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ORIGINAL ARTICLE

A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates

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Abstract
The need for global damage detection methods that can be applied in complex structures has led to the development of methods that examine the structural dynamic behavior. The damage detection problem can be considered as a inverse problem with minimization of a objective function. For those reasons, a new nature-inspired optimization method based on sunflowers' motion is introduced. The proposed sunflower optimization algorithm (SFO) technique is a population-based iterative heuristic global optimization algorithm for multi-modal problems. Compared to traditional algorithms, SFO employs terms as root velocity and pollination providing robustness. The new method is then applied in an inverse problem of structural damage detection in composite laminated plates.

Keywords Sunflower optimization · Vibrations · Laminated composite plate · Inverse problem

1 Introduction

The performance and behavior of composite structures can be significantly affected by degradation caused by exposure to environmental conditions or damage caused by operating conditions such as impacts and structural loads. As a result, corrosion, delamination, cracking and other failures occur once the structure is in service. In the case of composite laminates, such damages are not always visible on the surface, which can lead to catastrophic structural failure. To ensure the performance and integrity of a structure of high structural responsibility, prior recognition of damage is crucial.

Traditionally, visual inspection accompanied by some alternative methods is employed to obtain general information on structural conditions. However, the inspection is limited and time consuming. The development of a comprehensive on-site health monitoring system that can inspect a relatively large area, instantly providing reliable, quantitative structural health data such as type of defect, location, and severity level minimizes and eventually eliminates drawbacks caused by stoppages for monitoring [27].

The advantage of using metaheuristic is because those methods are zero order methods, especially designated for nonlinear and multi-modal problems [20]. In addiction , when working with optimization in the detection of damages, a functional with multiple local minimums appear [8, 10], that justify the use.

Nature is a wonderful source of inspiration for developing optimization techniques that can tackle difficult problems in science and engineering. Since the early 1970s, various nature-inspired optimization algorithms have emerged starting with the genetic algorithm (GA), some of which have proven to be very efficient global optimization methods. Along with the GA, particle swarm optimization (PSO), ant colony optimization (ACO), Differential Evolution and many others methods have been proposed and successfully implemented. However, because each algorithm possesses strengths and weaknesses, there is no single method within the family of nature-inspired numerical optimization algorithms that stands out as the best for solving all types of problems [2].

Most metaheuristic algorithms are nature-inspired as they have been developed based on some abstraction of nature. Nature has evolved over millions of years and has found perfect solutions to almost all the problems she met. We can thus learn the success of problem-solving from nature and develop nature-inspired heuristic and/or metaheuristic algorithms [25].

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Evolutionary algorithms have been adopted to solve various engineering optimization problems [12, 15]. Some, such as the genetic algorithm [7, 9] and particle swarm optimization (PSO) [13, 14], have been employed in optimization and applied inverse methods due to their excellent global search abilities.

The problem of damage detection has been studied over the last decades, and several methodologies have been proposed in the literature to solve it as GA [3, 11, 19, 24], PSO [5, 13, 22, 23] and ACO [4, 16, 17]. One of the types of methodology is one that uses the changes in the dynamic parameters of the structure, due to the damage, for the formulation of an inverse optimization problem.

In this paper, finite element method is used to solve the direct problem due to the complexity of an anisotropic material (carbon fiber composite). Optimization using a proposed sunflower optimization is used as the optimization procedure for being able to find a global optimum efficiently and not get stuck in a local optimum, allowing to properly locate the damage, as well as no need for derivatives valuation the objective function, which can become a problem for cases where discontinuities may be present or in our case do not exist a analytical well-defined equation that defines the dynamic changes in function of structural damages in different locations. In essence, SFO is a population-based iterative heuristic global optimization technique for multi-dimensional and multi-modal problems. The inspiration for SFO comes from sunflowers' motion to capture solar radiation. The damage is modeled as a circular hole with three optimization variables. The results obtained by the SFO are compared with the already widely used and known GA.

2 Sunflower optimization method

The cycle of a sunflower is always the same: every day, they awaken and accompany the sun like the needles of a clock. At night, they travel the opposite direction to wait again for their departure the next morning.

Yang [26] proposed a new algorithm based on the flower pollination process of flowering plants considering the biological process of reproduction. In this work, the authors take into account the peculiar behavior of sunflowers in the search for the best orientation towards the sun. The pollination considered here was take randomly along the minimal distance between the flower i and the flower $i+1$. In the real world, each flower patch often release millions of pollen gametes. However, for simplicity, we also assume that each sunflower only produces one pollen gamete and reproduces individually.

Another important nature-based optimization here is about the inverse square law radiation. The law says that the intensity of the radiation is inversely proportional to the square of the distance, i.e., the intensity (amount) of radiation reduces in proportion to the square of the increase in distance. If the distance doubles, the intensity reduces by a factor 4, triples, reduces to a factor 9, and so on. In our case, the less the distance from the plant to the sun, the greater the amount of radiation received, and it will tend to stabilize in these vicinity. On the other hand, the more distance a plant is from the sun, the lower the amount of heat received by it, so the same will be followed in this study which will take larger steps to get as close as possible to the global optimum (sun) [18].

Then, the amount of heat Q received by each plant is given by:

$$Q_i = \frac{P}{4\pi r_i^2}, \tag{1}$$

where P is the power of the source and r_i the distance between the current best and the plant i.

The direction of the sunflowers to the sun is:

$$\vec{s_i} = \frac{X^* - X_i}{||X^* - X_i||}, \quad i = 1, 2, \ldots, n_p. \tag{2}$$

The step of the sunflowers on the direction s is calculated by:

$$d_i = \lambda \times P_i(||X_i + X_{i-1}||) \times ||X_i + X_{i-1}||, \tag{3}$$

where λ is the constant value that defines a "inertial" displacement of the plants, $P_i(||X_i + X_{i-1}||)$ is the probability of pollination, i.e, the sunflower i pollinates with its nearest neighbor $i-1$ generating a new individual in a random position that varies according to each distance between the flowers. That is, individuals closer to the sun will take smaller steps in search of a local refinement while more distant individuals will move normally. It is also necessary to restrict the maximum step given by each individual, in order not to skip regions prone to be global minimum candidates. Here we define the maximum step as:

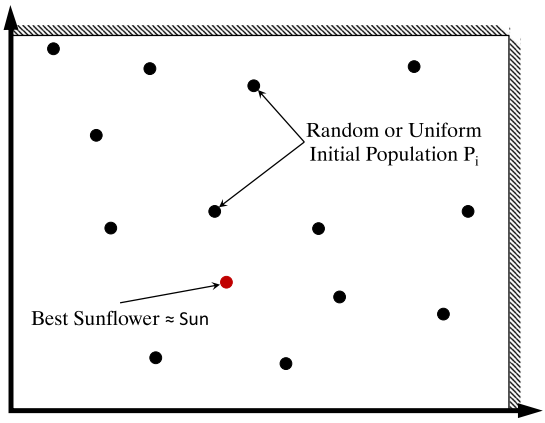
$$d_{\max} = \frac{||X_{\max} - X_{\min}||}{2 \times N_{\text{pop}}}, \tag{4}$$

where $X_{\max}$ and $X_{\min}$ are the upper and lower bounds values, and N_{pop} the number of plants of total population.

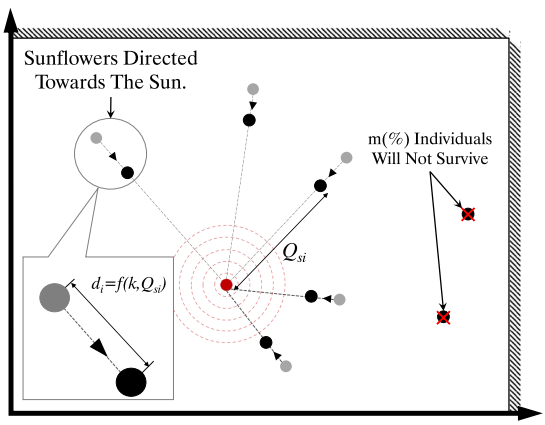
The new plantation will be:

$$\vec{X}_{i+1} = \vec{X}_i + d_i \times \vec{s_i}. \tag{5}$$

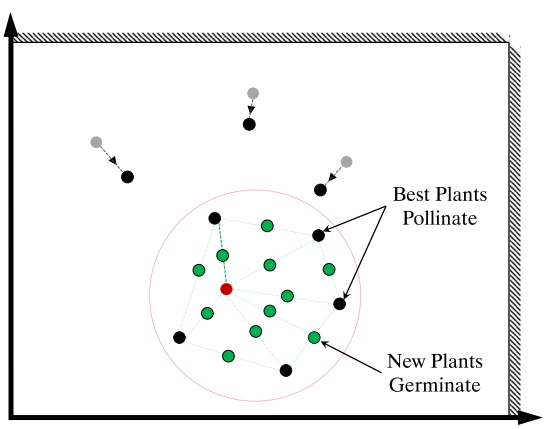
A simple visualization of the proposed algorithm steps are shown in the Fig. 1. The algorithm begins with the generation of a population of individuals. This population may be random or even. The evaluation of each individual allows to evaluate which one will be transformed into the sun, that is, the one with the best evaluation among all. Though in a future version, it is intended to adopt the possibility of



(a) Initial population of flowers and Identifications of the Sun(s).



(b) All sunflowers will be oriented toward the sun.



(c) Best flowers pollinate around the sun.

Fig. 1 Some concepts about the sunflower optimization methodology

Sunflower Optimization Algorithm

Initial a uniform/random population of *n* flowers
Find the sun (best solution *s**) in the initial population
Orient all plants toward the sun
while (*k* < MaxDays)
  Calculate the orientation vector for each plant
  Remove *m* (%) plants further away from the sun
  Calculate the step for each plant
  Best *b* plants will pollinate around the sun
  Evaluate the new individuals
  If a new individual is a global best, update the sun
end while
Best solution found

Fig. 2 Sunflower optimization (SFO) algorithm's pseudo code

working with multiple suns, here in this study it is restricted to only one. Then, all the other individuals will orient themselves, like the sunflowers, towards the sun and will move randomly controlled, that is, they will take random steps in a specific direction. The main steps of SFO, or simply the sunflower algorithm, are summarized in the Fig. 2.

3 Damage detection problem formulation

The damage detection problem can be formulated as an inverse problem solved via optimization methods. In this approach, it is desired to minimize an objective function that expresses the residues between the predicted and experimental responses. The design variables are the parameters of the parametric model assumed for the damage and once the optimal solution has been found it is assumed that the actual damage was identified (Fig. 3).

Mode shapes, natural frequencies and the difference between the results of the damaged and undamaged case are listed in Table 1. As seen, the presence of a hole (damage) affects the dynamic response of the laminate , then, the inverse problem is introduced to find optimal locations where the algorithms best fits the objective function. For this case, the results are obtained using fine mesh considering undamped shell element with eight nodes in each element.

Before meshing the model, and even before building the model, it is important to think about whether a free mesh or a mapped mesh is appropriate for the analysis. A free mesh has no restrictions in terms of element shapes, and has no specified pattern applied to it. Compared to a free mesh, a mapped mesh is restricted in terms of the element shape it contains and the pattern of the mesh. A mapped area mesh contains either only quadrilateral or only triangular elements, while a mapped volume mesh contains only hexahedron elements. In addition, a mapped mesh typically has a regular pattern, with obvious rows of elements [1].

Table 1 Natural frequencies of the undamaged and damaged plates using shell elements

Mode	Undamaged		Damaged		$\lvert 1 - \frac{\omega_d}{\omega_u} \rvert \times 100$
	Shape	ω_u	Shape	ω_d	
1		62.535		71.680	14.624
2		123.590		115.770	6.327
3		154.930		133.320	13.948
4		175.990		186.410	5.092
5		198.650		189.34	4.867
6		320.870		327.86	2.178

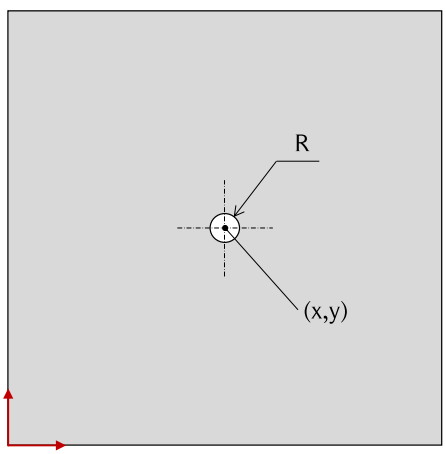
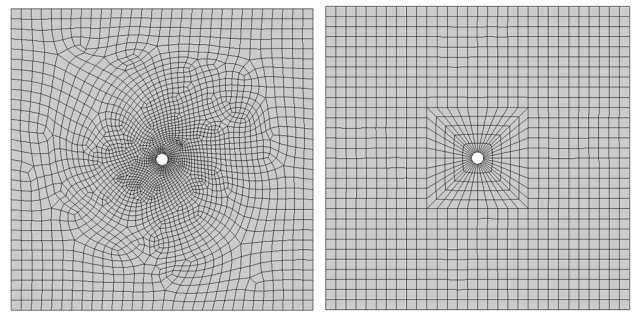


Fig. 3 Damage modeling on the plate considering three variables in the inverse problem

Then, an eight-node shell element with six degrees of freedom at each node: translations in the x, y, and z directions, and rotations about the x, y, and z axes were chosen. This element is considered suitable for analyzing thin to moderately thick shell structures. Figure 4 shows the difference between a good modeling. In this work, a mapped mesh was used to save computational cost and avoid convergence problems in composite modal response.

To obtain the unknown parameters of the damage, such as location and size, a functional can be defined as the difference between the known or measured values of the natural frequencies and the calculated values obtained from the optimization algorithm. The minimization of this function, also called in this work as "solar radiation" allows the damage detection algorithm to find the



(a) Bad Mesh **(b)** Good Mesh

Fig. 4 The difference of the mesh quality in FEA for structural hole detection

unknown parameters of the damage. The pristine structural values are simulated through FEM (as shown at Table 1). In this paper, the objective function J based on the change of natural frequencies defined in Gomes [6] is as follows:

$$J(\alpha) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\omega_i^{\text{real}}}{\omega(\alpha)_i^{\text{optimization}}}\right)^2}, \tag{6}$$

where ω_i^{real} are the natural frequencies obtained from the real damaged structure and $\omega_i^{\text{optimization}}$ are the natural frequencies obtained by the optimization procedure. When $J \sim 0$ means that the algorithm found a damage that exactly fits the real values. In addiction, α is the vector containing the project variables defined as the central position of the damage and its extension, i.e., $\alpha = \{x, y, r\}$ and $n = 6$.

4 Numerical results

4.1 Efficiency of the optimization algorithm

The efficiency of an optimization algorithm is studied using a set of standard functions. Several functions, involving different number of variables, representing a variety of complexities have been used as test functions. The purpose of testing the functions is to show how well the algorithm works compared to other algorithms. Usually, each test function is minimized from a standard starting point. The total number of function evaluations required to find the optimum solution is usually taken as a measure of the efficiency of the algorithm. Some of the commonly used test functions are given in the Table 2 [21].

The assumed configuration for the control parameters of the heuristics is presented in Table 3. In all cases, the maximum number of iterations was adopted (generations and days) as a criterion of stopping.

Table 2 Standard test functions used to verify the proposed algorithm

Function	Equation $f(x_1, x_2)$
Rosenbrok's parabolic valley	$100(x_2 - x_1^2)^2 + (1 - x_1)^2$
Quadratic function	$(x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$
Beales's function	$[1.5 - x_1(1 - x_2)]^2 + [2.25 - x_1(1 - x_2^2)]^2$

Table 3 Main parameters of global optimization algorithms

Genetic algorithm		Sunflower optimization	
Operator	Value	Operator	Value
Population	100	Sunflowers	100
Crossover	0.60	Pollination	0.60
Elitism	1	Sun	1
Generations	100	Days	100

Table 4 Results of the SO algorithm applied on standard test functions

Function	Global minimum X^*	SO minimum X^*_{SO}
Rosenbrok's parabolic valley	$\begin{Bmatrix} 1 \\ 1 \end{Bmatrix}$	$\begin{Bmatrix} 1.000000 \\ 1.000000 \end{Bmatrix}$
Quadratic function	$\begin{Bmatrix} 1 \\ 3 \end{Bmatrix}$	$\begin{Bmatrix} 0.999999 \\ 3.000000 \end{Bmatrix}$
Beales's function	$\begin{Bmatrix} 3 \\ 0.5 \end{Bmatrix}$	$\begin{Bmatrix} 2.999999 \\ 0.499999 \end{Bmatrix}$

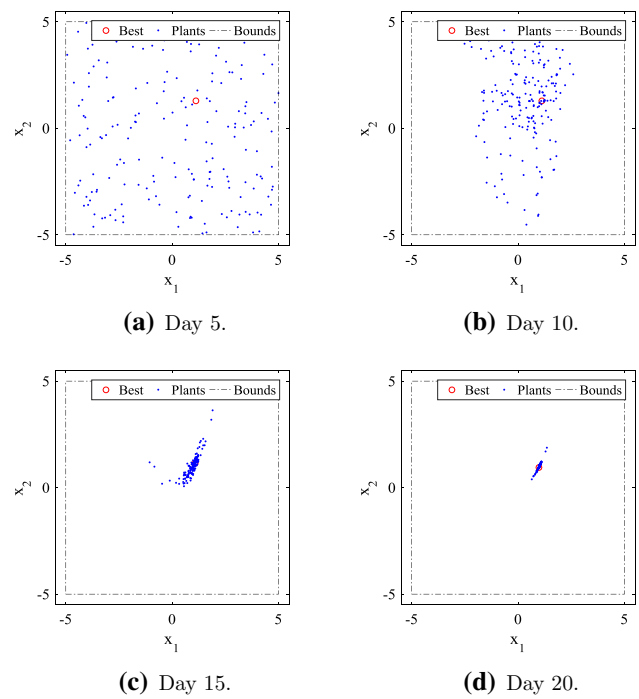


Fig. 5 Convergence of the population with the days or generations

Each of the functions selected have different properties, which should allow us to draw conclusions about the performance of the algorithm. The cases are multi-modal functions and the SFO parameters were the $N_{\text{flower}} = 20$ pollination equal to 60% and maximum numbers of the days (generations) $N = 100$. N_{flower} is the total number of individuals (sunflowers) in a population, while N is the generation number (defined as the stopping criteria). For all functions, the population was generated in the range of the lower and upper bounds of −5 to +5 in all dimensions. As can be seen in the Table 4, the proposed algorithm was able to converge to the optimal local region efficiently even with unrefined parameters. For example, the Fig. 5 shows a iterative convergence of the algorithm for the quadratic function test.

4.2 Structural damage detection

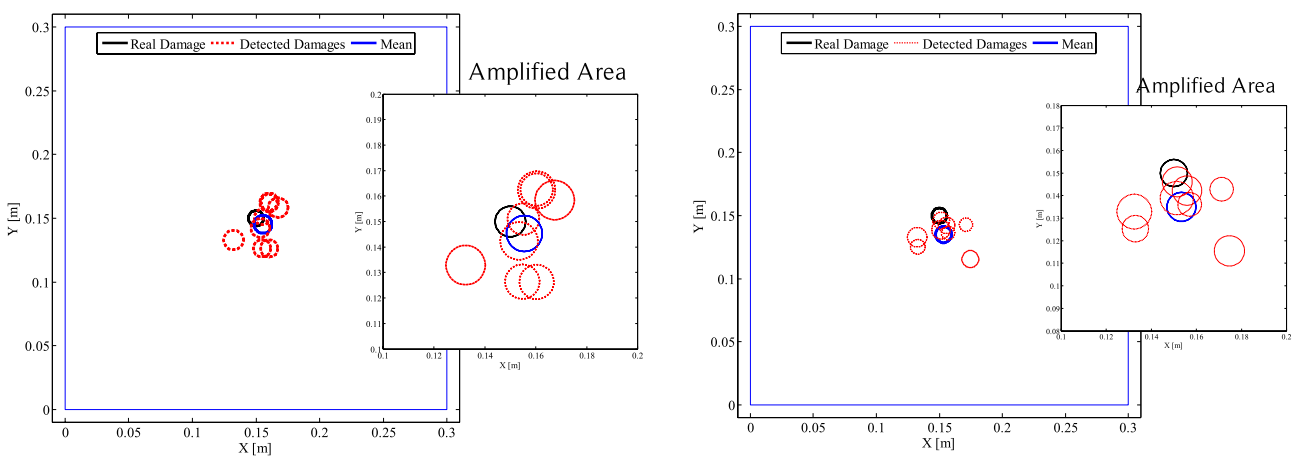
Table 5 shows the results obtained for eight simulations performed simultaneously for the damage detection problem. It is convenient to run several simulations, because the used optimization techniques used are heuristic method, i.e., are based on random searches. Then, eight runs were made to complete a full factorial, on the other hand 2^n where n is the number of variables. In our case we have $n = 3$ with $\alpha = \{x, y, r\}$.

As can be seen from Fig. 6, the results of the damage search were satisfactory in the detection of circular holes. In both methods (GA and SFO), the results were very close to known (induced) damage. However, the proposed OS optimization method behaved equally with GA. This is because the proposed method is still in a beta version, programmed in some command lines in MATLAB®, and GA is already a method with a large contribution of several researchers and very well-elaborated programming in the software used in this work in a commercial software. Figure 7 shows the final population distribution for both algorithms.

GA had a more varied final distribution of its population in relation to the SFO (Fig. 7). This fact may have promoted a better result of damage detection, and it did not get trapped in regions of great location. In relation to the convergence of the algorithm, Fig. 8 shows that GA is more robust. However, it is emphasized here that the GA used has years of development and several variables in its set-up. The proposed algorithm was a little slower in convergence,

Table 5 Damage detection results using GA and SFO algorithms

Objective	GA			SFO		
	x (m)	y (m)	r (mm)	x (m)	y (m)	r (mm)
	0.15	0.15	6.00	0.15	0.15	6.00
Run 1	0.1551	0.1510	6.2149	0.1558	0.1422	6.5224
Run 2	0.1324	0.1329	7.7145	0.1329	0.1253	5.8584
Run 3	0.1547	0.1264	6.7659	0.1746	0.1155	6.7098
Run 4	0.1603	0.1625	6.3470	0.1570	0.1361	5.2669
Run 5	0.1674	0.1584	7.7267	0.1712	0.1428	5.2302
Run 6	0.1534	0.1424	7.3959	0.1515	0.1461	6.6132
Run 7	0.1603	0.1263	6.7658	0.1324	0.1329	7.7145
Run 8	0.1603	0.1624	7.3469	0.1513	0.1389	7.3950
Mean	0.1555	0.1453	7.0347	0.1533	0.1350	6.4138
Std. Dev.	0.0103	0.0155	0.5926	0.0154	0.0102	0.9117



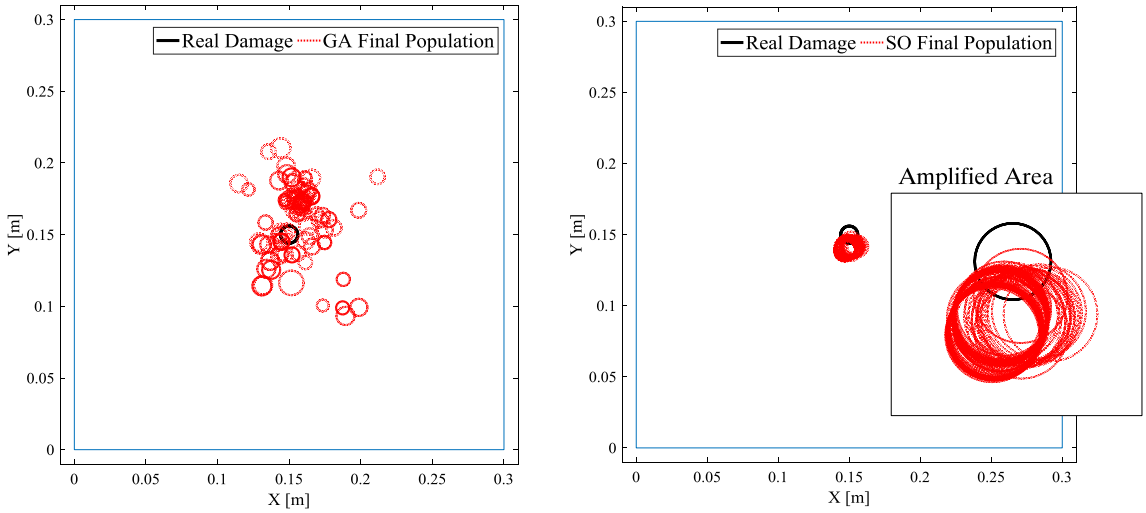
(a) Genetic **(b)** Sunflower

Fig. 6 Structural damage (holes) detection in composite plate using GA and SO algorithm

but managed to obtain the same expected values. It is also noteworthy that variable r, related to the extent of structural damage, was the most difficult variable to identify, that is, it had a higher standard deviation (Table 5) and varied more than the x and y position variables (Fig. 8).

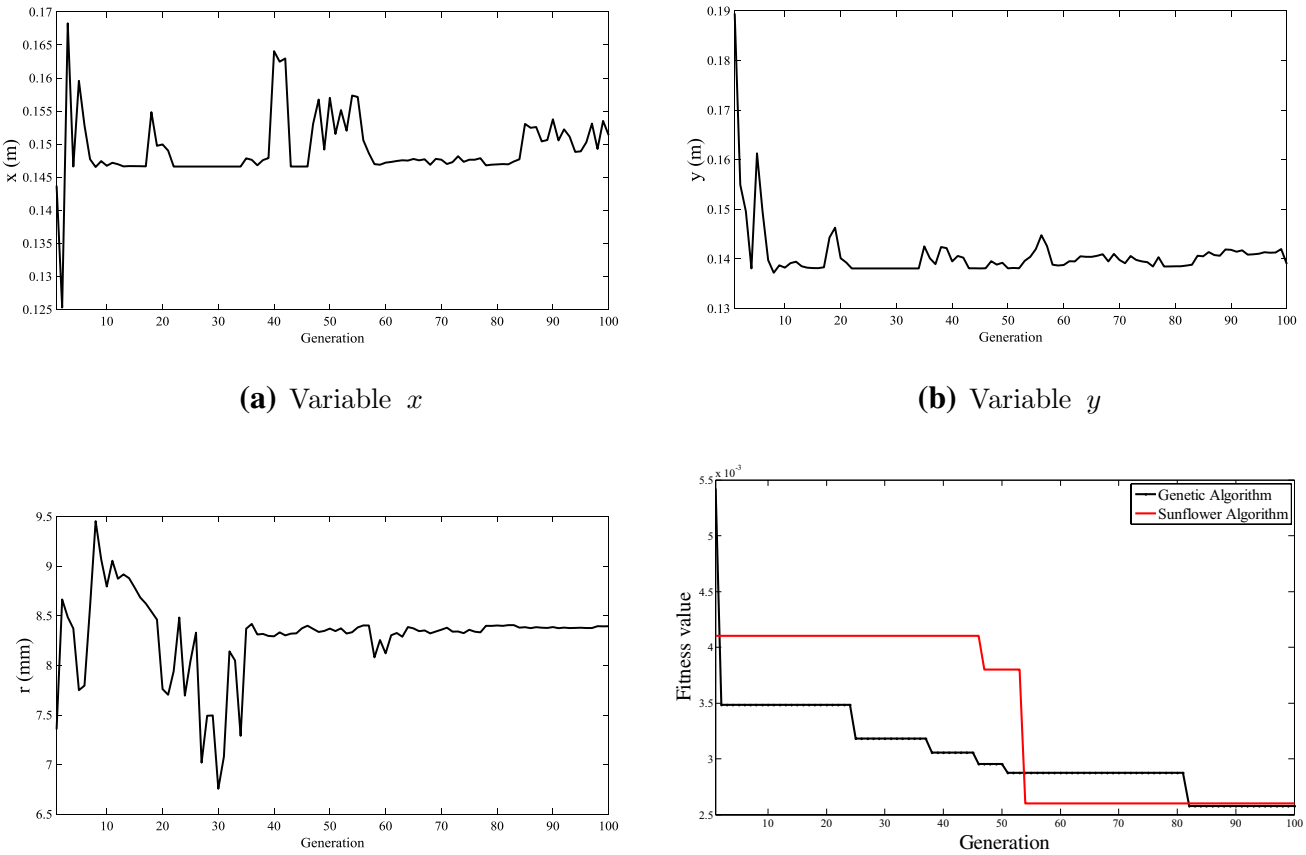
5 Conclusions

This paper introduced a new optimization algorithm based on the nature behavior applied to structural damage detection problems. The results of the optimization showed that the new optimization method introduced was able to find points of good locations in standard test functions, which proved its good performance. It is intended to improve the version of the OS algorithm for greater variability in the process of generating new individuals so that there is no stagnation in sub-regions of optimal location in relation to the application of the algorithm in a real non-trivial solution problem. The algorithm was still able to solve the damage identification and obtained a performance very similar to the widely known and used genetic algorithm. However, the SFO algorithm still needs to be refined in some parameters for better computational performance.



(a) Genetic **(b)** Sunflower

Fig. 7 The final population distribution around the damage



(a) Variable x **(b)** Variable y

(c) Variable r **(d)** Objective Function

Fig. 8 Variables x, y and r variation during the optimization and the objective function for both algorithms

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