




Structural Damage Identification in Trusses Using the African Vultures Optimization Algorithm



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Abstract: Structural damage identification and optimization in truss systems have increasingly relied on metaheuristic algorithms because of the high nonlinearity, multimodality, and computational complexity associated with conventional optimization methods. Among these approaches, swarm intelligence-based algorithms inspired by natural foraging and survival behaviors have demonstrated considerable effectiveness in solving continuous optimization problems. In this study, the African vultures optimization algorithm, a bio-inspired metaheuristic algorithm modeled on the navigation, foraging, and cooperative hunting behaviors of African vultures, was applied to the structural analysis and damage identification of planar and space truss systems. Finite element analysis was integrated with the optimization framework to evaluate the structural dynamic responses and natural frequency variations associated with different damage scenarios. Structural damage was identified through the minimization of objective functions. The exploration and exploitation capabilities of the African vultures optimization algorithm were systematically utilized to enhance global search performance and convergence stability during the optimization process. The effectiveness and robustness of the proposed approach were assessed through several benchmark truss structures subjected to varying damage conditions. Accurate localization and quantification of structural damage were achieved with high computational efficiency and strong convergence behavior. In comparison with conventional metaheuristic optimization techniques, improved stability, reliability, and solution accuracy were observed, particularly in complex and high-dimensional structural optimization problems. The findings demonstrate that the African vultures optimization algorithm can serve as an efficient and reliable computational tool for structural health monitoring, vibration-based damage detection, and optimization of truss structures. The proposed framework is expected to provide significant potential for advanced engineering applications involving large-scale structural systems and intelligent damage assessment.

Keywords: Metaheuristic algorithm; Truss structures; Finite element analysis; Natural frequency; Damage

1 Introduction

Artificial intelligence methods are now widely used in modern technology due to the quick development of science. Optimization is a crucial component of artificial intelligence since it can select the best solution from a variety of options. An optimization issue usually consists of three fundamental elements: the objective function or functions, design variables, and constraints that must be satisfied by the optimization process in order to achieve the global outcome. Metaheuristic algorithms, a stochastic optimization technique inspired by natural behaviors, have gained popularity in the optimization fields due to their many benefits, such as population-based mechanisms with multiple candidate solutions, ease of implementation, high flexibility, lack of gradient information, and black-box processes with only inputs and outputs. Metaheuristic algorithms are therefore very appropriate for optimization problems such as those in civil engineering and mechanical design. Researchers and engineers have already created a number of metaheuristic algorithms, including the genetic algorithm [1], the artificial bee colony [2], the grey wolf optimizer [3], the wild horse optimizer [4, 5], the black widow optimization algorithm [6, 7], the sine cosine algorithm [8], the chaos game optimization [9], the teaching-learning-based optimization [10], and so on. The main goal of the study by Muc and Gurba [1] was to explain the idea of applying the genetic algorithm techniques to composite structure layout optimization. Shape, dimension, and stacking sequence were all considered aspects of layout optimization. The employment of genetic algorithms in conjunction with the computation of objective functions using finite elements

was the main focus in this research. A field of study known as “swarm intelligence” simulates a population of interacting individuals or swarms that have the capacity to self-organize. Swarm intelligence was demonstrated by bees buzzing around their hive. The cognitive behavior of beehive swarms served as the basis for the artificial bee colony algorithm. Karaboga and Basturk [2] proposed the artificial bee colony method to optimize multivariable functions, and the outcomes were compared with those of other algorithms.

Inspired by grey wolves (*Canis lupus*), Mirjalili et al. [3] presented a metaheuristic known as the grey wolf optimizer. The grey wolf optimizer algorithm imitated the hunting strategy and leadership structure of grey wolves in the wild. The leadership hierarchy was simulated using four different sorts of grey wolves: alpha, beta, delta, and omega. The three primary phases of hunting—looking for prey, encircling prey, and attacking prey—were also carried out. After benchmarking the algorithm on 29 well-known test functions, a comparison analysis with other algorithms confirmed the findings. Inspired by the social behavior of wild horses, Naruei and Keynia [4] introduced an optimizer algorithm known as the wild horse optimizer. A stallion and a number of mares and foals typically make up a group of horses. Horses engage in a variety of activities, including grazing, pursuing, leading, dominating, and mating. The decency of horses is an intriguing trait that sets them apart from other animals. The foals of the horse leave the group before they reach adolescence and join other groups due to the horse’s decent behavior. The purpose of this departure is to stop the father from mating with the daughter or siblings. The horse’s polite behavior serves as the primary source of inspiration for the suggested algorithm.

Hayyolalam and Kazem [6] suggested a metaheuristic algorithm appropriate for issues involving continuous nonlinear optimization. Black widow spiders’ distinctive mating behavior served as the model for the black widow optimization algorithm. Cannibalism was one of the exclusive stages of this approach. Early convergence resulted from this stage, which excluded species with inappropriate fitness from the circle. The effectiveness of the black widow optimization algorithm in finding the best solutions for the problems was confirmed by evaluating it on 51 different benchmark functions. The acquired findings showed that, in comparison to other algorithms, the approach has several advantages in various aspects, including early convergence and obtaining optimized fitness value. Furthermore, Mirjalili [8] proposed the sine cosine approach, a population-based optimization approach for resolving optimization issues. Using a mathematical model based on sine and cosine functions, the sine cosine approach generated several initial random candidate solutions and forced them to fluctuate outward or toward the optimal answer. To encourage exploration and exploitation of the search space at various optimization milestones, a number of random and adaptive variables were also incorporated into the algorithm.

The chaos game optimization, another metaheuristic method, was created by Talatahari and Azizi [9] to address optimization issues. The chaos game optimization algorithm’s central idea was founded on some chaos theory concepts, which placed the self-similarity problems of fractals and their configuration by the chaos game notion in context. To assess this algorithm’s overall performance, a total of 239 mathematical functions were gathered and divided into four groups. In this study, three comparison assessments with various features were carried out to assess the chaos game optimization algorithm’s findings. For the optimization of mechanical design issues, another effective optimization technique known as the teaching–learning-based optimization was put forth by Rao et al. [10] The approach focused on how a teacher’s influence affects students. The teaching–learning-based optimization was a population-based approach that used a population of solutions to move on to the global answer, just like other algorithms inspired by nature. The population was seen as a class or group of students. The “teacher phase” and the “learner phase” comprised the first and second phases of the teaching–learning-based optimization process, respectively. Especially, a metaheuristic influenced by the lifestyle of African vultures was proposed by Abdollahzadeh et al. [11] The algorithm, known as the African vultures optimization algorithm, mimicked the foraging and navigational patterns of African vultures, as described in Figure 1. The African vultures optimization algorithm was originally evaluated on 36 common benchmark functions in order to assess its performance. A comparative analysis was carried out to show how much better this algorithm was than a number of other algorithms already in use.

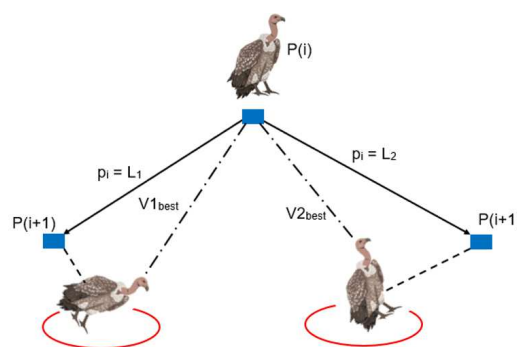


Figure 1. The African vultures optimization algorithm’s general representation

On the other hand, numerous academics have suggested various methods to forecast structural damage to trusses in order to get the best outcomes. A Bayesian-optimized image transformer model was proposed by Hiçyılmaz [12] for continuous wavelet transform analysis-based damage identification in steel truss constructions. To better understand the intricate dynamic behavior of steel truss structures, the continuous wavelet transform spectrograms produced from a 72-bar steel truss model and measurements of an actual steel truss bridge were taken into consideration. Based on dynamic acceleration data gathered under moving load conditions, Das and Guchhait [13] presented a hierarchical damage identification method for the localization and quantification of damage in steel truss bridges utilizing a unique dual-stage gated recurrent unit-long short-term memory model. SAP2000 was used to numerically model a 25-membered simply supported steel truss bridge for both undamaged and various damage situations. The dynamic acceleration response was observed at multiple nodes while a multi-axle moving train load was applied. To replicate a real-world situation, the numerically generated acceleration response was supplemented with Gaussian noise. In order to create an organized two-level decision-making process, this model used a hierarchical architecture in which the first stage determined the location of the damage and the second estimated its severity.

The combination of a one-dimensional convolutional neural network from deep learning models and bidirectional gated recurrent unit strengths was attempted by Pham-Hong et al. [14] While the bidirectional gated recurrent unit learned and classified sequential data bidirectionally, successfully capturing crucial temporal aspects, the one-dimensional convolutional neural network identified important characteristics from incoming data. To increase dataset diversity, data augmentation employed noise, reversal, and random shifts. By calculating class probabilities, a softmax layer enhanced the evaluation of model confidence per prediction. The technique performed exceptionally well in identifying, assessing, and analyzing structural damage when tested on an experimental bridge. To increase the accuracy of truss bridge damage assessment, a novel technique based on feature-transferable digital twins was presented by Huang et al. [15] In particular, simulated data for several truss damage scenarios were obtained using a finite element model as a benchmark digital model. In order to identify truss bridge damage, the deep residual sub-domain adaptation network was fed both the measured signals from the truss bridge and the simulated data from the model for feature alignment. For the purpose of evaluating the fatigue of current rail-cum-road bridges, the structural health monitoring system offered useful data. Using the structural health monitoring data, Hua-Peng et al. [16] sought to create an efficient fatigue evaluation method for the Jiujiang Yangtze River Bridge, a rail-cum-road bridge, with an emphasis on dynamic modal analysis, finite element model updating, fatigue assessment, and so on.

Back to the African vultures optimization algorithm, it is currently widely employed in many different disciplines. However, when it comes to tackling complicated multimodal problems, the African vultures optimization algorithm occasionally has certain drawbacks, including low searching accuracy, a lack of search capabilities, and a propensity to enter a local optimum. To balance the exploration and development capacities of the African vultures optimization algorithm, Liu et al. [17] presented quasi-antagonistic learning processes, differential evolution operators, and adaptive parameters. Fan et al. [18] optimized the global optimal solution and convergence performance of the African vultures optimization algorithm using time-varying tools and chaotic mapping. A novel African vulture-grey wolf hybrid optimizer was proposed by Soliman et al. [19] to increase the algorithm's stability and rate of convergence. Kannan et al. [20] proposed a hybrid optimization algorithm based on honey badger and African vulture; the global optimization search of the algorithm was implemented, and the probability of falling into the local optimum was reduced.

Therefore, this study aims to apply the African vultures optimization algorithm to predict damage of truss structures in order to assess whether the limitations mentioned above are present in the structure analysis. This research shows pretty convincing results about damage prediction based on the analysis of the structure's natural frequencies and accompanying vibration modes and employing them as target objects. It goes without saying that any pertinent finite element formulas to vibration analysis, like those found in the literature [21–25], should be used.

The sections below comprise this study. A brief theory is presented in Section 2. The results are presented in Section 3. Finally, the main conclusions are summarized in Section 4.

2 Brief of the African Vultures Optimization Algorithm and Damage Prediction Process

The African vultures optimization algorithm mimics the navigation and foraging habits of African vultures. Every member of the population completes the transition between the stages of exploration and development based on their hunger rate. The African vultures optimization algorithm is divided into four phases: determining the best vulture in any group, the rate of starvation of vultures, exploration, and exploitation. The algorithm can be summarized below. The inputs consist of the population size N and the maximum number of iterations T . The outputs are the vulture's location and fitness score.

Specifically, the random population $P_{i(i=1, N)}$ is first set up. While the stopping condition is not satisfied, the vulture's fitness values are determined. $P_{\text{BestVulture}_1}$, $P_{\text{BestVulture}_2}$, for each vulture P_i is set, and $R(i)$ is selected

using the following equation:

$$R(i) = \begin{cases} \text{BestVulture}_1 \text{ (or } V1_{\text{best}}), & \text{if } P_i = L_1 \\ \text{BestVulture}_2 \text{ (or } V2_{\text{best}}), & \text{if } P_i = L_2 \end{cases} \quad (1)$$

Then F is updated using the following equation:

$$F = (2 \times \text{rand}_1 + 1) \times z \times \left(1 - \frac{\text{iter}_i}{\text{max iter}}\right) + h \times \left[\sin^w \left(\frac{\pi}{2} \times \frac{\text{iter}_i}{\text{max iter}} \right) + \cos \left(\frac{\pi}{2} \times \frac{\text{iter}_i}{\text{max iter}} \right) - 1 \right] \quad (2)$$

When $|F| \geq 1$, if $P_1 \geq \text{rand}_{P_1}$, then $P(i+1) = R(i) - D(i) \times F$, with $D(i) = |X \times R_i - P(i)|$; otherwise, the following equation applies:

$$P(i+1) = R(i) - F + \text{rand}_2 \times [(ub - lb) \times \text{rand}_3 + lb] \quad (3)$$

When $|F| < 1$, if $|F| \geq 0.5$ and $P_2 \geq \text{rand}_{P_2}$, the following equation applies:

$$P(i+1) = D(i) \times (F + \text{rand}_4) - R(i) + P(i) \quad (4)$$

Otherwise, the following equation applies:

$$P(i+1) = R(i) \left[1 - \left(\frac{\text{rand}_5 \times P(i)}{2\pi} \right) \cos[P(i)] - \left(\frac{\text{rand}_6 \times P(i)}{2\pi} \right) \sin[P(i)] \right] \quad (5)$$

If $P_3 \geq \text{rand}_{P_3}$, then the following equation applies:

$$P(i+1) = \frac{\text{BestVulture}_1(i) + \text{BestVulture}_2(i)}{2} - \frac{\text{BestVulture}_1(i) \times P(i)}{\text{BestVulture}_1(i) - P(i)^2} \times \frac{F}{2} - \frac{\text{BestVulture}_2(i) \times P(i)}{\text{BestVulture}_2(i) - P(i)^2} \times \frac{F}{2} \quad (6)$$

Otherwise, the following equation applies:

$$P(i+1) = R(i) - |R(i) - P(i)| \times F \times \text{Levy}(d) \quad (7)$$

$P_{\text{BestVulture}_1}$ is returned.

Figure 2 displays the convergence graphs of the best vulture's fitness. It is clear from examining these graphs that all of them exhibit a quickly diminishing tendency. Furthermore, the objective function (ob) is created by combining natural frequencies and mode shapes. Respectively, Eq. (8) must be solved in order to determine these frequencies and mode shapes:

$$[\mathbf{M}]\ddot{\mathbf{d}} + [\mathbf{K}]\mathbf{d} = 0 \quad (8)$$

where,

$$\mathbf{d} = \xi \sin(\omega t + \varphi) \quad (9)$$

$$\ddot{\mathbf{d}} = -\omega^2 \xi \sin(\omega t + \varphi) \quad (10)$$

Therefore, Eq. (8) can be rewritten as follows:

$$([\mathbf{K}] - \omega^2[\mathbf{M}]) \xi = 0 \quad (11)$$

$$\det([\mathbf{K}] - \omega^2[\mathbf{M}]) = 0 \quad (12)$$

The following can be noted:

$$f_i = \omega_i / 2\pi \quad (13)$$

Damage in any truss member leads to a reduction in the global stiffness matrix \mathbf{K} of the structure. Let \mathbf{K}_ε denote the stiffness matrix of an individual element. If the elemental stiffness is reduced by $r\%$, a corresponding reduction is also induced in the global stiffness matrix \mathbf{K} .

$$\mathbf{K}_\varepsilon^d = (1 - r\%) \mathbf{K}_\varepsilon \quad (14)$$

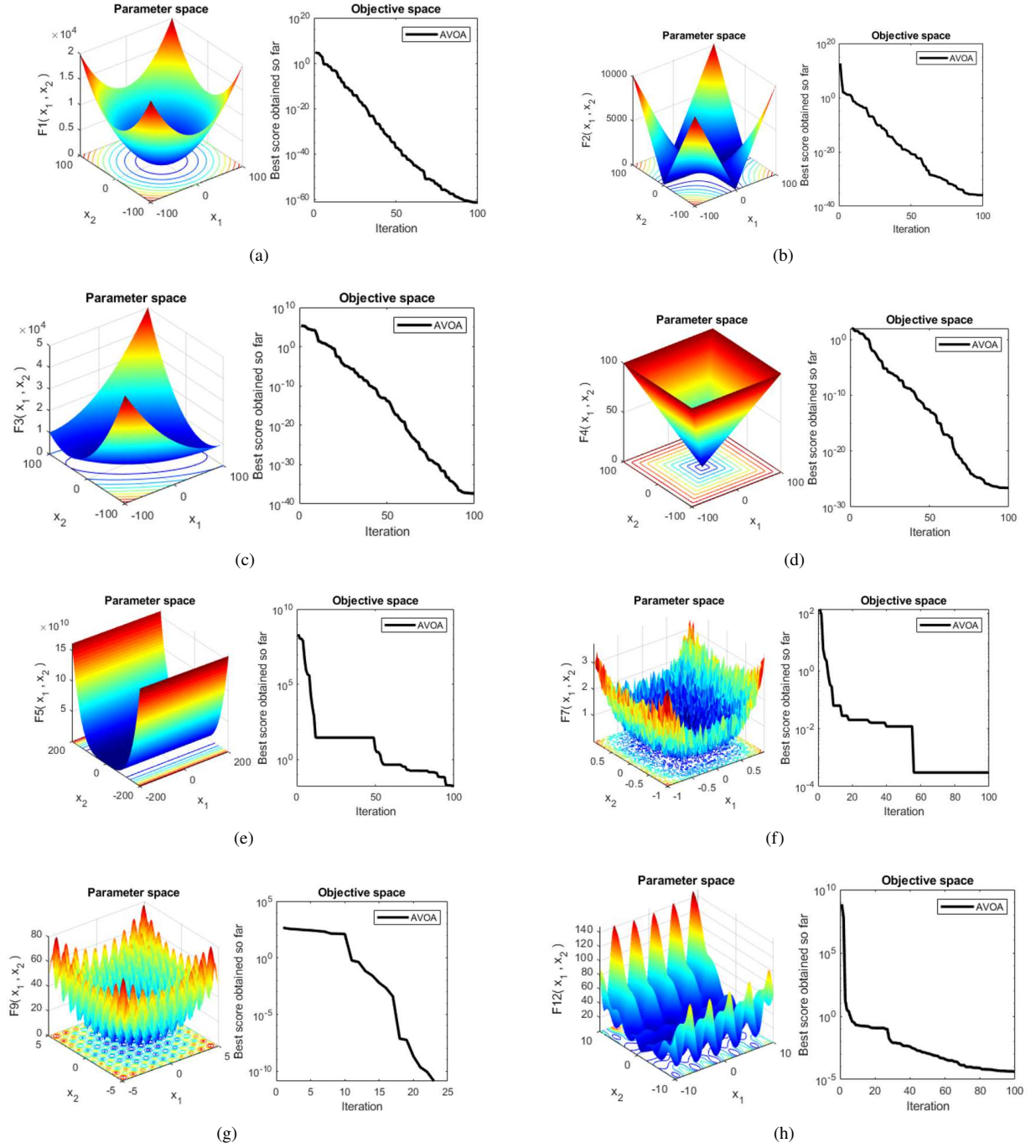


Figure 2. Qualitative results for the African vultures optimization algorithm: (a) benchmark function F_1 ; (b) benchmark function F_2 ; (c) benchmark function F_3 ; (d) benchmark function F_4 ; (e) benchmark function F_5 ; (f) benchmark function F_7 ; (g) benchmark function F_9 ; (h) benchmark function F_8 ; (h) benchmark function F_{12}

Note: AVOA = African vultures optimization algorithm

Then the objective function is depicted as follows:

$$ob = \zeta_1 \sqrt{\sum_{i=1}^4 \left[\frac{(f_i^c - f_i^m)^2}{(f_i^m)^2} \right]} + \zeta_2 \left\{ 1 - \left(\frac{\sum_{i=1}^4 \xi_i^c \xi_i^m}{\sum_{i=1}^4 (\xi_i^c)^2} \right)^2 / \left[\left(\sum_{i=1}^4 (\xi_i^c)^2 \right) \left(\sum_{i=1}^4 (\xi_i^m)^2 \right) \right] \right\} \quad (15)$$

If 4 is the number of considered natural frequencies and mode shapes, then m and c indicate the measured and computed quantities, f_i and ξ_i are the i -th natural frequency and mode shape, and S_1 and S_2 are the weight factors. The framework optimization according to the African vultures optimization algorithm is shown in Figure 3.

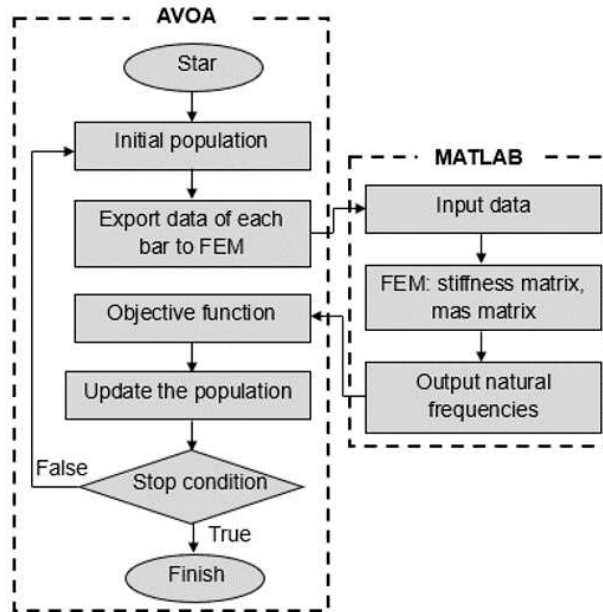


Figure 3. Framework optimization of the African vultures optimization algorithm

Note: AVOA = African vultures optimization algorithm, FEM = Finite element analysis

3 Test Results for Planar/Space Truss Structures and Discussion

This section examines two planar and two space truss structures with 9, 13, 25, and 72 bars as illustrated in Figure 4 and Figure 5 and detailed in Table 1 and Table 2. For simplicity, the geometric and material characteristics are kept the same across all examples: $A = 0.000707 \text{ m}^2$, $E = 205 \times 10^9 \text{ N/m}^2$, and $\rho = 7833 \text{ kg/m}^3$. Figure 6 and Figure 7 also depict the first four mode shapes of these planar/space truss structures.

To predict the damage for the 9-bar truss, this study proposes three damage scenarios from simple to complex, as shown in Table 3, to evaluate the capability of the African vultures optimization algorithm. This idea is repeated for the remaining three truss structures. The objective function is a combination between natural frequencies and mode shapes, as presented in Eq. (15). For all scenarios, the African vultures optimization algorithm consistently shows fairly good convergence results, as shown in Figure 8. Additionally, it is evident that the African vultures optimization algorithm only requires about 300 iterations to yield the stability outcomes. The increasing complexity of the truss structures, with established scenarios ranging from simple to complex, as depicted in Table 3, did not pose a challenge for the African vultures optimization algorithm in providing the final prediction. Figure 9, Figure 10 and Figure 11 demonstrate this assertion. Last but not least, to further convince the reader, this study compares the African vultures optimization algorithm with another superior algorithm, the genetic algorithm. The prediction results of the two algorithms converge quite well with each other, as illustrated in Figure 12.

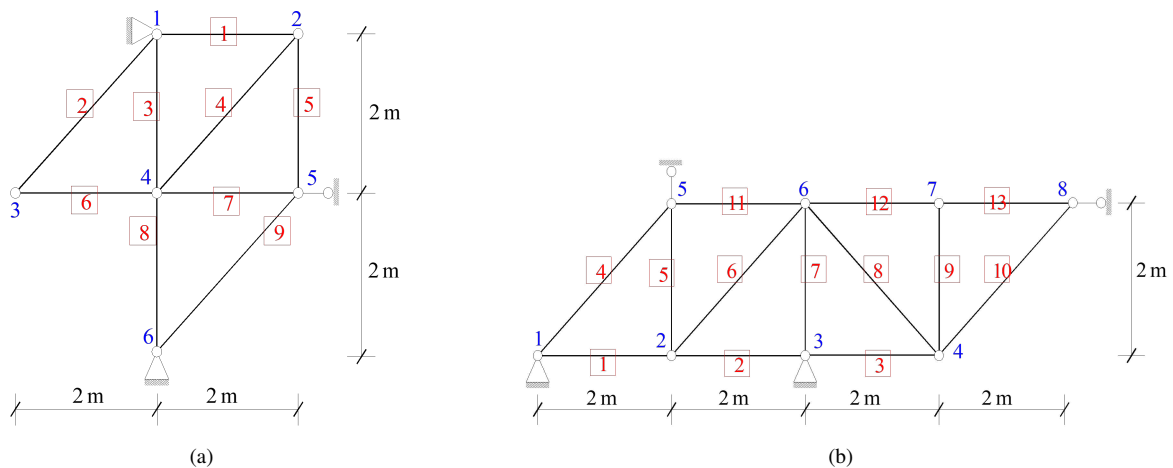


Figure 4. Two planar truss structures: (a) 9-bar truss; (b) 13-bar truss

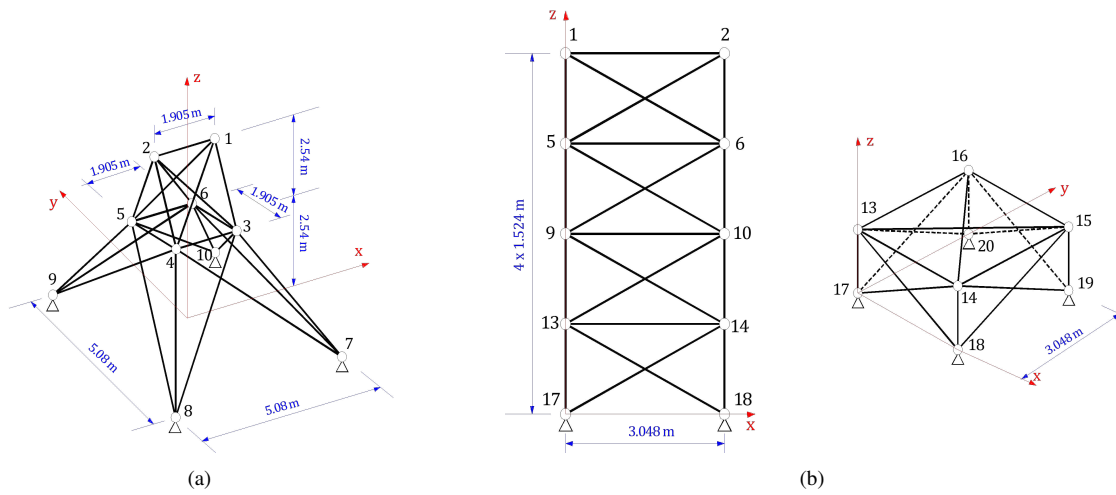


Figure 5. Two space truss structures: (a) 25-bar truss; (b) 72-bar truss

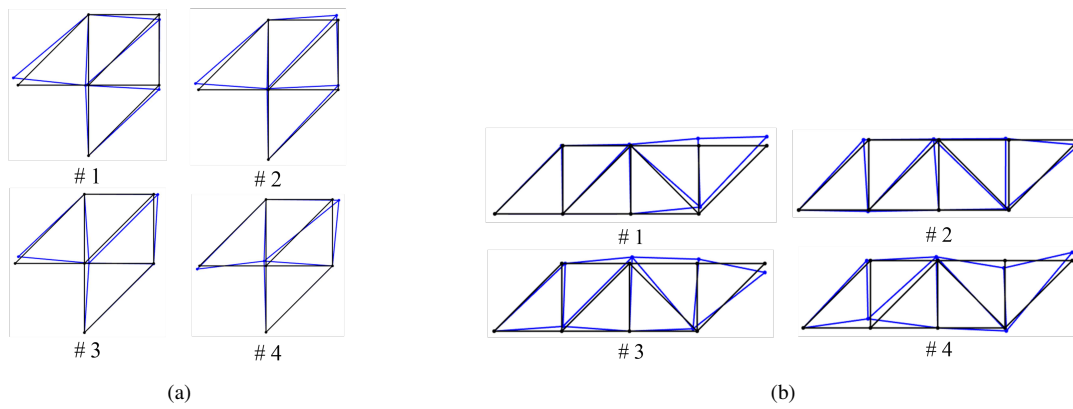


Figure 6. The first four mode shapes of two planar truss structures: (a) mode shapes for 9-bar truss; (b) mode shapes for 13-bar truss

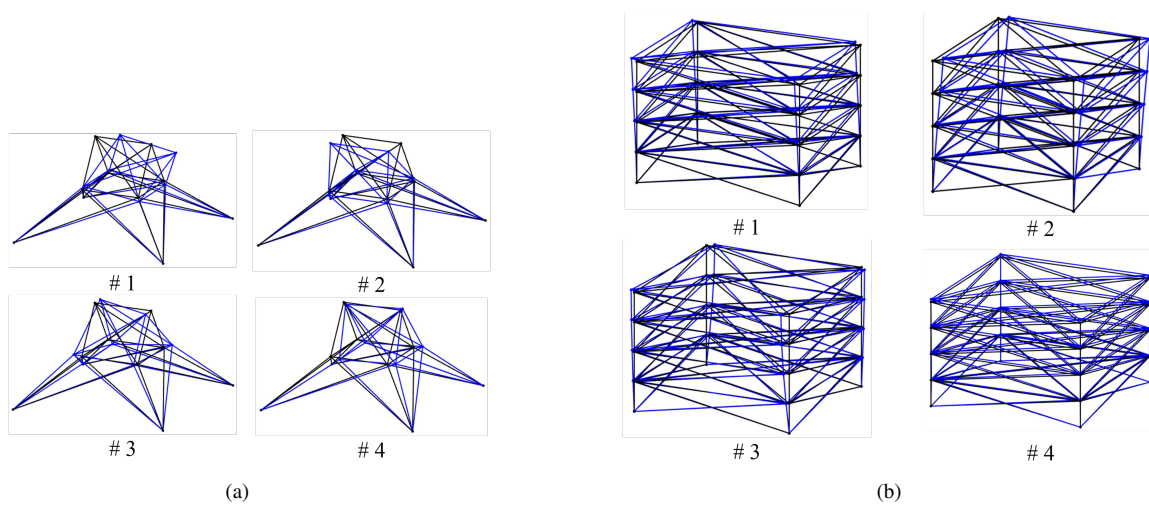
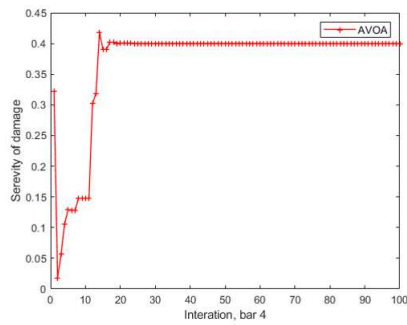


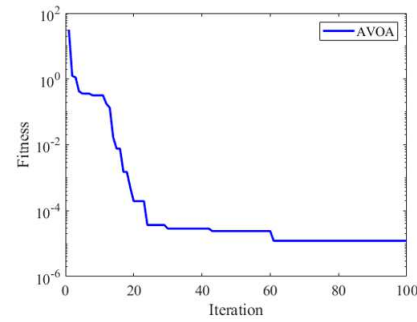
Figure 7. The first four mode shapes of two space truss structures: (a) mode shapes for 25-bar truss; (b) mode shapes for 72-bar truss

Table 1. Nodal coordinates of the 25-bar and 72-bar truss structures

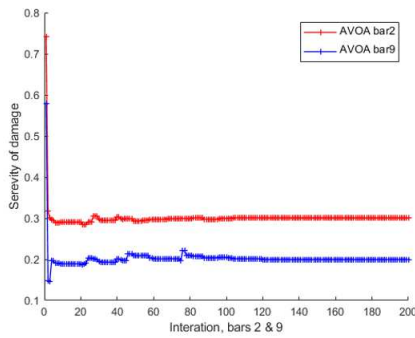
25-Bar Truss Structure				72-Bar Truss Structure							
Node	$x(m)$	$y(m)$	$z(m)$	Node	$x(m)$	$y(m)$	$z(m)$	Node	$x(m)$	$y(m)$	$z(m)$
1	-0.9525	0	5.08	1	0	0	6.096	11	3.048	3.048	3.048
2	0.9525	0	5.08	2	3.048	0	6.096	12	0	3.048	3.048
3	-0.9525	0.9525	2.54	3	3.048	3.048	6.096	13	0	0	1.524
4	0.9525	0.9525	2.54	4	0	3.048	6.096	14	3.048	0	1.524
5	0.9525	-0.9525	2.54	5	0	0	4.572	15	3.048	3.048	1.524
6	-0.9525	-0.9525	2.54	6	3.048	0	4.572	16	0	3.048	1.524
7	-2.54	2.54	0	7	3.048	3.048	4.572	17	0	0	0
8	2.54	2.54	0	8	0	3.048	4.572	18	3.048	0	0
9	2.54	-2.54	0	9	0	0	3.048	19	3.048	3.048	0
10	-2.54	-2.54	0	10	3.048	0	3.048	20	0	3.048	0



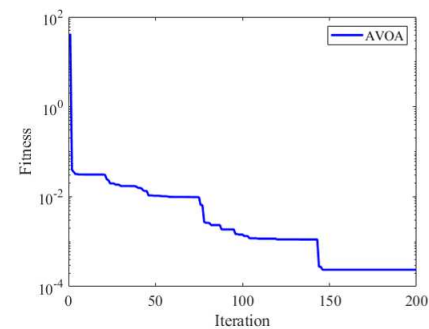
(a)



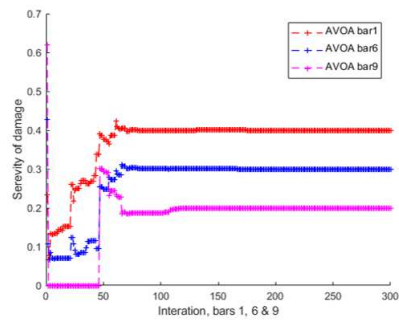
(b)



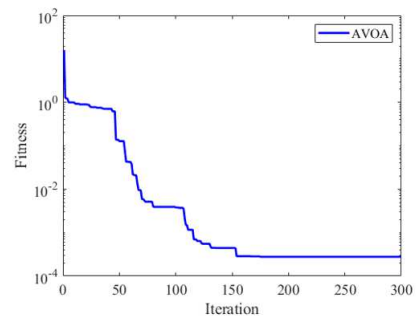
(c)



(d)



(e)



(f)

Figure 8. The African vultures optimization algorithm's convergence results for three scenarios of the 9-bar truss: (a) and (b) the first scenario; (c) and (d) the second scenario; (e) and (f) the third scenario

Note: AVOA = African vultures optimization algorithm

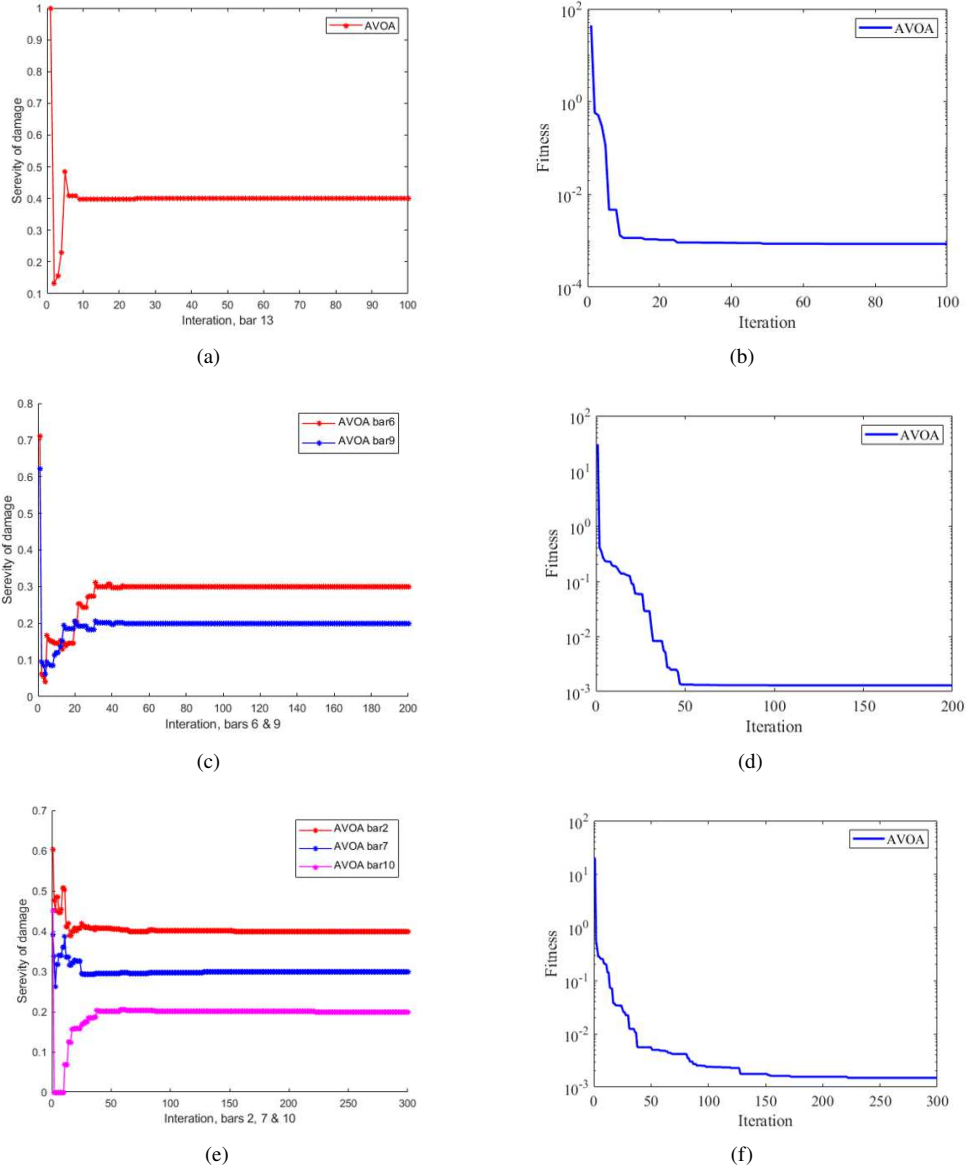


Figure 9. The African vultures optimization algorithm’s convergence results for three scenarios of the 13-bar truss: (a) and (b) the first scenario; (c) and (d) the second scenario; (e) and (f) the third scenario
 Note: AVOA = African vultures optimization algorithm

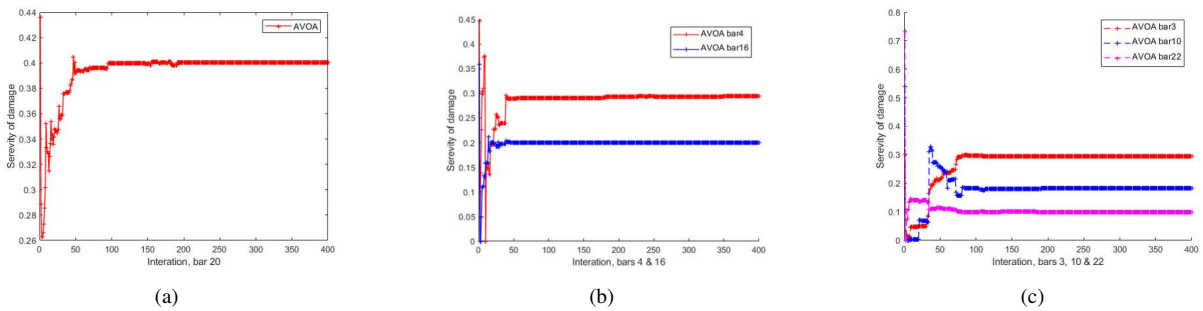


Figure 10. The African vultures optimization algorithm’s convergence results for three scenarios of the 25-bar truss: (a) the first scenario; (b) the second scenario; (c) the third scenario
 Note: AVOA = African vultures optimization algorithm

Table 2. Element connectivity of the 25-bar and 72-bar truss structures

25-Bar Truss Structure			72-Bar Truss Structure								
Bar	Node		Bar	Node		Bar	Node		Bar	Node	
1	1	2	1	1	5	26	6	11	51	11	12
2	1	4	2	2	6	27	8	12	52	9	12
3	2	3	3	3	7	28	7	12	53	9	11
4	1	5	4	4	8	29	8	9	54	10	12
5	2	6	5	1	6	30	5	12	55	13	17
6	2	4	6	2	5	31	5	6	56	14	18
7	2	5	7	3	6	32	6	7	57	15	19
8	1	3	8	2	7	33	7	8	58	16	20
9	1	6	9	4	7	34	5	8	59	13	18
10	3	6	10	3	8	35	5	7	60	14	17
11	4	5	11	4	5	36	6	8	61	15	18
12	3	4	12	1	8	37	9	13	62	14	19
13	5	6	13	1	2	38	10	14	63	16	19
14	3	10	14	2	3	39	11	15	64	15	20
15	6	7	15	3	4	40	12	16	65	16	17
16	4	9	16	1	4	41	9	14	66	13	20
17	5	8	17	1	3	42	10	13	67	13	14
18	4	7	18	2	4	43	11	14	68	14	15
19	3	8	19	5	9	44	10	15	69	15	16
20	5	10	20	6	10	45	12	15	70	13	16
21	6	9	21	7	11	46	11	16	71	13	15
22	6	10	22	8	12	47	12	13	72	14	16
23	3	7	23	5	10	48	9	16			
24	4	8	24	6	9	49	9	10			
25	5	9	25	7	10	50	10	11			

Table 3. Damage situations of planar/space truss structures

Truss Structure	Scenario	Damage Bar(s)	Severity of Damage
9-Bar Truss Structure	The first scenario	Bar 4	40% (0.4)
	The second scenario	Bar 2	30% (0.3)
		Bar 9	20% (0.2)
		Bar 1	40% (0.4)
	The third scenario	Bar 6	30% (0.3)
	13-Bar Truss Structure	The first scenario	Bar 9
The second scenario		Bar 13	40% (0.4)
		Bar 6	30% (0.3)
		Bar 9	20% (0.2)
The third scenario		Bar 2	40% (0.4)
25-Bar Truss Structure		The first scenario	Bar 7
	The second scenario	Bar 10	20% (0.2)
		Bar 20	40% (0.4)
		Bar 4	30% (0.3)
	The third scenario	Bar 16	20% (0.2)
	72-Bar Truss Structure	The first scenario	Bar 3
Bar 10			20% (0.2)
Bar 22			10% (0.1)
The second scenario		Bar 13	40% (0.4)
		Bar 4	35% (0.35)
		Bar 2	25% (0.25)
The third scenario	Bar 25	35% (0.35)	
	Bar 41	25% (0.25)	
	Bar 69	20% (0.2)	

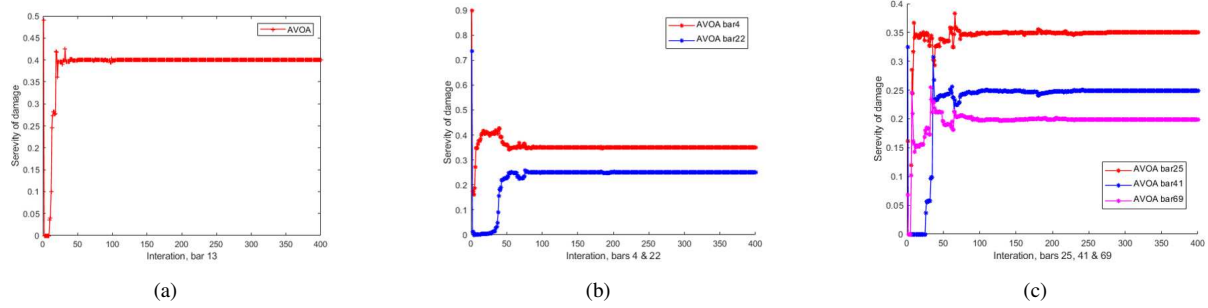


Figure 11. The African vultures optimization algorithm’s convergence results for three scenarios of the 72-bar truss: (a) the first scenario; (b) the second scenario; (c) the third scenario
 Note: AVOA = African vultures optimization algorithm

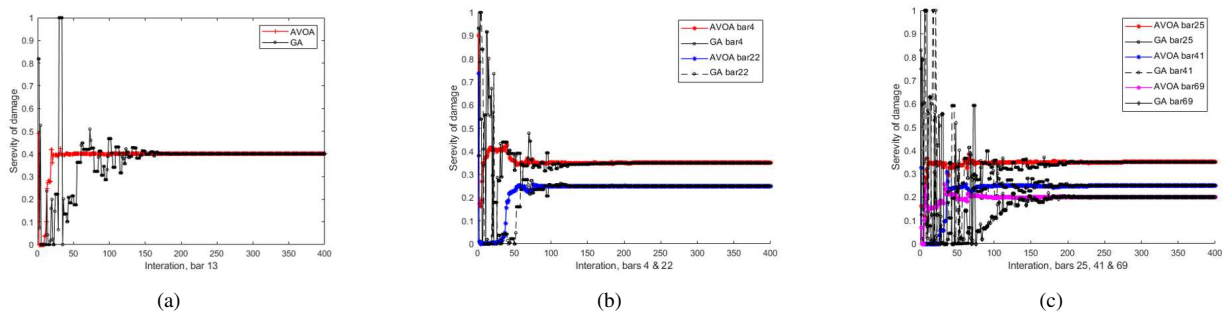


Figure 12. Comparison results for three scenarios of the 72-bar truss between the African vultures optimization algorithm and the genetic algorithm: (a) the first scenario; (b) the second scenario; (c) the third scenario
 Note: AVOA = African vultures optimization algorithm, GA = Genetic algorithm

In summary, specifically in the task of predicting structural damage to trusses, the African vultures optimization algorithm yields fairly reasonable results, although overall, it is believed that the African vultures optimization algorithm still has many shortcomings that need improvement. This study aims to help readers gain a more comprehensive understanding of the strengths and weaknesses of the African vultures optimization algorithm when they wish to apply it to more in-depth analyses later.

4 Conclusion

Inspired by the lifestyle, food quest, and competition of different vultures on the African continent, a metaheuristic algorithm was created and now applies to the analysis of truss structures. A balance between variety and resonance was produced as a result of the algorithm’s optimal usage of the two best solutions, which represented the two vultures’ more powerful groups than the other vultures. This improved the model’s performance. However, it differed entirely from previous metaheuristic algorithms due to the unique benefit of moving from the exploration phase to exploitation. This metaheuristic algorithm, the African vultures optimization algorithm, was compared with another potent algorithm, the genetic algorithm, in order to predict damage from truss structures. The promising results obtained in this study indicate that further investigation of the African vultures optimization algorithm and its application to other structural systems is warranted.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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Nomenclature

L_1, L_2	Parameters that must be assessed prior to the search process; their values range from 0 to 1, and their sum equals 1
h	A random number between -2 and 2
V_{1best}, V_{2best}	The two best adapted vultures in the vulture population
$rand$	Random values between 0 and 1
P_i	Probability of selecting the best vulture
$P_{1,2,3}$	Parameters between 0 and 1 to select strategies available
F	Vultures that are satiated
$P(t + 1)$	The vulture position vector in the next iteration
$iter_i$	The current iteration number
X	Random movement mechanism used by vultures to protect food sources from other vultures
$maxiter$	The total number of iterations
$R(i)$	One of the best vultures selected in the current iteration
z	A random number between -1 and 1
d	Problem dimensions
ub, lb	The upper bound and the lower bound of the variables
$Levy$	Levy flight was identified and used in the activities of many metaheuristic algorithms
w	A fixed parameter set before the algorithm works