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Co-operative co-evolutionary genetic algorithm for vibration based damage detection of truss structures

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ABSTRACT

Vibration-based damage detection is based on the fact that vibration characteristics such as natural frequencies and mode shapes of the structures are changed when the damage occurs. In this paper, co-operative co-evolutionary genetic algorithm (CCGA) is proposed to solve the vibration-based damage detection in truss structures. The minimized objective function is a numerical indicator of the differences between vibration characteristics of the true damage parameters and those of the predicted damage parameters. The damage detection of two-dimensional and three-dimensional truss structures is formulated as the test problems. CCGA can correctly identify the damage in the truss structures, although it uses only less than 10% generated solutions that had to be used in the previous works employing genetic algorithm (GA) and micro genetic algorithm (μGA).

1. Introduction

The vibration-based damage detection methods, non-destructive methods, are based on the fact that vibration characteristics such as natural frequencies and mode shapes of the structure are changed due to the occurred damage in a structure. Many applications in civil engineer and mechanical engineer (Mottershead et al., 1999; Gawronski and Sawicki, 2000) employed these methods. The residual force concept has received wide attentions with regard to the vibration-based damage detection (Yang and Liu, 2007; Rao et al., 2004; Panigrahi et al., 2009). This concept provides a minimized objective function numerically calculated from the differences between the vibration characteristics of actual damage and those of predicted damage.

Genetic algorithm (GA) (Holland, 1975; Goldberg, 1989) is a derivative-free population-based optimization method of which search mechanisms are based on the Darwinian concept of survival of the fittest. A number of works employed GAs to solve the structural damage detection problems such as (Rao et al., 2004; Guo and Li, 2007; Panigrahi et al., 2009; Nobaharia and Seyedpoorb, 2011). Rao et al. (2004) used a two-point crossover binary coded GA with tournament selection for reproduction of population for the damage detection of truss, frame, and beam structures. A direct concept of the residual force matrix is used to specify an objective function. (Panigrahi et al., 2009) employed GA with the concept of the residual force matrix for the damage detection in uniform strength beams. Kim and Lee (2013) proposed micro genetic algorithm (μGA) for the damage detection of two-dimensional and three-dimensional truss structures with elastic supports.

Co-operative co-evolutionary genetic algorithm (CCGA) originally developed by (Potter and De Jong, 1994) is capable for an optimization problem with weak coupling between decision variables. Many researches effectively applied CCGA to the particular optimization problems (Boonlong et al., 2004; Chandra and Zhang, 2012; Ibáñez et al., 2012). In CCGA, a population contains a number of species or sub-populations. An individual in each species represents only a decision variable or part of a solution to the optimization problem. CCGA had been successfully implemented in the damage detection of beams (Boonlong, 2014). This paper will propose CCGA for solving the damage detection problems in truss structures. Two-dimensional and three-dimensional truss models will be considered as the test problems.

2. Objective function calculation

This section shows how to calculate objective function. The calculation of objective function is adopted from Rao et al. (2004) and Panigrahi et al. (2009). The equations of motion of dynamics of a multi degree freedom system are given by:

$$[m]\{\ddot{x}(t)\}+[k]\{x(t)\}=\{F(t)\} \quad (1)$$

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Where $[m]$ and $[k]$ are $(n\times n)$ mass and stiffness matrices, while $\{x\}$ and $\{F\}$ are $(n\times 1)$ displacement and applied force vectors.

The j^{th} eigen equation associated with Eq. (1) is given by:

$$[k]\{v_j\}-\lambda_j[m]\{v_j\}=\{0\} \tag{2}$$

Where λ_j and $\{v_j\}$ are the eigen value and corresponding unit eigen vector of vibration mode j.

In the finite element model of the structure, the matrix $[k]$ can be represented as a sum of the expanded element stiffness matrices of all elements.

$$[k]=\sum_{i=1}^{N}[k]_i \tag{3}$$

Where $[k]_i$ represents the expanded stiffness matrix of an i^{th} element and N is the number of elements.

Similarly, the matrix $[m]$ is a sum of element mass matrices.

$$[m]=\sum_{i=1}^{N}[m]_i \tag{4}$$

Once the damage occurs in a structure, stiffness matrix of the damaged structure $[k_d]$ can be expressed as a sum of element stiffness matrices multiplied by stiffness factors associated with each of the N elements α_i (i = 1, 2, . . . , N), resulting from the damage as the following equation.

$$[k_d]=\sum_{i=1}^{N}\alpha_i[k]_i \tag{5}$$

The values of the parameters fall in the range 0 to 1. The stiffness factor α_i = 1 indicates that an undamaged element and α_i = 0 or less than 1 implies completely or partially damaged elements respectively. The experimental natural frequencies and unit amplitude vectors or mode shapes of the damaged structure are approximated to satisfy the eigen equation, Eq. (5), of j^{th} mode, therefore the equation can be rewritten as

$$[k_d]\{v_{jd}\}-\lambda_{jd}[m]\{v_{jd}\}=\{0\} \tag{6}$$

Where λ_{jd} and $\{v_{jd}\}$ are the approximated experimental eigenvalue and unit eigenvector of j^{th} mode. Moreover, it is assumed that the mass matrix is unchanged due to the damage.

If β_1, β_2, ..., β_N are decision variables which are the predicted stiffness factors. By substituting the predicted stiffness factors into Eqs. (1) and (2), an expression residual force vector of j^{th} mode in a function of β_i can be evaluated as follows.

$$\{R_j\}=-\lambda_{jd}[m]\{v_{jd}\}+\sum_{i=1}^{m}\beta_i[k]_i\{v_{jd}\} \tag{7}$$

The residual vector $\{R_j\}$ will be $\{0\}$, only if a correct set of β_i, which shows that $\beta_i=\alpha_i$ for all i, is introduced under the experimentally damaged modal information λ_{jd} and $\{v_{jd}\}$ for a particular mode j.

The $(n\times n)$ residual force matrix $[R]$ is therefore obtained by

$$[R]=[\{R_1\}\{R_2\}\ldots\{R_n\}] \tag{8}$$

If all β_i are correct, all elements of the matrix $[R]$ must be zero. The objective function f is then represented by

$$f(\beta_1,\beta_2,\ldots,\beta_N)=\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}R_{ij}^2} \tag{9}$$

Where N is the number of elements and n is the number of degrees of freedom.

3. Co-operative co-evolutionary genetic algorithm

Co-operative co-evolutionary genetic algorithm (CCGA) explores the search space by utilizing a population which contains a number of species or sub-populations. Each species is independently evolved as the procedure of genetic algorithm. In each species, an individual i represents only a decision variable or part of a solution to a problem. By partitioning the solution into species, the search space that each species has to cover is significantly reduced compared to the full solution searches. The CCGA produces best performances when there is no coupling between different species. However, if there is coupling between species, search performances deteriorate with increasing coupling strength.

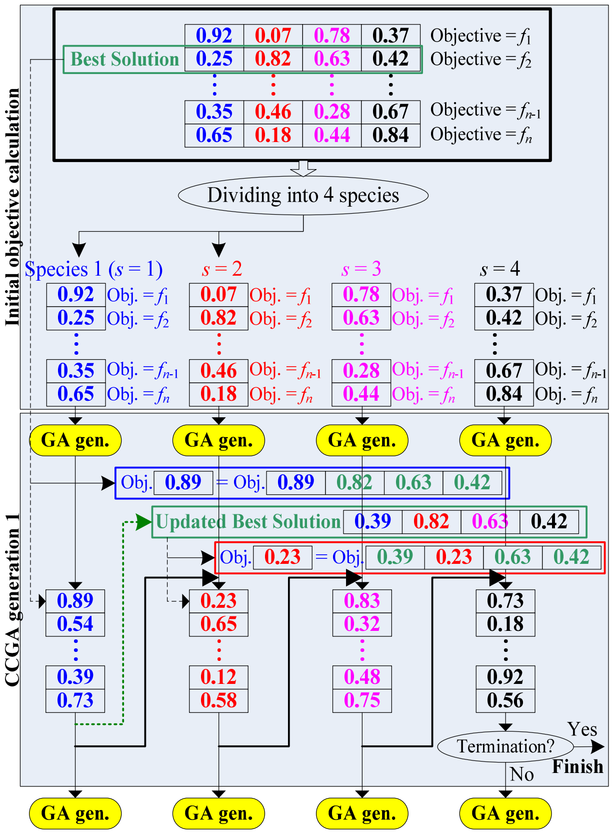

Fig. 1: CCGA procedure of an optimization problem with 4 decision variables.

In CCGA procedure, individuals of an initial population are randomly generated; the chromosome of every individual is then decoded in order to obtain solutions and calculated objective values. The individual having the best objective is assigned to be the current best individual. After that an individual in the initial population is divided into a number of parts in which each part represents for each species. The objective value of an individual in the initial population will be the initial objective value of a corresponding individual in each species. The fitness calculation and parent selection will be performed in order to obtain the resulting sub-population of each species. The initial objective calculation of the CCGA in this paper is quite different from the original initial objective calculation by Potter and De Jong (Potter and De Jong, 1994). It is proposed to reduce computational time. The individuals in each species are independently evolved as the GA procedure. Fig. 1 shows the main procedure of the CCGA of an optimization problem with 4 decision variables, where each species of CCGA represents a decision variable.

4. Test problems

Two truss models - two-dimensional (planar) and three-dimensional (space) truss structures - are used as the test problems. The first truss model (Rao et al., 2004) consists of 11 elements attaching to 6 nodes, and supported by simple supports (Fig. 2). The mechanical properties are modulus of elasticity (E) of 207 GPa, density (ρ) = 7860 kg/m^3, cross-sectional area (A) is 0.0011 m^2, and length of each bar (l) equals 0.75 m. Two test cases are considered - a) 70% and 30% partially damaged in elements 3 and 6 respectively, and b) completely damaged in an element 10. Therefore the actual stiffness factors α_i for cases (a) and (b) of this model are described by (10) and (11) respectively (Fig. 3).

$\alpha_3 = 0.3$, $\alpha_6 = 0.7$, and $\alpha_i = 1$ for other elements (10)

$\alpha_{10} = 0.0$ and $\alpha_i = 1$ for other elements (11)

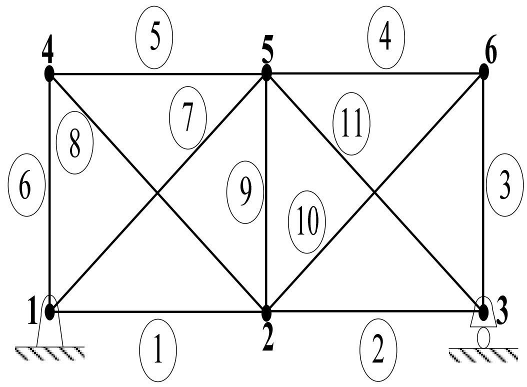

Fig. 2: A 11-bar two-dimensional truss model (Aanada et al., 2004)

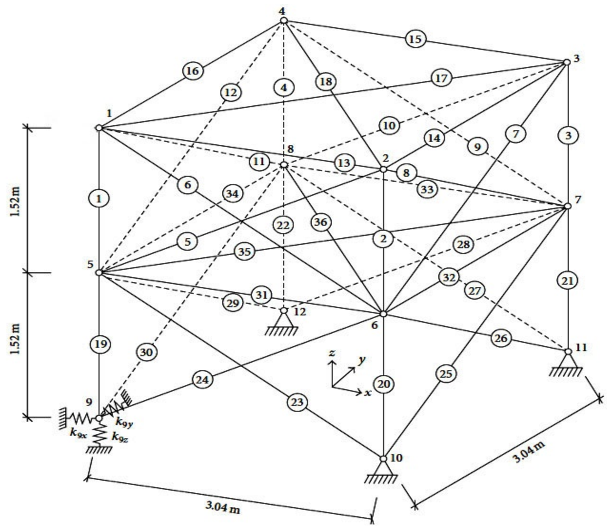

Fig. 3: A 36-bar three-dimensional truss model (Kim and Lee, 2013)

The second model is a space truss consisting of 36 elements and 12 nodes (Fig. 3). It is supported by three simply support ends and elastic foundation on one end as shown in the Fig. 3. Two test cases are a) 40% damaged in element 13 and b) 30% and 50% damaged in elements 1 and 21 respectively. The actual stiffness factors α_i for cases (a) and (b) of the space truss model are as (12) and (13) respectively. The mechanical properties are reserved as with the planar truss model.

$\alpha_{13} = 0.6$, and $\alpha_i = 1$ for other elements (12)

$\alpha_1 = 0.7$, $\alpha_{21} = 0.5$, and $\alpha_i = 1$ for other elements (13)

5. Simulation results and discussions

The parameter settings of CCGA for both truss models are illustrated in Table 1. A solution to each model is encoded by a real-value chromosome. The number of decision variables in the encoded chromosome is directly equal to number of elements of the truss model (N). Each species represents for a decision variable, the number of species is also equal to N. The number of decision variables (N) is then equal to 11 and 36 for the planar truss and space truss models respectively. Table 2 shows the numbers of generated solutions for solution search by CCGA and those from the previous studies. CCGA uses only 8.6% (planar truss) and 7.2% (space truss) generated solutions that had to be used in the previous works.

Table 1: Parameter settings

Parameter	Setting and Values
Chromosome coding	Real-value chromosome
Number of decision variables in a specie	1
Number of species	Number of decision variables
Population size	20
Selection method	Stochastic universal sampling selection
Crossover method	Simulated-binary crossover (Deb and Agrawal, 1995) with probability = 1.0
Mutation method	Variable-wise polynomial mutation (Deb, 1997) with probability = 0.5
Number of generations	25

Table 2: Number of generated solutions for solution search

Planar truss model cases (a) and (b)		Space truss model cases (a) and (b)	
GA (Rao et al., 2004)	CCGA	µGA (Kim and Lee, 2013).	CCGA
64,000	5,500	250,000	18,000

Table 3: Comparison of predicted stiffness for the planar truss model

Element	Case (a)			Case (b)		
	Actual	GA (Rao et al., 2004)	CCGA	Actual	GA (Anada et al., 2004)	CCGA
1	1.0	0.9974	1.0000	1.0	0.9882	1.0000
2	1.0	0.9784	1.0000	1.0	0.9941	1.0000
3	0.3	0.3176	0.2999	1.0	0.9804	1.0000
4	1.0	1.0000	1.0000	1.0	1.0000	1.0000
5	1.0	0.9892	1.0000	1.0	0.9941	1.0000
6	0.7	0.6920	0.7000	1.0	0.9723	1.0000
7	1.0	0.9970	1.0000	1.0	0.9920	1.0000
8	1.0	0.9361	1.0000	1.0	0.9991	1.0000
9	1.0	1.0000	1.0000	1.0	1.0000	1.0000
10	1.0	0.9853	1.0000	0.0	0.0009	0.0000
11	1.0	0.9967	1.0000	1.0	1.0000	1.0000

Table 3 shows that the solutions obtained from the CCGA are closer to the actual stiffness factors than those obtained from the standard GA (Rao et al., 2004). It also shows that CCGA can correctly identify the damage occurred in the planar truss. Figs. 4 and 5 plots the predicted stiffness factors obtained from the CCGA versus number of generated solutions for the planar truss cases (a) and (b) respectively. In Figures, the stiffness factors searched by the CCGA are quickly converged to the actual stiffness factors.

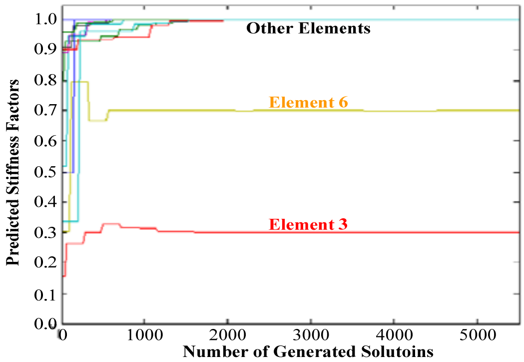

Fig. 4: Predicted stiffness factors by CCGA versus number of generated solutions for the planar truss case (a)

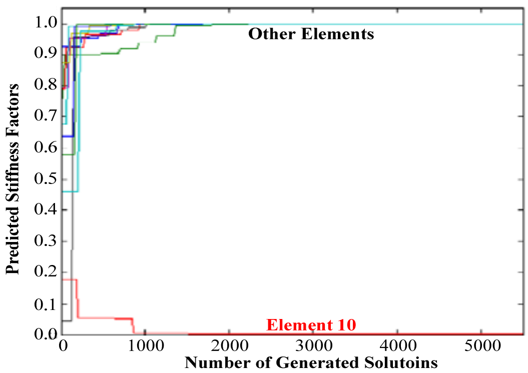

Fig. 5: Predicted stiffness factors by CCGA versus number of generated solutions for the planar truss case (b)

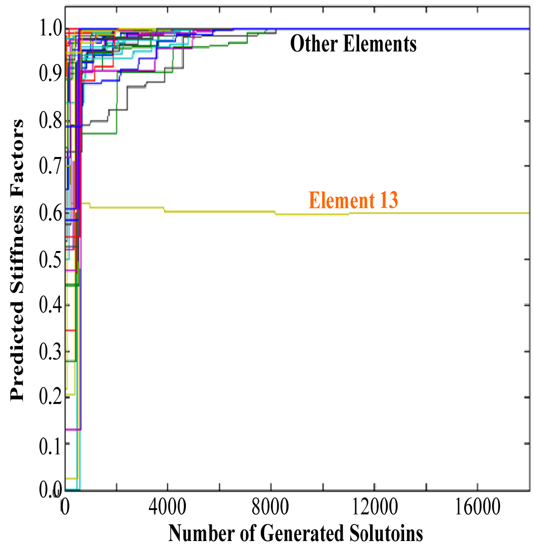

Fig. 6: Predicted stiffness factors by CCGA versus number of generated solutions for the space truss case (a)

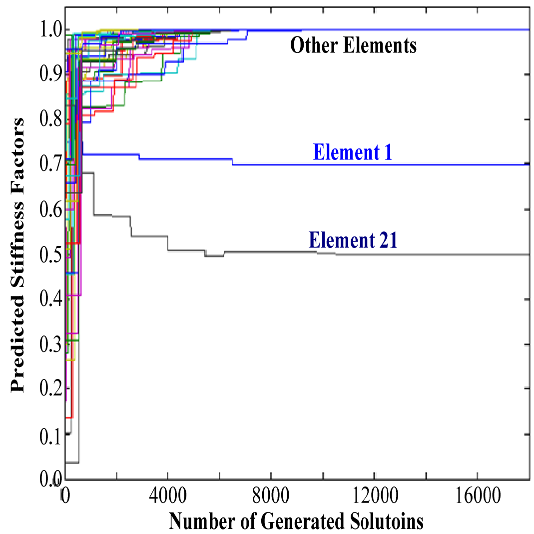

Fig. 7: Predicted stiffness factors by CCGA versus number of generated solutions for the space truss case (b)

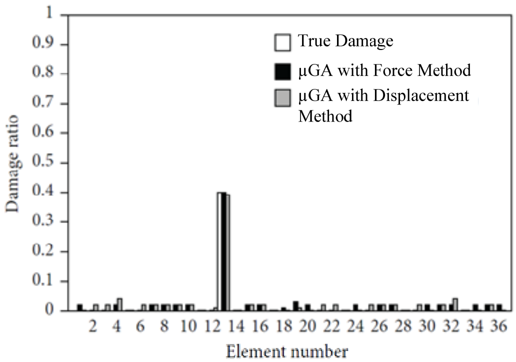

Fig. 8: Predicted damage ratio by μGA for the space truss case (a) (Bar graph from Kim and Lee 2013)

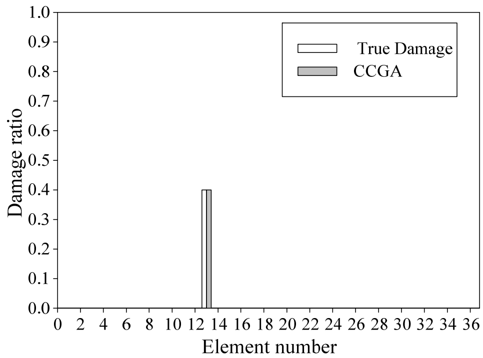

Fig. 9: Predicted damage ratio by CCGA for the space truss case (a)

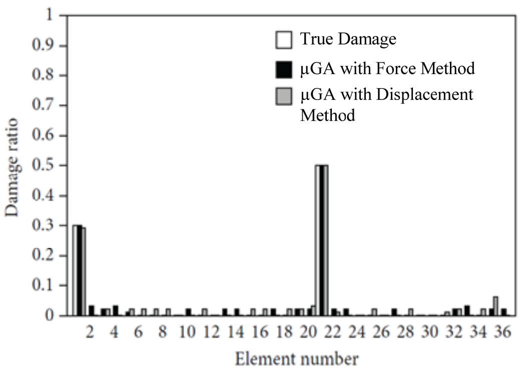

Fig. 10: Predicted damage ratio by μGA for the space truss case (b) (Bar graph from Kim and Lee 2013)

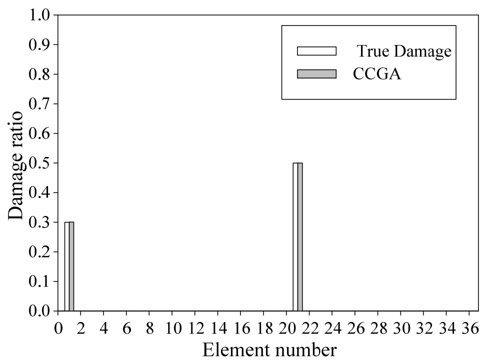

Fig. 11: Predicted damage ratio by CCGA for the space truss case (b)

For the space truss model, the stiffness factors searched by the CCGA are quickly converged to the actual stiffness factors as shown in Figs. 6 and 7. Figs. 8 – 11 show the bar graphs of predicted damage ratio of each element obtained from the previous work and that obtained from CCGA, in which stiffness factor of an element is equal to one minus damage ratio of the element. Figures show that the damage factors searched by CCGA are closer to the actual stiffness factors than those from the previous work (Kim and Lee 2013).

6. Conclusion

In this paper, CCGA, which is suitable for an optimization problem with weak coupling between decision variables, is proposed to solve the vibration-based damage detection in two-dimensional and three-dimensional truss structures. A numerical indicator of the differences between vibration characteristics of the true damage parameters and those of the predicted damage parameters is considered as the objective function. Simulation results show that CCGA can correctly identify the damage in both two-dimensional and three-dimensional truss models although it use less generated solutions than that used in the previous works employing GA and μGA.

References

Boonlong K (2014). Vibration-based damage detection in beams by cooperative coevolutionary genetic algorithm. Advances in Mechanical Engineering, (2014): Article ID 624949, 13 pages.

Boonlong K, Chaiyaratana N and Kuntanapreeda S (2004). Optimal Control of a Hysteresis System by Means of Co-Operative Co-Evolution. International Journal of Computational Intelligence and Applications, 4(4): 321-336.

Chandra R and Zhang M (2012). Cooperative coevolution of Elman recurrent neural networks for chaotic time series prediction. Neurocomputing, 86: 116-123.

Deb K and Agrawal RB (1995). Simulated binary crossover for continuous search space. Complex Systems, 9(2): 115-148.

Deb K (1997). Mechanical component design using genetic algorithms. Evolutionary algorithms in engineering applications (Eds. Dipankar Dasgupta and Z. Michalewicz) New York: Springer-Verlag (pp. 495-512)

Gawronski W and Sawicki JT (2000). Structural damage detection using modal norms. Journal of Sound and Vibration, 229(1): 194-198.

Goldberg DE (1989). Genetic algorithms in search optimization and machine learning (Vol. 412). Reading Menlo Park: Addison-Wesley.

Guo HY and Li ZL (2012). Structural damage identification based on Bayesian theory and improved immune genetic algorithm. Expert Systems with Applications, 39(7): 6426-6434.

Holland JH (1975). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press.

Ibánez O, Cordón O and Damas S (2012). A cooperative coevolutionary approach dealing with the skull–face overlay uncertainty in forensic identification by craniofacial superimposition. Soft Computing, 16(5): 797-808.

Kim NI and Lee J (2013). Damage identification of trusses with elastic supports using FEM and genetic algorithm. Advances in Mechanical Engineering, 5: 584901.

Mottershead JE, Friswell MI and Mares C (1999). A Method for Determining Model-Structure Errors and for Locating Damage in Vibrating Systems. Meccanica, 34(3): 153-166.

Nobahari M and Seyedpoor SM (2011). Structural damage detection using an efficient correlation-based index and a modified genetic algorithm. Mathematical and Computer Modelling, 53(9): 1798-1809.

Panigrahi SK, Chakraverty S and Mishra BK (2009). Vibration based damage detection in a uniform strength beam using genetic algorithm. Meccanica, 44(6): 697-710.

Potter MA and De Jong KA (1994). A cooperative coevolutionary approach to function optimization. In Parallel problem solving from nature—PPSN III (pp. 249-257). Springer Berlin Heidelberg.

Rao MA, Srinivas J and Murthy BSN (2004). Damage detection in vibrating bodies using genetic algorithms. Computers and Structures, 82(11): 963-968.

Yang QW and Liu JK (2007). Structural damage identification based on residual force vector. Journal of Sound and Vibration, 305(1): 298-307.