DAMAGE DETECTION IN A STEEL BEAM STRUCTURE USING PARTICLE SWARM OPTIMIZATION AND EXPERIMENTALLY MEASURED RESULTS

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Abstract: *This paper presents an approach for damage detection in a steel beam by employing particle swarm optimization (PSO), which is an evolutionary algorithm based on global search techniques. PSO is used to identify damage location and level in structure by minimizing the deviation between experimental and the numerical results. A steel beam calibrated on measurement is used to evaluate the efficiency of the proposed approach. While the experimental measurements are carried out under excitation sources of a hammer using peak picking technique, a finite element model is created in MATLAB to represent the dynamic characteristics of the beam. Dynamic behavior of the beam is selected as an objective function. The results demonstrate that PSO can accurately detect damage location and extent in the considered structure.*

Keywords: *Structural health monitoring, Damage detection, Evolutionary algorithm, Particle swarm optimkzation.*

I. INTRODUCTION

Structural health monitoring (SHM) based on dynamic nondestructive testing has become a continuous interest for the scientific community over the last decades. Numerous successful applications of SHM based on nondestructive method as a tool for damage detection have been reported in the literature. Kaveh et al. [1] applied Enhanced Colliding Bodies Optimization (ECBO) and Colliding Bodies Optimization (CBO) combined with structural modal information for damage identification of a steel beam. The results showed that the proposed method could accurately predict damage location and level in the considered structure. Hwang et al. [2] detected damage in a cantilever beam, and a helicopter rotor blade using frequency response function (FRF) data by minimizing the deviation between analytic and test FRFs. The proposed approach identified the damage location and severity in the tested structures to a satisfactory level of precision. Hassiotis et al. [3] proposed a technique based on natural frequency measurements to identify localized reductions in the stiffness of a beam and a steel frame. The results showed that this approach successfully identified 10 % to 90 % localized reduction in stiffness in the considered structures. Miguel et al. [4] employed a hybrid stochastic/deterministic optimization algorithm to deal with the problem of damage identification in a series of numerical examples including a Portal plane frame, a cantilever beam, a 10 bar planar truss. They pointed out that the proposed method not only accurately detected damages but also required a low computational cost. Kaveh et al. [5] identified the damage location and level in structures consisting of a six-storey steel shear frame, a 15-bar planar truss, a 25-bar spatial truss, a 40-element beam, a 56-element concrete portal frame, a 20-element planar jacket-type offshore platform by solving an inverse problem. Enhanced thermal exchange optimization was applied for damage detection. Hao et al. [6] identified damage location and extent in a cantilever beam, and a portal frame using genetic algorithm based on an objective function of mode shape changes, natural frequency changes and a combination of the two. Kaveh et al. [7] presented an improved Charged System Search algorithm to detect damages in a 10-bar planar truss, and a 72-bar spatial truss based on the deviation between structural behavior before and after a catastrophic event. Chou et al. [8] employed genetic algorithm to deal with an inverse problem of structural damage. Measurements of static displacements are selected as an objective function based on uncertain parameters of structural members such as cross-sectional area and Young's modulus. Miguel et al. [9] presented a fresh approach for damage identification by combining an evolutionary harmony search algorithm with a time domain modal identification technique. The proposed approach was applied to identify damage location and level in a cantilever beam with different damage scenarios in which the effect of noise was fully assessed.

Particle swarm optimization is an evolutionary algorithm based on global search techniques, which acts as a precursor to a better opportunity for finding the global best and avoiding local minima. Many researchers have been achieved considerable success when using PSO to tackle different problems of numerous fields. Kang et al. [10] combined PSO with the artificial immune system to identify damage in a simply supported beam, and a truss structure based on an objective function of vibration characteristic, such as natural frequencies and mode shapes. Khatir et al. [11] detected an open crack in beam-like structures using PSO combined with experimentally measured natural frequencies. Tran-Ngoc et al. [12], Shabbir et al. [13] and other authors Shao et al. [14], Wu et al. [15], Eberhart et al. [16], Fallahian et al. [17], Ghodrati Amiri et al. [18] also successfully applied PSO to deal with a wide range of problems of different fields. In this paper, PSO is used to identify damage location and level in the steel beam with free-free boundary condition.

The layout of paper is organized as follows: firstly, the introduction is presented, PSO algorithm is introduced in section 2. Numerical examples and experimental evaluation are performed to assess the efficiency of the proposed method in the next section. Finally, some conclusions are highlighted.

II. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

Particle swarm optimization is an evolutionary algorithm developed by Eberhart and Kennedy [16] in 1995. The PSO algorithm imitates animal (element) behaviors such as fish schooling and bird flocking based on global search techniques to look for the best solution. Each element randomly swarms or flies through the search space, remembers and shares with other ones about the global best that they have discovered. PSO is built based on two equations.

The first one updates the position of each element:

$$x(t+1)=x(t)+v(t+1) \tag{1}$$

The second one updates the velocity of each element:

$$v(t+1)=w.v(t)+r_1.c_1.(p(t)-x(t))+r_2.c_2.(G_b-x(t)) \tag{2}$$

Where v (t), and v (t+1) indicate the velocity vectors of elements at the time t and t+1, respectively, x is the position vector. W represents the weight parameter coefficient, whereas c_1, c_2 are the social learning factor, and the cognition learning factor. G_b is the best position of all elements (the global best) and, p (t) is the best position of each element (the local best); r_1, r_2 are random values (0,1). Each element is featured by its physical position and velocity vector in the space. Elements (particles) can record the local best p (t) when moving, and communicate with other particles to find the best solution (G_b). Evolutionary algorithms such as PSO apply iterations based on an objective function to identify the fitness of each element. The best solution (G_b) is achieved if the objective function is minimum. The procedure for damage detection in the steel beam employing PSO illustrated by the diagram as shown in figure 1.

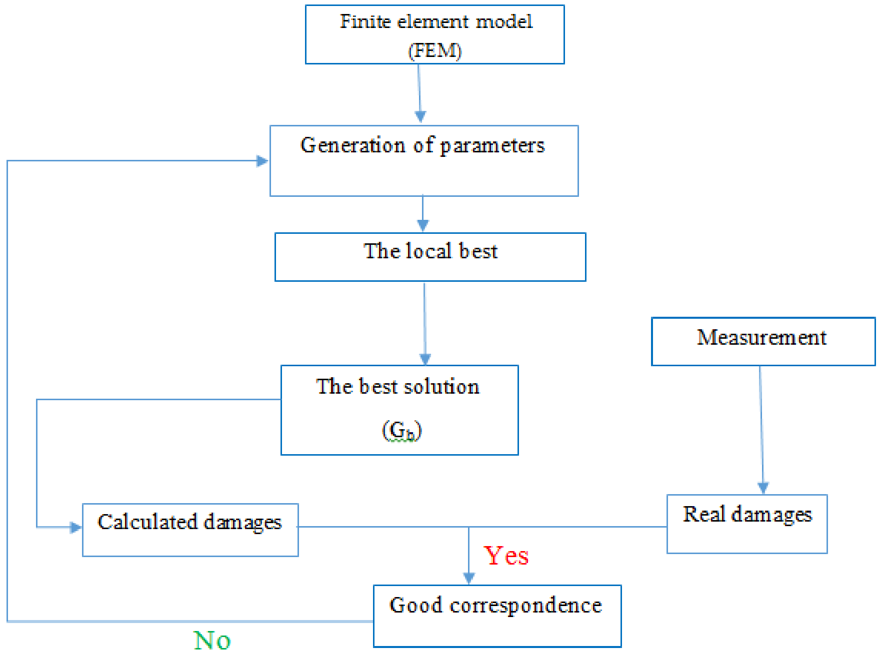

Figure 1. *Methodological approach for damage identification in the steel beam applying PSO*

III. NUMERICAL MODEL AND EXPERIMENTAL EVALUATION

This section employs a steel beam with free-free boundary condition to assess the efficiency of the proposed approach. The width, height, and span length of the steel beam are 0.006 m, 0.038 m, and 0.6 m, respectively. The material properties of the steel beam are listed as table 1.

Table 1. *Material properties of the steel beam*

Components	Value	Unit
Young's modulus	2×10^{11}	N/m^2
Volumetric mass density	7850	kg/m^3
Poisson's ratio	0.3	/

The Finite element model (FEM) of the steel beam is created by using the MATLAB toolbox Dooms et al. [19]. The beam consists of 11 elements (figure 2) utilizing a two-dimensional beam element whose each node has 2 degrees of freedom including translations in the x, y axis (figure 2).

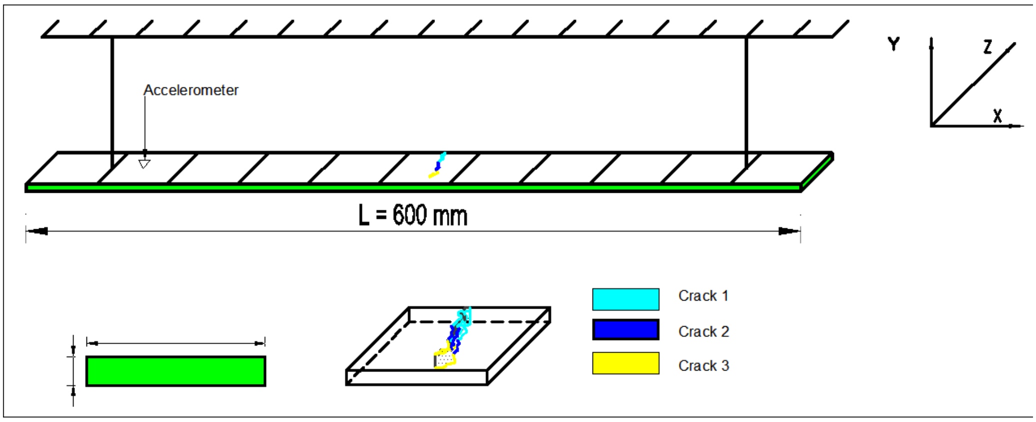

Figure 2*. The steel beam with free-free boundary condition*

The experimental measurements are performed under vibration sources utilizing hammer combined with PCB Accelerometers 356A15. The experimental setup is shown as figure 2. To obtain the impulse response of the steel beam; a PCB Accelerometers 356A15, the NI 9234 data acquisition card, and a Hammer PCB 086C03 were employed. The accelerometers were put near the edge of the beam. After the average of 10 positions of strike, the natural frequencies and mode shapes were obtained. The steel beam was created damage at the middle position (element 6) with damage level of 22%, 40% and 68% calculated based on experimental formula [20]. The experimentally measured natural frequencies of undamaged and damaged cases collected are shown in table 2.

Table 2*. Experimentally measured natural frequencies of undamaged and damaged cases of first three modes*

Mode	Undamaged structure (Hz)	Damaged structure (Case 1 - 22%) (Hz)	Damaged structure (Case 2 - 40%) (Hz)	Damaged structure (Case 3 - 68%) (Hz)
1	526	523	514	500
2	1410	1409	1406	1403
3	2751	2707	2673	2624

PSO is applied to identify the damage location and level in the steel beam by minimizing the difference between experimental and analytical results. The number of population used for PSO is 30. The values of the social learning factor and the cognition learning factor are $c_1 = 2$ and $c_2 = 2$, respectively, whereas the inertia weight parameter (w) is 0.3. This selection assists the algorithm in looking for the best solution more stable and faster. For a detailed explanation about the selection of parameters of PSO algorithm, the reader is referred to [21].

The stop criteria of iteration of both algorithms are set up as follows: the maximum number of iterations is 100 or the difference of objective function between two consecutive iterations is lower than 10^{-5}.

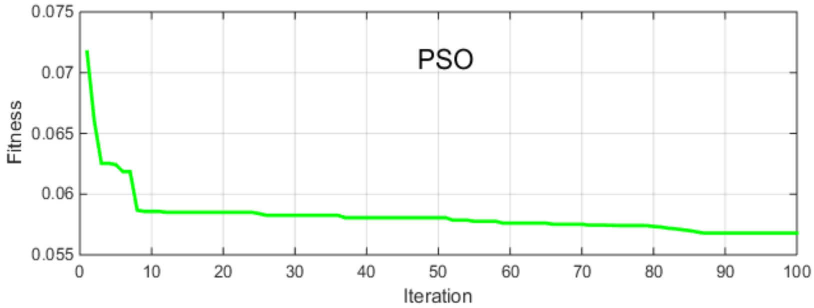

Figure 3. *Fitness tolerance of PSO*

Figure 3 shows that PSO can look for the result of the best solution after 7 iterations and the tolerance of objective function using PSO (fitness) is approximately 0.06.

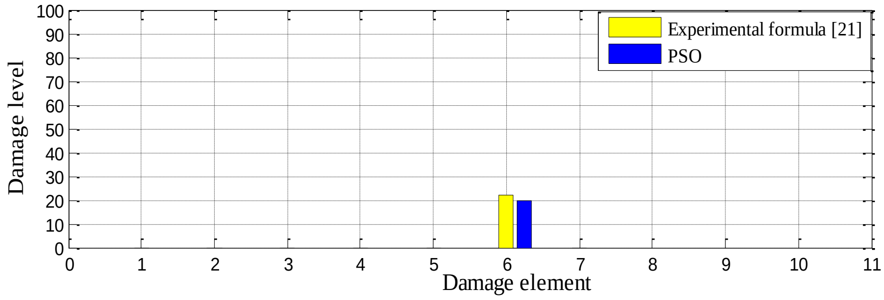

Figure 4. *Damage detection in the steel beam using PSO (22% of damage)*

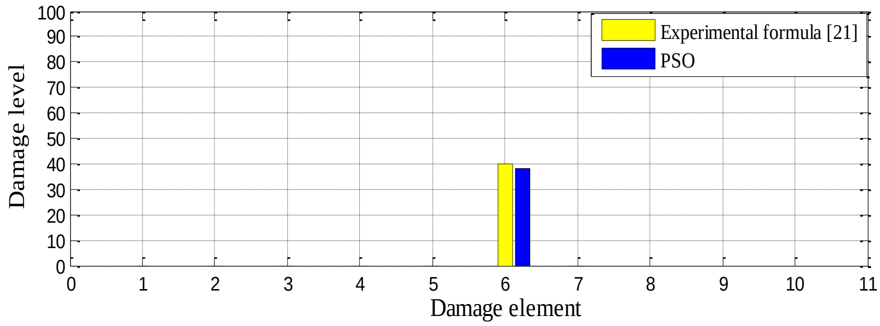

Figure 5. *Damage detection in the steel beam using PSO (40% of damage)*

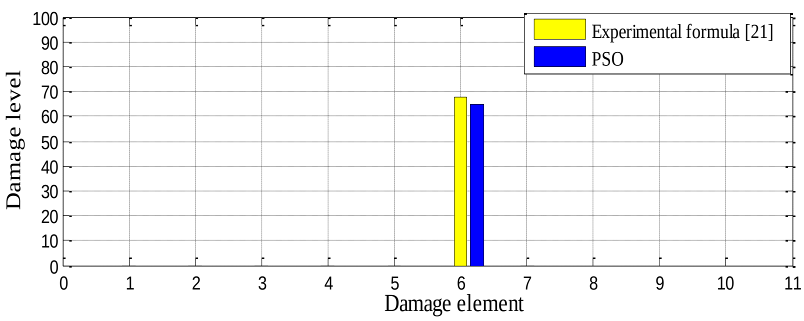

Figure 6. *Damage detection in the steel beam using PSO (68% of damage)*

The figures 4-6 show that in all cases, PSO can exactly identify damage location. Besides, the level of damages detected by PSO is close to the results calculated by experimental formula.

IV. CONCLUSIONS

This paper presents an approach using PSO for damage detection in a steel beam. PSO is an evolutionary algorithm based on global search techniques to look for the best solution. In this paper, PSO is applied to identify damage location and level in a steel beam. In order to assess the effectiveness of the proposed approach, a vibration measurement of the steel beam is carried out using under excitation sources of a hammer combined with peak picking techniques. Damage scenarios with different damage levels are introduced at the middle of the steel beam. In most cases, PSO identifies accurately the damage location, and the severity of damages identified by PSO is close to the results calculated by the experimental formula. These results demonstrate the applicability of PSO to damage identification. Further investigation should be done to evaluate the applicability of PSO for damage identification in more complex structures with more elements and multiple damages.

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