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APPLYING THE ALIBABA AND FORTY THIEVES OPTIMISATION ALGORITHM TO PREDICT DAMAGE IN PLANE TRUSS STRUCTURES

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Abstract

In contrast to traditional algorithms, metaheuristic methods have become startlingly trendy. This reputation is due to the fact that these methods are very flexible, do not require gradient information, and have proven their success in escaping from local minimums when solving real-world scientific or engineering problems that have several local solutions. Consider the well-known story of Ali Baba and the Forty Thieves, in which Ali Baba saw a group of forty thieves breaking into a strange cave that was filled with valuables. Then an algorithm, namely the Ali Baba and the Forty Thieves (AFT) optimisation algorithm, was built around the strategy used by the Forty Thieves to find Ali Baba. It was one of the metaheuristic algorithms with many advantages, as mentioned above. Specifically, in the present work, the damage of planar truss structures is predicted by using the AFT. In addition, the natural frequencies of these planar trusses are also calculated based on the traditional finite element method to provide information for constructing the objective function for optimisation purposes. A number of situations, from simple to complex, are given to evaluate this algorithm's performance. The obtained results demonstrate how well the AFT predicts the location and magnitude of damage.

Keywords: metaheuristic, planar truss, damage, finite element analysis, natural frequency.

1. Introduction

In practically every field of engineering, optimisation problems must be solved, and there is a constant need for stronger solutions. This indicates the necessity for dependable algorithms capable of addressing the complex nature of current scientific and technical challenges. There are many different optimisation techniques available when looking through the literature. Each of them has advantages and disadvantages, ranging from the more recent nature-inspired metaheuristics to more conventional optimisation methods that employ both linear and nonlinear programming. Unlike conventional algorithms, metaheuristic approaches have grown surprisingly popular. Because of their great adaptability, lack of gradient information, and proven ability to avoid local minimums when solving real-world scientific or engineering issues with several local solutions, these strategies have gained this reputation. The benefits of metaheuristics are especially notable since they consider optimisation problems as black boxes, needing just the input and output sets of the variables. Consequently, it is not necessary to compute a derivative of the search space.

The following are some well-known algorithms. Recent developments in genetic algorithms were analysed in a work by K. Sourabh et al. [1]. For analysis, the genetic algorithms that the research community was most interested in were chosen. The fresh and demanding researchers might benefit from this review by having a broader understanding of genetic algorithms. The advantages and disadvantages of the popular algorithms and their use were discussed. One popular evolutionary computing method, genetic programming (GP), has bloat, or the issue of individuals growing too big. Its capacity to effectively

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explore intricate search spaces consequently diminished. The final solutions lacked generalisability and robustness. Furthermore, models with bloat were challenging to comprehend and describe. According to J. Noman et al. [2], they reviewed the literature from an explainability point of view by examining how simplification could make GP models more explainable by reducing their sizes. This phenomenon was extensively studied, mostly from the perspective of controlling bloat. Furthermore, nature has long served as an inspiration for swarm intelligence (SI), an important branch of artificial intelligence that mimics collective behaviours found in biological systems to address difficult optimisation problems. The simplicity and effectiveness of particle swarm optimisation (PSO) led to its widespread adoption among SI algorithms. The many learning strategies that were proposed to enhance PSO's performance in terms of convergence speed, robustness, and adaptability were not thoroughly and systematically examined. To close this gap, scientists C. Dikshit et al. [3] examined and categorised a number of learning techniques while evaluating how they affected optimisation performance. Researchers Y. Peng et al. [4] proposed a metaheuristic called the wave optics optimiser (WOO). The Fraunhofer diffraction experiment, which revealed the wave nature of light, inspired WOO. Scientists T. Ai-Qing et al. [5] gave a nature-inspired metaheuristic algorithm named the Snow Geese Algorithm. It was inspired by the migratory behaviour of snow geese and emulated the distinctive “herringbone” and “straight line” shaped flight patterns observed during their migration and so on.

Returning to AFT, it was inspired by human interactions and behaviour in a human-related scenario, which is why it was classified as a human-based algorithm. The acts of the thieves in the story of Ali Baba and the forty thieves in identifying Ali Baba and the clever ways in which Ali Baba's maid saved him from the thieves motivated the writers, researchers B. Malik et al. [6], to mimic this behaviour using an optimisation algorithm. They proposed that the town of Ali Baba was the search space, the thieves were the search agents, the objective function was the home of Ali Baba, Ali Baba was the global solution, and each place in the town corresponded to a realisable solution.

2. Materials and Methods

This study relies on the AFT algorithm and natural frequencies to predict the damage level of plane truss structures. More clearly, for using the AFT optimisation algorithm, natural frequencies are used as the objective function, and the finite element model, according to H.L. Ton-That [7], D.Q. Vo & H.L. Ton-That [8], H.L. Ton-That [9], T. Chau-Dinh [10], is utilised to achieve the behaviour of these structures, and then final AFT results are shown to confirm the possible application.

First, review the basic assumptions of the AFT algorithm in this section: *i*) The Forty Thieves will band together and ask someone or one of them for advise on where to find Ali Baba's house. This information might or might not be correct. *ii*) From a starting point, these Forty Thieves will set out to locate Ali Baba's home. *iii*) Marjaneh can use clever strategies to fool these thieves several times in order to shield Ali Baba. The following are the main steps of the AFT algorithm, according to researchers B. Malik et al. [6]:

Step 1: The search space's upper and lower boundaries in the *j* dimension are denoted by ub_j and lb_j & randomly initialize the position *x* of all *n* thieves in search space.

Step 2: Initialize the best position $(best_t^i)$ and global best position $(gbest_t)$ for the thieves. Initialize the intelligence degree of Marjaneh with respect to all thieves.

Step 3: Evaluate each thief's position using a fitness function $\left(f(x)\right)$.

Step 4: Set $t \leftarrow 1$

Step 5: While $(t < T)$ do

$$Td_t = e^{-2(t/T)^2}, \quad Pp_t = 0.1 \times \log\left(2(t/T)^{0.1}\right) \tag{1}$$

Step 6: For $i = 1..n$ do

If $(rand \geq 0.5)$ then

If $(rand \geq Pp_t)$ then

$$x_{t+1}^i = gbest_t + \begin{bmatrix} Td_t\left(best_t^i - y_t^i\right)r_1 + \\ +Td_t\left(y_t^i - m_t^{a(i)}\right)r_2 \end{bmatrix} \text{sgn}\left(rand - 0.5\right) \tag{2}$$

Else

$$x_{t+1}^i = Td\left[\left(u_j - l_j\right)rand + l_j\right] \tag{3}$$

End

$$x_{t+1}^i = gbest_t - \begin{bmatrix} Td_t\left(best_t^i - y_t^i\right)r_1 + \\ +Td_t\left(y_t^i - m_t^{a(i)}\right)r_2 \end{bmatrix} \text{sgn}\left(rand - 0.5\right) \tag{4}$$

End

Step 7: For $i = 1..n$ do

Verify the new positions' viability; assess and revise the thieves' new positions; update $best_t^i$ and $gbest_t$; update

$$m_t^{a(i)} = \begin{cases} x_t^i & if \quad f\left(x_t^i\right) \geq f\left(m_t^{a(i)}\right) \\ m_t^{a(i)} & if \quad f\left(x_t^i\right) < f\left(m_t^{a(i)}\right) \end{cases} \quad (5)$$

End

Step 8: $t = t + 1$

Step 9: End while.

Finally, Fig. 1 displays the qualitative outcomes of the AFT algorithm for up to 500 iterations in solving a chosen set of test functions as in the Appendix.

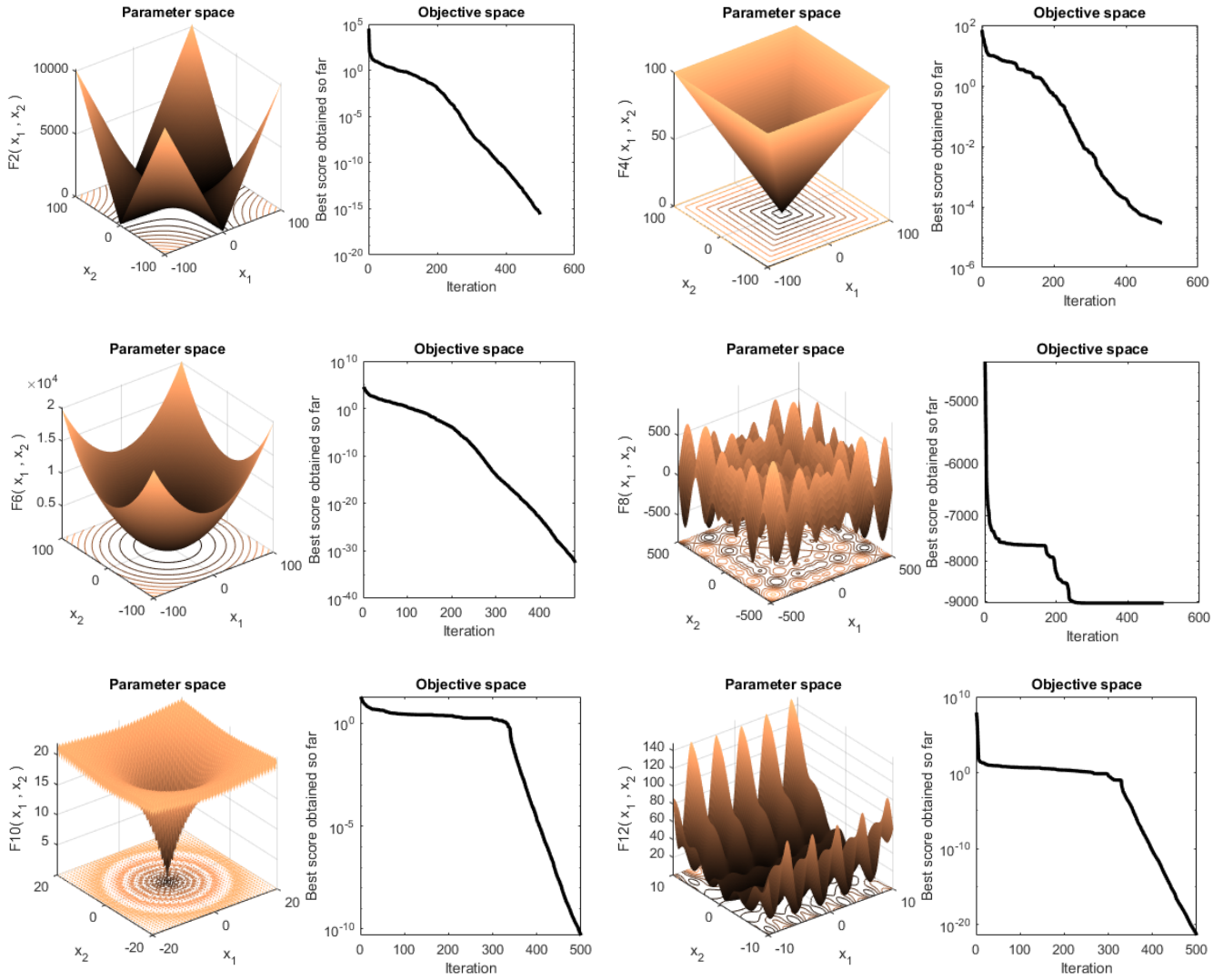
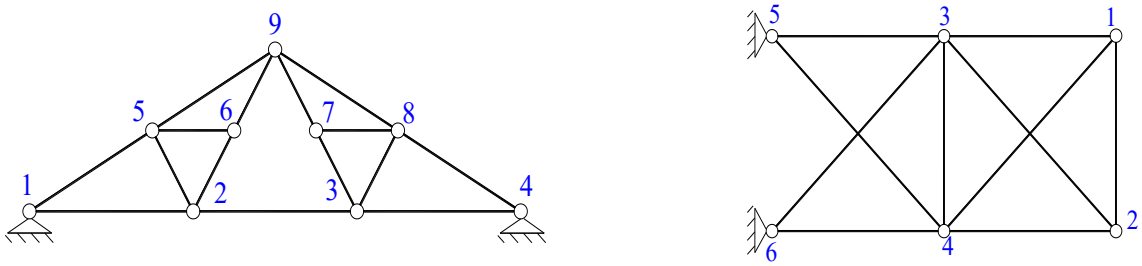


Figure 1. Qualitative results of AFT for test functions F2, F4, F6, F8, F10, F12

3. Results and Discussion

In this section two plane truss structures with 15 bars and 10 bars are considered as in Fig. 2 and Table 1.



(a) (b)

Figure 2. Truss structures (a) 15 bars, (b) 10 bars

Table 1. The data of two truss structures

15-bar truss						10-bar truss					
Node	x (m)	y (m)	Node	x (m)	y (m)	Node	x (m)	y (m)	Node	x (m)	y (m)
1	0	0	**6**	2.5	1	**1**	4	2	**6**	0	0
2	2	0	**7**	3.5	1	**2**	4	0			
3	4	0	**8**	4.5	1	**3**	2	2			
4	6	0	**9**	3	2	**4**	2	0			
5	1.5	1				**5**	0	2			
Bar	Nodes		Bar	Nodes		Bar	Nodes		Bar	Nodes	
1	1	2	*9*	4	8	*1*	1	3	*9*	2	4
2	2	3	*10*	5	6	*2*	3	5	*10*	4	6
3	3	4	*11*	7	8	*3*	1	2			
4	1	5	*12*	5	9	*4*	3	4			
5	2	5	*13*	6	9	*5*	1	4			
6	2	6	*14*	7	9	*6*	2	3			
7	3	7	*15*	8	9	*7*	3	6			
8	3	8				*8*	4	5			
$E = 205\times10^9$ N/m^2, $A = 7.9686\times10^{-4}$ m^2 and $\rho = 7850$ kg/m^3											

The difference in natural frequencies between the finite element model and actual measurements is known as an objective function. Thereby, the severity and location of damage will be predicted. The definition of damages in which a decrease in the member's modulus of elasticity is crucial is demonstrated by equation (6):

$$E_b = (1-r)E, \quad 0 \le r \le 1 \tag{6}$$

where r is the variable that indicates how much damage each bar has sustained. By minimising the objective function, it is then simple to determine the location and extent of the damage(s):

$$ob = \sqrt{\sum_{i=1}^{n}\left(f_i^a - f_i^{fe}\right)^2 / \left(f_i^a\right)^2} \tag{7}$$

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

Table 2. The damage situations

15-bar truss		
Situations	Damage bar(s)	Damage severity
The first situation	Bar 2	40%
The second situation	Bar 4	30%
	Bar 15	20%
The third situation	Bar 1	35%
	Bar 7	25%
	Bar 12	20%
10-bar truss		
Situations	Damage bar(s)	Damage severity
The first situation	Bar 1	40%
The second situation	Bar 3	30%
	Bar 7	20%

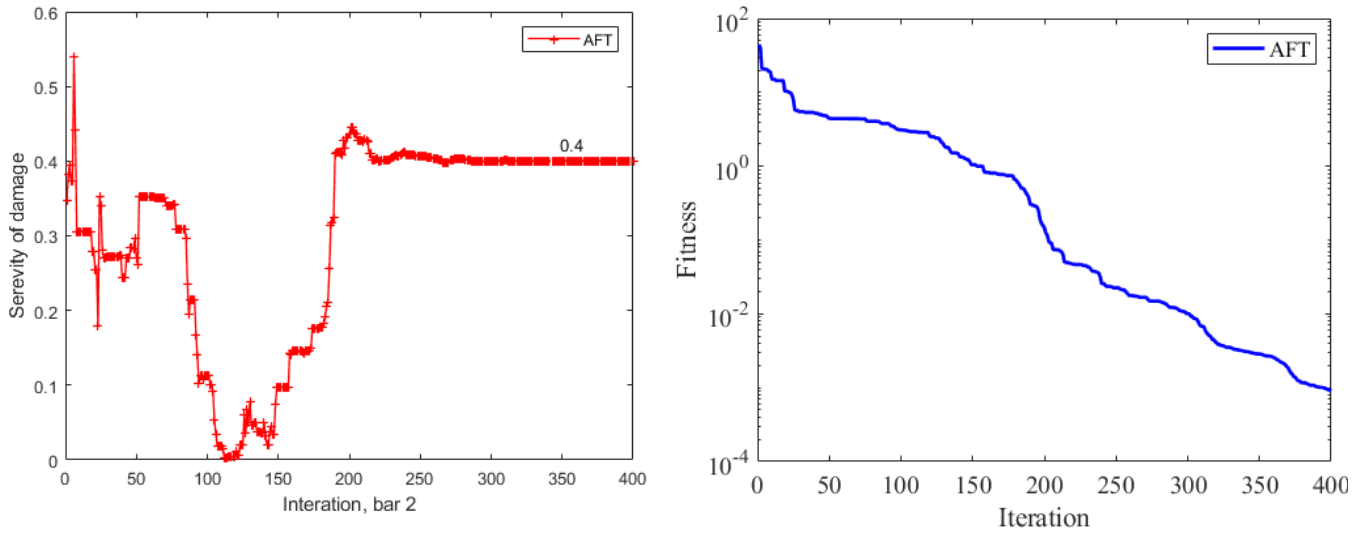


Figure 3. Describe the convergence for the first damage situation of 15-bar struss

To check the accuracy, some damage situations are given in Table 2. The results reveal that AFT provides the desired results for predicting damage structure, which are depicted in Figs. 3 to 7 in detail. It can also be seen that the AFT algorithm gets the desired results with about 200 to 300 iterations. Specifically, in the simplest situation, convergence is only reached after the 300th iteration for the 15-bar truss and the 200th iteration for the 10-bar truss. The same thing occurs in the next situation. Last but not least, this short research merely ends at the scope of suggesting the application of the AFT for predicting damage to trusses and does not compare with other metaheuristic algorithms or delve into its advantages and disadvantages.

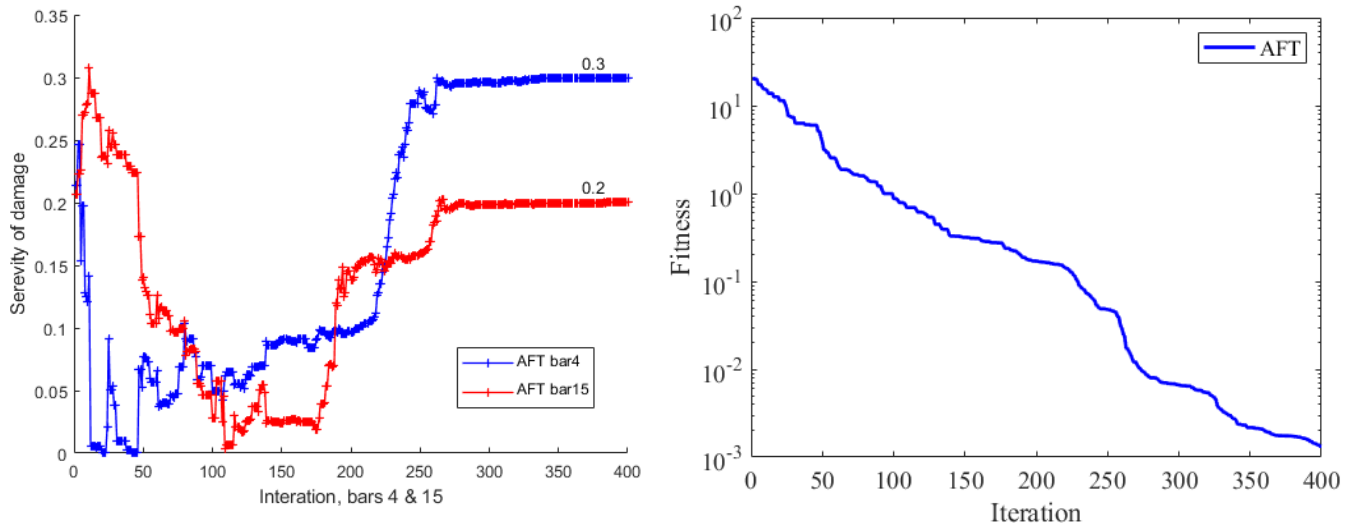


Figure 4. Describe the convergence for the second damage situation of 15-bar struss

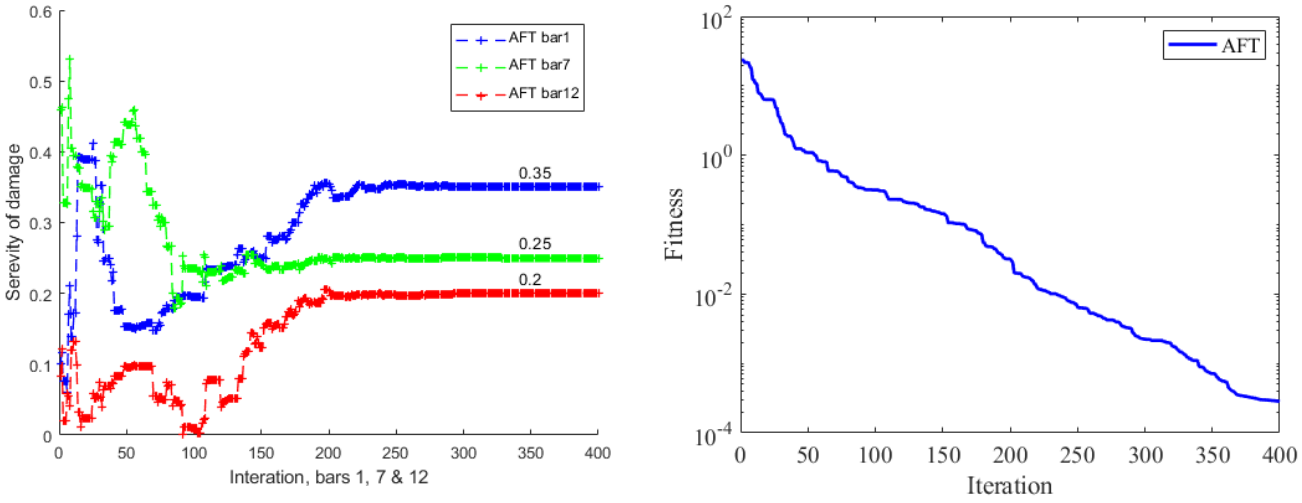


Figure 5. Describe the convergence for the third damage situation of 15-bar struss

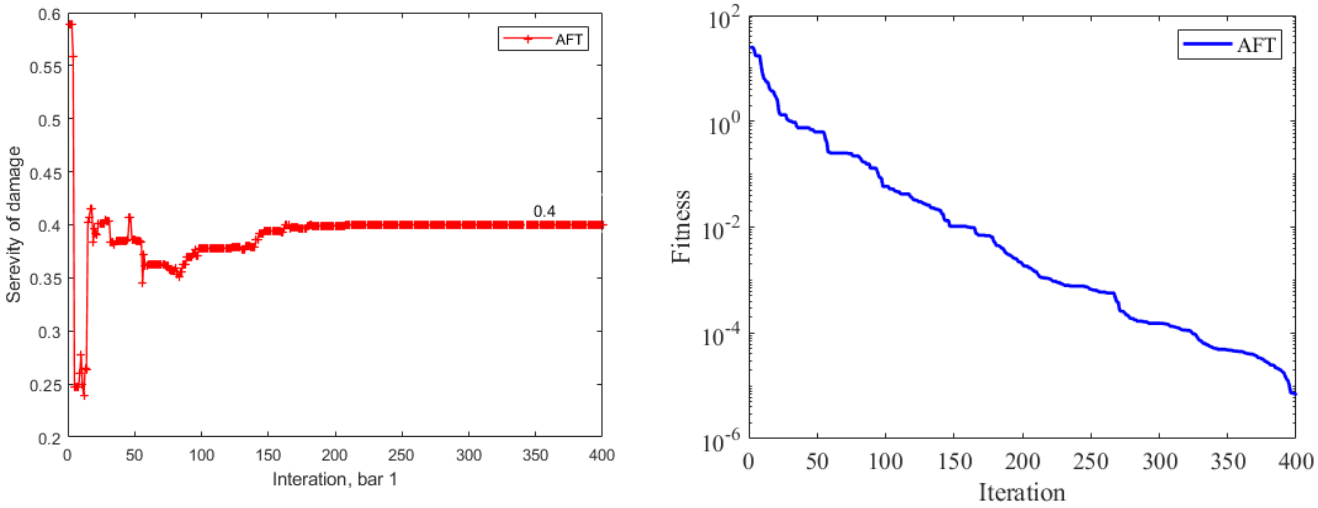


Figure 6. Describe the convergence for the first damage situation of 10-bar struss

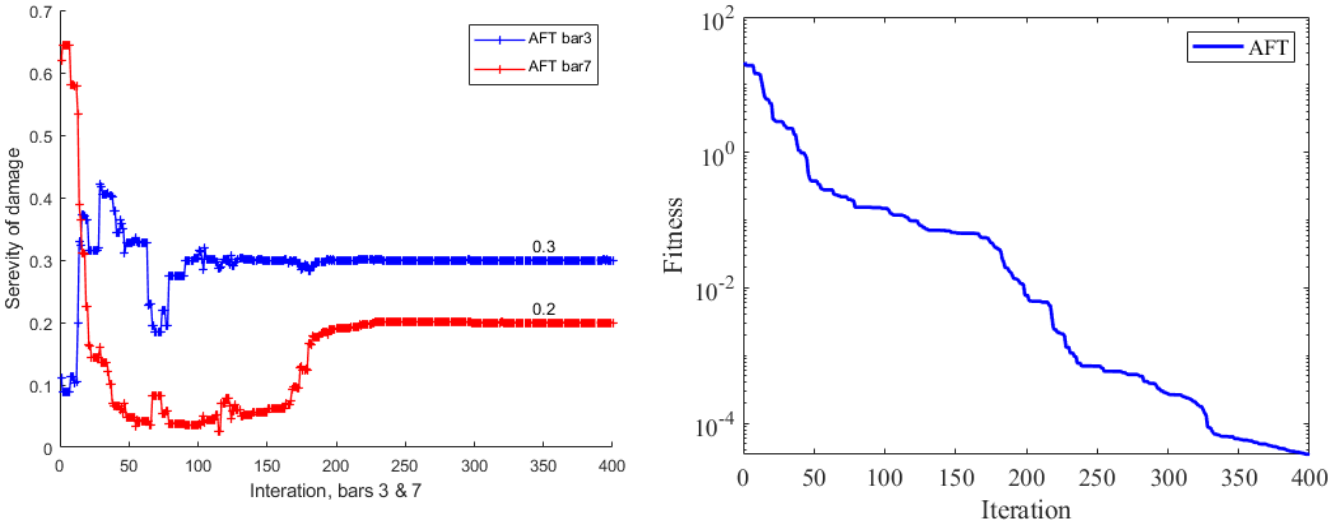


Figure 7. Describe the convergence for the second damage situation of 10-bar struss

4. Conclusions

This article presents how to use the Ali Baba and the Forty Thieves (AFT) optimisation algorithm to detect damage in plane truss structures. A number of situations, from simple to complex, are given to evaluate this algorithm's performance. The outcomes demonstrate how well the AFT algorithm predicts the location and magnitude of damage. Finally, in order to tackle increasingly complicated real-world problems, future research may offer an improved method based on the AFT algorithm to raise its performance level even more.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix

Function (f_i)	Range	f_{min}
$f_2 = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	$[-10,10]$	0
$f_4 = \max\{\lvert x_i \rvert, 1 \le i \le n\}$	$[-100,100]$	0
$f_6 = \sum_{i=1}^{n} (x_i + 0.5)^2$	$[-100,100]$	0
$f_8 = \sum_{i=1}^{n} -\left(x_i \sin\sqrt{\lvert x_i \rvert}\right)$	$[-500,500]$	0
$f_{10} = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e$	$[-32,32]$	0
$f_{12} = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left[1 + 10\sin^2(\pi y_{i+1})\right] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}; \quad u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	$[-50,50]$	0

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