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Damage Detection and Localization in Beam Structures Based on Vibration Analysis and Cuckoo Search Algorithm

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Abstract

This paper presents a damage detection and localization based on vibration analysis in beam using Cuckoo search Algorithm. The damage is represented by a reduction in Young's modulus. The finite element method is used to apply damage at specific element(s) of the considered beams. The identification of damage is formulated as an optimization problem using objective function based on changes in natural frequencies. A procedure for detecting and locating damage of H-beam with thin plates structures based on Cuckoo search Algorithm is used. This approach presents a method that can be used to detect the single and multiple-damage positions and the rate of damage in structural elements with high accuracy after the first iteration. The noise introduced in the damage problem, it is shown that our approach based on Cuckoo search Algorithm can detect the damage with high accuracy. Making a comparative study of the obtained results with three well-known optimization algorithms confirms that the proposed Cuckoo search Algorithm produces better performance in damage detection and localization based on vibration analysis and optimization in beam.

Keywords: Damage detection and localization, vibration analysis, optimization, Cuckoo Search Algorithm.

1- Introduction

The principle of monitoring and detecting damaged structures to ensure user safety is a very important issue in civil and mechanic engineering. The damage detection methods based on vibration analysis have received considerable attention in literature in recent years. Since there is a considerable scientific and technical interest in the resolution of the structural damage identification problem. Not only extension of techniques that are based upon structural linear vibration analysis, but also the emergence of non-linear methodology and analysis have been investigated [1]. It is generally admitted that Rytter gave the four principal damage stages of structural health monitoring:

1- The determination of the presence of damage in the structure.
2- The determination of the damage location in the structure.

3- The quantification of the severity of the damage.
4- The prognosis of the remaining service life of the damaged structure.

In most investigations of damage identification based on modal parameters, the combination of natural frequency and mode shape were widely utilized by [2, 3]. In references [4, 5], the authors used the Chebyshev pseudo spectral modal curvature formulation for damage detection in beam-like composite structures. An extensive literature review [6] of the state of the art of damage detection and health monitoring from vibration characteristics has recently been published. This interest is attested by the large number of bibliographic reviews [7] dedicated for damage detection.Several developments made in the 1970s and early 1980s are used in the offshore oil industry, for example, Vandiver 1975 [8], Loland 1976 [9] Coppolino 1980 [10] Nataraja 1983 [11]. Later, the damage detection methods based on the vibratory responses are approved and are widely used for many types of structures. We can mention here of applications in industry, for example for the frames of planes West 1986 [12], and Tsyfansky Beresnevich 2000 [13] Trendafilova 2008 [14], or ball bearings Dron 2004 [8]. In particular, the vibration methods are often applied in mechanical and civil engineering, for example to detect damage in airplane wings, bridges and beams: Yuen 1985 [15], Luck 1994 [16] and Doebling1997 [17]. In recent years, damage detection and localization based on vibration analysis using the optimization method by Metaheuristic algorithms is of interest to many researchers. Genetic Algorithms were employed by many researchers for structural damage detection and localization based on model updating methods [18]. A damage detection and localization technique in beam-like structure using MAC (modal assurance criterion), COMAC (coordinate modal assurance criterion) and LFCR (Local Frequency Change Ratio) was introduced [19]. A genetic algorithm (GA) was used to detect damage in beam structure using three objective functions based on frequencies and eigenvectors [20], while a new damage detection and localization technique based on the changes in vibration parameters using BAT and Particle Swarm Optimization algorithm is used in [21]. In order to allow a comparison between different techniques, the following classification is proposed [22]: Detection, Localization, Assessment and Consequence. [23] Presents an approach of inverse damage detection and localization based on model reduction. Other part the detection and modeling of local buckling on thin plates of steel-concrete composite beam are presented by [24] and [25]. In the present work, a damage identification method using BAT algorithm to detect and locate single and multiple damages in H-beam with thin plates structures is considered. The objective functions used in the optimization process are based on vibration data of the structure. A finite element analysis will be performed on simply supported beams discretized into 10 elements.

2- Cuckoo search Algorithm (Cs)

Cuckoo Search (CS) is a powerful meta-heuristic search algorithm, inspired by the reproduction strategy of cuckoo birds. Basically, cuckoos lay their eggs in the nests of other birds, who may discover that and either destroy the eggs or abandon the nest. In this algorithm, three approximation rules are used as presented below [26-27].

- In the beginning, the cuckoos select random nest for laying their eggs and can lay only one egg at the time.
- In the second, Elitist selection process is applied and the eggs with highest quality are passed to the next generation.

- Finally, the number of hosts nests is specified and a host can detect a foreigner egg with a probability *Pa* between 0 and 1. If cuckoo's egg is discovered by the host, it may be thrown away, or the host may abandon its own nest and commit it to the cuckoo intruder

The last assumption is the approximation by a factor P_a of the n nests being exchanged by new nests. The best solution is relative to the objective function for a minimization problem. A flowchart for the CS algorithm is shown in Figure (1). The input parameters of CS are given in Table (1). The new solution of cuckoo at iteration is generated by using the following equation:

$$x_i^{t+1} = x_i^t + \alpha \times levy(\lambda) \tag{1}$$

Where x_i^{t+1} is the previous solution and denotes the step size, which corresponds to the scale of problem and should be greater than zero. If the step length is chosen too large then the next solution will be too far from the current solution, whereas if the step length is too short then the solution will be very close to the current solution. Therefore, in most cases $\alpha = 1$ is used because $levy(\lambda)$ is the random walk, i.e. its step length is calculated from levy distribution for levy flight.

$$levy(\lambda) \sim u = t^{-\lambda} \quad (1 \le \lambda \le 3) \tag{2}$$

Table 1- Input parameters of CS Algorithm

Input parameters	**Value**
Number of nests	**200**
maximum l number of generation	**100**
probability of detecting (P_a)	**0.25**
Levy exponent (λ)	**1.5**
number of Iterations to stop the algorithm is solution is not improve	**500**

3- Genetic Algorithm (GA)

Genetic Algorithm (GA) is a general probabilistic algorithm inspired by Darwin's survival-of-the fittest theory. In GA, information about a problem to study, such as variable parameters, 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 minimized based on the description of the problem. GA has been shown to be able to solve the optimization problem using mutation, crossover and selection operation applied to individuals in the population [28]. A flowchart for the GA shown in Figure (2). The input parameters of GA are given in Table (2).

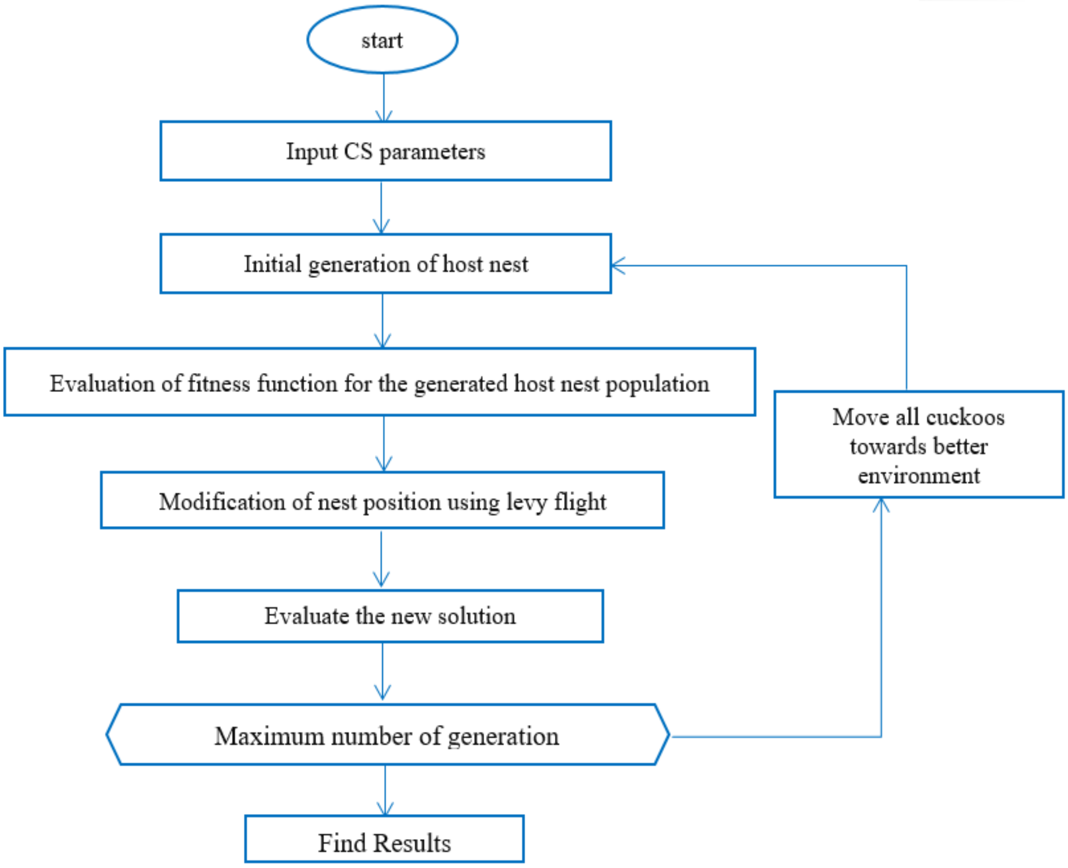

Figure 1- flowchart of CS Algorithm

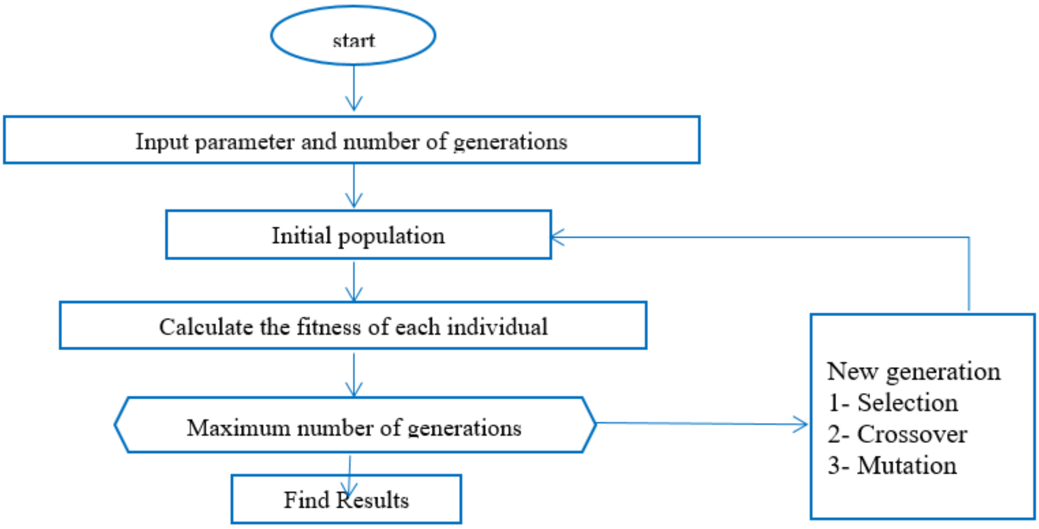

Figure 2- flowchart of GA Algorithm

Table 2- Input parameters of GA Algorithm

Input parameter	Value
Number of particles	200
maximum number of Iterations	100
inertia weighting parameter (w)	w
number of Iterations to stop the algorithm is solution is not improve	50
Parameter $c_1 = c_2$	0.2

4- Particle Swarm Optimization (PSO)

The PSO algorithm was first proposed by Kenne-dy and Eberhart, has been used widely in the recent years and has been modified in a variety of versions that could handle the majority of optimization problems with or with-out the presence of constraints. It involves a swarm, modeled as a number of individual particles, moving through the search space in searching for a global optimum. The particles communicate with their neighbors over the progress made so far and adjust their moving velocity according to that information. First, a population of candidate solutions is created randomly, each of which is considered to be a particle moving through the multidimensional de-sign space in search of the position of a global optimum. The particle can be characterized by its physical position in the space and its velocity vector, while it has the ability to remember two important information; i.e. the best position it has passed so far or a personal best (P_best) and the best position that any other particle of the swarm has passed so far or a global best (G_best). The acceleration coefficients of PSO, c1 and c2, represent the degree of "confidence" in the best solution found by the individual particle. The latter is possible because each particle has the ability to communicate with a number of neighboring particles, which are defined by a predetermined network topology. fitness of each particle shows the quality of each solution and is evaluated by a fitness function. In every iteration the speed of the particle is updated in a stochastic way [29]. Fig. 6 illustrates a pseudo code for a particle swarm optimization PSO. The update equations for the speed and position of a particle are:

$$v_i^{t+1} = wv_i^t + c_1r_1\left[x_i^{Pbest,t} - x_i^t\right] + c_2r_2\left[x_i^{Gbest,t} - x_i^t\right] \quad (3)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (4)$$

Where w is inertia weight parameter, $x_i^{Pbest,t}$ is vector of the personal best location found by the particle i until current iteration, $x_i^{Gbest,t}$ is vector of the global best location found by the entire swarm up to the current iteration, v_i^t is the velocity vector of particle i at time t, x_i^t is the position vector of particle i at time t, r_1 and r_2 are vectors containing random numbers with uniform distribution in the interval [0, 1]. The input parameters of Pso are given in Table (3), a flowchart for the Pso shown in Figure (3).

Table 3- Input parameters of PSO Algorithm

Input parameter	Value
Number of particles	200
maximum number of Iterations	100
number of Iterations to stop the algorithm is solution is not improve	50
Crossover rate	0.8
Mutation rate	0.2

5- Proposed work

In This study we used optimization method refers to solving a problem in the best possible way Based on inverse problem. In most cases, the goal is to minimize an objective function based on changes in natural frequencies by choosing values for its variables within an acceptable range. The damage detection and localization procedures, which we propose here in, are carried out according to the following steps:

1- Create a damage by reducing Young's modulus using FEM and calculating the natural frequencies.

2- Quantifying damage using Cuckoo Search algorithm.
3- Solving the inverse problem after providing frequencies of real damage to the objective function in order to calculate damage locations and severity using Cuckoo Search algorithm and FEM (estimated damage).

The proposed work In This study to the damage detection and localization problems is illustrated by a flow chart as is shown in Figure (4).

5-1- Damage Detection with Noise

To study the effects of noise on the results of our approach (Eq.5), the answer N^{th} noise is simulated by [30]:

$$N_{d_i}(\text{Noise}) = (1 + \sigma\gamma)N_{d_i} \tag{5}$$

Where σ is the noise and γ is a random number in the interval [-1, 1]. σ in this study is considered 5% and 10%.

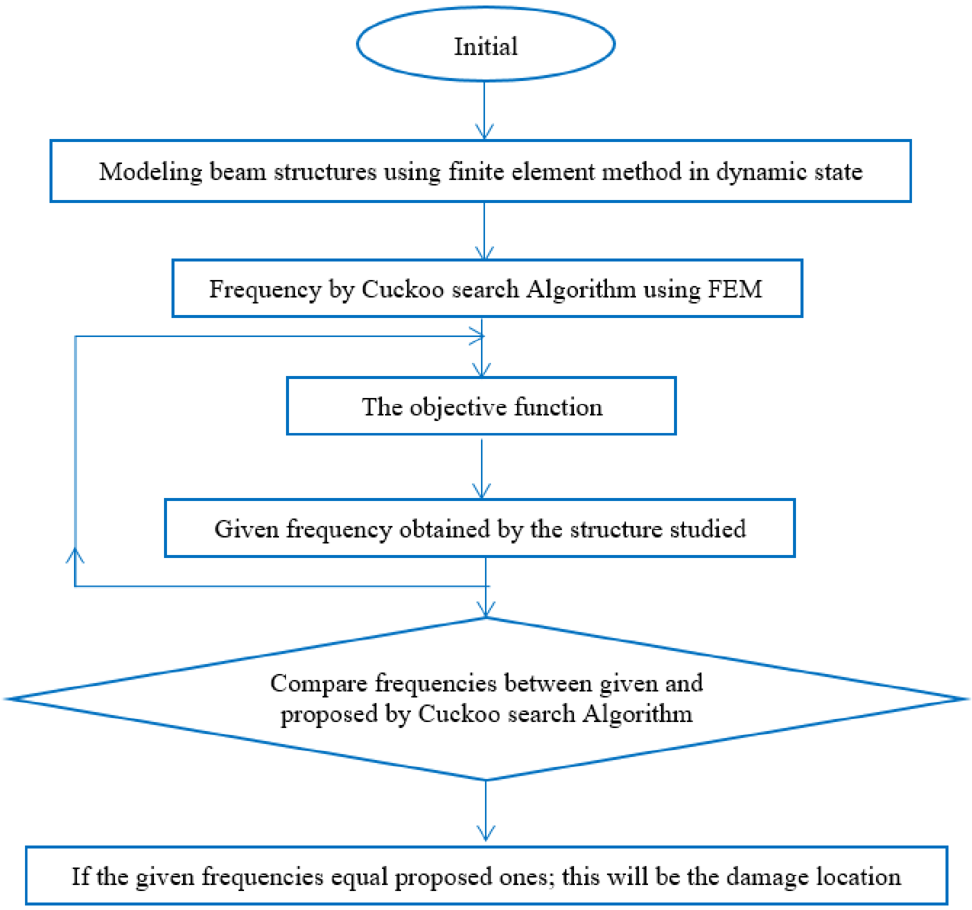

Figure 4- Approach using Cuckoo search Algorithm

6- Numerical model of the beam structure

In our study we consider a simply supported beam as shown in figure 1, with the following mechanical properties: cross-section area: $A = 0.09m^2$, density: $\rho = 2500\text{Kg}/\text{m}^3$, and stiffness:

$EI = 20.25 \times 10^6 N.m^2$[32]. A simply-supported finite element beam model is constructed using 10 beam elements as shown in Figure (5). For the intact beam, a constant stiffness EI is assumed for all elements, while the damaged beam is modeled by reducing EI of damaged elements.

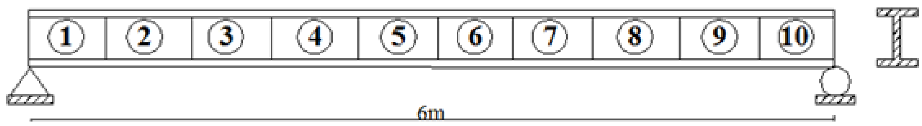

Figure 5- Simply-supported beam structure without damage discretized in 10 elements

The analytical and numerical natural frequencies of the intact simply-supported beam are given in Table (4) for the first five modes.

Table 4- Comparison of natural frequencies of intact beam

Mode	*Numerical frequencies (FEM) (This study)*	*frequencies Using Analytical* [33]	*Numerical frequencies (FEM)* [33]
1	13.9987	14.3393	13.9967
2	57.0822	57.3574	57.0609
3	126.2543	129.0541	126.2425
4	225.8206	229.4295	225.8134
5	351.3531	358.4836	351.2631

7- Results and discussion

In this study, six different damage scenarios were applied to the simply support beam. Different locations and severity of damage are investigated to check the performance of the method as follows:

Scenario (1): A simple damage where the stiffness of element 2 was reduced by 50 percent.

Scenario (2): A simple damage where the stiffness of element 8 was reduced by 50 percent.

Scenario (3): A Multiple damage where the stiffness of elements 2 and 8 was reduced by 50 percent.

Scenario (4): A simple damage where the stiffness of element 8 was reduced by 50 percent with noise rate 5%

Scenario (5): A simple damage where the stiffness of element 8 was reduced by 50 percent with noise rate 10%

The results of these scenarios are represented on the following Figures 3, 4 and 5 successively.

7-1- Scenario (1)

The results of Scenario (1) is shown in Table (5).

Table 5- The results of damage detection and localization in Scenario (1)

Elements	*Real damage*	CS	GA	*PSO*	*BAT* [33]
1	0	0.0022	0.0036	0.0032	0.0027
2	0.5	0.5000	0.501	0.5008	0.5005
3	0	0.0053	0.0071	0.0067	0.0063
4	0	0.0029	0.0041	0.0037	0.0034
5	0	0	0.0009	0.0004	0.0002
6	0	0.0001	0.0011	0.0008	0.0005
7	0	0.0024	0.0037	0.0034	0.0029
8	0	0	0.0008	0.0005	0.0001
9	0	0.0035	0.0049	0.0044	0.0040
10	0	0.0001	0.0012	0.001	0.0006

7-2- Scenario (2)

The results of Scenario (2) is shown in Table (6).

Table 6- The results of damage detection and localization in Scenario (2)

Elements	*Real damage*	CS	GA	*PSO*	*BAT* [33]
1	0	0.0076	0.0088	0.0084	0.0080
2	0	0.0014	0.0026	0.0022	0.0018
3	0	0.0048	0.006	0.0057	0.0053
4	0	0.00044	0.0058	0.0054	0.0049
5	0	0.0016	0.0027	0.0024	0.0020
6	0	0.0005	0.0016	0.0013	0.0010
7	0	0.0055	0.0075	0.007	0.0066
8	0.5	0.5002	0.5013	0.5009	0.5007
9	0	0.0038	0.0049	0.0045	0.0042
10	0	0.0078	0.0126	0.0121	0.0118

7-3- Scenario (3)

The results of Scenario (3) is shown in Table (7).

Table 7- The results of damage detection and localization in Scenario (3)

Elements	*Real damage*	CS	GA	*PSO*	*BAT* [33]
1	0	0	0.0009	0.0005	0.0002
2	0.5	0.5003	0.4941	0.4958	0.4973
3	0	0.0003	0.0015	0.0012	0.0007
4	0	0.0017	0.0031	0.0027	0.0022
5	0	0.0005	0.0019	0.0015	0.0010
6	0	0.0009	0.0016	0.0013	0.0015
7	0	0.0033	0.0055	0.0045	0.0039
8	0.5	0.5	0.5013	0.5009	0.4998
9	0	0.0001	0.0011	0.0008	0.0006
10	0	0.0006	0.0023	0.0017	0.0011

7-4- Scenario (4)

The results of Scenario (4) is shown in Table (8).

Table 8- The results of damage detection and localization in Scenario (4)

Elements	*Real damage*	CS	GA	*PSO*	*BAT* [33]
1	0	0.0056	0.0078	0.0071	0.0065
2	0	0.0025	0.0039	0.0035	0.0032
3	0	0.0023	0.0041	0.0039	0.0032
4	0	0.0064	0.0081	0.0075	0.0070
5	0	0	0.001	0.0007	0.0001
6	0	0.0001	0.0016	0.0012	0.0009
7	0	0.0011	0.0025	0.0022	0.0019
8	0.5	0.5004	0.5013	0.5009	0.5012
9	0	0	0.0007	0.0004	0

10	0	0.0021	0.0035	0.0033	0.0029

7-5- Scenario (5)

The results of Scenario (5) is shown in Table (9).

Table 9- The results of damage detection and localization in Scenario (5)

Elements	*Real damage*	CS	GA	*PSO*	*BAT* [33]
1	0	0.0028	0.0038	0.0036	0.0033
2	0	0.0035	0.0049	0.0045	0.0043
3	0	0.0037	0.0048	0.0046	0.0043
4	0	0.0134	0.0162	0.0156	0.0152
5	0	0.00012	0.0021	0.0019	0.0016
6	0	0.0018	0.0027	0.0025	0.0023
7	0	0.0065	0.0076	0.0074	0.0070
8	0.5	0.4951	0.4926	0.4929	0.4934
9	0	0	0.0009	0.0006	0.0003
10	0	0.0096	0.0119	0.0115	0.0111

From the results, we can observe that, when the noise is included in the problem of fault detection, our approach based on Cuckoo Search Algorithm can detect damage with high accuracy.

8- Conclusion

In this study we used Cuckoo Search Algorithm to evaluate a position and level of damages assignment by minimizing the objective function based on the natural frequencies undamaged and damaged tested beam with and without noise and considering different damage scenarios. The results showed high accuracy of the method using Cuckoo search Algorithm, even when two damages is present, within the first few iterations. The noise is taken into account in the damage detection problem, our approach based on Cuckoo Search Algorithm can detect the damage locations correctly with high accuracy even if the noise. Making a comparative study of the obtained results with three well-known optimization algorithms confirms that the proposed Cuckoo Search Algorithm produces better performance in damage detection and localization based on vibration analysis and optimization in beam.

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