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Damage detection in 3D truss structures using grey wolf optimization algorithm and natural frequencies

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ABSTRACT

This research presents the prediction of damage in 3D truss structures using the Grey Wolf Optimization algorithm (GWO). Natural frequencies are adopted as an objective function for optimization. To assess the behavior of 3D truss structures, a finite element model is used. The results, which are based on MATLAB code, are shown to validate the potential practical use of GWO.

KEYWORDS

3D truss structure, Damage, Grey Wolf Optimization algorithm, Natural frequency.

1. INTRODUCTION

Over the past 20 years, metaheuristic optimization techniques have gained a lot of popularity. Interestingly, some of them—like Particle Swarm Optimization (PSO) [1, 2], Ant Colony Optimization (ACO) [3, 4], and Genetic Algorithm (GA) [5, 6]—are fairly well-known. Apart from the vast amount of theoretical work, these optimization approaches have been used in a variety of academic disciplines. The question of why metaheuristics have become so prevalent is raised here. Four key factors can be used to characterize the response to this question: local optima avoidance, simplicity, flexibility, and derivation-free mechanism. The three primary categories of metaheuristics are evolutionary algorithms (EAs), physics-based algorithms, and SI algorithms. The ideas of evolution in nature are typically the source of inspiration for evolutionaries (EAs). GA is the most widely used algorithm in this field. In general, an initial random solution in EAs is performed for the optimization. The individuals from the previous generation combine and undergo mutation to form each new population. The new population is likely to be superior to the previous generation(s) since the best individuals are more likely to be involved in creating it. This can ensure that over generations, the initial random population is optimized. Differential Evolution (DE) [7], Evolutionary Programming (EP) [8], and Evolutionary Strategy (ES) [9] are a few examples of EAs. Techniques based on physics constitute the second major area of metaheuristics. Usually, these optimization algorithms imitate physical laws. Gravitational Search (GSA) [10], Big-Bang Big-Crunch (BBBC) [11], and others are among the most often used algorithms. These algorithms differ from EAs in that they use a random group of search agents that follow physical rules to communicate and navigate the search space. For instance, gravitational force, ray casting, electromagnetic force, inertial force, weights, and so forth are used to accomplish this movement. The SI methods are the third subclass of metaheuristics. The social behaviour of swarms, herds, flocks, or schools of species in nature is largely imitated by these algorithms. The mechanism is almost similar to a physics-based algorithm, but the search agents navigate using the simulated collective and social intelligence of creatures. PSO is the most widely used SI approach. Another popular SI algorithm is Grey Wolf Optimization

(GWO) [12, 13]. Hunting and seeking behaviours have served as inspiration for many of the SI strategies that have been presented thus far. Nevertheless, as far as one is aware, no SI technique in the literature imitates the leadership structure of grey wolves, which are renowned for their pack hunting, like GWO. To mimic the leadership structure, four different kinds of grey wolves—alpha, beta, delta, and omega—were used. The three primary hunting steps—finding prey, enclosing prey, and attacking prey—were also used in [12, 13]. Some other studies related to damage prediction for truss structures can be found in [14-18]. In addition, finding the natural frequencies of structural forms is also easily achieved through the finite element method, as published documents [19, 20] show.

Back to this study, the GWO algorithm is used to forecast damage in 3D truss structures. For optimization, natural frequencies are used as the objective function. A conventional finite element model is utilized to achieve the behaviour of 3D truss structures, and the final GWO results are shown to confirm the possible usefulness. This research's subsequent sections are as follows: Part 2 provides brief theory. Part 3 displays the results, and the final section offers some remarks.

2. BRIEF THEORY

The authors in [12] believe that alpha (α) is the best-suited solution for mathematically modeling the social hierarchy of wolves. As a result, beta (β) and delta (δ), respectively, are the second and third best solutions. It is assumed that the remaining potential solutions are omega (ω). The GWO algorithm uses α, β, and δ to guide hunting, or optimization. These three wolves are followed by ω wolves. When hunting, grey wolves encircle their prey. To model encircling behavior quantitatively, the following formulas are shown:

$$\vec{D}=\left|\vec{C}\cdot\vec{X}_p(t)-\vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1)=\vec{X}_p(t)-\vec{A}\cdot\vec{D} \tag{2}$$

in which $\vec{X}_p$ is the position vector of the prey, $\vec{X}$ represents the position vector of a grey wolf, $\vec{A}$ and $\vec{C}$ are coefficient vectors, and *t* denotes the current iteration:

$$\vec{A}=2\vec{a}\cdot\vec{r}_1-\vec{a} \tag{3}$$

$$\vec{C}=2\cdot\vec{r}_2 \tag{4}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations, and $\vec{r}_1$ and $\vec{r}_2$ are random vectors in [0,1]. Implement formulas (1) and (2) specifically for three types of grey wolves α, β, and δ to conduct hunting. Noted that each ω wolf is an updated location based on its position and the three best positions (α, β, and δ) as in Figure 1.

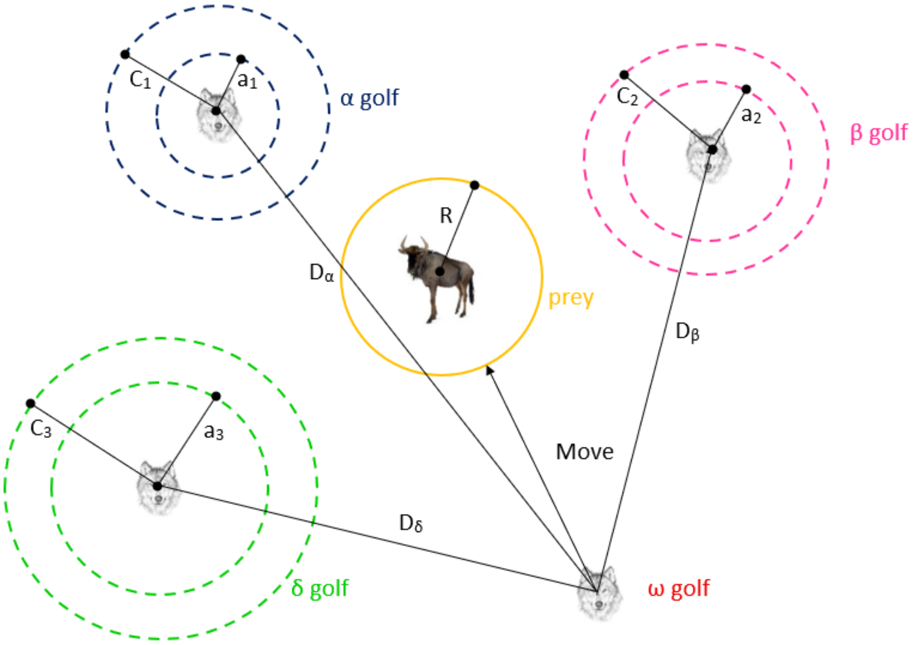
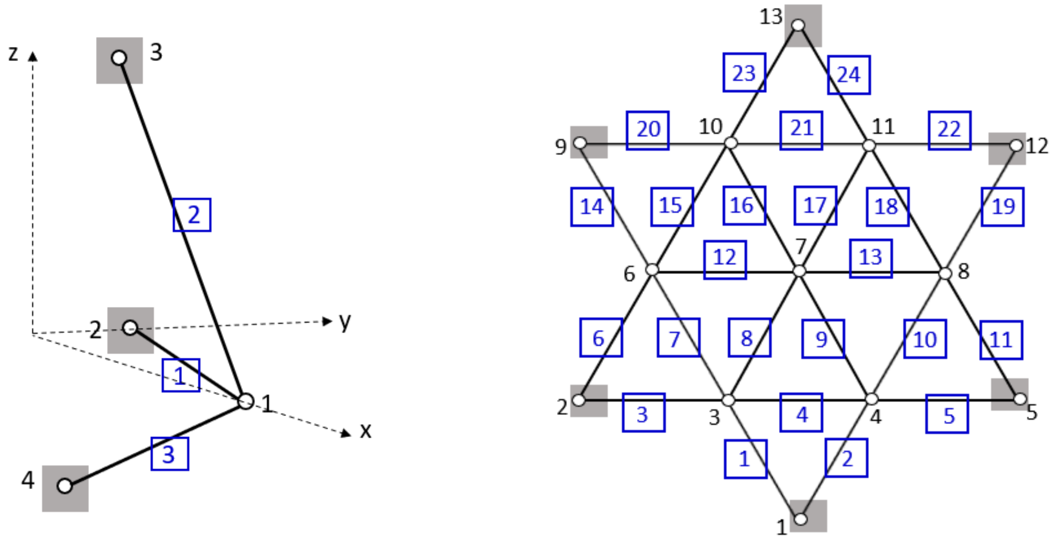


Figure 1: Position updating in GWO algorithm

3. RESULTS

In this section two 3D truss structures with 3 bars and 24 bars are considered as in Figure 2.



3-bar truss

24-bar truss

Figure 2: 3D truss structures

Modulus of elasticity E = 1.2e6 N/cm2, area of cross section A = 0.302 cm2, and density ρ = 1 kg/cm3 are used. Besides, the coordinates of nodes are also presented in Table 1.

Table 1: The coordinates of nodes for two truss structures

3-bar truss				24-bar truss							
Node	x(cm)	y(cm)	z(cm)	Node	x(cm)	y(cm)	z(cm)	Node	x(cm)	y(cm)	z(cm)
1	72	0	0	1	0	-50	0	8	28.8675	0	6.216
2	0	36	0	2	-43.3013	-25	0	9	-43.3013	25	0
3	0	36	72	3	-14.4338	-25	6.216	10	-14.4338	25	6.216
4	0	0	-48	4	14.4338	-25	6.216	11	14.4338	25	6.216
				5	43.3013	-25	0	12	43.3013	25	0
				6	-28.8675	0	6.216	13	0	50	0
				7	0	0	8.216				

In order to use the GWO algorithm, the applied objective function is the difference in natural frequencies between the finite element model and the actual damage without constraints. Formula (5) shows how to define the damages in which reduction in member's modulus of elasticity plays a key role:

$$E_b = (1-s)E, \quad 0 \le s \le 1 \tag{5}$$

where *s* is the variable showing the damage severity of each bar. The location and severity of the damage(s) can then be easily ascertained by minimizing the following objective function:

$$obj = \sqrt{\sum_{i=1}^{n} \frac{\left(f_i^a - f_i^{fe}\right)^2}{\left(f_i^a\right)^2}} \tag{6}$$

with *n* is the number of considered frequencies, (*a*) and (*fe*) indicate the "actual" and "finite element".

Apparently, Table 2 presents one damage scenario for the 3-bar truss structure, and Table 3 presents three damage scenarios for the 24-bar truss structure.

Table 2: The damage scenario of 3-bar truss

Scenario	Damage bar	Severity of damage
	Bar 3	35%

Table 3: The three damage scenarios of 24-bar truss

Scenarios	Damage bar(s)	Severity of damage
The first scenario	Bar 8	35%
The second scenario	Bar 6 Bar 13	40% 30%
The third scenario	Bar 4 Bar 12 Bar 20	30% 25% 20%
	Bar 24	20%

In addition, the optimization algorithm according to GWO is also shown in Figure 3.

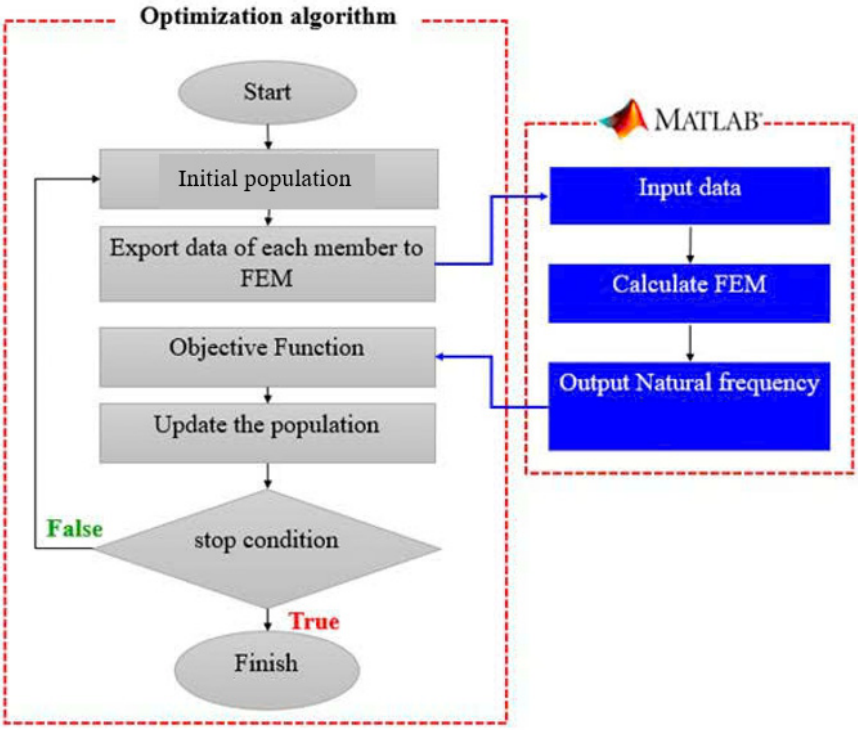


Figure 3: Framework optimization

With a set of scenarios, from simple to complex, in Tables 2 and 3, Figures 4 to 7 show that GWO delivers the intended results for predicting damage to 3D truss structures with a population size of 30 individuals. Additionally, it is evident that the GWO algorithm requires roughly 150 iterations to get the intended results.

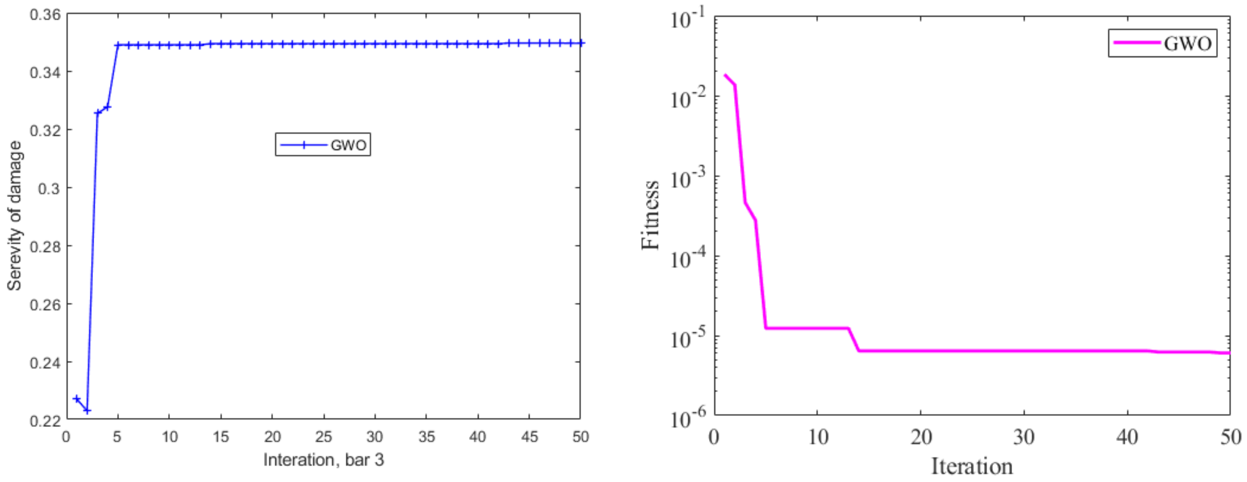


Figure 4: Describe the convergence for the damage scenario of 3-bar truss

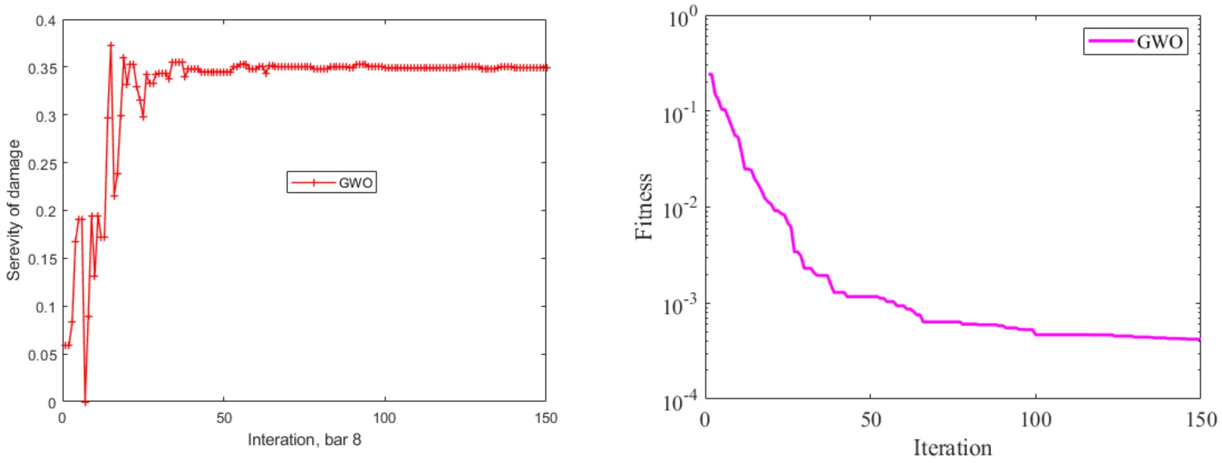


Figure 5: Describe the convergence for the first damage scenario of 24-bar truss

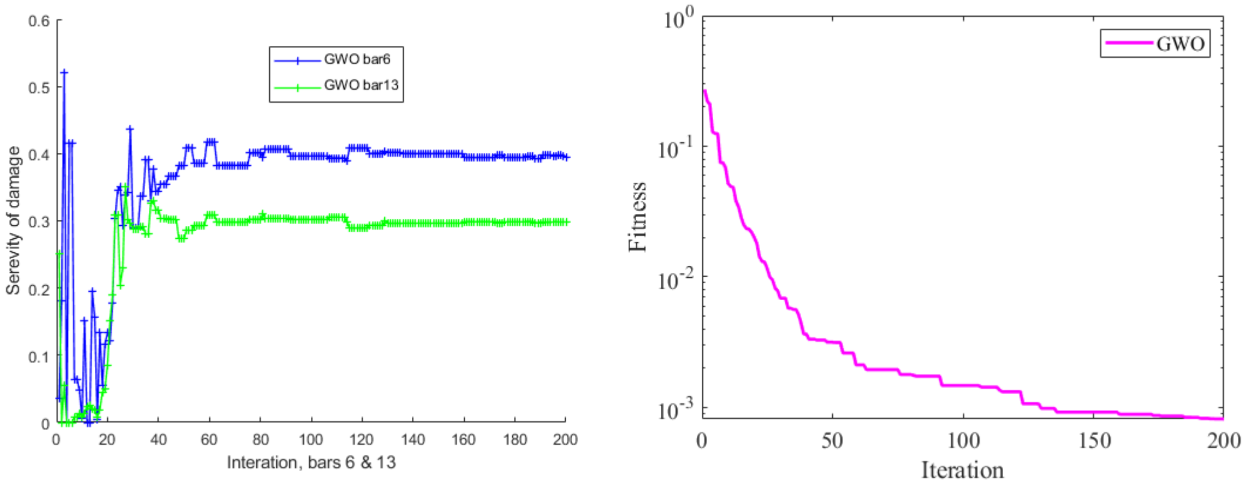


Figure 6: Describe the convergence for the second damage scenario of 24-bar truss

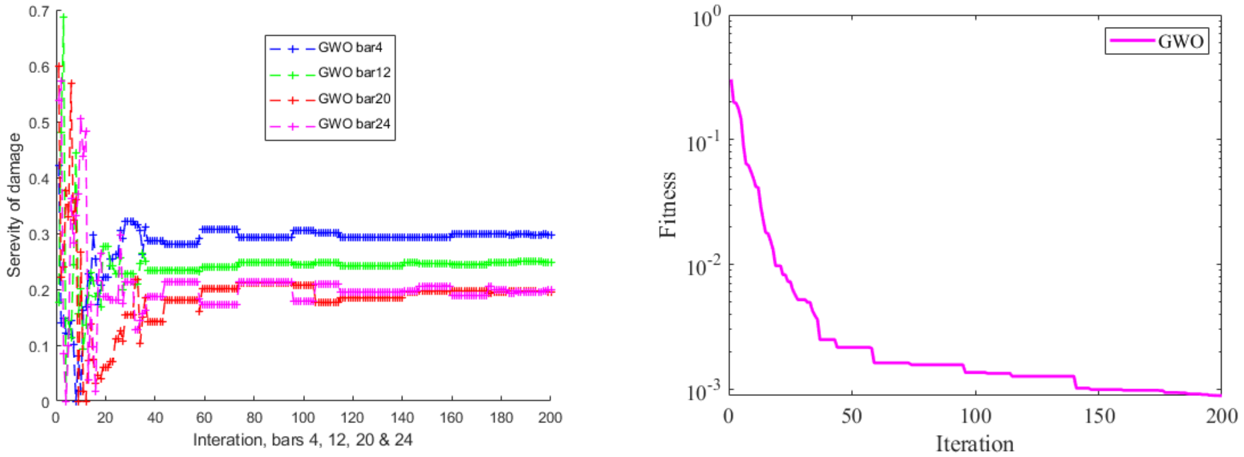


Figure 7: Describe the convergence for the third damage scenario of 24-bar truss

4. CONCLUSION

In this research, 3D truss structures are subjected to damage detection using the GWO algorithm. To evaluate the effectiveness of the optimization methods, a range of scenarios—from straightforward to intricate—is suggested. The results obtained demonstrate excellent performance in instances involving damage detection. These results depict that GWO accurately predicts the location and extent of damage.

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