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# Performance of Ant Lion Optimization and Artificial Bee Colony Algorithm for Structural Health Monitoring of ASCE Benchmark Structure

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**Abstract**

Structural health Monitoring (SHM) has been a fast-moving tread for monitoring the health status of civil engineering structures. The SHM strategy involves application of different techniques involving the use of modal parameters, such as natural frequencies and mode shapes, to detect and localize the damage. Though localization of damage in structure plays an important role, damage quantification, which helps in performing repair works, is also essential. However, very few algorithms have been developed which calculates the amount of damage in structure. In view to this situation, the swarm-based optimization algorithms have been developed which can detect the damage severity in a structure. Some of the algorithms developed so far are Grey Wolf Algorithm (GWO), Artificial Bee Colony (ABC) algorithm, Firefly algorithm, Ant Lion Optimization (ALO) algorithm and others. Out of these algorithms, ALO and ABC have been used in limited number of cases for performing SHM. No real-life structures, considering the effect of noise, has been analysed using ALO and ABC. In this paper, the ALO and ABC optimization algorithm has been studied for damage analysis using an objective function based on the eigen value problem. The structure chosen for analysis is the ASCE Benchmark building which is a quarter scale model of an original building which give the real-life sense of SHM. Damage considered in the structure is of less severity occurring at multiple locations under an external noise, which is also a real-life challenge for damage analysis. The experimental results show that both ABC and ALO algorithms are able to quantify both major and minor damages in the presence of moderate amount of noise, proving the robustness of these algorithms.

*Keywords*: Meta-heuristic optimization, Swarm Intelligence based techniques, ASCE benchmark structure, Eigen value based objective function

## 1. Introduction

Structural Health Monitoring has been an integral part of modern-day civil engineering construction practices. It helps determine the damage areas in a structure so that repair work can be made to prolong the durability of the structure [1]. This involves use of different modal based damage detection techniques, such as frequency response method, mode shape methods and their derivatives, strain energy method, which can pinpoint the damage location in the structure [2]. These algorithms mainly use the structural parameters obtained using the acceleration data from the sensors installed in the structures [3, 4]. However, few structural health monitoring algorithms are present which can also indicate the damage severity in the structure, which helps in determining the amount of repair works needed or the life span of the structure. In view to this situation, different optimization techniques have been developed to address the detection of damage severity. Following this development, the no free lunch theory was proposed by Wolpert and Macready [5], which states that no optimization algorithm is effective against all kinds of objective functions, i.e. if an optimization algorithm gives satisfactory results for one objective function, it is not mandatory for the algorithm to work for another objective function. The meta-heuristic optimization techniques have been divided into four categories namely, Physical – based optimization techniques, Evolution based optimization techniques, Swarm Intelligence (SI) technique, and Human based techniques [6].

These optimization techniques can be further sub - grouped under two classes; namely, Single solution based, in which solution of single candidate is optimized during iterations, and Population based, in which the a set of multiple solution is initialized and are optimized [7]. Hence different meta-heuristic algorithms have been developed based on Swarm Intelligence (SI) theory. Some of the new meta-heuristic algorithms developed are Grey Wolf Optimization Algorithm (GWO) [7], Artificial Bee Colony algorithm (ABC) [8], Ant Lion Optimization Algorithm (ALO) [9], Cuckoo Search Algorithm (CS) [10, 11] and Firefly Algorithm (FA). Most of these algorithms have been used for different functions and damage detection in structures. Out of these, Ant Lion Algorithm and Artificial Bee-Colony Algorithm has not been explored much for damage detection in real life structure. ALO algorithm is a single solution based algorithm based on

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the hunting behaviour of the ant lions, which is implemented to entrap the ant, hence optimizing a particular function. ABC algorithm on the other hand is a population based swarming algorithm based on the foraging behaviour of the bees to find the best source of food or the optimum solution.

One of the common real-life structure considered for study of the health monitoring techniques is the quarter scaled ASCE Benchmark structure [12]. This real-life structure has been used by a number of researchers to study different SHM techniques [13]. However, the structure has not been explored

the use of optimization techniques. Grey Wolf Optimization and Cuckoo Algorithm have only been used for damage analysis using objective functions based on modal residue and flexibility of the structure, respectively [14, 15]. Therefore, the scope of study for damage analysis using optimization using the real-life structure is open for the researchers. Some of the notable optimization techniques which showed good results in modelled civil engineering structures are Ant Lion Optimization Algorithm and Artificial Bee Colony Algorithm [16, 17].

To check the performance of these algorithms on eigen value based objective function, single solution based ALO and population based ABC have been implemented on the benchmark structure for damage detection and quantification under environmental noise. The damages considered for the study include major damages as well as minor damages. The main challenge of health monitoring algorithms is to detect damages of smaller magnitude under non-favourable environments, such as noise contaminated environment [18]. Hence damage study involving minor damage detection in the presence of 20% noise has been addressed in this paper using ABC and ALO algorithm to quantify damage. As per the knowledge of the authors, these algorithms have not been implemented on the ASCE Benchmark structure. Hence a scope is open for the performance study of these two algorithms with respect to accuracy of damage detection and quantification and the time required to detect the results accurately.

## 2. Objective Function formulation

Natural frequencies and mode shapes are the primary structural parameters used for the purpose of damage identification. The modal parameters can be calculated from the eigenvalue equation:

$$([K] - \omega_i^2[M])\{\varphi_i\} = 0 \tag{1}$$

where M and K are the global mass and stiffness matrices respectively, $\varphi_i$ and $\omega_i$ are eigen values and eigen vectors of the undamaged structure respectively and i represents the number of modes (i = 1,….,n = total number of modes).

In the event of damage occurring in the structure, stiffness is the main physical parameter that changes, and the change can be presented as [19]:

$$K^d = K + \Delta K \tag{2}$$

where $K^d$ and $\Delta K$ represent the damaged stiffness matrix and the reduction in stiffness matrix, which is not known to the engineers.

Hence in the case of damage, the eigen value equation can be written as:

$$\left([K^d] - \left(\omega_i^d\right)^2[M]\right)\{\varphi_i^d\} = 0 \quad (i = 1,\ldots,n) \tag{3}$$

where $[K^d]$ is the global damaged stiffness matrix, $\omega_i^d$ and $\varphi_i^d$ are the damaged natural frequencies and damaged modes shapes respectively. Hence an objective function was formulated to determine the severity of damage in structure considering the unknown damage severity as x.

Therefore, the damaged stiffness matrix ($K^d$) can be represented as:

$$K_i^d = K_i(1 - x_i) \qquad (i = 1,\ldots,n) \tag{4}$$

where $x_i$ is the unknown damage severity provided to the undamaged stiffness matrix $K_i$, value 0 indicating no damage and value 1 indicating full damage.

The objective function, from Eq.4, can be written as [20]:

$$f(x_i) = [K_i(1 - x_i) \; - \left(\omega_i^d\right)^2 M]\{\varphi_i^d\} \qquad (i = 1,\ldots, r) \tag{5}$$

$$F = \sqrt{\frac{1}{N}\sum(f(x_i))^2} \tag{6}$$

where F is the cost function, r is the number of available vibrational modes and N is the total modes. The function F is a minimization function (having true value 0), optimizing which the unknown values of $x_i$. can be obtained.

## 3. Optimization Techniques

### *3.1 Ant Lion Optimization*

Ant Lion Optimization (ALO) is based on the prey hunt behaviour of antlions [9]. The antlions first lay sandpit traps to lure the ants in. In the algorithm, it is considered that one ant gets into one trap. The trap creation model is used roulette wheel selection to select one antlion trap for one ant. On the ants getting trapped, a random walk of ants is modelled to slide them down to the antlion. The rest of the ants then abandon the trap area and use random walk to search for other food source. This ensures that the other ants have the knowledge of trap and they become more fitter than the trapped ant. This ensures that the algorithm does not get trapped in local optima. This behaviour is referred as Elitism in the ALO algorithm. The antlions change their position and rebuild trap following a subsequent iterative behaviour. This mechanism promotes the behaviour that if an antlion is less fit than the corresponding ant, then the hunting position of antlion is changed. The mathematical details can be found in the manuscript by Mirjalili [9]. The population of ants considered for the study is 50.

### *3.2 Artificial Bee Colony Algorithm*

The Artificial Bee Colony (ABC) Algorithm works on the principle of collective effort of bees to find food [8]. The bee colony is divided into three groups according to their functionality, employer bees, onlooker bees and scout bees. The first group consisting of half of the hive strength as assigned as employed bees which are tasked to find food source. The number of food source decides the number of employer bees as one employer bee is appointed for one food source. The second half of bees is assigned as onlooker bees, who are appointed with the task of selecting the food source and deciding which food source is better according to the information collected by the employer bees. On selecting the best food source, the rest of them are abandoned and the respective bees become the scout bees. These bees move out in search of new food sources. As they find a food source, they are again become employer bees and the cycle continues. The mathematical formulation for the algorithm can be found in the manuscript of Karaboga and Basturk [8]. The mathematical parameters considered are: population = 50.

## 4. Numerical studies

### *4.1 ASCE Benchmark Structure*

The ASCE Benchmark structure has been chosen for the study as it is a four storey quarter scale model of a real-life 3D building structure (Fig. 1), the details can be found in the research article in manuscript by Johnson et al. [12].

Due to complex arrangement of sensors and huge cost of sensor setup and data acquisition, the ASCE Benchmark structure was proposed to be used as a real-life experimental problem for performing SHM on a 3D framed building structure, considering 12 Degrees of Freedom (DOF), three DOFs each storey. The structure has been developed considering 6 real-life damage conditions occurring due to reduction of stiffness only, out of which two damage patterns P1 and P2 were considered for the present SHM analysis of the 12 DOF ASCE Benchmark model, as shown in Table 1.

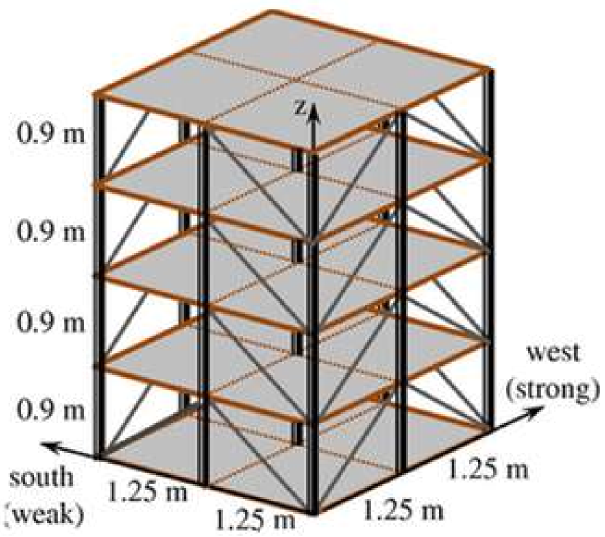


Fig. 1. ASCE benchmark Structure [21]

Table-1**.** Damage patterns in ASCE Benchmark structure considered for analysis

| Damage Pattern | ASCE Benchmark Damage Pattern | Damage Condition | Damage Severity |
|---|---|---|---|
| P1 | Pattern 1 | Removal of all the braces in the first storey considering only reduction in stiffness | Storey 1 – X axis – 45.24% Storey 1 – Y axis – 71.03% Storey 1 – Z axis – 64.96% |
| P2 | Pattern 4 | Removal of one brace in first storey and third storey considering only reduction in stiffness | Storey 1 – Y axis – 17.76% Storey 1 – Z axis – 9.87% Storey 3 – X axis – 11.31% Storey 3 – Z axis – 9.16% |

The two different damage patterns have been considered keeping in mind the real-life situation in which the damage applied are of high severity and occurring at the first storey and of low severity at multiple locations, patterns P1 and P2, as shown in Fig. 2(a) and (b) respectively. The damaged braces are shown in green lines.

The modal parameters for the damaged structure have been provided by the developers and the theoretical damage severity has also been provided as in Table 1. An algorithm is said to function properly if it can detect the theoretical damage severities with accuracy. The unknown variables for stiffness reductions has been assigned along x – axis, y – axis and z – axis and are shown in Table 2.

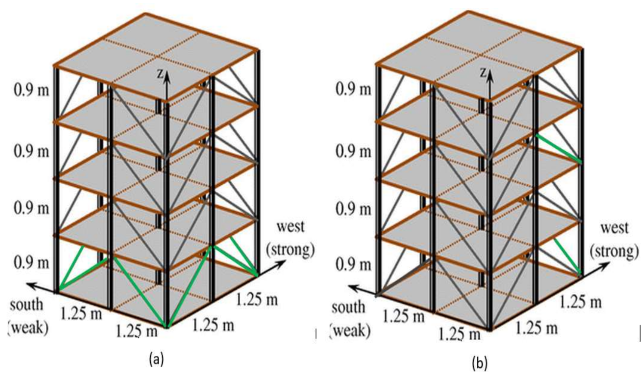


Fig. 2. Damage in ASCE Benchmark structure for damage case: (a) P1 and (b) P2. (The dotted lines show the damaged members in the structure)

Table-2. Unknown variables for stiffness reduction

| Unknown Variable for damaged stiffness | Axis | Storey |
|---|---|---|
| x1, x2, x3, x4 | X axis | 1st, 2nd, 3rd, 4th |
| x5, x6, x7, x8 | Y axis | 1st, 2nd, 3rd, 4th |
| X9, x10, x11, x12 | Z axis | 1st, 2nd, 3rd, 4th |

In real-life practical structures, it is not always possible to obtain all the sensor data due to the complex nature of structure which hinders installation of sensors. Therefore, the optimization algorithm needs to perform with limited number of modal data in order to monitor the structure. In case of the benchmark structure, the main evaluation is done for damage in structure with respect to the direction of the axis, i.e., along x axis, y axis or z axis, as can be seen from Table 1. In this case, the damage evaluation is not performed for damage location and quantification in members. Hence, the algorithms have been implemented for the ASCE Benchmark structure using first five modal parameters, as has been used by the previous researcher [14]. In this case the reduced modal parameters can be used as in the case of dynamic analysis the first few modes, having high modal participation factors, are regarded as the principle modes responsible for vibrational study. All the analysis have been performed in MATLAB platform [22].

*4.2 Damage analysis*

The damage detection capability of the single solution-based ALO and population-based ABC algorithm. The number of iterations has been limited to 500 for both the algorithms, in order to make a direct comparison between the damage detection capabilities of both [23]. For real time health monitoring, it is not feasible to obtain all the mode shape data from the structure. Hence the first 5 modes out of 12 DOF model of the ASCE Benchmark structure, has been considered for diagnosis to check the success rate of the algorithms when dealing with less modes [14]. The main aim of the study is not to identify the optimal value, but to evaluate the potential of the algorithms detect damage [24]. The damage location and severity may be identified if the optimization algorithm is able to identify the unknown variables of Table 2 by minimizing the objective function, thus converging into the minimum value. The error in damage results have also been evaluated in the study and the equation is given as:

$$error\ (\%) = Experimental\ Stiffness\ reduction\ (\%) - Theoritical\ Stiffness\ Reduction (\%) \quad (7)$$

The damage results for pattern P1 are shown in Fig. 3. It can be observed that both ALO and ABC is able to detect the multiple located damages of high severity in the structure. This confers that both the algorithms are equally capable of detecting and quantifying the structural damages. Also, the error in damage results are also minimal, 0.4% for ALO and 0% for ABC, as can be seen from Fig. 4.

However, when compared with regards to the time taken for the damage analysis, it can be observed that ABC takes 42.91s to optimize the function whereas ALO takes 250.84s.

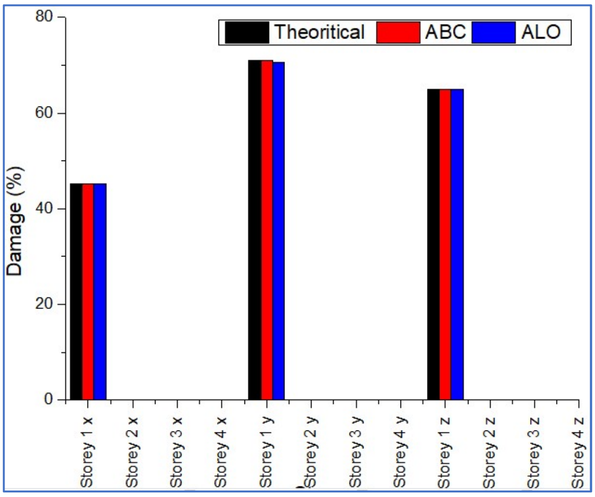


Fig. 3. Damage results for damage pattern P1 using ALO and ABC

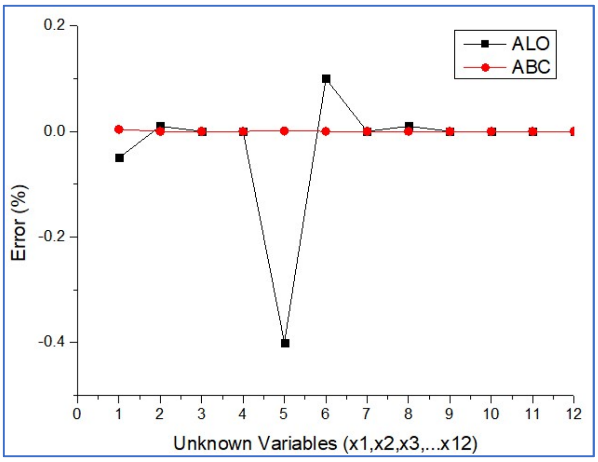


Fig. 4. Error in damage results for detecting damages for pattern P1

Similarly, the damage analysis was carried out for damage pattern P2, which consists of damages of low severity occurring at multiple locations. The damage results shown in Fig. 5 shows that both the algorithms are able to detect damages in the structure.

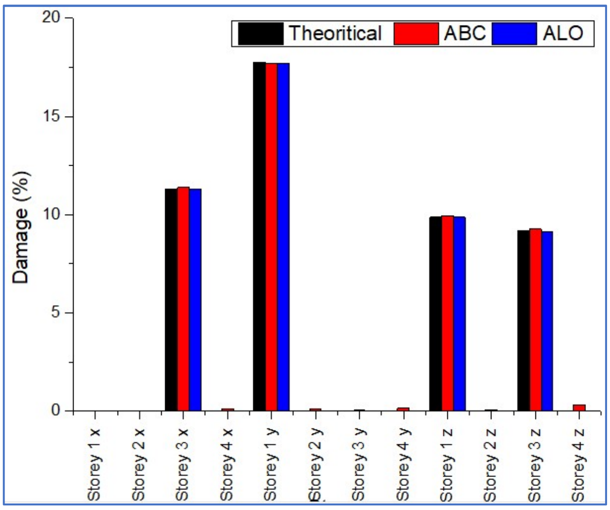


Fig. 5. Damage results for damage pattern P2 using ALO and ABC

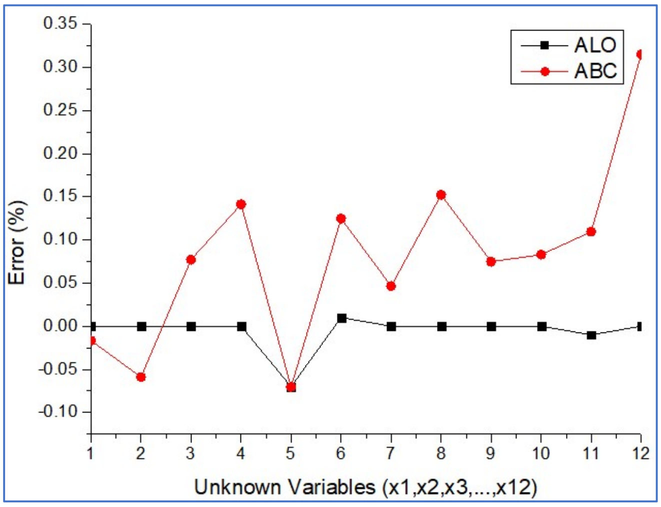


Fig. 6. Error in damage results for detecting damages for pattern P2

The error results (Fig. 6) obtained shows minimum error both for ABC algorithm, 0.3%, and ALO algorithm, 0.1%. Therefore, both ABC and ALO can be used for damage analysis.

However, when compared with respect to the time required for optimization, it can be observed that ABC can detect the damage at 50.13s, whereas ALO takes 248.87s to detect. Hence, it can be seen that the population based optimization algorithm, ABC, can detect the damages in structure much faster than that of single solution based algorithm, ALO.

*4.3 Check for robustness against noise contamination*

The ASCE benchmark structure has been studied for damage analysis using noise contaminated modal parameters. This study has been performed as the sensor data obtained from the structures may be contaminated with noise. Hence, the structural parameters identified using the noise contaminated sensor data may also be contaminated. Therefore, it is important that the algorithms used to diagnose the structure shall filter the noise and identify the damage in the structure. The noise was mathematically implemented as:

$$\omega_i^{dn} = \omega_i^d(1 + e\varepsilon_i) \quad (8)$$

where $\omega_i^d$ and $\omega_i^{dn}$ are the ith natural frequency without and with noise respectively, $\varepsilon_i$ is the Gaussian distribution based random value ranging between -1 and 1 and e is the noise intensity.

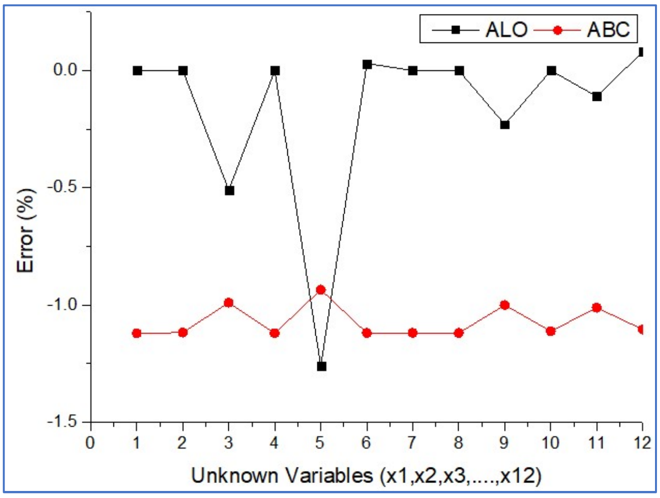


Fig. 7. Error in damage results for detecting damages for pattern P2 for 20% noise contamination in the natural frequencies.

The ABC and ALO algorithm have been tested for damage analysis for damage pattern P2 using a noise contamination of 20% in the natural frequencies. The pattern P2 has been considered as it comprises of damages of low intensity at multiple locations and these low level damages are hard to detect for an algorithm, when tested under noisy conditions. Most of the algorithms tested for damage detection in ASCE Benchmark structure has considered noise upto 5% [14, 15, 25]. Therefore, to check the robustness of the algorithms against noise greater than 5%, 20% noise has been considered. Also 20% noise means a high level of noise in the surroundings due tot which there may be deviations in the damage analysis results.

The damage results, shown in Fig. 7, shows the ability of both the algorithms to detect damage in noisy conditions. It can be observed that ALO though being slow in optimizing the objective function, shows good noise robustness in determining the damage by showing a maximum error of 1.3% and minimum of 0%. On the other hand, ABC shows a minimum error of 1% and maximum error of 1.1%. In both the cases, the algorithms are able to detect the damages with a minimal error, even in the presence of noise.

## 5. Conclusion

The performance of single solution based optimization algorithms, ALO algorithm and population based, ABC algorithm, for damage detection, low intensity damages at multiple locations, in real-life ASCE Benchmark structure has been investigated. From the study the following conclusions can be made.

- Both population based, ABC algorithm, and single solution based optimization algorithms, ALO algorithm, are able to detect damages in the real-life Benchmark structure, with a minimum error of 0.4%.
- ABC algorithm is much faster than ALO, approximately 5.84 times faster when detecting damages of higher severity and 4.96 times faster when dealing with damages of low severity. This is due to its swarming approach in which all the members of the swarm work together to solve the problem.
- Both the algorithms show good robustness in detecting damage in the presence of 20% noise with a minimal error of approximately 1.3%.

## Disclosures

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