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Damage detection in skeletal structures based on charged system search optimization using incomplete modal data

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Abstract

It is well known that damaged structural members may considerably alter the behaviour of the structures. Careful observation of these changes has often been viewed as a means to identify and assess the location and severity of damages in structures. Among the responses of a structure, natural frequencies and mode shapes are both relatively easy to obtain and independent from external excitation, and therefore, can be used as a measure of the structural behaviour before and after an extreme event which might have led to damage in the structure. This paper applies Charged System Search algorithm to the problem of damage detection using vibration data. The objective is to identify the location and extent of multi-damage in a structure. Both natural frequencies and mode shapes are used to form the required objective function. To moderate the effect of noise on measured data, a penalty approach is applied. Varity of numerical examples including beams, frames and trusses are examined, and the results show that the present methodology can reliably identify damage scenarios using noisy measurements and incomplete data.

Keywords: Damage detection, Vibration-based, Charged System Search, Incomplete modal data.

1. Introduction

During the past two decades, structural damage identification has gained increasing attention from the scientific and engineering communities, since damage that is not detected and not repaired may lead to catastrophic failure. Former methods structural of identification are either visual or localized experimental methods require that the vicinity of the damage is known and accessible. Hence, the vibration-based damage identification method as a global damage identification technique is developed to overcome these difficulties. The basic idea of vibration-based damage methods is that modal parameters (notably frequencies, mode shapes, and modal damping) are functions of the physical properties of the structure (mass, damping, and stiffness). Therefore, changes in the physical properties will cause changes in the modal properties [1].

The usual model-based damage detection methods minimize an objective function, which is defined in terms of the discrepancies between the mathematical model and real structural system.

There are two general methods to optimize the objective function, namely, mathematical programming and meta-heuristic methods. Unlike the mathematical methods, one of the important characteristics of metaheuristic methods is their effectiveness and robustness is coping with uncertainty, insufficient information and noise. Many successful applications of damage detection using the meta-heuristic algorithm have been reported in the literature. Perera and Torres [2] proposed a method based on mode shapes and frequencies using genetic algorithm on beams. Laier et al. [3] improved the genetic algorithm to solve damage detection problem for 2D-truss type structures. They used natural frequencies and mode shapes to form objective function. Miguel et al. [4] combined time domain modal identification technique (SSI) with evolutionary harmony search algorithm (HS) to detect damages under ambient vibration, they studied three cantilever beams under different damage scenarios. Kang et al. [5] proposed an immunity enhanced particle swarm optimization (IEPSO) for damage detection of structures, they tested this method on a simple beam and a truss. Majumdar et al. [6] presented a method to identify structural damages in truss structures from changes in natural frequencies by using ant colony optimization.

Natural frequencies and modal shapes are the most popular parameters used in the damage identification. These gain their popularity because the modal properties have their physical meanings and are easier to be interpreted or interrogated than those abstract mathematical features extracted from the time or

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frequency domain [7].

Metaheuristic optimization methods are the recent generation of optimization methods. These methods are inspired from natural phenomena. Particle Swarm Optimization proposed by Eberhart and Kennedy [8], Ant colony optimization proposed by Dorigo et al. [9] simulates social behavior of animals. Harmony Search presented by Geem et al. [10], Big Bang-Big Crunch algorithm proposed by Erol and Eskin [11], Charged System Search proposed by Kaveh and Talatahari [12], Magnetic Charged System Search (MCSS) proposed by Kaveh et al. [13], Ray optimization of Kaveh and Khayatazad [14], Colliding Bodies Optimization of Kaveh and Mahdavi [15], and Democratic Particle Swarm Optimization of Kaveh and Zolghadr [16] are other metaheuristic algorithms which have sources in nature. Some application can be found in Refs. [17-18].

In this paper an objective function based on natural frequency and mode shapes are used to solve damage detection problem. Charged System Search algorithm and Enhance Charged System Search are utilized to search for global optimum of the proposed objective function. The damage detection methodology is applied to four different types of structures.

2. Damage Identification Methodology

The proposed damage detection method consists of performing an optimization problem through an objective function based on vibration data. Here, damage is considered as a reduction in the elastic modulus.

2.1. Objective function

The objective function is based on natural frequencies and mode shapes and is given by Eq. (1). Due to measurement noise, tendency will always be to find damage at most of the elements [19]. Thus, a penalty is introduced to weight against an increased number of damage sites.

$$cost = E(1 + \beta * penalty)$$
 , $E = E_{\phi} + E_{\omega}$ (1)

$$E_{\phi} = \sum_{j=1}^{r} \left\| \frac{\phi_j^m - \phi_j^a}{\phi_j^m + \phi_j^a} \right\| \tag{2}$$

$$E_{\omega} = \sum_{i=1}^{r} \left(\frac{\left(\omega_{j}^{m} - \omega_{j}^{a}\right)^{2}}{\left(\omega_{j}^{m}\right)^{2}} \right)$$
(3)

Where ω_j^m and ω_j^a are the *j*th measured and analytical natural frequencies of the damaged structure, respectively. Φ_j^m and Φ_j^a are the measured and analytical value of the *j*th mode shape, respectively. r is the number of measured modes and β is a penalty factor which is related to the type of structure and the closeness of the measured data and the exact data. Here, *penalty* is the number of damaged elements in the analytical model.

3. Optimization Algorithm

3.1. Standard Charged Search System

Charged System Search is a population based metaheuristic algorithm proposed by Kaveh and Talatahari [12]. This algorithm is based on laws from electrostatics of physics and Newtonian mechanics. The pseudo-code of the CSS algorithm is presented as follows [20]:

Level 1: Initialization

Step 1. Initialization. Initialize the parameters of the CSS algorithm. Initialize an array of charged particles (CPs) with random positions. The initial velocities of the CPs are taken as zero. Each CP has a charge of magnitude (q) defined considering the quality of its solution as:

$$q_i = \frac{fit(i) - fit_{worst}}{fit_{best} - fit_{worst}} \tag{4}$$

Where *fitbest* and *fitworst* are the best and the worst fitness of all the particles respectively; fit(i) represents the fitness of agent i. The separation distance r_{ij} between two charged particles is defined as:

$$r_{ij} = \frac{\left\| X_i - X_j \right\|}{\left\| \frac{\left(X_i + X_j \right)}{2} - X_{best} \right\| + \varepsilon}$$
(5)

Where X_i and X_j are the positions of the *i*th and *j*th CPs, respectively; X_{best} is the position of the best current CP; and ε is a small positive to avoid singularities.

Step 2. CP ranking. Evaluate the values of the fitness function for the CPs, compare with each other and sort them in increasing order.

Step 3. CM creation. Store the number of the first CPs equal to charged memory size (CMS) and their related values of the fitness functions in the charged memory (CM).

Level 2: Search

Step 1. Attracting force determination. Determine the probability of moving each CP toward the others considering the following probability function:

$$pm_{ji} = \begin{cases} 1 \Leftrightarrow & fit(i) > fit(j) \lor 0.02(1 - \left(\frac{iter}{iter_{max}}\right)) > rand \\ 0 \Leftrightarrow & else, \end{cases}$$
 (6)

and calculate the attracting force vector for each CP as follows:

$$F_{j} = q_{j} \sum_{i,i\neq j} \left(\frac{q_{i}}{a^{3}} r_{ij} \cdot i_{1} + \frac{q_{i}}{r_{ij}^{2}} \cdot i_{2} \right) p_{ij} \left(X_{i} - X_{j} \right), \begin{cases} i_{1} = 1, i_{2} = 0 \Leftrightarrow r_{ij} < a, \\ i_{1} = 0, i_{2} = 1 \Leftrightarrow r_{ij} \geq a, \end{cases}$$

$$(7)$$

Where F_j is the resultant force affecting the jth CP. Step 2. Solution construction. Move each CP to the new position and find its velocity using the following equations:

$$X_{j,new} = rand_{j1} \cdot k_a \cdot \frac{F_j}{m_j} \cdot \Delta t^2 + rand_{j,2} \cdot k_v \cdot V_{j,old}$$

$$\cdot \Delta t + X_{j,old}$$

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t}$$

$$(9)$$

$$V_{j,new} = \frac{X_{j,new} - X_{j,old}}{\Delta t} \tag{9}$$

Where $randj_2$ and $randj_2$ are two random numbers uniformly distributed in the range (1,0); mj is the mass of the CPs, which is set to unity in this paper. Δt is the time step, and it is set to 1. k_a is the acceleration coefficient; k_v is the velocity coefficient to control the influence of the previous velocity. In this paper k_v and k_a are taken as:

$$k_a = c_a \left(1 + \frac{iter}{iter_{max}} \right) \tag{10}$$

$$k_{v} = c_{v} \left(1 - \frac{iter}{iter_{max}} \right) \tag{11}$$

Where c_a and c_v are two constants to control the exploitation and exploration of the algorithm; iter is the iteration number and itermax is the maximum number of iterations.

Step 3. CP position correction. If each CP exits from the allowable search space, correct its position.

Step 4. CP ranking. Evaluate and compare the values of the fitness function for the new CPs; and sort them in an increasing order.

Step 5. CM updating. If some new CP vectors are better than the worst ones in the CM, in terms of their objective function values, include the better vectors in the CM and exclude the worst ones from the CM.

Level 3: Controlling the terminating criterion

Repeat the search level steps until a terminating criterion is satisfied.

3.2. Enhanced Charged Search System

As mentioned before, CSS is a population-based algorithm. For multi-agent methods, the updating process is performed after all agents have created their solutions. Similarly, for the CSS algorithm, when the calculations of the amount of forces are completed for all CPs and the new

locations of agents are determined, the CM updating is performed. In the present case, it is assumed that after creating each solution, all updating processes are performed. In this way, the new position of each agent can affect on the moving of the subsequent CPs while in the standard CSS unless an iteration is completed, the new positions cannot be utilized. Due to using the information obtained by the CPs immediately after creation, this modification enhances the intensification of the algorithm [21].

4. Numerical Examples

In this section, the efficiency and effectiveness of the proposed methods is evaluated through some numerically simulated damage identification tests using incomplete modal data; a continuous beam, a three-story and threespan plane frame, a 2D-truss and a 3D-truss are considered with two different damage scenarios for each of them. Due to the stochastic nature of the meta-heuristic algorithms for each scenario the algorithm is run ten times and the solution with the lowest cost is selected as the ultimate damage scenario. The mode shapes are measured with less accuracy than the natural frequencies. Therefore, in order to simulate the conditions of a real test, the measured parameters are numerically perturbed by 1% for natural frequencies and 3% for mode shapes to consider the presence of the noise.

4.1. A continuous beam

For the first example a continuous beam depicted in Figure 1 is considered. Beam length is equally divided into 26 elements with a uniform section (IPE240). Area of cross section and moment of inertia of the simulated beam are 39.1cm² and 3892cm⁴, respectively. The modulus of elasticity and the material density are 200 GPa and 7780kg/m³, respectively. The first 6 natural frequencies and mode shapes of the structure are used to form the objective function. Figures 2 and 3 represent the damage states found by both optimization algorithms with the actual damage states in different scenarios.



Fig. 1 A beam modeled with 26 finite elements

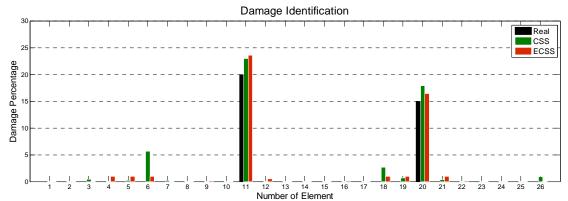


Fig. 2 Damage detection results of the algorithms for the beam (scenario I)

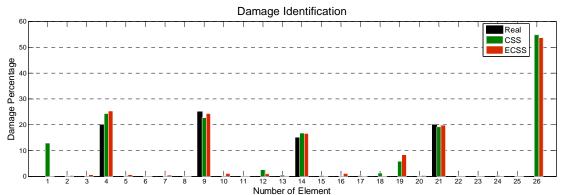


Fig. 3 Damage detection results of the algorithms for the beam (scenario II)

4.2. A planar frame

The frame with three spans and three story depicted in Figure 4 is considered as the second example. The sections used for the beams and columns are IPE240 and IPE300, respectively. The modulus of elasticity and material density are identical to those of the previous model. The

first 6 natural frequencies and 6 mode shapes of the structure are utilized to form the objective function. Figures 5 and 6 represent the damage states found by both optimization algorithms with the actual damage states in different scenarios.

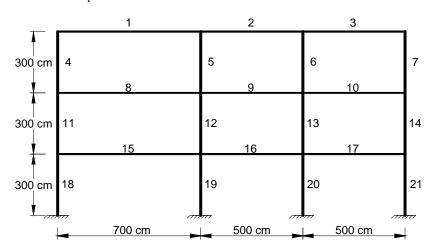


Fig. 4 A three-span three-story frame

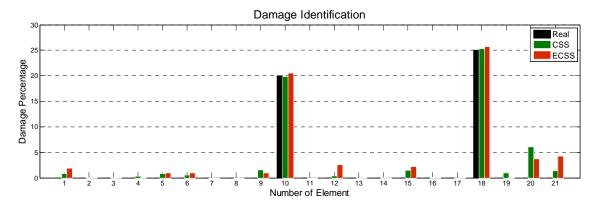


Fig. 5 Damage detection results of the algorithms for the three-span three-story frame (scenario I).

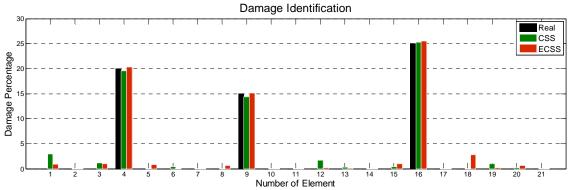


Fig. 6 Damage detection results of the algorithms for the three-span three-story frame (scenario II)

4.3. A planar truss

As the third example, a statically determinate truss bridge shown in Figure 7 is considered. Area of cross section for all elements is taken as 10cm^2 . The modulus of elasticity and material density are the same as the previous

model. The first 5 natural frequencies and mode shapes of the structure are used to form the objective function. Figures 8 and 9 represent the damage states found by both optimization algorithms with the actual damage states in different scenarios.

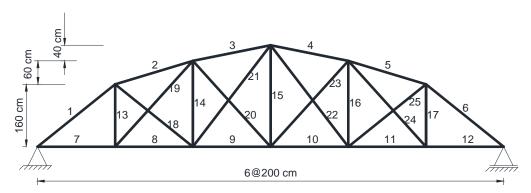


Fig. 7 A truss with 25 elements

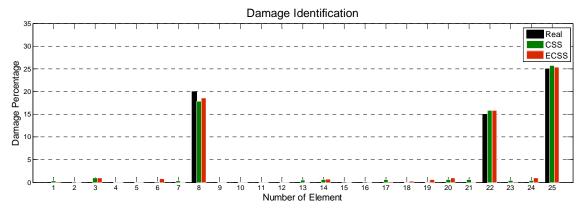


Fig. 8 Damage detection results of the algorithms for the planar truss (scenario I)

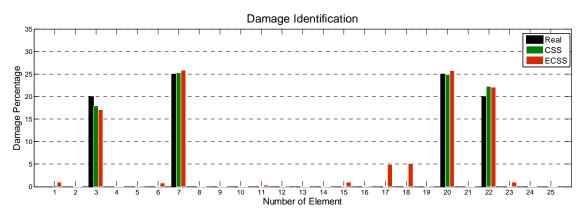


Fig. 9 Damage detection results of the algorithms for the planar truss (scenario II)

4.4. A space truss

A space truss is considered as the last example. The geometry, element numbering and material properties are shown in Figure 10. The first 6 natural frequencies and

mode shapes of the structure are utilized to form the objective function. Figures 11 and 12 represent the damage states found by both optimization algorithms with the actual damage states in different scenarios.

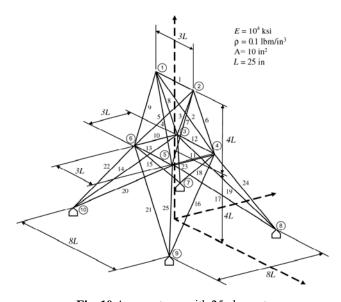


Fig. 10 A space truss with 25 elements

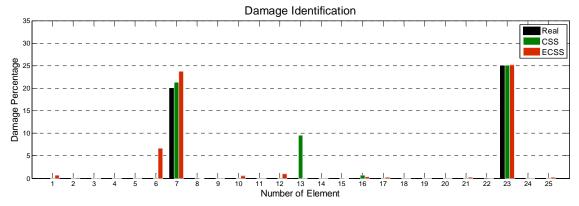


Fig. 11 Damage detection results of the algorithms for the space truss (scenario I)

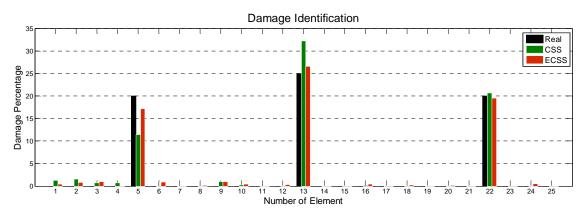


Fig. 12 Damage detection results of the algorithms for the space truss (scenario II)

5. Conclusions

A damage detection technique in skeletal structures based on natural frequencies and mode shapes are studied in this paper, and a penalty approach is applied to moderate the effect of noise on modal data. Two versions of the CSS are utilized for searching the correct damage scenarios. In order to verify the performance of the proposed methodologies, damage detection is conducted on variety of numerical problems with different scenarios. In most of the cases, the results show that the algorithm successfully finds the location and the severity of the damages. In the continuous beam, the cantilever part is adversely affected by the noise which causes a missidentification in the second scenario for both algorithms. Generally, it can be concluded that the both proposed algorithms are quite efficient and robust for damage detection problems, and they can identify the locations and severities of damages using incomplete modal data which contaminated by random noise.

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