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Benchmark Fonksiyonları için Altın Kartal Optimizasyon Algoritmasının Parametrelerini Optimize Etme

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ÖZET

Bu çalışmada, Altın Kartal Optimizasyon (AKO) algoritmasının performansını iyileştirmek için AKO algoritmasının parametreleri optimize edilmiştir. Bu sayede algoritmanın parametresinin en iyi değerinin elde edileceği ve elde edilen parametre değerleri için algoritmanın daha kararlı bir işlem gerçekleştireceği öngörülmektedir. Algoritmanın parametre optimizasyonu birçok çalışmada kullanılmaktadır. AKO algoritmasının iki farklı parametre değeri vardır. Bu parametreler sırasıyla saldırı ve seyirdir. Seyir parametre değeri [0.5-1], saldırı parametresi değeri [0.5-2] arasındadır. Algoritmanın her bir parametre değeri için 23 farklı kıyaslama fonksiyonu üzerinde deneysel çalışmalar yapılmıştır. Deneysel çalışma sonuçlarında en iyi parametrelerin değerleri belirlenmeye çalışılmıştır. Unimodal benchmark test fonksiyonlarında seyir parametresi 0.75 değeri ile iyi sonuçlar elde etmiştir. Saldırı parametresi ise fonksiyonlara bağlı olarak 1.5'e yaklaştığında optimum sonuca doğru yakınsadığı tablo ve grafiklerde verilmiştir. Benzer şekilde, multimodal kıyaslama testi sonuçlarında, seyir parametresi 0.75 değeri ile benzer şekilde iyi sonuçlar hesaplamıştır. Fonksiyonların özelliklerine bağlı olarak, değer 1.5'e yaklaştıkça saldırı parametresinin değerinin daha iyi bir çözüm bulduğu tablo ve grafiklerde gösterilmiştir.

Optimizing the Parameters of the Golden Eagle Optimizer Algorithm for Benchmark Functions

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ABSTRACT

In this study, in order to improve the performance of the Golden Eagle Optimization (GEO) algorithm, the parameters of the algorithm were optimized. In this way, it is predicted that the best value of the algorithm's parameter will be obtained and the algorithm will perform a more stable operation for the obtained parameter values. The algorithm’s parameter optimization is used in many studies. There are two different parameter values of the GOE algorithm. These parameters are attack and cruise, respectively. Cruise parameter value is between [0.5-1] and attack parameter value is between [0.5-2]. Experimental studies were carried out on 23 different benchmark functions for each parameter value of the algorithm. In the experimental study results, the values of the best parameters were tried to be determined. It is shown in the tables and graphics that the solutions converge to the optimum result when the cruise parameter approaches 0.75 and the attack parameter 1.5 for the unimodal benchmark test functions. Similarly, for multimodal benchmark functions, it is seen in the tables and graphs that the attack parameter is 1.5 and the cruise parameter is 0.75.

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Introduction

Optimization is the process of obtaining the best value of the objective function under certain constraints (Beşkirli and Dağ, 2022). Metaheuristic algorithms do not guarantee that they will obtain exact results for all optimization problems (Beşkirli and Dağ, 2020; Beşkirli et. al., 2020). However, they try to achieve the best results. Metaheuristic algorithms give better results than classical methods. In this study, Golden Eagle Optimization (GEO) algorithm was used. Although optimization algorithms try to achieve good results, the algorithm will be able to achieve better results with the improvements to be made on the algorithm. The best parameter level of the GEO algorithm was investigated in this study. It affects the success of the result to be obtained by parameter arrangement of the algorithm. For this reason, the parameter values that we think will be suitable for many problems in the literature have been applied to the benchmark functions and the best parameter values have been recommended. There are many studies in the literature on this subject. When these studies are examined, it is stated that the performance of the algorithm is at the highest level when the parameters of the algorithms are at the best value. Some of these studies are (Akay and Karaboga, 2012; Brest et. al., 2017; Brest et. al., 2008; Cicirello and Smith, 2000; Grefenstette, 1986; Luo et. al., 2016; Michalewicz and Schoenauer, 1996; Rao et. al., 2012; Zhangqi et al., 2011). Some studies on GOE in the literature are as follows: GOE algorithm was developed by Pan et al. (2022) and 3D UAV path planning process was performed. The method proposed by Pan et al. (2022) was called the GEO-DLS method and this method was used to improve the search capability of GEO. In GEO-DLS, it has been seen that the parameters are used with the values in the original form of GEO. A secure Ad Hoc optional distance vector routing protocol study with the improved GEO algorithm by Joshi and Biradar (2021). In this study, it was observed that no changes were made in the parameters of the GEO algorithm. Ilango et al. (2021) proposed a hybrid approach with GEO in order to achieve an optimum distribution over the distribution network. Thus, they aimed to minimize the cost through optimal allocation as parking space for electric vehicles. However, it was observed that no change was made in the parameter values of the GEO algorithm. Selimyan and Musavi (2021) used the GEO aggregation to design the organ transplant supply chain network problem. In this study, it has been seen that the parameters of the GEO algorithm are used in their original form. Abdel-Basset et al. (2022) made a comparison with the algorithms recently proposed by high-dimensional knapsack problems. These algorithms include the GEO method, but it has been observed that no changes have been made in the parameters of the GEO method. Vijh et al. (2021) solved the feature selection method for histological images using the GEO algorithm. An innovation has been made on the GEO algorithm, but it has been observed that no changes have been made on the parameters.

In this study, the parameter determination of the GEO algorithm was made by taking the cruise parameter between [0.5-1] and the attack parameter between [0.5-2] values. The improved parameters of the GEO algorithm are applied to 7 unimodal and 16 multimodal benchmark functions. When the attack and cruise parameters were 1.5 and 0.75, respectively, better solutions were obtained than the original parameter values of GEO. Obtained results are given with tables and convergence curves.

Material and Methods

The Golden Eagle Optimizer Algorithm (GEO)

The golden eagle optimizer algorithm (GEO), one of the nature-inspired algorithms, was proposed by Muahmmadi-Balani (Mohammadi-Balani et. al., 2021) in 2021 based on the superior vision, high speed and very strong claws of golden eagles. During the hunting process of golden eagles, they first draw a circular trajectory for hunting and follow a straight path for hunting. The mathematical modeling of this algorithm is firstly the spiral movement of golden eagles. Afterwards, the prey selection process takes place. Then it is attacked. Then the travel vector is calculated. Then, the transition to new positions is made to replace the golden eagles. There is a transition from exploration to exploitation. A related image is given in Figure 1.

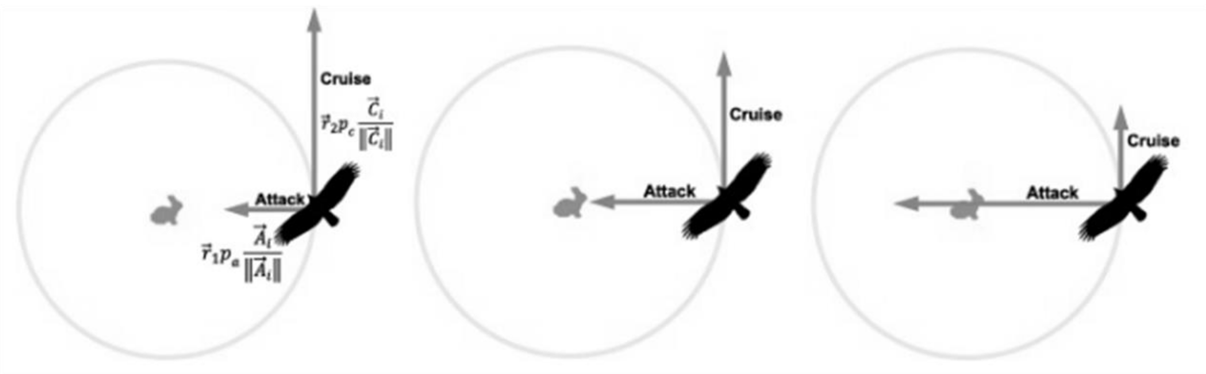


Figure 1. Correlation steps between exploration and exploitation in golden eagles (Mohammadi-Balani et al., 2021)

The main steps of golden eagles are shown in Figure 2. The prey is selected first, respectively. Then vector calculation for the attack is performed. Then the cruise plane is created. A vector is then randomly selected from the generated course plane. Finally, the process is terminated with the step vector.

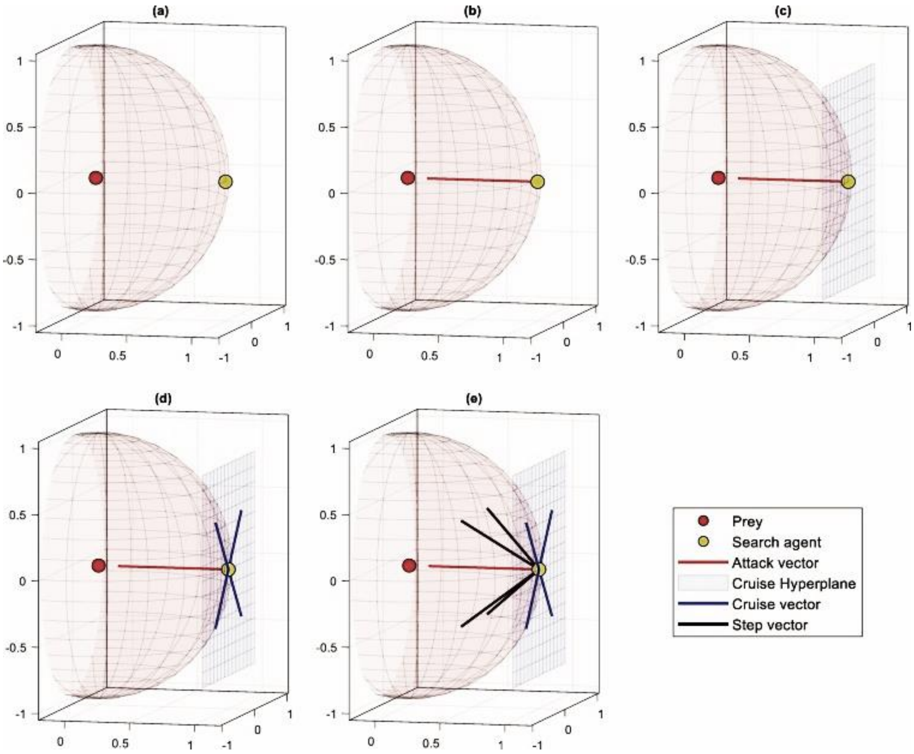


Figure 2. The main steps of golden eagles (Mohammadi-Balani et al., 2021)

Benchmark Functions

The parameters of the GEO algorithm were applied to 23 different benchmark problems to obtain the optimum value. These problems consist of unimodal and multimodal functions. Unimodal benchmark functions are given in Table 1. Multimodal benchmark functions are given in Table 2.

Table 1. Unimodal benchmark functions (D: Dimension)

Fn.	Name	D	Search Range	Function	f_{min}
F1	Beale	2	$[-4.5, 4.5]^D$	$f_1(x) = (1.5 - x_1 - x_1x_2)^2 + (2.25 - x_1 + x_1x_2^2)^2 + (2.625 - x_1 + x_1x_2^3)^2$	0
F2	Matyas	2	$[-10, 10]^D$	$f_2(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$	0
F3	Three-hump camel	2	$[-5, 5]^D$	$f_3(x) = 2x_1^2 - 1.05x_1^4 + \frac{x_1}{6} + x_1x_2 + x_2^2$	0
F4	Exponential	30	$[-1, 1]^D$	$f_4\,(x) = -e^{(-0.5\sum_{i=1}^{n} x_i^2)}$	0
F5	Ridge	30	$[-5, 5]^D$	$f_5(x) = x_1 + 2\left(\sum_{i=2}^{n} x_i^2\right)^{0.1}$	-5
F6	Sphere	30	$[-100, 100]^D$	$f_1(x) = \sum_{i=1}^{N} x_i^2$	0
F7	Step	30	$[-5.12, 5.12]^D$	$f_7(x) = \sum_{i=1}^{n}(\lfloor x_i + 0.5\rfloor)^2$	0

Table 2. Multimodal benchmark functions (D: Dimension)

Fn.	Name	D	Search Range	Function	f_{min}
F8	Drop Wave	2	$[-5.2, 5.2]^D$	$f_8(x) = -\frac{1+cos\left(12\sqrt{x_1^2+x_2^2}\right)}{0.5(x_1^2+x_2^2)+2}$	-1
F9	Egg holder	2	$[-512, 512]^D$	$f_9(x) = -(x_2+47)sin\left(\sqrt{\left\|x_2+\frac{x_1}{2}+47\right\|}\right) - x_1 sin\left(\sqrt{\|x_1-x_2-47\|}\right)$	-959.6407
F10	Himmelblau	2	$[-5, 5]^D$	$f_{10}(x) = (x_1^2+x_2-11)^2+(x_1+x_2^2-7)^2$	0
F11	Levi 13	2	$[-10, 10]^D$	$f_{11}(x) = sin^2(3\pi x_1)(x-1)^2\left(1+sin^2(3\pi x_2)\right) + (x_2-1)^2\left(1+sin^2(2\pi x_2)\right)$	0
F12	Ackley 1	30	$[-32, 32]^D$	$f_{12}\ (x) = 20 + \ e\ - 20\mathrm{e}^{\left(-0.2\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}\right)} - e^{(\frac{1}{N}\sum_{i=1}^{N}\cos(2\pi x_i)}$	0
F13	Griewank	30	$[-600, 600]^D$	$f_{13}\ (x) = \sum_{i=1}^{N}\frac{x_i^2}{4000} - \prod_{i=1}^{N}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	0
F14	Happy cat	30	$[-2, 2]^D$	$f_{14}(x) = \sqrt[8]{(\|\|x\|\|^2-n)^2} + \frac{1}{n}\left(\frac{1}{2}\|\|x\|\|^2+\sum_{i=1}^{n}x_i\right)+\frac{1}{2}$	0
F15	Michalewicz	10	$[0, \pi]^D$	$f_{15}(x) = \sum_{i=1}^{n} sin(x_i)\left(sin\left(\frac{ix_i^2}{\pi}\right)\right)^{20}$	-9.6602
F16	Penalized 1	30	$[-50, 50]^D$	$f_{16}(x) = \frac{\pi}{n}\{10sin^2(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2[1+10sin^2(\pi y_{i+1})]+(y_n-1)^2\}+\sum_{i=1}^{n}u(x_i,10,100,4)$ $y_i = 1+\frac{1}{4}(x_i+1)\ u_{x_i,a,k,m} = \begin{cases} k(x_i-a)^m\ x_i>a \\ 0 \quad -a\le x_i\le a \\ k(x_i-a)^m\ x_i<a \end{cases}$	0
F17	Penalized 2	30	$[-50, 50]^D$	$f_{17}(x) = \frac{1}{10}\{sin^2(\pi x_1)+\sum_{i=1}^{n-1}(x_i-1)^2[1+sin^2(3\pi x_{i+1})]+(x_n-1)^2[1+sin^2(2\pi x_{i+1})]\}+\sum_{i=1}^{n}u(x_i,5,100,4)$	0
F18	Periodic	30	$[-50, 50]^D$	$f_{18}(x) = \ 1+\sum_{i=1}^{n}sin^2(x_i)-\frac{1}{10}e^{(\sum_{i=1}^{n}x_i^2)}$	0.9
F19	Qing	30	$[-500, 500]^D$	$f_{19}(x) = \ \sum_{i=1}^{n}\left(x_i^2-i\right)^2$	0
F20	Rastrigin	30	$[-5.12, 5.12]^D$	$f_{20}\ (x) = \sum_{i=1}^{n}\left(x_i^2-10\,cos(2\pi x_i)\right)+10\mathrm{n}$	0
F21	Rosenbrock	30	$[-5, 10]^D$	$f_{21}\ (x) = \sum_{i=1}^{n}\ \left(100\left(x_{i+1}-x_i^2\right)^2+(1-x_i)^2\right)$	0
F22	Salomon	30	$[-100, 100]^D$	$f_{22}\ (x) = 1-cos\left(2\pi\sqrt{\sum_{i=1}^{n}x_i^2}\right)+0.1\sqrt{\sum_{i=1}^{n}x_i^2}$	0
F23	Yang 4	30	$[-10, 10]^D$	$f_{23}(x) = (\sum_{i=1}^{n}sin^2(x_i))e^{(-\sum_{i=1}^{n}sin^2\sqrt{\|x_i\|})}$	-1

Results and Discussion

To find the best parameter values, 23 different comparison functions were applied to the GEO algorithm. The best values obtained for the unimodal benchmark functions solution are given in Table 3-4. The best values obtained for the solution of multimodal benchmark functions are given in Table 7-8. Convergence curves obtained for unimodal benchmark functions according to different attack and cruise parameter values are given in Tables 5 and 6, and multimodal benchmark functions are given in Table 9-10.

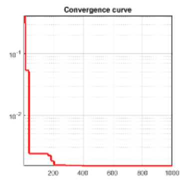
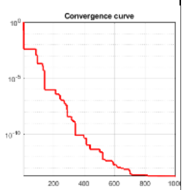
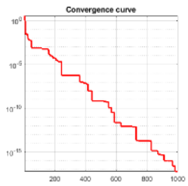
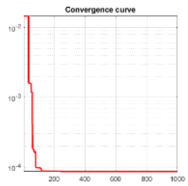
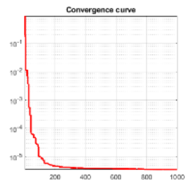
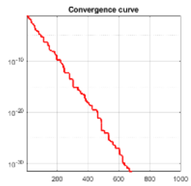
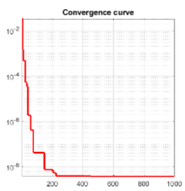
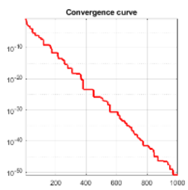
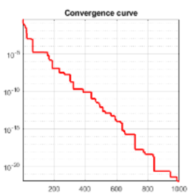
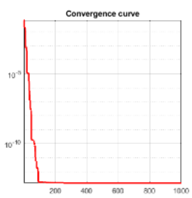
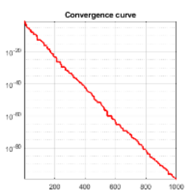
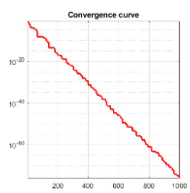
Table 3. Best values of unimodal functions according to attack and cruise parameters

		Values of Parameters					
Func.	**Attack**		**0.5**			**1**	
	Cruise	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F1	Best	1.52E-03	1.89E-14	6.23E-18	8.71E-05	3.52E-06	**0.00E+00**
F2	Best	3.85E-09	1.03E-51	1.16E-22	1.55E-13	4.59E-100	9.20E-77
F3	Best	2.53E-13	2.13E-66	2.18E-28	**5.87E-189**	5.44E-20	1.02E-96
F4	Best	-9.53E-01	**-1.00E+00**	**-1.00E+00**	-9.86E-01	**-1.00E+00**	**-1.00E+00**
F5	Best	-2.57E+00	-4.40E+00	-4.16E+00	-2.59E+00	-1.00E+00	-4.91E+00
F6	Best	8.23E+02	2.94E-04	6.71E-03	6.74E+02	4.35E-10	8.31E-13
F7	Best	4.57E+00	3.53E-07	3.49E-05	3.36E+00	1.03E-11	2.26E-15

Table 4. Best values of unimodal functions according to attack and cruise parameters

		Values of Parameters					
Func.	**Attack**		**1.5**			**2**	
	Cruise	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F1	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F2	Best	**2.14E-140**	9.90E-103	1.94E-73	5.87E-103	7.92E-75	1.74E-54
F3	Best	6.67E-182	2.30E-143	1.07E-104	7.92E-136	2.01E-103	2.71E-73
F4	Best	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**
F5	Best	-4.78E+00	**-4.94E+00**	-4.77E+00	-4.86E+00	-4.76E+00	-4.37E+00
F6	Best	4.52E-09	**3.53E-14**	7.99E-10	1.43E-10	2.19E-08	4.82E-04
F7	Best	5.77E-11	**2.31E-16**	7.20E-13	2.13E-12	3.52E-11	1.25E-06

Table 5. Convergence curves by parameter values for unimodal benchmark functions (A: Attack, C: Cruise)

Values of Parameters						
A	**0.5**			**1**		
C	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F1						
F2						

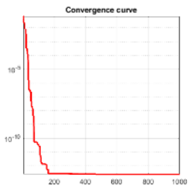
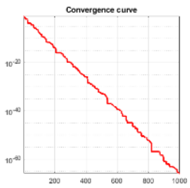
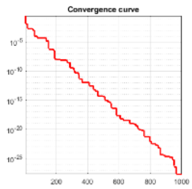
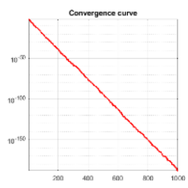
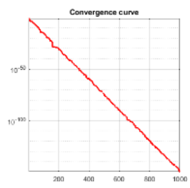
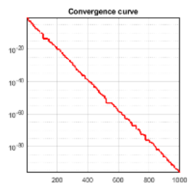
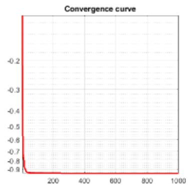
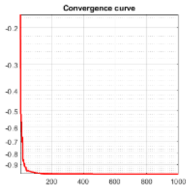
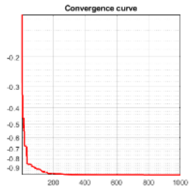
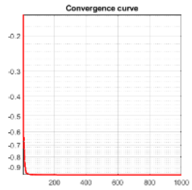
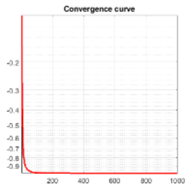
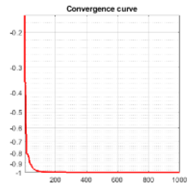
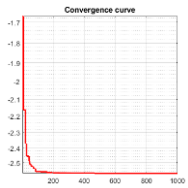
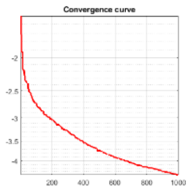
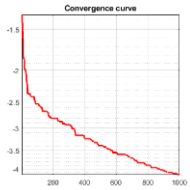
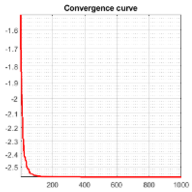
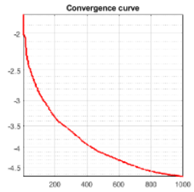
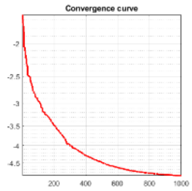
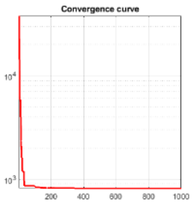
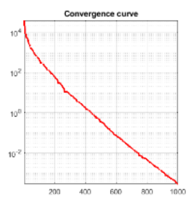
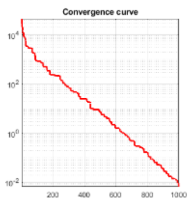
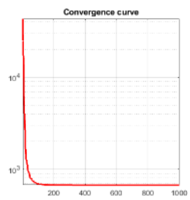
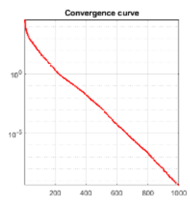
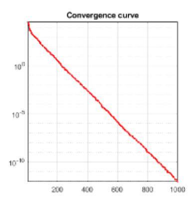
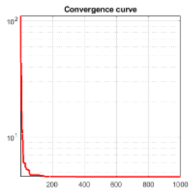
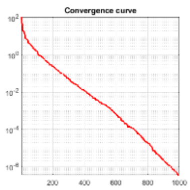
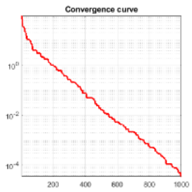
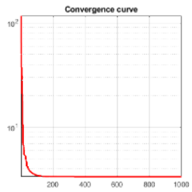
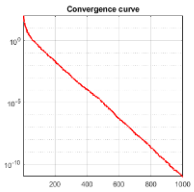
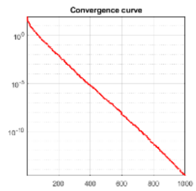
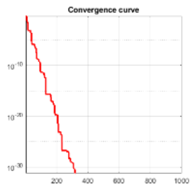
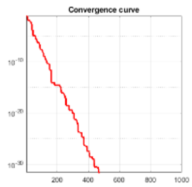
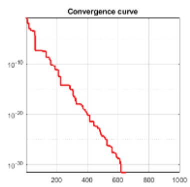
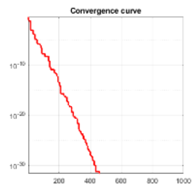
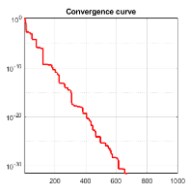
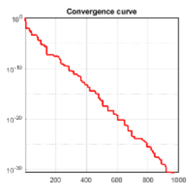
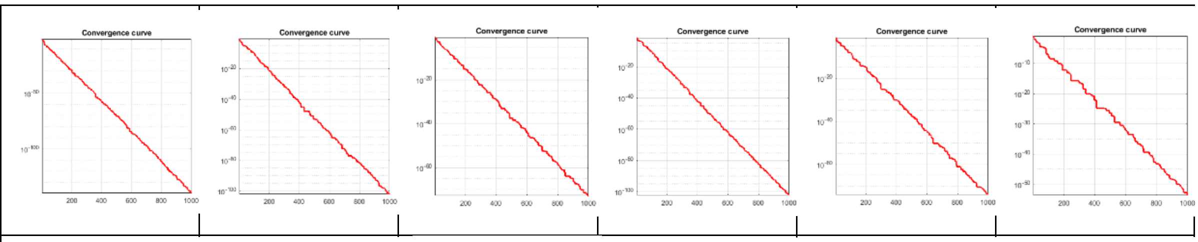
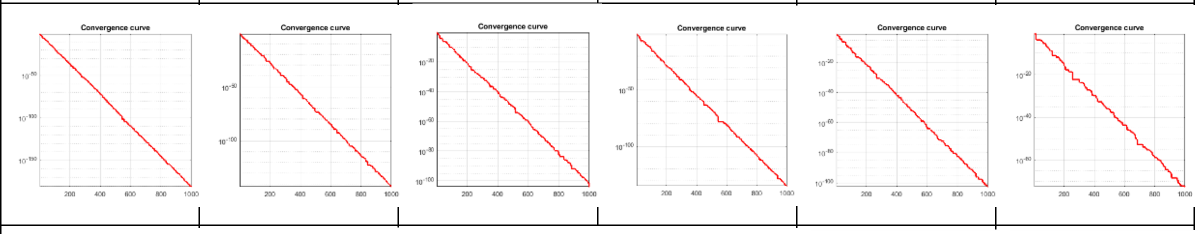
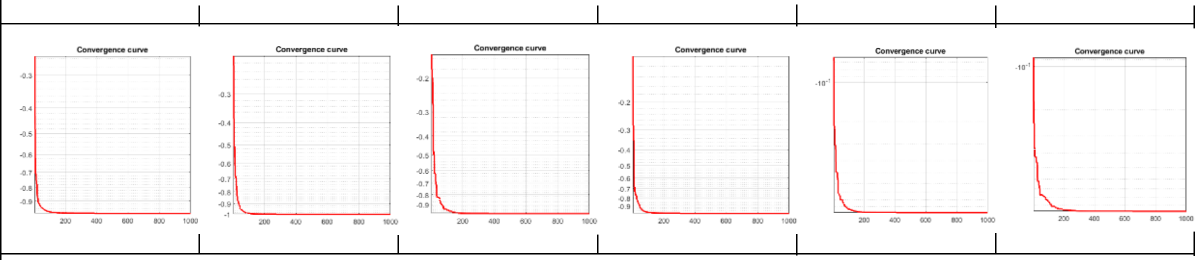
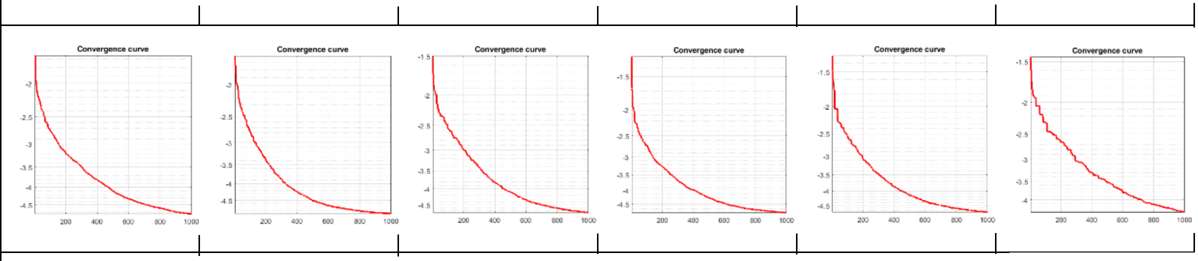
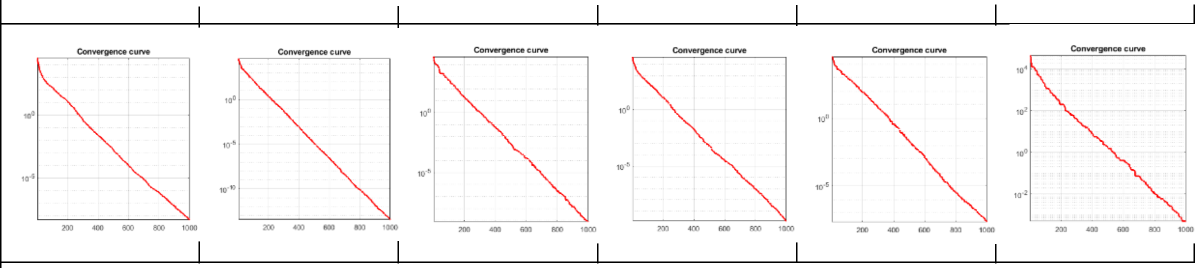
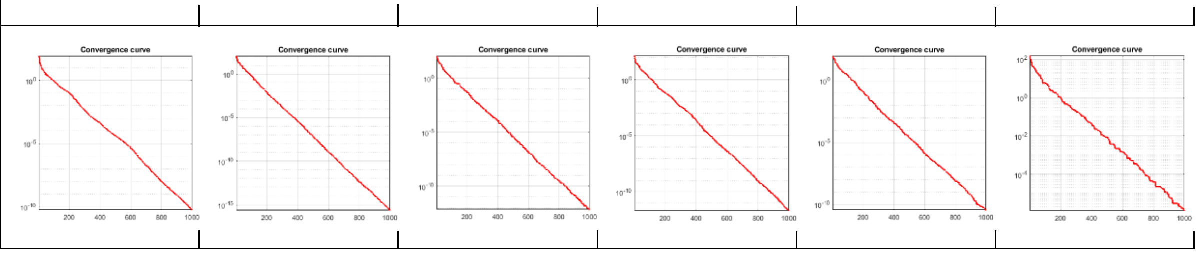
F3						
F4						
F5						
F6						
F7						

Table 6. Convergence curves by parameter values for unimodal benchmark functions (A: Attack, C: Cruise)

Values of Parameters						
A	**1.5**			**2**		
C	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F1						

F2	
F3	
F4	
F5	
F6	
F7	

When the results and convergence curves for the unimodal functions are examined, it is seen that the algorithm achieves the best value when the Attack and Cruise parameters are 1.5 and 0.75, respectively.

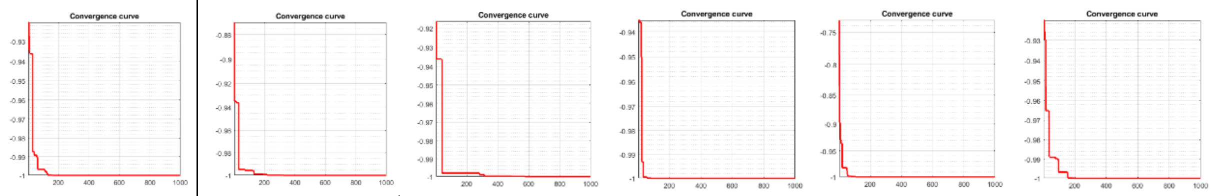
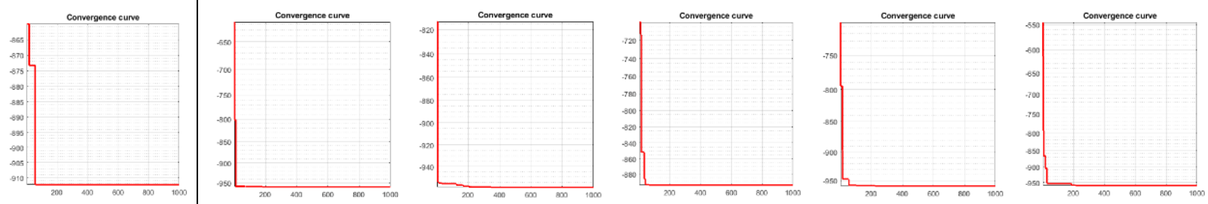
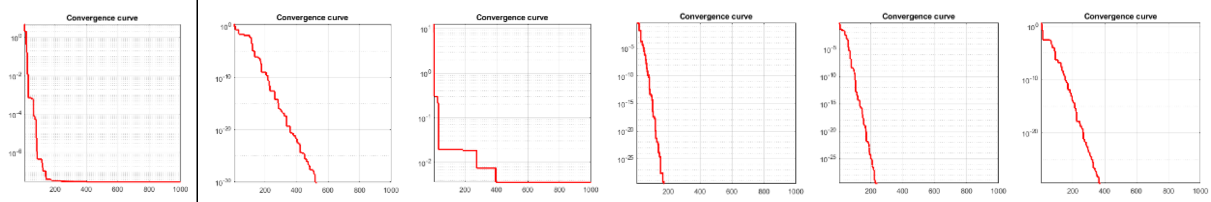
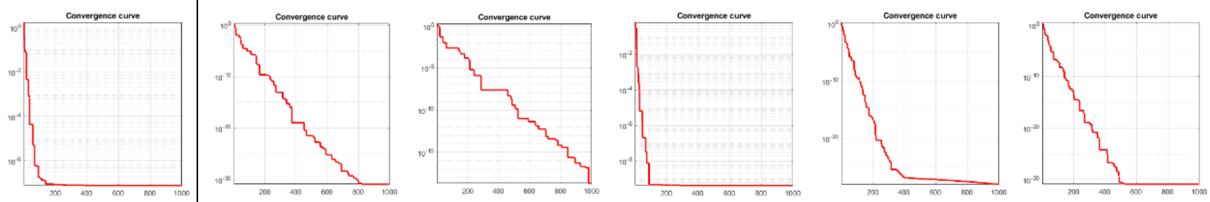
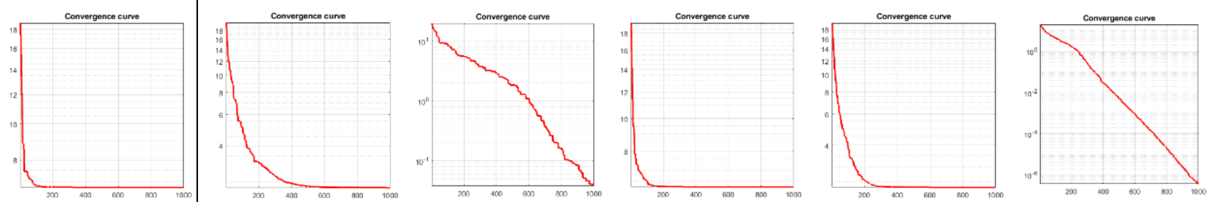
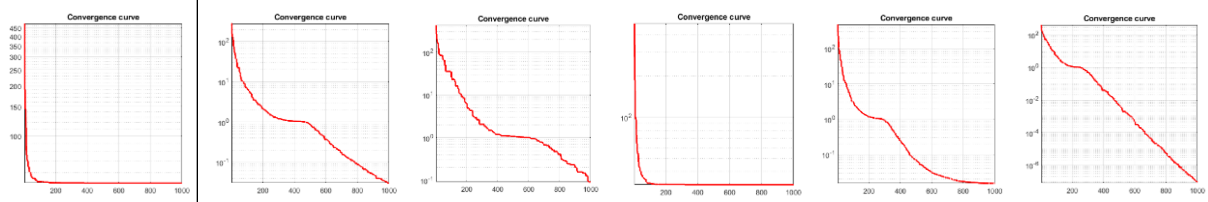
Table 7. Best values of multimodal functions according to attack and cruise parameters

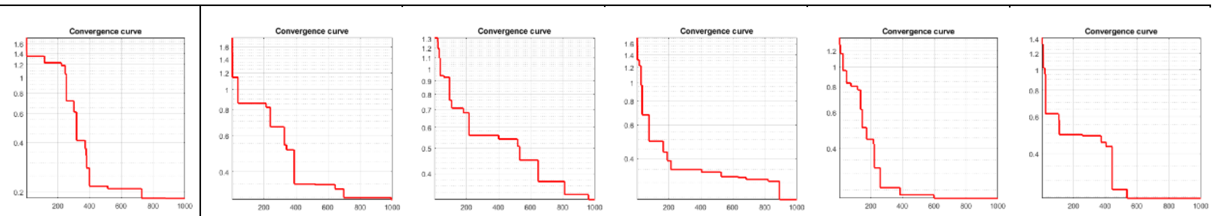
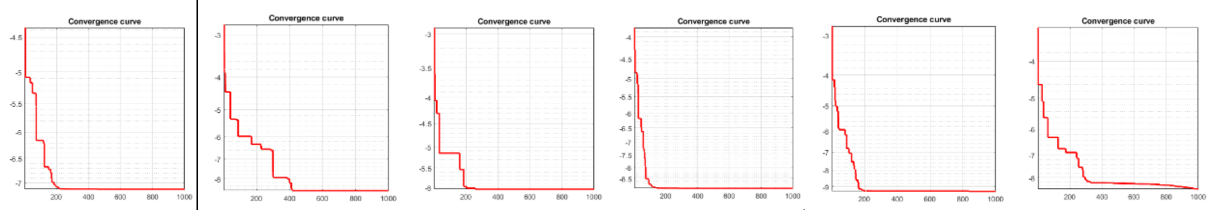
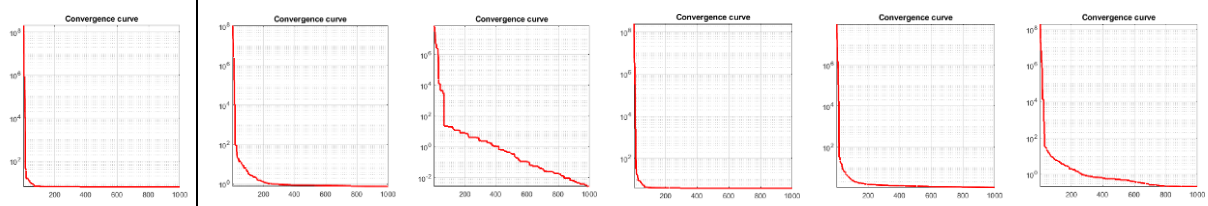
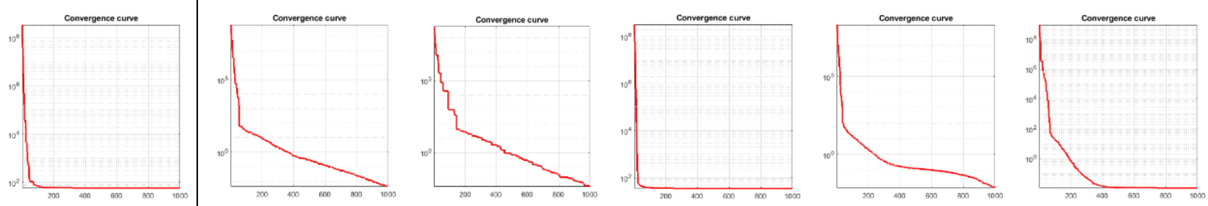
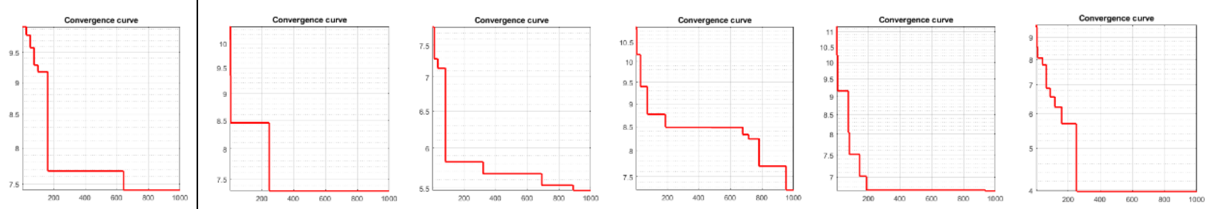
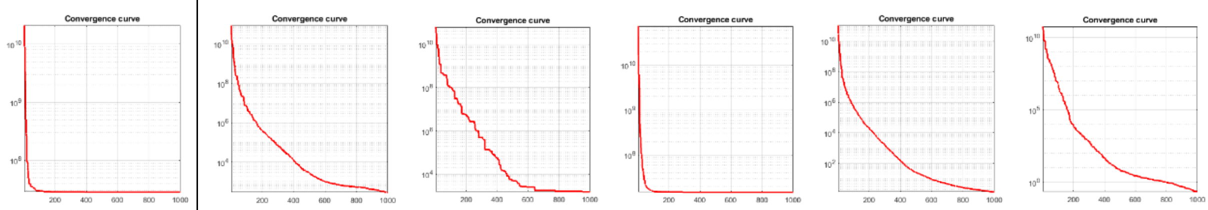
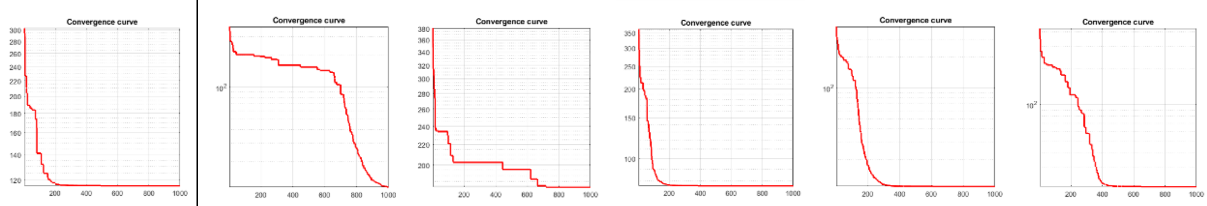
		Values of Parameters					
Func.	**Attack**		**0,5**			**1**	
	Cruise	**0,5**	**0,75**	**1**	**0,5**	**0,75**	**1**
F8	Best	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**
F9	Best	-9.12E+02	**-9.60E+02**	**-9.60E+02**	-8.95E+02	**-9.60E+02**	**-9.60E+02**
F10	Best	3.11E-08	**0.00E+00**	3.64E-03	**0.00E+00**	**0.00E+00**	**0.00E+00**
F11	Best	7.65E-08	**1.35E-31**	1.97E-19	4.16E-10	9.56E-29	**1.35E-31**
F12	Best	6.75E+00	2.32E+00	3.82E-02	6.25E+00	2.32E+00	3.65E-07
F13	Best	5.19E+01	3.06E-02	9.29E-02	3.21E+01	1.51E-02	8.10E-08
F14	Best	**1.83E-01**	2.94E-01	3.19E-01	2.44E-01	2.27E-01	2.46E-01
F15	Best	-7.14E+00	-8.68E+00	-6.05E+00	-8.95E+00	**-9.31E+00**	-8.57E+00
F16	Best	6.22E+00	7.35E-01	2.66E-03	3.92E+00	1.03E+00	2.09E-01
F17	Best	5.93E+01	4.38E-03	4.06E-03	3.54E+01	7.22E-03	1.10E-02
F18	Best	7.42E+00	7.32E+00	5.47E+00	7.26E+00	6.71E+00	3.97E+00
F19	Best	2.86E+07	2.87E+02	1.56E+03	1.52E+07	1.39E+00	2.19E-01
F20	Best	1.16E+02	1.15E+01	1.80E+02	7.63E+01	**1.09E+01**	2.09E+01
F21	Best	3.81E+04	4.35E+00	1.12E+02	1.83E+04	**2.39E+00**	6.91E+01
F22	Best	2.70E+00	4.00E-01	3.00E-01	3.20E+00	6.00E-01	**2.00E-01**
F23	Best	1.49E-11	2.63E-11	3.75E-11	7.17E-12	5.53E-21	6.14E-24

Table 8. Best values of multimodal functions according to attack and cruise parameters

		Values of Parameters					
Func.	**Attack**		**1.5**			**2**	
	Cruise	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F8	Best	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**
F9	Best	**-9.60E+02**	**-9.60E+02**	**-9.60E+02**	**-9.60E+02**	**-9.60E+02**	**-9.60E+02**
F10	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
F11	Best	**1.35E-31**	**1.35E-31**	**1.35E-31**	**1.35E-31**	**1.35E-31**	**1.35E-31**
F12	Best	3.98E+00	**5.78E-08**	1.54E-05	8.68E-04	9.31E-01	9.30E-03
F13	Best	7.48E-03	**8.09E-09**	5.88E-06	9.86E-03	4.67E-05	1.80E-02
F14	Best	4.18E-01	2.77E-01	4.10E-01	2.37E-01	3.21E-01	2.19E-01
F15	Best	-9.13E+00	-9.24E+00	-8.94E+00	-8.35E+00	-8.77E+00	-7.67E+00
F16	Best	1.53E-01	1.04E-01	1.46E-07	**1.15E-07**	1.90E-07	1.15E-03
F17	Best	1.10E-02	**2.42E-10**	1.98E-07	6.91E-09	3.10E-07	7.00E-04
F18	Best	**1.56E+00**	1.58E+00	1.93E+00	1.98E+00	2.28E+00	1.80E+00
F19	Best	8.10E-01	**3.39E-03**	2.88E-01	3.08E-01	2.18E+00	6.07E+01
F20	Best	1.39E+01	4.38E+01	4.38E+01	3.88E+01	2.49E+01	1.44E+02
F21	Best	8.08E+01	6.85E+01	2.21E+01	5.48E-01	1.06E+01	9.73E+01
F22	Best	1.10E+00	3.00E-01	3.00E-01	5.00E-01	3.00E-01	4.01E-01
F23	Best	6.70E-22	**5.48E-27**	3.84E-21	4.02E-22	2.37E-19	3.07E-16

Table 9. Convergence curves by parameter values for multimodal benchmark functions (A: Attack, C: Cruise)

Values of Parameters						
A	**0.5**			**1**		
C	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F8						
F9						
F10						
F11						
F12						
F13						

F14	
F15	
F16	
F17	
F18	
F19	
F20	

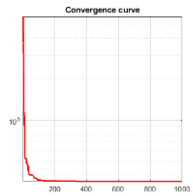
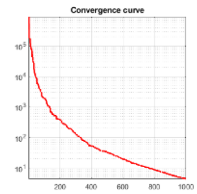
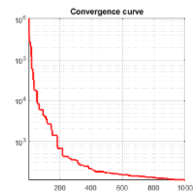
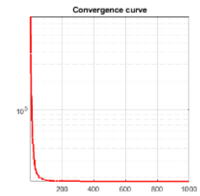
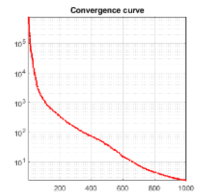
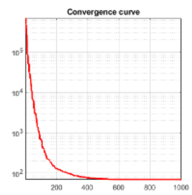
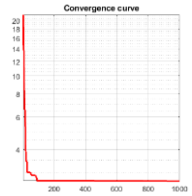
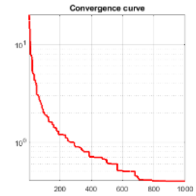
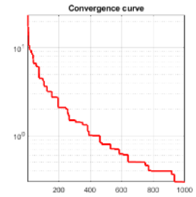
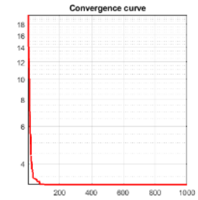
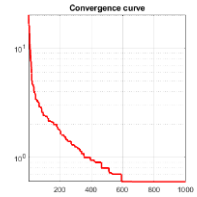
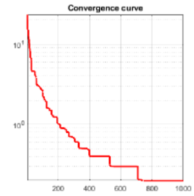
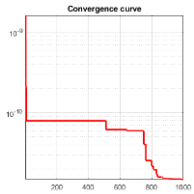
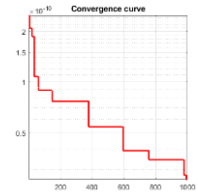
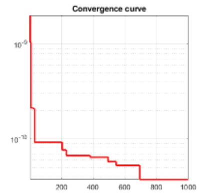
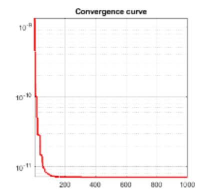
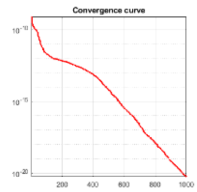
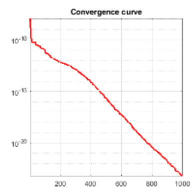
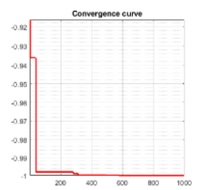
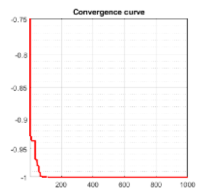
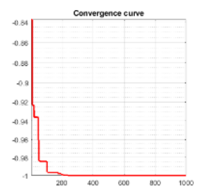
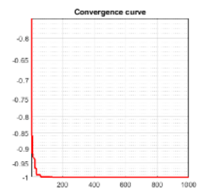
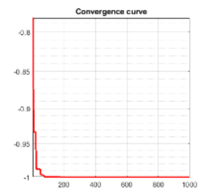
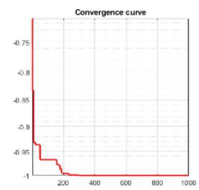
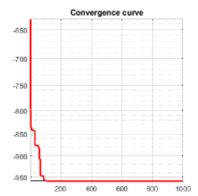
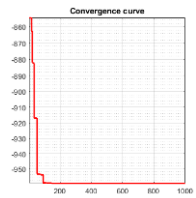
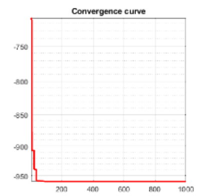
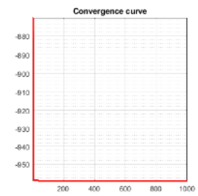
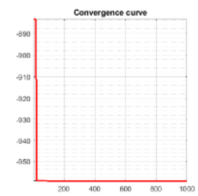
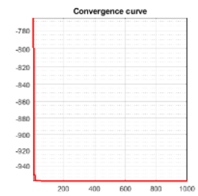
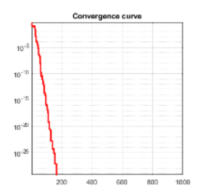
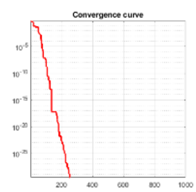
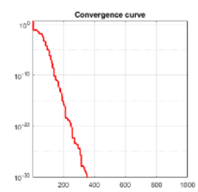
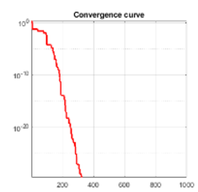
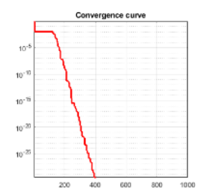
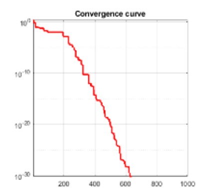
F21						
F22						
F23						

Table 10. Convergence curves by parameter values for multimodal benchmark functions (A: Attack, C: Cruise)

Values of Parameters						
A	**1.5**			**2**		
C	**0.5**	**0.75**	**1**	**0.5**	**0.75**	**1**
F8						
F9						
F10						

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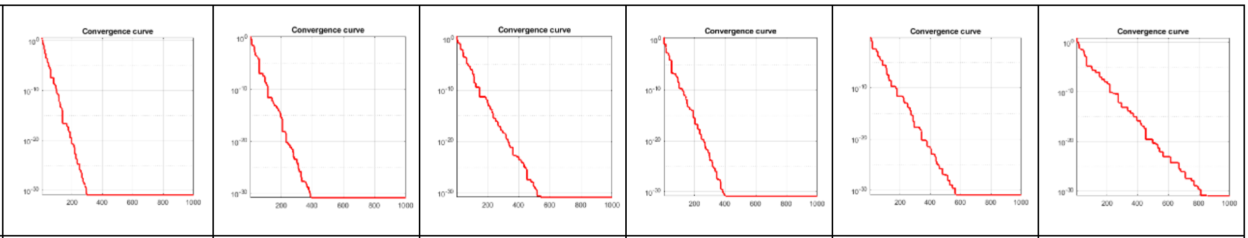

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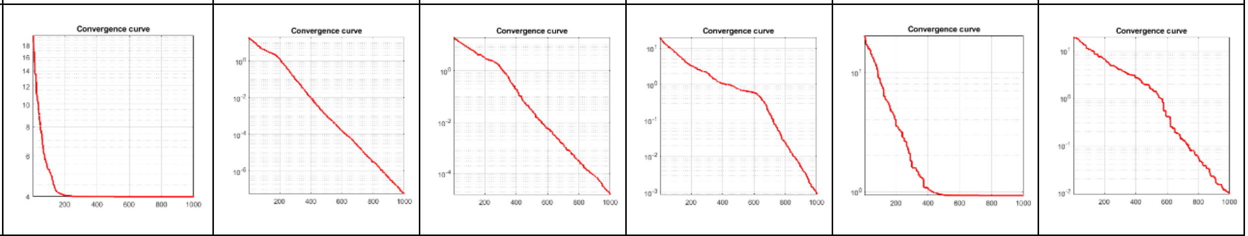

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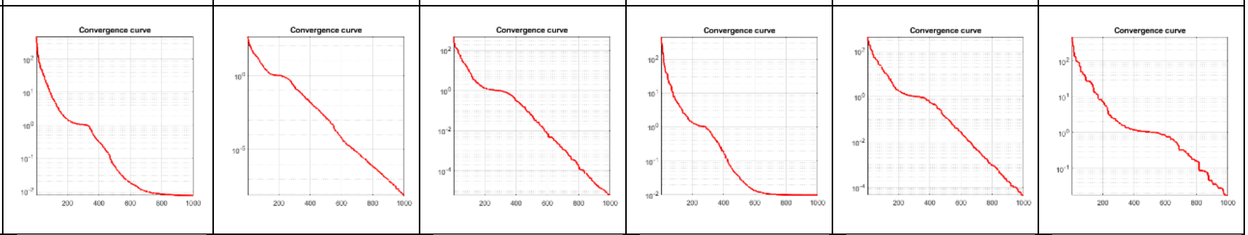

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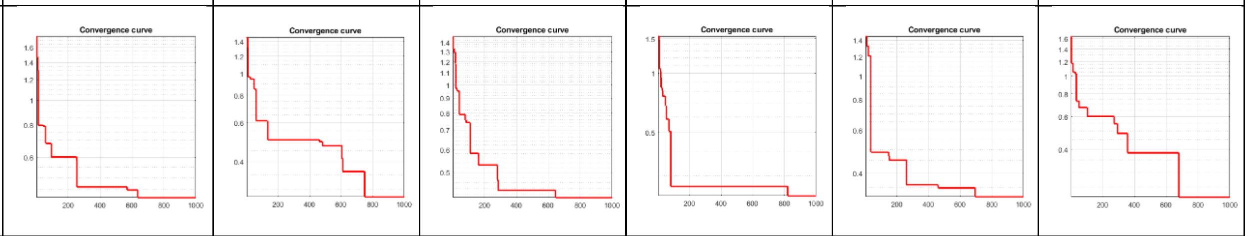

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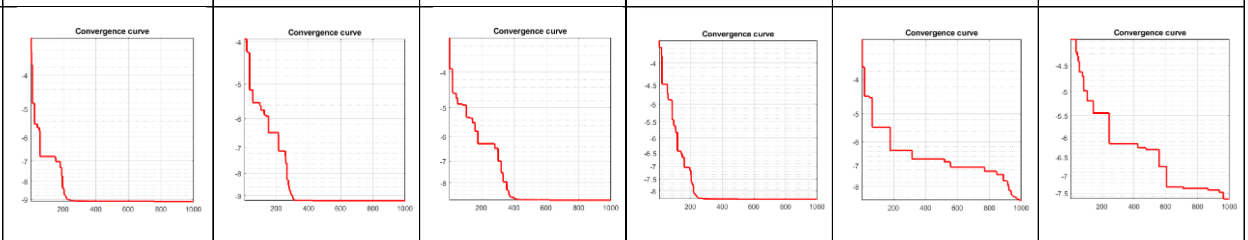

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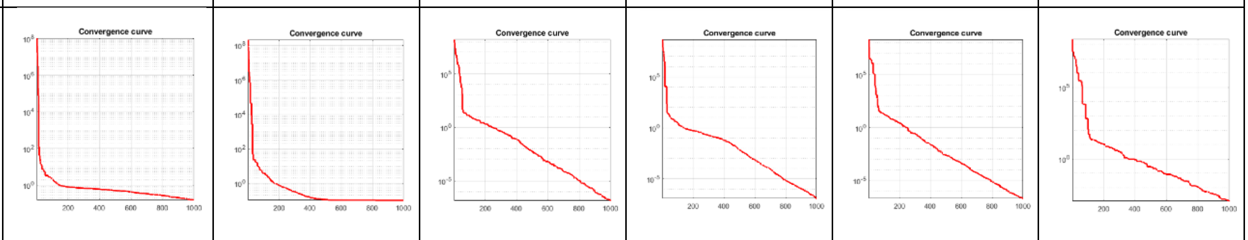

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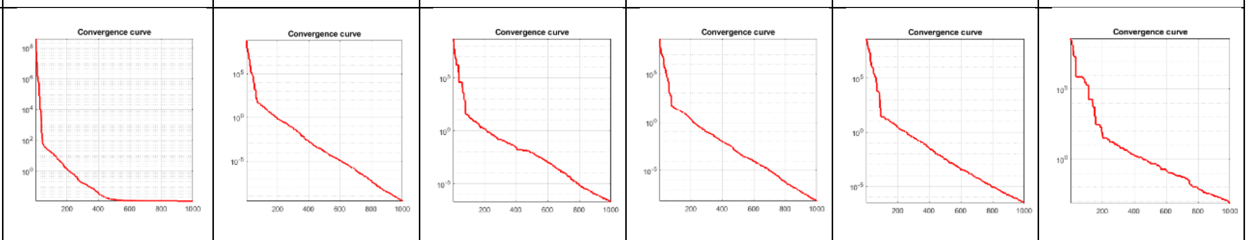

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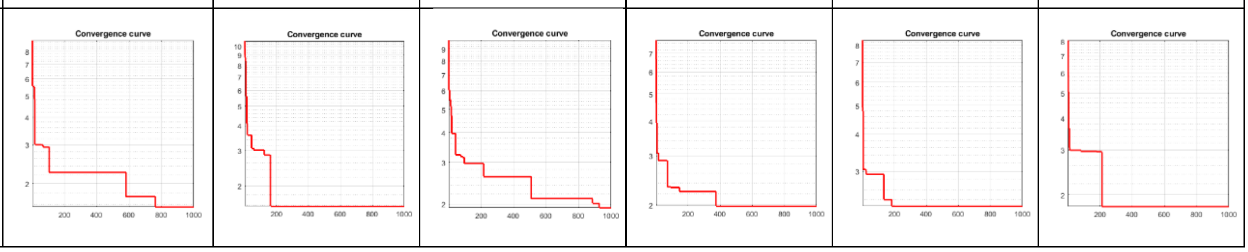

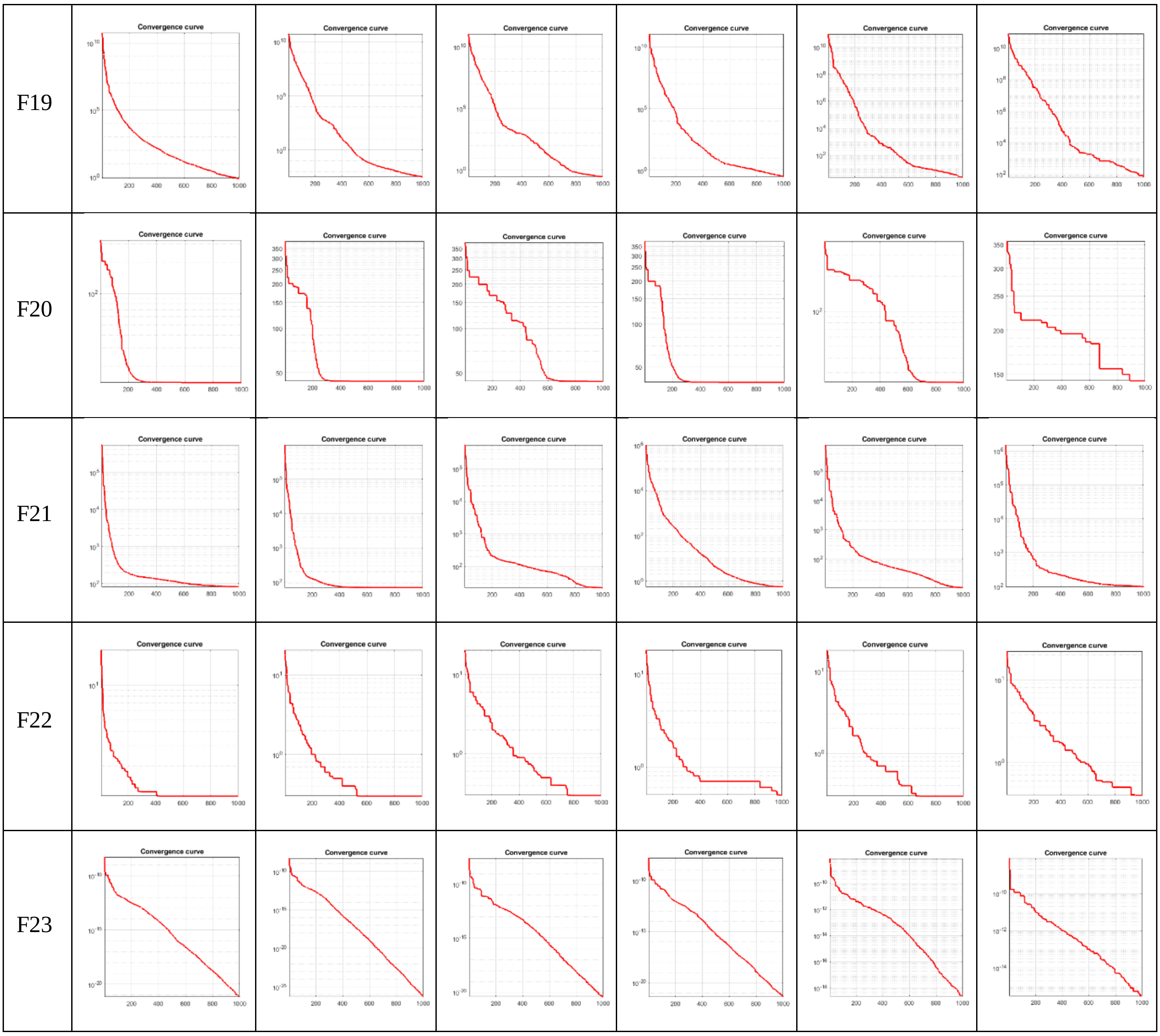

When the results and convergence curves for the multimodal functions are examined, it is seen that the algorithm achieves the best value when the Attack and Cruise parameters are 1.5 and 0.75, respectively.

In this study, cruise and attack parameters of the GEO algorithm are optimized using unimodal and multimodal benchmark functions. In Table 3 and Table 4, rank analysis based on the number of functions in which unimodal benchmark functions are successful is performed. In Figure 3, rank success numbers for Unimodal benchmark functions are given. According to the rank analysis, when the attack parameter of the GEO algorithm is 1.5 and the cruise parameter is 0.75, it is seen in Figure 3 that the best values are obtained in unimodal functions.

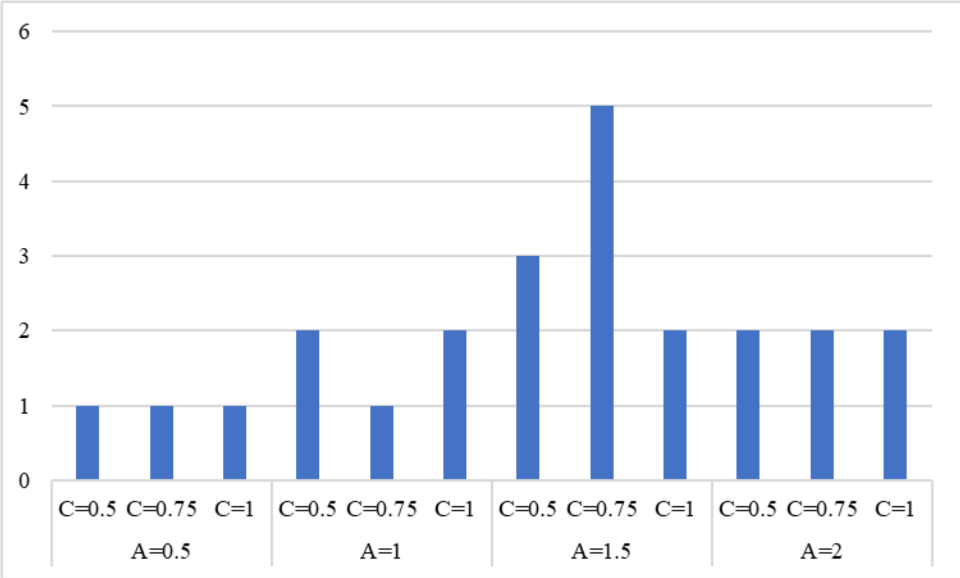

Figure 3. Rank Analyses for Unimodal Benchmark Functions (A: Attack, C: Cruise)

In Table 7 and Table 8, rank analysis based on the number of functions in which the multimodal benchmark functions were successful was performed. In Figure 4, rank success numbers for Multimodal benchmark functions are given. According to the rank analysis, when the attack parameter of the GEO algorithm is 1.5 and the cruise parameter is 0.75, it is seen in Figure 4 that the best values are obtained in multimodal functions.

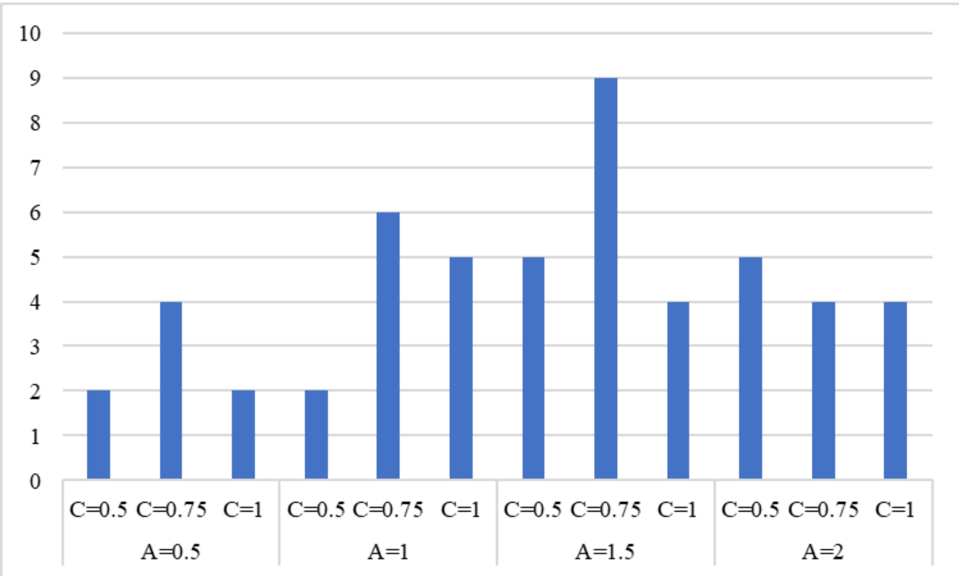

Figure 4. Rank Analyses for Multimodal Benchmark Functions (A: Attack, C: Cruise)

In the original article of the GEO algorithm, it was stated that the lowest objective function value was obtained in the range of attack parameter [0.5-2.0] and cruise parameter [1.0-0.5] (Mohammadi-Balani et al., 2021). The parameter values of GEO are taken as linear increasing for attack parameter and linear decreasing for cruise parameter (Mohammadi-Balani et al., 2021). However, in this study, it is proved both in the tables and in Figures 3 and 4 that better results are obtained if the attack parameter is 1.5 and the cruise parameter is 0.75.

Conclusion

In this study, the best parameter value for the benchmark functions of the attack and cruise parameters of the golden eagle's optimization (GEO) algorithm is calculated. An evaluation was made according to the effect of these parameters on the functions. The attack parameter of the algorithm is between [0-2] and the cruise parameter is between [0-1]. As a result of the calculation on the functions of the algorithm, it is seen that the attack parameter is 0.75 and the cruise parameter is 1.5, and it is the best. The algorithm achieved the best results in both unimodal functions and multimodal functions at the specified parameter values. Separate convergence plots were found to be the best in these results. In the rank analysis, it has been determined that the GEO algorithm attack and cruise parameters are more successful in benchmark functions when they are 0.75 and 1.5, respectively. As a result, it is recommended that the golden eagles optimization algorithm achieves the best result in these parameter values and it is recommended to use these parameter values in overnight studies. In the next studies, it is aimed to solve real world problems by making improvements on the algorithm by using this parameter value and providing a performance shot.

Statement of Conflict of Interest

Authors have declared no conflict of interest.

Author's Contributions

The contribution of the authors is equal.

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