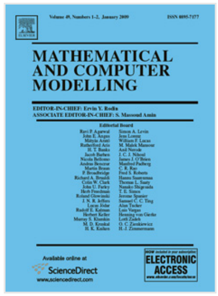

Structural damage detection using an efficient correlation based index and a modified genetic algorithm

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Structural damage detection using an efficient correlation based index and a modified genetic algorithm

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Abstract:

An efficient optimization procedure is proposed to detect the multiple damages in structural systems. Natural frequency changes of a structure are considered as a criterion for damage presence. In order to evaluate the required natural frequencies the finite element analysis (FEA) is utilized. A modified genetic algorithm (MGA) with two new operators including health and simulator operators is presented to accurately detect the locations and extents of eventual damages. An efficient correlation based index (ECBI) as the objective function for the optimization algorithm is also introduced. The numerical results of two benchmark examples considering the measurement noise demonstrate the computational advantages of the proposed method to precisely determine the sites and extents of multiple structural damages.

Keywords: structural damage detection; natural frequency; finite element analysis; modified genetic algorithm; efficient correlation based index

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1. Introduction

Many structural systems may experience some local damages during their functional age. In order to enhance the efficiency of the structures, it is necessary to properly identify the damage sites and extents and then rehabilitate them. Therefore, the damage identification problem has recently attracted a significant attention. During these years, many methods have been introduced to correctly determine the locations and extents of structural damages. One type of these methods is based on employing the optimization algorithms to solve the damage identification problems. In a study, *Koh and Dyke* [1] have determined the locations and sizes of multiple damages by iteratively searching for a combination of structural response that maximizes a correlation coefficient named the multiple damage location assurance criterion (MDLAC) via genetic algorithm (GA). Damage detection by a hybrid technique consisting of a real-parameter genetic algorithm and grey relation analysis has been presented by *He and Hwang* [2]. They used firstly, a grey relation analysis to exclude the impossible damage locations such that the number of design variables could be reduced. Secondly, a real-parameter genetic algorithm has been combined with simulated annealing for finding the actual damages. A fault diagnosis method based on the GA and a model of damaged structure has been proposed by *Vakil-Baghmisheh et al.* [3]. The damage identification of a beam-like structure has been formulated as an optimization problem, and GA has been employed to find the damage locations and extents by minimizing the cost function which is based on the difference of measured and calculated natural frequencies. A two-stage method of determining the locations and extents of multiple structural damages by using information fusion technique and GA has been presented by *Guo and Li* [4]. In the first stage, the damages have been localized by using the evidence theory and then, a micro-search genetic algorithm (MSGA) has been proposed to determine the damage extents. A two-stage method for determining the locations and sizes of multiple structural damages by combining the adaptive neuro-fuzzy inference system (ANFIS) and particle swarm optimization (PSO) has been proposed by *Fallahian and Seyedpoor* [5]. A multi-stage particle swarm optimization (MSPSO) for accurately detecting the structural damages has been introduced by Seyedpoor [6]. In another study, *Begambre and Laier* [7] proposed a hybrid particle swarm optimization–simplex algorithm (PSOS) for structural damage identification using frequency domain data.

In this study, a modified genetic algorithm (MGA) is introduced to identify the multiple structural damages. This modified version of GA has two new tools including a health operator (HO) and a simulator operator (SO) in order to recognize the actual damages correctly and rapidly. An efficient correlation based index (ECBI) is also proposed as the objective function for the optimization algorithm. Two illustrative test examples are considered to show the performance of the method. Numerical results demonstrate that the combination of the MGA and ECBI can provide a robust tool for determining the sites and extents of multiple structural damages precisely and quickly.

2. Structural damage detection

Structural damage detection techniques can be generally classified into two main categories [8]. They include the dynamic and static identification methods requiring the dynamic and static test data, respectively. Furthermore, the dynamic identification methods have shown their advantages in comparison with the static ones. Among the dynamic data, the natural frequencies of a structure can be found as a valuable data. Determining the level of correlation between the measured and predicted natural frequencies can provide a simple tool for finding the locations and extents of structural damages [9]. A parameter vector used for evaluating correlation coefficients consists of the ratios of the first n_f natural frequency changes ΔF due to structural damage, i.e.

$$\Delta F = \frac{F_h - F_d}{F_h} \tag{1}$$

where F_h and F_d denote the natural frequency vectors of the healthy and damaged structure, respectively. Similarly, the corresponding parameter vector predicted from an analytical model can be defined as:

$$\delta F(X) = \frac{F_h - F(X)}{F_h} \tag{2}$$

where $F(X)$ is a natural frequency vector that can be predicted from an analytic model and $X^{\mathrm{T}} = \{x_1, \ldots, x_i, \ldots, x_n\}$ represents a damage variable vector containing the damage extents $(x_i,\ i = 1, \ldots, n)$ 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 multiple damage location assurance criterion (MDLAC) expressed in the following form [9]:

$$MDLAC\ (X) = \frac{\left| \Delta F^{\mathrm{T}} . \delta F(X) \right|^2}{(\Delta F^{\mathrm{T}} . \Delta F)(\delta F^{\mathrm{T}}(X) . \delta F(X))} \tag{3}$$

The *MDLAC* compares two frequency change vectors, one obtained from the tested structure and the other from an analytical model of the structure. The *MDLAC* varies from a minimum value 0 to a maximum value 1. It will be maximal when the vector of analytical frequencies becomes identical to the frequency vector of damaged structure, that is, $F(X) = F_d$. This concept can be utilized to find a set of damage variables maximizing the *MDLAC* using an optimization algorithm:

$$
\begin{aligned}
&\text{Find} && X^{\mathrm{T}} = \{x_1, x_2, ..., x_n\} \\
&\text{Maximize}\ : && w(X) = MDLAC\,(X) \\
& && x_i \in R^d\ ,\quad i = 1,..., n
\end{aligned}
\tag{4}
$$

where R^d is a given set of discrete values so that the damage extents x_i $(i = 1,..., n)$ can take values only from this set. Also, w is an objective function that should be maximized.

Due to occurrence of damage in a structural element, the element stiffness decreases. Therefore, in many studies related to the damage identification problem, damage has been simulated by decreasing one of the stiffness parameters of the element such as the elasticity module (E), cross sectional area (A), moment of inertia (I) and so on. In this study, the damage variables are defined via a relative reduction of elasticity modulus of an element as:

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

where E is the initial modulus of elasticity and E_i is the final modulus of elasticity of *i*th element.

In this study, before solving the Eq. (4) by an optimization method, an initial study was made on the performance of the *MDLAC* as an objective function and for brevity only the final outcomes are provided. The *MDLAC* as an objective function for optimization algorithm is very sensitive to damaged elements while its sensitivity to healthy elements is low. In the other words, it can find the true locations of the damaged elements, however, it may find a healthy element as a damaged one. Therefore, in this study a new function having a high sensitivity to healthy elements is firstly presented as:

$$obj(X) = \frac{1}{n_f} \sum_{i=1}^{n_f} \frac{\min(f_{xi}, f_{di})}{\max(f_{xi}, f_{di})} \tag{6}$$

where f_{xi} and f_{di} are the *i*th component of $F(X)$ and F_d vectors, respectively.

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 two Eqs. (3) and (6) called here as an efficient correlation based index (ECBI) is proposed as:

$$ECBI(X) = \frac{1}{2}(MDLAC(X) + obj(X)) \tag{7}$$

In the test examples, the performance of the *ECBI* for damage identification is assessed in comparison with that of the *MDLAC*.

3. A modified genetic algorithm

The selection of an efficient algorithm for solving the damage optimization problem is a critical issue. Needing fewer structural analyses for achieving the global optimum without trapping into local optima must be the main characteristic of the algorithm. In this study, a modified version of genetic algorithm working with discrete design variables is proposed to properly solve the damage problem. In this section, the simple genetic algorithm (SGA) is firstly described and then the modified genetic algorithm (MGA) is explained.

3.1. Simple genetic algorithm

The genetic algorithm is a probabilistic search algorithm inspired by the evolutionary laws of living creatures [10]. In this algorithm, information regarding an optimization problem, such as design variables, is coded into a genetic string known as an individual (chromosome). Each of these individuals has an associated fitness value, which is usually determined by the objective function to be maximized or minimized. The genetic algorithm proceeds by taking an initial population, which is comprised of different individuals with different fitness. The initial population can be randomly generated or it can also be selected by a supervisory method [11]. All individuals are decoded to evaluate their fitness function values. Then, the best individuals of current generation (parents) are selected to produce the new generation (offspring) having better fitness by crossover and mutation operators. The previous individuals are replaced by the new individuals and this process will be continued until the convergence criteria are met. Finally, the best individual of last generation according to its fitness function is selected as the optimal solution.

The SGA has been shown to be capable of solving the various optimization problems via some basic concepts and operators including the coding, initial population, decoding, selection, crossover and mutation [11-13]. However, it has been revealed from some research works [1, 4 and 14] that the SGA can not solve the damage identification problems properly. Therefore, in this study two new operators are introduced to enhance the performance of the SGA.

3.2. Health operator

The number of flawed elements in a damaged structure is usually much less than the total number of healthy elements. If this idea is considered in the optimization process, the convergence to the actual damages will be accelerated. Therefore, in this study a new operator named here as the health operator (HO) is applied to each generation of the standard genetic algorithm for randomly considering some elements of each structure as the healthy elements. The operation of HO can be clarified by a simple example as follows: it is assumed that for identifying the damaged elements in a structure having 20 total elements, the initial population consists of 30 individuals. Therefore, each chromosome has 20 genes and then the total number of genes will be 20×30=600. If the probability of applying the HO to the problem be 0.08, therefore the total number of 0.08×600=48 genes (elements) in each generation should be assumed to be zero (healthy).

3.3. Simulator operator

The SO is an operator for improving the best solution of genetic algorithm, obtained up to current generation while it needs fewer analyses in comparison with an ordinary generation. Using this new operator, the best individuals of two preceding generations are compared and a new individual is created synthetically. Therefore, the SO can work after third generation. The procedure of SO is explained here by a simple example as follows:

It is assumed that in optimization problem each chromosome comprises of 12 genes that can take values 0 to 0.5 by a step of 0.05 and the best chromosomes of two last generations are shown in Fig. 1. It is also assumed that the chromosome 1 is fitter than chromosome 2. It can be seen that the values of genes 1, 4, 8, 9, 10 and 12 are different and the total number of this genes are nj=6. By using SO, the new chromosome is simulated by considering some instructions as:

1. The value of a gene having the identical values in chromosomes 1 and 2 is not changed. So, in the new chromosome, the values of genes 2, 3, 5, 6, 7 and 11 do not change.

2. If the value of a gene in chromosome 1 is less than the value of corresponding gene of chromosome 2 (genes 1, 8, 9 and 12), the value of the gene by a probability of $1/nj = 1/6$ will be reduced by the step size of our problem (for this example the step size is equal to 0.05). It should be noted that if the gene has a minimum value (0), its value is not changed (gene 9).
3. If the value of a gene in chromosome 1 is more than the value of corresponding gene of chromosome 2 (genes 4 and 10), the value of the gene by a probability of $1/nj = 1/6$ will be increased by the step size of our problem (for this example it is equal to 0.05). It should be noted that if the gene has a maximum value (0.5), its value is not changed (gene 10).

By considering the notes above, the new chromosome produced can be shown in Fig 1. It is observed that the values of genes 1 and 8 are the same as those of the chromosome 1 and are not decreased because the probability of decreasing is $1/6$. Now, the new chromosome is evaluated, if it is fitter than chromosome 1, the chromosome 2 is replaced by chromosome 1 and the chromosome 1 is replaced by the new chromosome. This operation is continued until the new chromosome simulated is not fitter than chromosome 1 that at this stage an individual of current generation randomly selected is replaced by the chromosome 1. Then, a new optimization iteration is performed to produce a new generation. If in the new generation a better chromosome than those of previous generation is generated the SO will be also active, otherwise, the worst individual of current generation is replaced by the best individual of last generations (elitism selection).

At this stage, the flowchart of SGA employing the HO and SO called here as MGA can be shown in Fig. 2.

4. Test examples

In order to show the capabilities of the proposed approach for identifying the multiple structural damages, two illustrative test examples bellow are considered. The first example is a 20-element cantilevered beam discussed in detail and the second one is a 31-bar truss element discussed in brief.

4.1. Twenty-element cantilevered beam

The finite element model of a cantilevered steel beam with 20 elements leading to 40 degrees of freedom, shown in Fig. 3, is considered as the first example [4]. The length, height and width of the beam are 1.0, 0.01, and 0.01 m, respectively. The mass density is 7860 kg/m^3 and the elasticity modulus is 210 GPa. In this example, the first ten natural frequencies are used for damage detection. For this example, two damage cases listed in Table 1 are studied. Here, small damage is mainly considered, and the stiffness reduction caused by the damage is smaller than 50% [4]. The parameters of GA are selected here from the experiences of our previous works [11], the guideline of other works found in the literature [1 and 14] and a trial and error method as: the probability of crossover *pc* is 1.0, the probability of mutation *pm* is 0.002, the health parameter *hp* is 0.08, the maximum number of generations *ng* is 1000, and the population size *ps* is 20. The convergence of the algorithm is met when the objective function reaches to 0.999999 or the maximum number of generations attains. The machine used in this research is a personal computer with a core™ 2 Duo 2GHz CPU and a 2 GB memory.

With the mentioned conditions, the damage is identified using the following methods and the results are compared:

1) SGA with the MDLAC function (SGA+MDLAC)
2) SGA with the ECBI function (SGA+ECBI)
3) MGA with the MDLAC function (MGA+MDLAC)
4) MGA with the ECBI function (MGA+ECBI)

In order to consider the stochastic nature of the optimization process using various methods, ten independent sample runs are made for each damage case. The damage identification results of damage case 1 using four different methods are given in Tables 2-a to 2-d, respectively. The damage identification results of damage case 2 using four different methods are also given in Tables 3-a to 3-d, respectively.

By comparing the damage detection results of four various methods some interesting points can be concluded. It is reveal that the MGA and ECBI are of better performance when compared to SGA and MDLAC, respectively. The ordinary method SGA-MDLAC can not identify the actual damages accurately. The results of the method can be enhanced when each of the proposed MGA or ECBI are utilized instead of SGA or MDLAC, respectively. All of the numerical results reported in the tables demonstrate that the best solutions in terms of actual damage identification and the total number of FEA required are obtained by means of MGA employing the ECBI. It is impressive to mention that most of the different optimization runs made by this method are led to actual damages induced.

The convergence history of various methods for cases 1 and 2 are depicted in Figs 4-a and 4-b, respectively, where the objective function (MDLAC or ECBI) versus finite element analyses is shown. In these figures, each curve is related to the result of a typical optimization run for each method. It should be mentioned that for cases 1 and 2, the sites and extents of all damages induced are accurately detected using methods 2 and 4. The convergence history of the various methods achieved by a single optimization run demonstrates that the combination of MGA and ECBI can also provide a robust tool for identifying the actual damages.

In order to investigate the noise effects on the performance of the proposed method (MGA+ECBI), measurement noise is considered here by a standard error of ±0.15% for the natural frequencies [4 and 9]. The damage identification results for damage cases 1 and 2 with considering noise and *ng*= 450 are given in Tables 4-a to 4-b, respectively. It can be observed that when noise is taken into account in the damage detection problem, the MGA-ECBI can detect the damage sites and extents correctly for most of the independent runs. In these cases, the maximum number of generations controls the convergence of the algorithm.

4.2. Thirty one-bar planar truss

The 31-bar planer truss shown in Fig. 5 selected from Ref. [9] is modeled using the conventional finite element method without internal nodes leading to 25 degrees of freedom. In this example, the first ten natural frequencies are utilized for damage detection.

The material density and elasticity modulus are 2770 kg/m^3 and 70 GPa, respectively. Damage in the structure is also simulated as a relative reduction in the elasticity modulus of individual bars. Three different damage cases given in Table 5 are induced in the structure and the MGA employing the ECBI is tested for each case. All optimization parameters are the same as the first example.

The prediction of damage levels for cases 1 to 3 without considering noise are given in Tables 6-a to 6-c, respectively. As it can be seen in the tables, the damage identification method proposed here (MGA+ECBI) can accurately detect the damage sites and sizes for most of the simulations. It can also be observed that only for one optimization run of case 1 the damage extents are not accurately determined. In order to assess the effects of measurement noise on the efficiency of the method, the damage identification results of cases 1 to 3 when noise is considered for natural frequencies are given in Tables 7-a to 7-c, respectively. The numerical results demonstrate the efficiency of the method for locating the damaged element.

5. Conclusions

An optimization based damage identification method is proposed here to identify the multiple damages in the structural systems. For the optimization, a modified genetic algorithm (MGA) including two new operators is proposed. The new operators are called here as the health and simulator operators. An efficient correlation based index (ECBI) is also introduced as the objective function for the optimization algorithm. Two illustrative test examples with and without considering measurement noise are selected to assess the advantages of the proposed method. Numerical results for various damage cases with different sample runs demonstrate that the combination of MGA and ECBI can create a robust tool for structural damage detection in terms of actual damage sites and extents, and the total number of finite element analyses when comparing with the available tools such as SGA-MDLAC.

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Figure captions:

Fig. 1. The combination of chromosomes 1 and 2 for creating a new chromosome via SO

Fig. 2. The flowchart of MGA

Fig. 3. The finite element model of a cantilevered beam having 20 elements

Fig. 4-a. The convergence history of 20-element beam for case 1 obtained by four methods

Fig. 4-b. The convergence history of 20-element beam for case 2 obtained by four methods

Fig. 5. A planar truss having 31 elements

Gene number	1	2	3	4	5	6	7	8	9	10	11	12
Chrom 1	0.25	0.50	0.20	0.25	0.30	0.25	0.15	0.10	0.0	0.5	0.25	0.05
					+							
Chrom 2	0.35	0.50	0.20	0.20	0.30	0.25	0.15	0.15	0.1	0.4	0.25	0.10
					‖							
New Crom	0.25	0.50	0.20	0.30	0.30	0.25	0.15	0.10	0.0	0.5	0.25	0.0

Fig. 1. The combination of chromosomes 1 and 2 for creating a new chromosome via SO

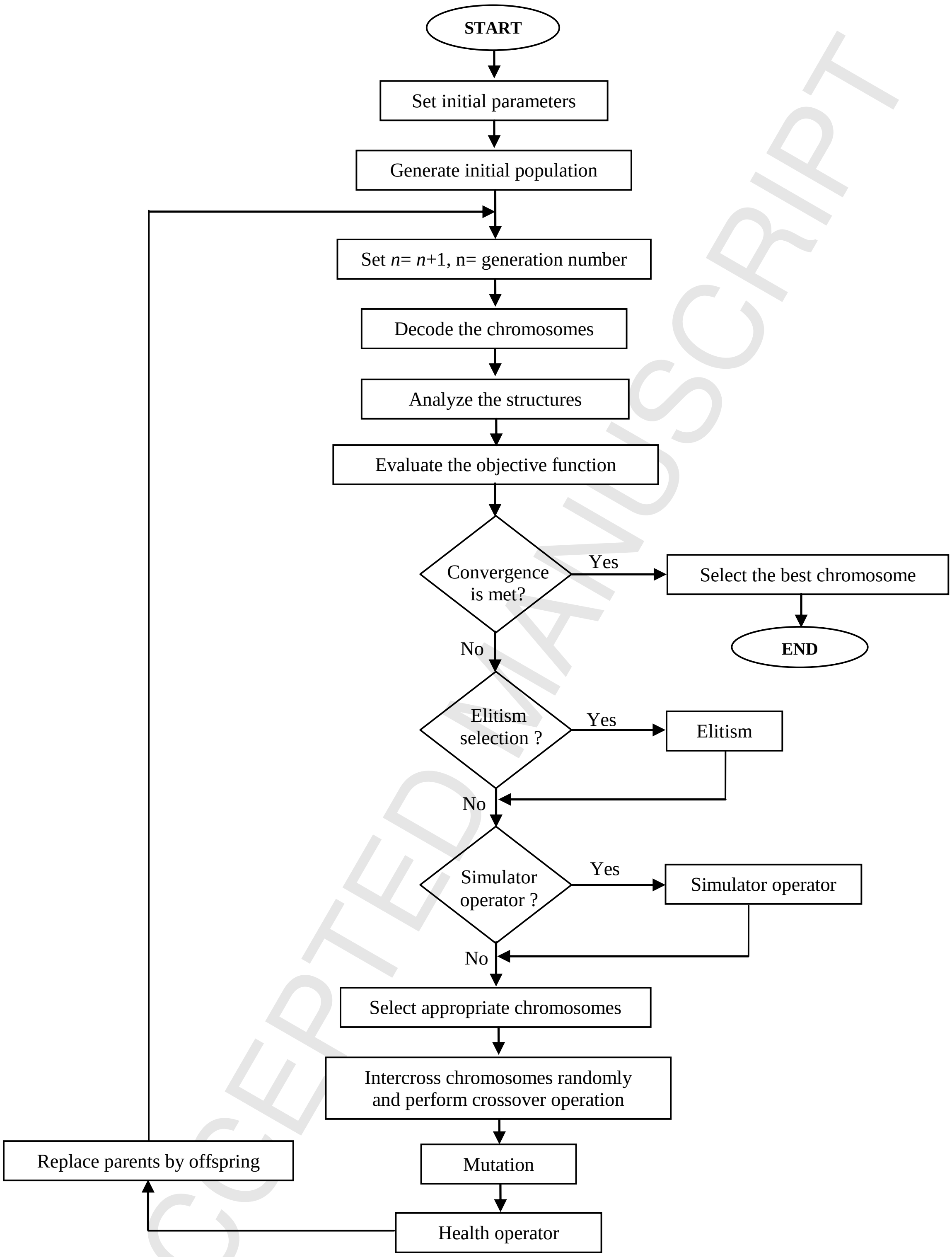

Fig. 2. The flowchart of MGA

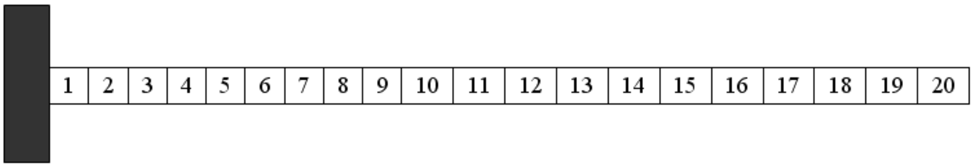

Fig. 3. The finite element model of a cantilevered beam having 20 elements

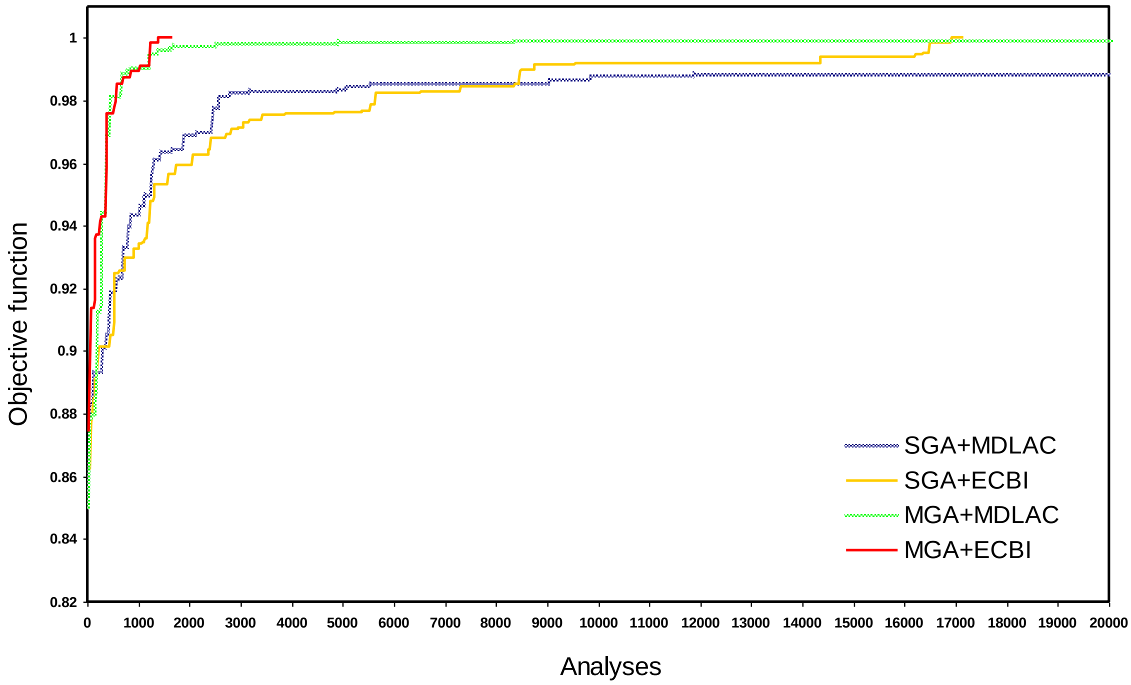

Fig. 4-a. The convergence history of 20-element beam for case 1 obtained by four methods

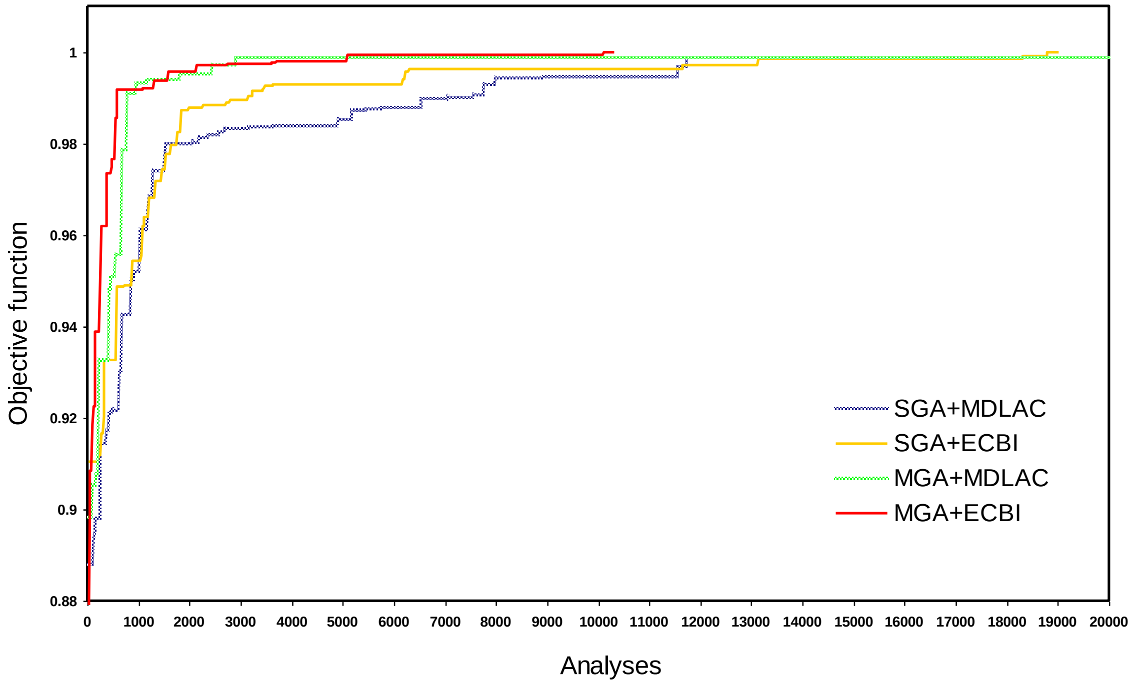

Fig. 4-b. The convergence history of 20-element beam for case 2 obtained by four methods

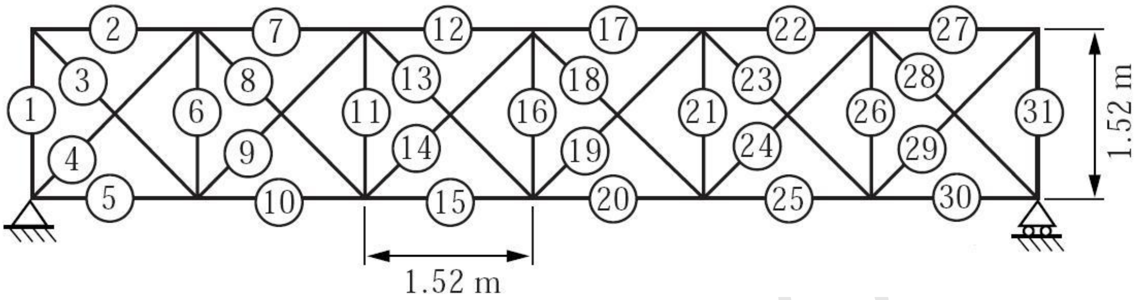

Fig. 5. A planar truss having 31 elements

Table 1. Two different damage cases induced in 20-element beam

Case 1		Case 2	
Element number	Damage ratio	Element number	Damage ratio
15	0.20	12	0.20
16	0.15	13	0.30
17	0.20	15	0.30

Table 2-a. The damage ratios of 20-element beam for case 1 using SGA with MDLAC

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1						0.05									0.35	0.35	0.40			0.10	20000
2			0.1			0.00									0.40	0.45	0.50			0.15	20000
3			0.1			0.00	0.15								0.35	0.50	0.50			0.20	20000
4						0.15									0.35	0.40	0.50			0.15	20000
5						0.10									0.40	0.40	0.50			0.15	20000
6						0.15									0.35	0.45	0.50			0.10	20000
7						0.05									0.40	0.40	0.50			0.15	20000
8						0.05									0.35	0.40	0.45			0.15	20000
9						0.05									0.40	0.40	0.50			0.15	20000
10						0.10									0.40	0.40	0.50			0.15	20000
Average	0	0	0.02	0	0	0.07	0.015	0	0	0	0	0	0	0	0.375	0.415	0.485	0	0	0.145	20000
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.20	0.15	0.20	0	0	0	-

Table 2-b. The damage ratios of 20-element beam for case 1 using SGA with ECBI

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1															0.25	0.15	0.20				20000
2															0.20	0.20	0.20			0.15	20000
3	0.1														0.30	0.25	0.30			0.15	20000
4						0.05									0.15	0.15	0.20			0.10	20000
5															0.20	0.20	0.20			0.15	20000
6					0.1										0.25	0.15	0.25				20000
7							0.1								0.20	0.15	0.20				20000
8															0.20	0.15	0.20			0.15	20000
9		0.1													0.25	0.25	0.30				20000
10															0.20	0.15	0.20				20000
Average	0.01	0.01	0	0	0.01	0.005	0.01	0	0	0	0	0	0	0	0.22	0.18	0.225	0	0	0.07	20000
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.15	0.2	0	0	0	-

Table 2-c. The damage ratios of 20-element beam for case 1 using MGA with MDLAC

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1						0.05									0.40	0.40	0.45			0.10	20024
2						0.05									0.40	0.40	0.45			0.05	20030
3															0.20	0.15	0.20				2742
4						0.05									0.40	0.40	0.45			0.15	20023
5						0.05									0.40	0.40	0.45			0.15	20020
6						0.05									0.40	0.40	0.45			0.15	20034
7						0.05									0.40	0.40	0.45			0.15	20025
8						0.05									0.40	0.40	0.45			0.15	20023
9															0.20	0.15	0.20				7085
10															0.20	0.15	0.20				17318
Average	0	0	0	0	0	0.035	0	0	0	0	0	0	0	0	0.34	0.32	0.375	0	0	0	16732
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.20	0.15	0.20	0	0	0	-

Table 2-d. The damage ratios of 20-element beam for case 1 using MGA with ECBI

Sample No.	Element numbers																			FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1															0.2	0.15	0.2				3327.
2															0.2	0.15	0.2				1254.
3															0.2	0.15	0.2				1056.
4															0.2	0.15	0.2				2803.
5															0.2	0.15	0.2				11550
6															0.2	0.15	0.2				6094.
7															0.2	0.15	0.2				8288.
8															0.2	0.15	0.2				3858.
9															0.2	0.15	0.2				8107.
10															0.2	0.15	0.2				4375.
Average	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.15	0.2	0	0	0	5071.2
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.15	0.2	0	0	0	-

Table 3-a. The damage ratios of 20-element beam for case 2 using SGA with MDLAC

Sample No.	Element numbers																			FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1									0.10			0.25	0.5	0.05	0.50					0.10	20000
2									0.15			0.25	0.5	0.05	0.50					0.00	20000
3									0.15			0.25	0.5	0.05	0.50					0.10	20000
4									0.10			0.25	0.5	0.05	0.50					0.10	20000
5		0.1							0.15			0.15	0.4	0.05	0.45			0.05		0.00	20000
6									0.10			0.25	0.5	0.05	0.50					0.15	20000
7					0.1				0.00			0.25	0.5	0.05	0.50					0.10	20000
8						0.05			0.10			0.25	0.5	0.05	0.45					0.05	20000
9									0.10			0.25	0.5	0.05	0.50					0.10	20000
10									0.10			0.25	0.5	0.05	0.50			0.10		0.00	20000
Average	0	0.01	0	0	0.01	0.005	0	0	0.105	0	0	0.24	0.49	0.05	0.49	0	0	0.075	0	0.07	20000
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0	0.3	0	0	0	0	0	-

Table 3-b. The damage ratios of 20-element beam for case 2 using SGA with ECBI

Sample No.	Element numbers																			FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1												0.20	0.35		0.35					0.15	20000
2									0.10			0.15	0.30		0.30						20000
3									0.05			0.15	0.35		0.35						20000
4												0.20	0.30		0.30					0.10	20000
5									0.05			0.15	0.30		0.30						20000
6									0.05			0.15	0.30		0.30						20000
7						0.05						0.20	0.30		0.25					0.05	20000
8												0.20	0.35		0.30						20000
9												0.20	0.30		0.30						18580
10									0.05			0.15	0.30		0.30				0.1	0.03	20000
Average	0	0	0	0	0	0.005	0	0	0.03	0	0	0.175	0.315	0	0.305	0	0	0	0.01	0.	19858
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0	0.3	0	0	0	0	0	-

Table 3-c. The damage ratios of 20-element beam for case 2 using MGA with MDLAC

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1												0.25	0.4		0.4					0.1	20025
2												0.25	0.4		0.4					0.1	20019
3												0.15	0.2		0.2					0.0	20013
4												0.15	0.2		0.2					0.0	20024
5												0.25	0.4		0.4					0.1	20022
6												0.25	0.4		0.4					0.1	20016
7												0.25	0.4		0.4					0.1	20021
8												0.25	0.4		0.4					0.1	20020
9												0.25	0.4		0.4					0.1	20024
10												0.25	0.4		0.4					0.1	20016
Average	0	0	0	0	0	0	0	0	0	0	0	0.23	0.36	0	0.36	0	0	0	0	0.08	20020
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0	0.3	0	0	0	0	0	-

Table 3-d. The damage ratios of 20-element beam for case 2 using MGA with ECBI

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1												0.2	0.30		0.3						7503.
2												0.2	0.30		0.3						8022.
3												0.2	0.30		0.3						12903
4												0.2	0.30		0.3						4002.
5												0.2	0.30		0.3						10386
6												0.2	0.30		0.3						2262.
7												0.2	0.30		0.3						1756.
8												0.2	0.35		0.4						20024
9												0.2	0.35		0.4						20018
10												0.2	0.25		0.3						20020
Average	0	0	0	0	0	0	0	0	0	0	0	0.2	0.305	0	0.32	0	0	0	0	0	10690
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0	0.3	0	0	0	0	0	-

Table 4-a. The damage ratios of 20-element beam for case 1 using MGA with ECBI considering noise

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1															0.25	0.15	0.2				9028
2															0.25	0.10	0.2				9016
3															0.2	0.15	0.2				9020
4															0.2	0.15	0.2				9024
5															0.2	0.15	0.2				9029
6															0.2	0.15	0.2				9025
7															0.2	0.15	0.2				9026
8															0.2	0.05	0.2				9020
9															0.2	0.15	0.2				9023
10															0.2	0.15	0.2				9015
Average	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.21	0.135	0.2	0	0	0	9022.6
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.15	0.2	0	0	0	-

Table 4-b. The damage ratios of 20-element beam for case 2 using MGA with ECBI considering noise

Sample No.	Element numbers																				FEA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
1												0.2	0.3		0.4						9022
2								0.05				0.2	0.25		0.3						9019
3												0.2	0.3		0.3						9029
4												0.2	0.3		0.3						9023
5									0.1	0.05		0.1	0.3		0.3						9021
6												0.2	0.3		0.3						9019
7												0.2	0.3		0.4						9025
8								0.1				0.2	0.2		0.3						9013
9												0.2	0.4		0.4						9011
10												0.2	0.4		0.4						9021
Average	0	0	0	0	0	0	0	0.015	0.01	0.005	0	0.19	0.305	0	0.34	0	0	0	0	0	9020.3
Actual damages	0	0	0	0	0	0	0	0	0	0	0	0.2	0.3	0	0.3	0	0	0	0	0	-

Table 5. Three different damage cases induced in 31-bar planar truss

Case 1		Case 2		Case 3	
Element number	Damage ratio	Element number	Damage ratio	Element number	Damage ratio
11	0.25	16	0.30	1	0.30
25	0.15	-	-	2	0.20

Table 6-a. The damage ratios of 31-bar truss for case 1 using MGA with ECBI

Sample No.	Element numbers																					FEA
	1	2	…	10	11	12	13	14	15	16	17	…	24	25	26	27	28	29	30	31		
1					0.25									0.15								16501
2					0.25									0.15								6045.
3					0.25									0.15								7419.
4					0.25									0.15								2181.
5					0.25									0.15								6130.
6					0.40									0.25								20025
7					0.25									0.15								18403
8					0.25									0.15								3398.
9					0.25									0.25								7701.
10					0.25									0.25								1298.
Average	0	0	0	0	0.265	0	0	0	0	0	0	0	0	0.18	0	0	0	0	0	0		8910.1
Actual damages	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0.15	0	0	0	0	0	0		-

Table 6-b. The damage ratios of 31-bar truss for case 2 using MGA with ECBI

Sample No.	Element numbers																					FEA
	1	2	…	10	11	12	13	14	15	16	17	…	24	25	26	27	28	29	30	31		
1										0.30												1365.
2										0.30												4739.
3										0.30												1907.
4										0.30												2588.
5										0.30												4328.
6										0.30												2090.
7										0.30												4673.
8										0.30												4451.
9										0.30												1290.
10										0.30												3646.
Average	0	0	0	0	0	0	0	0	0	0.30	0	0	0	0	0	0	0	0	0	0		3107.7
Actual damages	0	0	0	0	0	0	0	0	0	0.30	0	0	0	0	0	0	0	0	0	0		-

Table 6-c. The damage ratios of 31-bar truss for case 3 using MGA with ECBI

Sample No.	Element numbers																					FEA
	1	2	…	10	11	12	13	14	15	16	17	…	24	25	26	27	28	29	30	31		
1	0.3	0.2																				1557
2	0.3	0.2																				19974
3	0.3	0.2																				9958
4	0.3	0.2																				1493
5	0.3	0.2																				9507
6	0.3	0.2																				3646
7	0.3	0.2																				2728
8	0.3	0.2																				3758
9	0.3	0.2																				8931
10	0.3	0.2																				2359
Average	0.3	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		6391.1
Actual damages	0.3	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		-

Table 7-a. The damage ratios of 31-bar truss for case 1 using MGA with ECBI with considering noise

Sample No.	Element numbers																				FEA
	1	2	…	10	11	12	13	14	…	21	22	23	24	25	26	27	28	29	30	31	
1					0.20					0.05				0.10							13028
2					0.40					0.10				0.20							13020
3					0.20					0.05				0.10							13029
4					0.40					0.20				0.10							13043
5					0.40									0.20				0.05			13021
6					0.40					0.10				0.20					0.05		13026
7					0.30					0.05				0.15							13023
8					0.20									0.10					0.10		13024
9					0.10					0.05				0.10							13026
10					0.25									0.10		0.05					13025
Average	0	0	0	0	0.285	0	0	0	0	0.06	0	0	0	0.135	0	0.005	0	0.005	0.015	0	13027
Actual damages	0	0	0	0	0.25	0	0	0	0	0	0	0	0	0.15	0	0	0	0	0	0	-

Table 7-b. The damage ratios of 31-bar truss for case 2 using MGA with ECBI considering noise

Sample No.	Element numbers																				FEA
	1	2	…	10	11	12	13	14	15	16	17	…	20	…	26	27	28	29	30	31	
1										0.25											13014
2										0.30											13031
3										0.40			0.05								13027
4										0.30											13029
5										0.30											13019
6										0.30											13027
7										0.30											13025
8										0.30											13017
9										0.40						0.05					13020
10										0.25											13028
Average	0	0	0	0	0	0	0	0	0	0.31	0	0	0.005	0	0	0.005	0	0	0	0	13024
Actual damages	0	0	0	0	0	0	0	0	0	0.30	0	0	0	0	0	0	0	0	0	0	-

Table 7-c. The damage ratios of 31-bar truss for case 3 using MGA with ECBI considering noise

Sample No.	Element numbers																				FEA
	1	2	…	10	11	12	13	14	15	16	17	…	24	25	26	27	28	29	30	31	
1	0.25	0.25																			13022
2	0.25	0.2																			13024
3	0.30	0.25																			13018
4	0.30	0.25																			13027
5	0.30	0.25																			13025
6	0.40	0.10																			13019
7	0.40	0.20																			13020
8	0.40	0.10													0.05						13024
9	0.40	0.10																			13021
10	0.30	0.25																			13018
Average	0.33	0.195	0	0	0	0	0	0	0	0	0	0	0	0	0.005	0	0	0	0	0	13021.8
Actual damages	0.3	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-