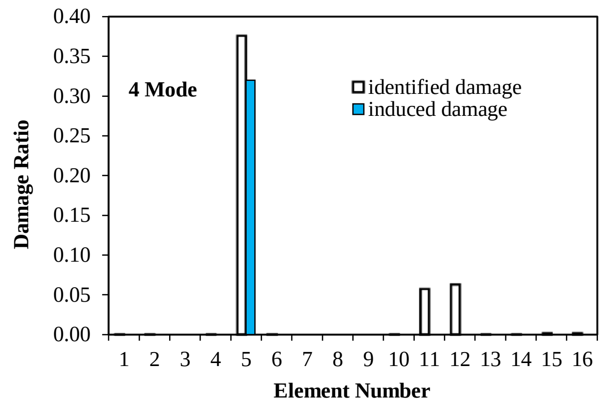

Figure 4b. Final damage ratios of the 16-element beam for scenario 1 via MSGSA

Table 6a.
The damage detection results of 16-element beam for scenario 2 via GSA

Run numbers	Element numbers 1	...	5	...	11	...	16	Required modal analyses	*ECBI*
1	0		0.431		0.062		0	22900	-0.992
2	0		0.431		0.062		0	23650	-0.992
3	0		0.431		0.062		0	24300	-0.992
4	0		0.431		0.062		0	25150	-0.992
5	0		0.431		0.062		0	22250	-0.992
6	0		0.431		0.062		0	23150	-0.992
7	0		0.431		0.062		0	22050	-0.992
8	0		0.431		0.062		0	26600	-0.992
9	0		0.431		0.062		0	24200	-0.992
10	0		0.431		0.062		0	24450	-0.992
Average	0		0.431		0.062		0	23470	-0.992
Actual damage	0		0.48		0		0	-	-1

Table 6b.
The damage detection results of 16-element beam for scenario 2 via MSGSA

Run numbers	Element numbers 1	...	5	...	11	...	16	Required modal analyses	*ECBI*
1	0		0.525		0.031		0	8080	-0.9945
2	0		0.525		0.038		0	8080	-0.9945
3	0		0.566		0.037		0	8080	-0.9946
4	0		0.53		0.038		0	8080	-0.9945
5	0		0.604		0.015		0	8080	-0.994
6	0		0.527		0.032		0	8080	-0.9944
7	0		0.561		0.036		0	8080	-0.9944
8	0		0.56		0.037		0	8080	-0.9946
9	0		0.556		0.048		0	8080	-0.9945
10	0		0.519		0.044		0	8080	-0.9946
Average	0		0.547		0.036		0	8080	-0.9945
Actual damage	0		0.48		0		0	-	-1

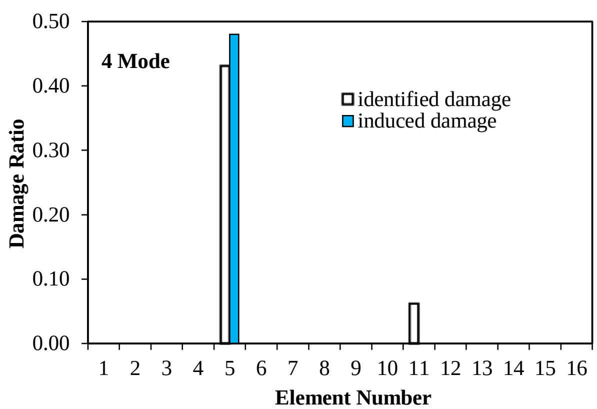

Figure 5a. Final damage ratios of the 16-element beam for scenario 2 via GSA

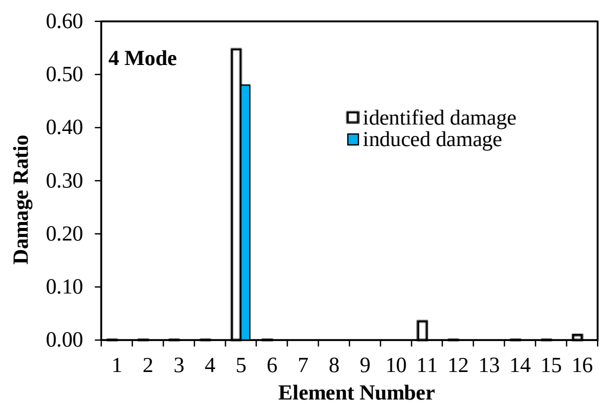

Figure 5b. Final damage ratios of the 16-element beam for scenario 2 via MSGSA

All of the results shown in the tables and figures demonstrate that the best solutions in terms of actual damage identification and the total number of finite element analyses (FEAs) required are obtained by the MSGSA. The average number of FEAs requiring for scenarios 1 and 2 of MSGSA are 8080, while the average number of FEAs needing for GSA is 23440 and 23470, respectively. It is revealed that the MSGSA has a better performance when compared to the GSA.

4.2. Forty-seven-bar planar truss

The 47-bar planar power line tower [11], shown in Fig. 6, is considered to show the robustness of the proposed method. The structure has 47 members and 22 nodes. The truss is modeled using the conventional finite element method without internal nodes, leading to 41 degrees of freedom. All members are made of steel, and the material density, modulus of elasticity and area of each element are 0.3 lb/in^3, 30000 ksi and 2 in^2, respectively. Damage in the structure is simulated as a relative reduction in the elasticity modulus of individual elements. Therefore, the optimization problem of damage identification has 47 damage variables. Four different damage scenarios, given in Table 7, are induced in the structure, and the MSGSA and the GSA are tested for each scenario. For identifying the damage scenarios 1 and 2, the first 10 natural frequencies and for identifying the damage scenarios 3 and 4, the first 15 natural frequencies of the structure are considered. In order to investigate the noise effect on the performance of the proposed method, measurement noise is considered here by polluting the natural frequencies using a standard error of ±0.15 % [3, 4, 11 and 12]. For identifying the damage scenarios 1 and 2, agent numbers and the maximum numbers of GSA iterations are set to 40 and 1000, respectively. Also, for identifying the damage scenarios 3 and 4, agent numbers and the maximum numbers of GSA iterations are set to 50 and 2000, respectively. For identifying the damage scenarios 1 and 2, agent numbers, the maximum numbers of MSGSA iterations and the maximum number of optimization stages are set to 25, 700 and 20, respectively. Also, for identifying the damage scenarios 3 and 4, agent numbers and the maximum numbers of MSGSA iterations and the maximum number of optimization stages are set to 20, 200 and 20, respectively.

The convergence of the GSA is met when the objective function reaches -0.995 or the maximum number of iterations is attained. For identifying the damage scenarios 1 and 2, the convergence of the MSGSA is met when the objective function reaches -0.967. Also, for identifying the damage scenarios 3 and 4, the convergence of the MSGSA is met when the objective function reaches -0.994. In order to consider the stochastic nature of the optimization process using GSA and MSGSA ten independent sample runs are made for each damage scenario. The solutions of GSA and MSGSA for damage scenarios 1 to 4 are given in Tables 8–15 and Figs. 7-14.

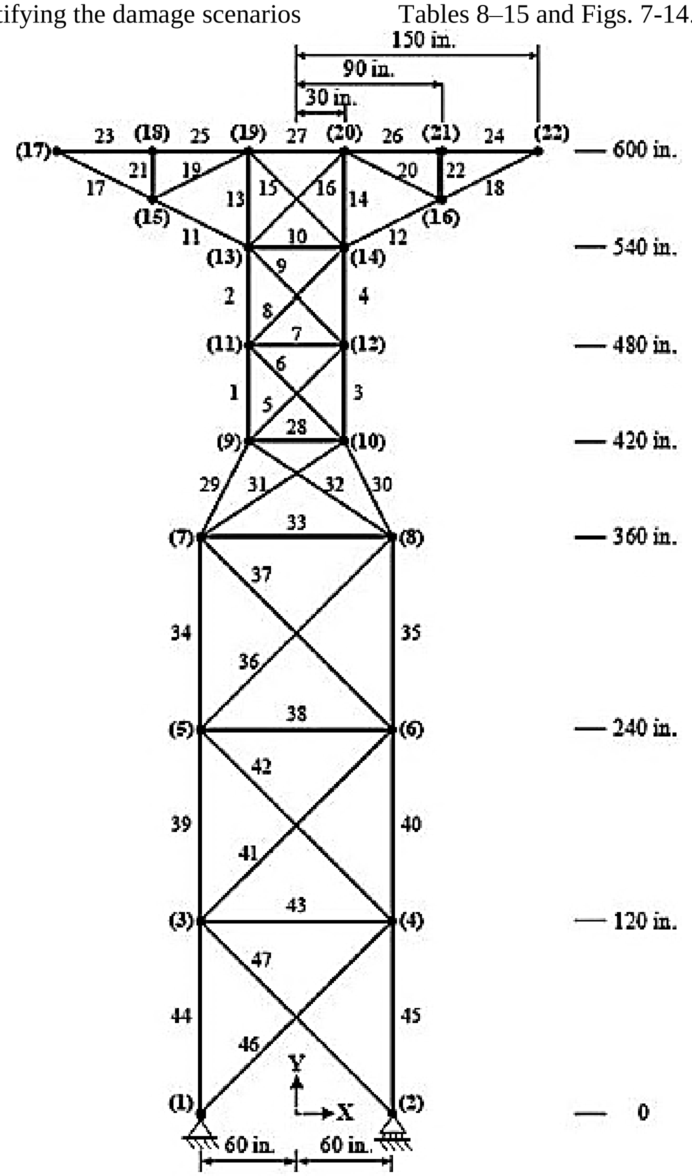

Figure 6. The finite element model for the 47-bar planar truss

Table 7.
Four different damage scenarios induced in 47-bar planar truss

Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Element number	Damage extent	Element number	Damage extent	Element number	Damage extent	Element number	Damage extent
10	0.30	30	0.30	10	0.30	40	0.30
-	-	-	-	30	0.30	41	0.20

Table 8.
The damage detection results of 47-bar planar truss for scenario 1 via GSA

Run numbers	Element numbers 1	...	10	...	47	Required modal analyses	*ECBI*
1	0		0.295		0	40040	-0.9858
2	0		0.158		0	40040	-0.9722
3	0.016		0.263		0	40040	-0.9681
4	0		0.204		0	40040	-0.9707
5	0		0.244		0	40040	-0.9733
6	0		0.252		0	40040	-0.9726
7	0.01		0.256		0	40040	-0.9647
8	0		0.185		0	40040	-0.9791
9	0		0.323		0	40040	-0.9858
10	0		0.14		0	40040	-0.9725
Average	0.0026		0.232		0	40040	-0.9749
Actual damage	0		0.3		0	-	-1

Table 9.
The damage detection results of 47-bar planar truss for scenario 1 via MSGSA

Run numbers	Element numbers 1	...	10	...	47	Required modal analyses	*ECBI*
1	0		0.284		0	17525	-0.9922
2	0		0.279		0	17525	-0.99
3	0		0.146		0	17525	-0.9821
4	0		0.108		0	17525	-0.9871
5	0		0.276		0	17525	-0.9909
6	0		0.267		0	17525	-0.9932
7	0		0.255		0	17525	-0.9725
8	0		0.116		0	17525	-0.974
9	0		0.136		0	17525	-0.9881
10	0		0.161		0	35050	-0.968
Average	0		0.203		0	19278	-0.9838
Actual damage	0		0.3		0	-	-1

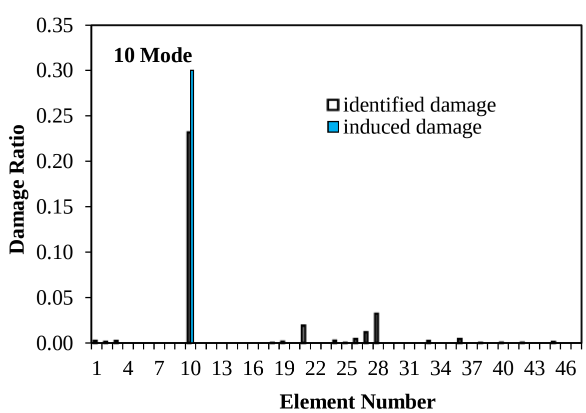

Figure 7. Final damage ratios of the 47-bar planar truss for scenario 1 via GSA

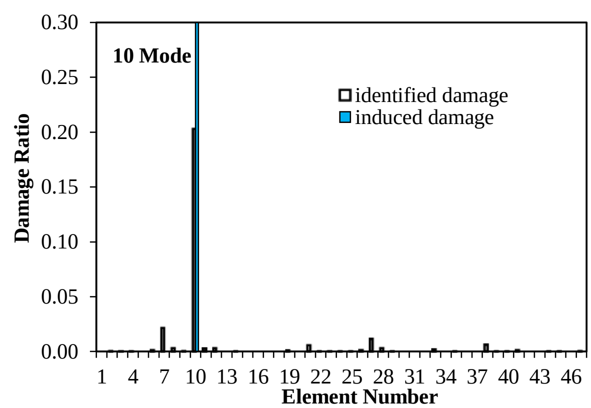

Figure 8. Final damage ratios of the 47-bar planar truss for scenario 1 via MSGSA

Table 10.
The damage detection results of 47-bar planar truss for scenario 2 via GSA

Run numbers	Element numbers 1	...	30	...	47	Required modal analyses	*ECBI*
1	0		0.28		0	40040	-0.9929
2	0.042		0.246		0	12160	-0.9951
3	0		0.304		0	5520	-0.9983
4	0		0.337		0	8128	-0.9955
5	0		0.323		0	8000	-0.9972
6	0.028		0.286		0	12840	-0.995
7	0.013		0.268		0	40040	-0.9948
8	0		0.273		0	40040	-0.9926
9	0		0.272		0	8720	-0.9954
10	0		0.278		0	10760	-0.9951
Average	0.008		0.287		0	18624	-0.9952
Actual damage	0		0.3		0	-	-1

Table 11.
The damage detection results of 47-bar planar truss for scenario 2 via MSGSA

Run numbers	Element numbers 1	...	30	...	47	Required modal analyses	*ECBI*
1	0		0.306		0	17525	-0.9955
2	0		0.299		0	17525	-0.9975
3	0.024		0.272		0	17525	-0.9965
4	0.033		0.171		0	17525	-0.9986
5	0.026		0.297		0	17525	-0.9965
6	0		0.289		0	17525	-0.995
7	0		0.272		0	17525	-0.9955
8	0		0.262		0	17525	-0.9957
9	0		0.181		0	17525	-0.998
10	0		0.261		0	17525	-0.9987
Average	0.008		0.261		0	17525	-0.9968
Actual damage	0		0.3		0	-	-1

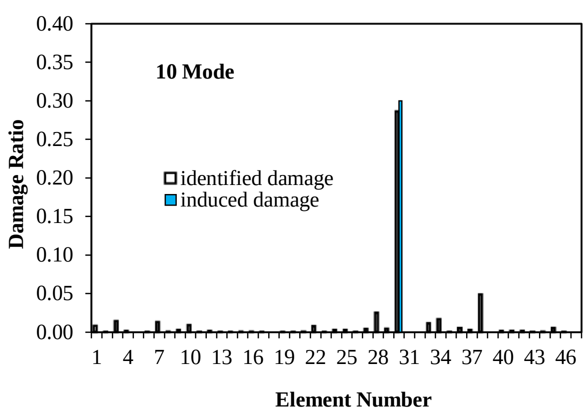

Figure 9. Final damage ratios of the 47-bar planar truss for scenario 2 via GSA

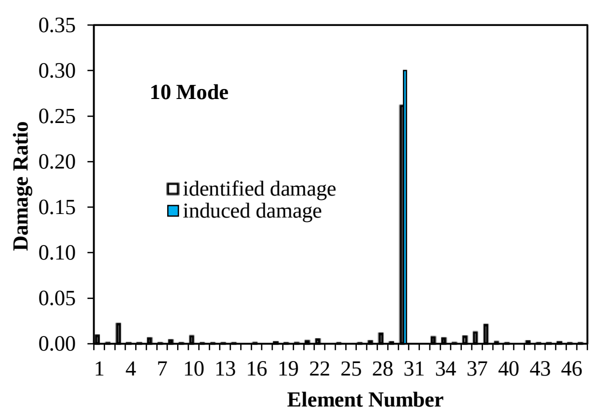

Figure 10. Final damage ratios of the 47-bar planar truss for scenario 2 via MSGSA

Table 12.
The damage detection results of 47-bar planar truss for scenario 3 via GSA

Run numbers	Element numbers: 1	...	10	...	30	...	47	Required modal analyses	*ECBI*
1	0		0.306		0.276		0	24700	-0.9955
2	0		0.32		0.323		0	24650	-0.9951
3	0.022		0.345		0.344		0	23350	-0.9954
4	0.043		0.317		0.334		0	24000	-0.9951
5	0.045		0.27		0.261		0	21750	-0.9955
6	0.011		0.307		0.316		0	25000	-0.9956
7	0		0.209		0.31		0	22100	-0.9951
8	0		0.35		0.288		0	22000	-0.9952
9	0.012		0.328		0.336		0	24700	-0.9954
10	0		0.35		0.332		0	24200	-0.9957
Average	0.014		0.31		0.312		0	23645	-0.9953
Actual damage	0		0.3		0.3		0	-	-1

Table 13.
The damage detection results of 47-bar planar truss for scenario 3 via MSGSA

Run numbers	Element numbers: 1	...	10	...	30	...	47	Required modal analyses	*ECBI*
1	0		0.304		0.283		0	16080	-0.9992
2	0		0.285		0.254		0	20100	-0.9982
3	0		0.352		0.395		0	16080	-0.9989
4	0.032		0.264		0.197		0	12060	-0.9991
5	0		0.286		0.281		0	4020	-0.9994
6	0		0.276		0.297		0	8040	-0.9991
7	0		0.293		0.227		0	16080	-0.9983
8	0		0.265		0.267		0	4020	-0.9988
9	0		0.281		0.238		0	4020	-0.9992
10	0		0.289		0.291		0	4020	-0.999
Average	0.0032		0.289		0.273		0	10452	-0.9989
Actual damage	0		0.3		0.3		0	-	-1

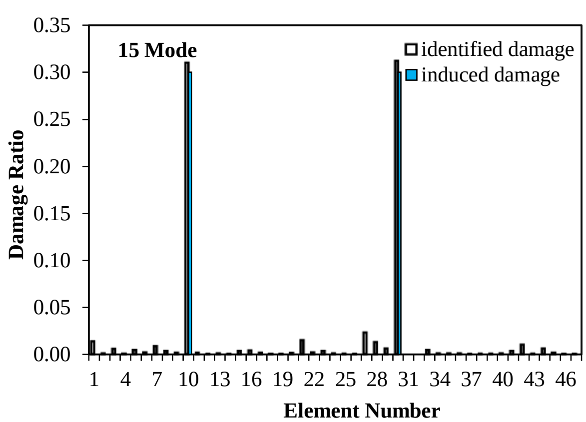

Figure 11. Final damage ratios of the 47-bar planar truss for scenario 3 via GSA

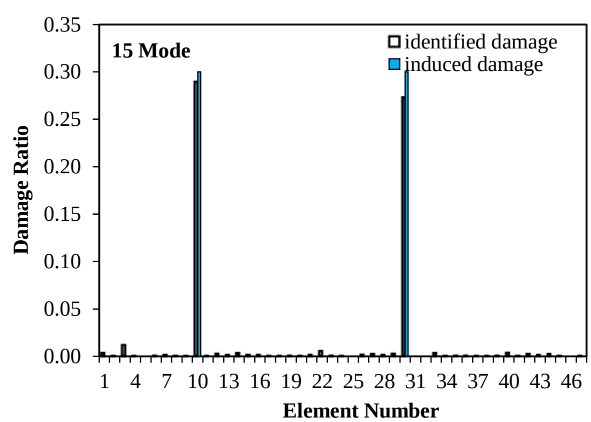

Figure 12. Final damage ratios of the 47-bar planar truss for scenario 3 via MSGSA

Table 14.
The damage detection results of 47-bar planar truss for scenario 4 via GSA

Run numbers	Element numbers							Required modal analyses	*ECBI*
	1	...	40	...	41	...	47		
1	0		0.279	0		0	100050	-0.9946	0.279
2	0		0.338	0.251		0	23400	-0.9955	0.338
3	0		0.359	0.247		0	23300	-0.9957	0.359
4	0		0.303	0.201		0	23450	-0.9953	0.303
5	0		0.345	0.245		0	21400	-0.9952	0.345
6	0		0.358	0.235		0	23900	-0.9953	0.358
7	0		0.365	0.232		0	23700	-0.9951	0.365
8	0		0.381	0.305		0	21450	-0.9959	0.381
9	0		0.34	0.215		0	24650	-0.9951	0.34
10	0		0.264	0.174		0	26050	-0.995	0.264
Average	0		0.333	0.21		0	31105	-0.9953	0.333
Actual damage	0		0.3	0.3		0	-	-1	0.3

Table 15.
The damage detection results of 47-bar planar truss for scenario 4 via MSGSA

Run numbers	Element numbers							Required modal analyses	*ECBI*
	1	...	40	...	41	...	47		
1	0		0.274	0.164		0	4020	-0.9944	0.274
2	0		0.258	0.155		0	8040	-0.9981	0.258
3	0		0.271	0.181		0	4020	-0.997	0.271
4	0		0.254	0.146		0	32160	-0.9945	0.254
5	0		0.277	0.164		0	4020	-0.9953	0.277
6	0		0.225	0.153		0	4020	-0.9953	0.225
7	0		0.207	0.141		0	12060	-0.9949	0.207
8	0		0.239	0.108		0	4020	-0.9946	0.239
9	0		0.277	0.213		0	4020	-0.9948	0.277
10	0		0.264	0.179		0	8040	-0.9976	0.264
Average	0		0.255	0.162		0	8424	-0.9957	0.255
Actual damage	0		0.3	0.3		0	-	-1	0.3

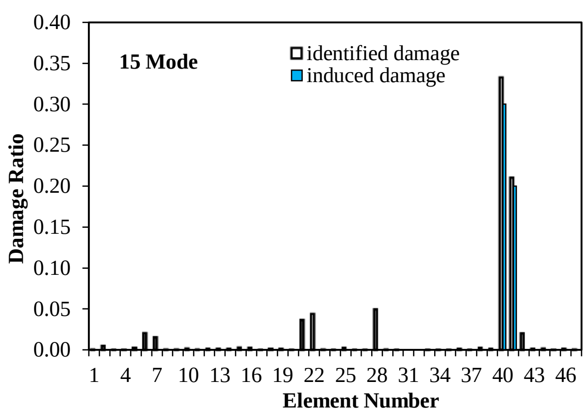

Figure 13. Final damage ratios of the 47-bar planar truss for scenario 4 via GSA

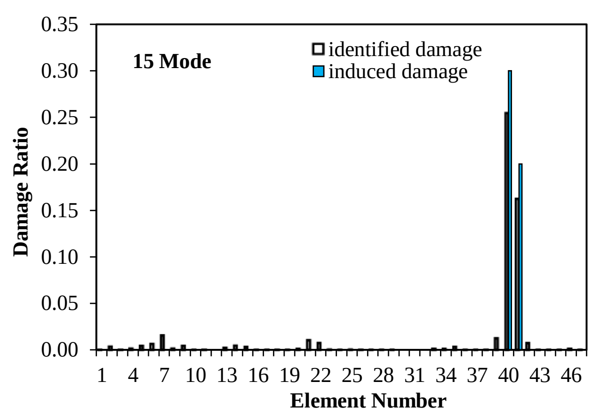

Figure 14. Final damage ratios of the 47-bar planar truss for scenario 4 via MSGSA

All of the results shown in the tables and figures demonstrate that the best solutions in terms of actual damage identification and the total number of FEAs required are obtained by means of the MSGSA. The average number of FEAs requiring for scenarios 1, 2, 3 and 4 of MSGSA are 19278, 17125, 10452 and 8442, respectively, while the average number of FEAs needing for GSA are 40040, 18628, 23645 and 31105, respectively. It is revealed that the MSGSA has a better performance when compared to the GSA.

4.3. Forty-five-element planar frame

A five-story and four-span frame [12] as depicted in Fig. 15 is considered as the last example. The structure has 45 members and 30 nodes. This frame is modeled using the finite element method, leading to 75 degrees of freedom. The sections used for the beams and columns are (W14×145). The area and inertia moment of each element are 0.0276m2 and 0.000712 m4, respectively. The modulus of elasticity is 210 GPa and the material density is 7780 kg/m3.Damage in the structure is also simulated as a relative reduction in the elasticity modulus of individual elements. Two different damage scenarios are considered as listed in Table 16. For identifying the damage scenarios 1 and 2, the first 12 and 14 natural frequencies of the structure are considered, respectively. The measurement noise is considered here by polluting the natural frequencies using a standard error of ±0.15 % [3, 4, 11 and 12].

In this example, the GSA could not converge to an appropriate solution, accordingly only the results of MSGSA have been reported here. For identifying the damage scenario 1 using MSGSA, agent numbers, the maximum numbers of iterations and the maximum number of optimization stages are set to 50, 500 and 10, respectively. Also, for identifying the damage scenario 2 using MSGSA, agent numbers and the maximum numbers of iterations and the maximum number of optimization stages are set to 40, 300 and 5, respectively. The convergence of the MSGSA is met when all optimization stages is attained. In order to consider the stochastic nature of the optimization process, ten independent sample runs are made for each damage scenario. The damage identification results for damage scenarios 1 and 2 using MSGSA are given in Tables 17 and 18, respectively. The average damage ratios for scenarios 1 and 2 are also shown in Figs. 16 and 17, respectively.

As can be seen in the tables and figures, the MSGSA proposed here can accurately detect the damage sites and extent for most of the simulations. It is observed that the optimization process can achieve to the site and extent of actual damage truthfully. The average number of FEAs requiring for scenarios 1 and 2 of MSGSA are 250500 and 60200, respectively.

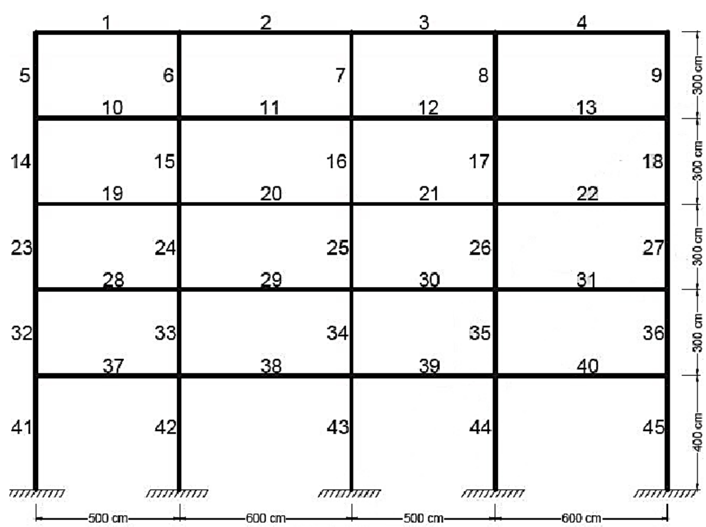

Figure 15. The finite element model for the 45-element frame

Table 16.
Different damage scenarios for planar frame

Scenario 1		Scenario 2	
Element number	Damage extent	Element number	Damage extent
14	0.35	9	0.30
28	0.30	18	0.20
38	0.35	36	0.25

Table 17.
The damage detection results of 45-element frame for scenario 1 via MSGSA

Run numbers	Element numbers 1	...	14	...	28	...	38	...	45	Required modal analyses	*ECBI*
1	0		0.33		0.28		0.07		0	250500	-0.9974
2	0		0.32		0.28		0.3		0	250500	-0.9981
3	0		0.27		0.09		0.34		0	250500	-0.9993
4	0		0.3		0.29		0.04		0	250500	-0.999
5	0		0		0.21		0		0	250500	-0.9996
6	0		0.19		0.17		0.19		0	250500	-0.9995
7	0		0.3		0.2		0		0	250500	-0.9975
8	0		0.31		0.12		0.4		0	250500	-0.9983
9	0		0.32		0.08		0		0	250500	-0.9977
10	0		0.34		0.02		0.17		0	250500	-0.9976
Average	0		0.27		0.17		0.15		0	250500	-0.9984
Actual damage	0		0.35		0.3		0.35		0	-	-1

Table 18.
The damage detection results of 45-element frame for scenario 2 via MSGSA

Run numbers	Element numbers 1	...	9	...	18	...	36	...	45	Required modal analyses	*ECBI*
1	0		0.32		0.14		0.22		0	60200	-0.9994
2	0		0.27		0.2		0.23		0	60200	-0.9985
3	0		0.23		0.31		0.19		0	60200	-0.9992
4	0		0.28		0.24		0.25		0	60200	-0.9985
5	0		0.3		0		0.13		0	60200	-0.9989
6	0		0.3		0.21		0.23		0	60200	-0.9977
7	0		0.31		0.14		0.26		0	60200	-0.9993
8	0		0.33		0.15		0.25		0	60200	-0.9986
9	0		0.29		0.14		0.25		0	60200	-0.9991
10	0		0.28		0.21		0.25		0	60200	-0.9986
Average	0		0.29		0.17		0.23		0	60200	-0.9988
Actual damage	0		0.3		0.2		0.25		0	-	-1

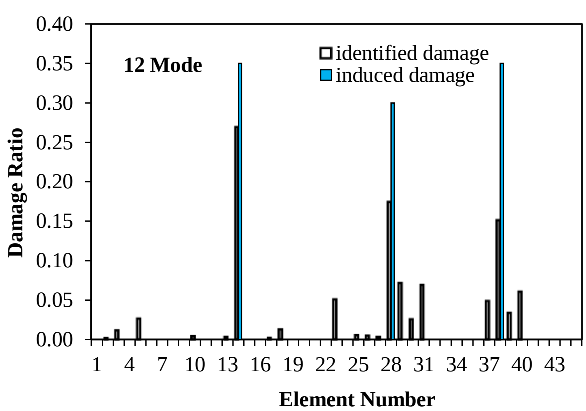

Figure 16. Final damage ratios of the 45-element frame for scenario 1 via MSGSA

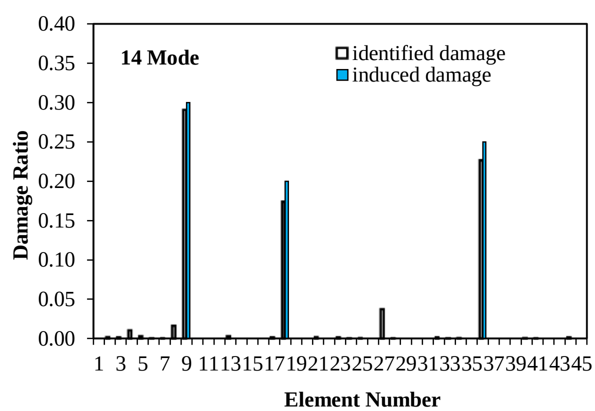

Figure 17. Final damage ratios of the 45-element frame for scenario 2 via MSGSA

5. Conclusions

An efficient optimization procedure has been introduced to solve the problem of structural damage detection that is a highly nonlinear problem with a great number of local solutions. The structural damage detection problem is firstly formulated as a standard optimization problem aiming to minimize an ECBI for finding real damage variables. The MSGSA is proposed to properly solve the optimization problem. In order to assess the competence of the proposed approach for structural damage detection, three illustrative examples are tested. The results demonstrate that the combination of ECBI and MSGSA can provide a robust tool for damage detection. The results of the proposed approach have shown a high performance for the method when compared with actual damage induced and those of standard GSA.

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