An Efficient Growth Optimizer with Adaptive Parameters and Targeted Stochastic Mutation Strategies for Global Optimization

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Abstract. Growth optimizer (GO) is a metaheuristic algorithm that simulates the learning and internal self-reflection mechanisms during human growth. The algorithm exhibits stable and efficient convergence capabilities on mathematical bench-mark functions of various types and complexities. However, it still suffers from trapping into local optimal solution. Thus, in this paper, we propose an improved growth optimizer algorithm named ASGO. The features of ASGO are summarized as follows: first, it adopts a dynamic adjustment mechanism combining individual learning and reflection speeds, and achieves adaptive adjustment during iteration through decay factors. Second, in the reflection phase, the targeted random mutation strategies is introduced to increase population diversity. The results showed that ASGO can reduce the premature convergence and enhance the algorithm's global search efficiency and adaptability. To verify the effectiveness of the proposed method, the comprehensive experiments were con-ducted on 30 benchmark functions of CEC2017 and compared against nearly 50 popular efficient metaheuristic algorithms, and the statistical results confirm the high performance of the ASGO algorithm.

Keywords: Growth optimizer · Adaptive parameters · Targeted stochastic mutation strategies · Global optimization

1 Introduction

Optimization problems are widely applied in fields such as engineering, economics, and management. However, traditional algorithms often struggle with finding global optimal solution in the face of complex challenges like large solution spaces or complex objective functions. To address these challenges, a large number of bio-inspired metaheuristic algorithms have been proposed [1]. For example, Ant Colony Optimization (ACO) [2], Cuckoo Search Algorithm (CS) [3] and Butterfly Optimization Algorithm (BOA) [4], etc. They are essentially a probabilistically parallel global optimal search method [5] and are divided into individual-inspired and swarm intelligence. Most of these algorithms are inspired by nature. Humans have superior logic and thinking skills compared to plants

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and animals in nature, so optimization methods inspired by human creative behaviors should be superior to optimization methods inspired by the behaviors of plants and animals in nature [6].

The growth optimizer [7] (GO) is a new metaheuristic optimization algorithm proposed by Qingke Zhang, et al. in 2022, which is inspired by the learning and reflection mechanisms. Compared with other algorithms, GO algorithm has a unique algorithmic structure, which provides a new mechanism for the balance between exploration and exploitation in the optimization process. The algorithm has a strong global optimization ability, especially when dealing with problems of high-dimensional, multimodal and composite functions. The algorithm was proposed in a relatively short period of time, and is currently in the phase of improvement and development, and there is still much room for improvement in the convergence speed and global search capabilities.

In order to solve the problems of GO algorithm, this paper introduces an improved algorithm based on adaptive parameters and targeted random mutation strategies. By dynamically adjusting learning and reflection speeds using a decay factor, it achieves balanced exploration and exploitation. Meanwhile, the targeted random mutation strategies introduced during the reflection phase increases population diversity and avoids premature convergence to local optimal solution. Experimental results show that the performance of the algorithm is significantly better than the existing algorithms on several test problems, which provides an effective method for solving complex optimization problems and makes an important contribution to the development of related fields.

The rest of the paper is organized as follows. Section 2 introduces the traditional growth optimizer (GO). Section 3 describes the improved growth optimizer (ASGO) in detail and Sect. 4 includes experiments and result analysis. Then, comprehensive statistical experimental results and analysis of ASGO and nearly 50 advanced metaheuristic algorithms are listed. Finally, Sect. 5 contains conclusions.

2 Growth Optimizer (GO)

In the growth optimizer (GO), the social structure of individuals is divided into upper, middle and bottom level. This hierarchical division helps to promote differential learning among individuals and enriching evolutionary information. The algorithm consists of the following two phases: learning and reflection.

2.1 Learning Phase

The learning phase is divided into the following four steps:

1. Knowledge Acquisition: In the algorithm, there are four types of gaps. The mathematical model of gaps is described by Eq. (1).

$$\begin{cases} \boldsymbol{Gap}_1 = \boldsymbol{x}_{best} - \boldsymbol{x}_{better} \\ \boldsymbol{Gap}_2 = \boldsymbol{x}_{best} - \boldsymbol{x}_{worse} \\ \boldsymbol{Gap}_3 = \boldsymbol{x}_{better} - \boldsymbol{x}_{worse} \\ \boldsymbol{Gap}_4 = \boldsymbol{x}_{L1} - \boldsymbol{x}_{L2} \end{cases} \tag{1}$$

where $\boldsymbol{x}_{best}$ represents the leader, $\boldsymbol{x}_{better}$ represents one of the elites, and $\boldsymbol{x}_{worse}$ is one of the bottom individuals. $\boldsymbol{x}_{L1}$ and $\boldsymbol{x}_{L2}$ are both random individuals that are different from the i th individual. $\boldsymbol{Gap}_k$, $(k = 1, 2, 3, 4)$ is the gap between the two individuals.

2. Knowledge Processing: For the ith individual, LF_k affects its learning effect on the k th set of gaps, and the mathematical model of LF_k is described by Eq. (2).

$$LF_k = \frac{\left|\left|\boldsymbol{Gap}_k\right|\right|}{\sum_{k=1}^{4}\left|\left|\boldsymbol{Gap}_k\right|\right|}, (k = 1, 2, 3, 4) \tag{2}$$

LF_k increases as the group k gap increases.

3. Knowledge Digestion: Individual i uses SF_i to assess its acceptable range of knowledge. The mathematical model of SF_i is described by Eq. (3).

$$SF_i = \frac{GR_i}{GR_{max}} \tag{3}$$

where GR_i is the rate at which the ith individual grows; the less resistance an individual has to grow, the more likely it is to become an elite member of society.

4. Knowledge Absorption: Individual i absorbs some knowledge from gap ($\boldsymbol{KA}_k$). The mathematical model of the process is described by Eq. (4).

$$\boldsymbol{KA}_k = SF_i \cdot LF_k \cdot \boldsymbol{Gap}_k, (k = 1, 2, 3, 4) \tag{4}$$

By absorbing the knowledge gaps, individual i completes the knowledge accumulation process, and the mathematical model is described by Eq. (5).

$$\boldsymbol{x}_i^{It+1} = \boldsymbol{x}_i^{It} + \boldsymbol{KA}_1 + \boldsymbol{KA}_2 + \boldsymbol{KA}_3 + \boldsymbol{KA}_4 \tag{5}$$

where It is the number of current iterations.

After going through the learning phase, it is verified that the quality of the candidate solution has really progressed. This process is described by Eq. (6).

$$\boldsymbol{x}_i^{It+1} = \begin{cases} \boldsymbol{x}_i^{It} & if\ f\left(\boldsymbol{x}_i^{It+1}\right) < f\left(\boldsymbol{x}_i^{It}\right) \\ \begin{cases} \boldsymbol{x}_i^{It+1} & if\ r_1 < P_2 \\ \boldsymbol{x}_i^{It} & else \end{cases} & else \end{cases} \tag{6}$$

where r_1 is a uniformly distributed random number in the range [0,1], $ind(i)$ is the ranking of the i th individual according to GR ascending order, and the value of P_2 is 0.001, controlling the retention probability.

2.2 Reflection Phase

The mathematical model of the reflection process is described by Eq. (7) and Eq. (8).

$$\boldsymbol{x}_i^{It+1} = \begin{cases} \begin{cases} lb + r_4 \times (ub - lb) & if\ r_3 < AF \\ \boldsymbol{x}_{i,j}^{It} + r_5 \times \left(R_j - \boldsymbol{x}_{i,j}^{It}\right) & else \end{cases} & if\ r_2 < P_3 \\ \boldsymbol{x}_{i,j}^{It} & else \end{cases} \tag{7}$$

$$AF = 0.01 + 0.99 \times \left(1 - \frac{FEs}{MaxFEs}\right) \tag{8}$$

where ub and lb are the upper and lower bounds of the search domain, and r_2, r_3, r_4, and r_5 are uniformly distributed random numbers in the range of [0,1]. The value of P_3 controls the probability of reflection, which is usually set to 0.3. The attenuation factor (AF) is composed of the current number of evaluations (FEs) and the maximum number of evaluations ($MaxFEs$). When the j th aspect of the i th individual needs to learn from others, there is an upper level individual $\boldsymbol{R}$ to guide it.

When completing the reflection, one should validate whether one has grown or not. The validation process is still performed according to Eq. (6).

3 The Proposed ASGO Algorithm

3.1 Adaptive Adjustment Mechanisms

In the early phase of the algorithm, the individual learning and reflection speeds are relatively high, promoting extensive exploration in the solution space. As the iteration progress, the speeds of learning and reflection decrease, shifting the algorithm's focus towards in-depth exploitation of known high-quality solutions. Through this dynamic adjustment strategy, the algorithm is able to adaptively balance the exploration and exploitation, improving the algorithm's adaptability for various optimization problems.

In the learning phase, the above idea is integrated into Eq. (5). The modified mathematical model is described by Eq. (9) and Eq. (10).

$$V_l(i) = V_l(i-1) \times V_{ld} \tag{9}$$

$$\boldsymbol{x}_i^{It+1} = \boldsymbol{x}_i^{It} + (\boldsymbol{KA}_1 + \boldsymbol{KA}_2 + \boldsymbol{KA}_3 + \boldsymbol{KA}_4) \times \exp(V_l(i)) \tag{10}$$

where the learning speed of the i th individual $V_l(i)$ is a uniformly distributed random number in the range [0.5,1], V_{ld} is the decay factor, which is set to a value of 0.8.

3.2 Targeted Randomized Mutation Strategies

In optimization algorithms, in order to enhance the population diversity and prevent premature convergence to local optimal solutions, a method called the targeted random mutation strategies is employed. This approach allows the algorithm to explore the solution space more extensively, especially those regions that were previously under-explored, thus significantly increasing the likelihood of discovering a global optimal solution. The mathematical model of the process is described by Eq. (11).

$$\boldsymbol{x}_i^{It+1} = \begin{cases} \begin{cases} \boldsymbol{x}_{i,d}^{It} + exp(V_r(i)) \times \left(R_d - \boldsymbol{x}_{i,\mathrm{d}}^{It}\right) \times r_1 & if\ r_2 < P_4 \\ \boldsymbol{x}_{i,j}^{It} + exp(V_r(i)) \times \left(R_j - \boldsymbol{x}_{i,\mathrm{j}}^{It}\right) \times r_3 & else \\ lb + (ub - lb) \times unifrnd(0,1) & if\ r_5 < AF \end{cases} & if\ r_4 < P_3 \\ \boldsymbol{x}_{i,j}^{It} & else \end{cases} \tag{11}$$

In the GO algorithm, the value of P_3 is followed to control the reflection probability, which is set to 0.3. The value of the new parameter P_4 is set to 0.5 to control the probability of the targeting operation, which indicates whether or not a certain dimension is randomly selected for the mutation.

3.3 Parameter Adjustments

The parameter P_2 controls the probability of an individual entering the next generation of the population when the individual update fails, and the traditional GO algorithm takes the same value in the two phases. In the early phases of the algorithm, exploration is usually more important than exploitation. By accepting some suboptimal solutions, the algorithm can increase the diversity of the population and avoid premature convergence. In the later phases of the algorithm, the population has been optimized to some extent, and thus local search using current information becomes more important. By reducing the probability of accepting suboptimal solutions, the algorithm encourages a greater focus on exploiting the known best solutions for optimization. So in ASGO, the P_2 value is set to 0.009 for the learning phase and 0.001 for the reflection phase.

4 Experiments and Results Analysis

4.1 Experimental Setup and Involved Algorithms

In order to assess the performance of ASGO algorithm, nearly 50 state-of-the-art meta-heuristic algorithms are selected for comparison, such as Genetic Algorithm (GA) [8], Simulated Annealing Algorithm (SA) [9], and the traditional Growth Optimizer (GO) [7]. The algorithms were tested on 30 benchmark functions from CEC2017, and the results are statistically analyzed. All comparison algorithms were run using their standard configuration parameters, with the termination criterion being the maximum number of evaluations (*MaxFEs*). Tests were conducted on benchmark problems of dimensions 30/50/100, with 31 runs per algorithm.

By calculating the mean and standard deviation of the fitness values of each algorithm and using Friedman test and Wilcoxon signed-rank test, which are used to test whether there is a significant difference between the results of ASGO and the other algorithms at the 5% significance level. The various algorithm parameters are set as shown in Table 1.

4.2 Results on CEC2017 Benchmark Functions

In the CEC2017 tests, the experimental results of ASGO compared to the top ten algorithms for $D = 30$ are presented in Table 2. The table lists the mean (mean), standard deviation (std), and h-value (h) of the fitness function values for each algorithm after 31 runs. The results show that in most cases, the ASGO algorithm obtains better mean fit-ness function values compared to the traditional GO algorithm and other comparative algorithms. In addition, in 20 out of 30 test cases, ASGO's optimization performance was better compared to the GO algorithm. The experimental results from F1 to F30 show that ASGO is more competitive than most of the comparative algorithms by reducing the

Table 1. The algorithm information and parameter settings.

NO.	Algorithms	Parameters Settings
1	Genetic Algorithm (GA) [8]	pc = 0.8, pm = 02
2	Simulated Annealing (SA) [9]	$T_0 = 0.1$, $\alpha = 0.99$, c = 5, $\mu = 0.5$, $\sigma = 0.1 \times (ub - 1b)$
3	Cultural Algorithm (CA)	pAccept = 0.35, $\alpha = 0.3$
4	Particle Swarm Optimization (PSO)	w = 1, $w_p = 0.99$, $c_1 = 1.5$, $c_2 = 2.0$
5	Differential Evolution (DE) [10]	F = 0.5, CR = 0.9
6	Harmony Search (HS)	HMCR = 0.9, PAR = 0.1, FW = $0.02 \times (ub - 1b)$, $FW_{damp} = 0.995$
7	Ant Colony Optimization (ACO) [2]	q = 0.5, $\zeta = 1$
8	Covariance Matrix Adaptation Evolution Strategy (CMA-ES)	$\sigma = 0.3$
9	Shuffled Frog-Leaping Algorithm (SFLA)	Memeplexes = 5, Offsprings = 3, Step = 2, Run = 5
10	Artificial Bee Colony (ABC)	a = 1, L = $round(0.6 \times N \times D)$
11	Biogeography-Based Optimization (BBO)	KeepRate = 0.2, $\alpha = 0.9$, Mutation = 0.1, $\sigma = 0.02 \times (ub - 1b)$
12	Firefly Algorithm (FA)	$\alpha = 0.2$, $\beta = 2$, $\gamma = 1$, $\delta = 0.05 \times (ub - lb)$, Damping Ratio = 0.98
13	Cuckoo Search (CS) [3]	$P_a = 0.25$, $\alpha = 1$, $\beta = 1.5$, $\sigma_v = 1$
14	Gravitational Search Algorithm (GSA)	$G_0 = 100$, $\alpha = 20$, Rpower = 1
15	Bacterial Foraging optimization (BFO)	c = 25, s = 4, r = 4, p = 0.5, Sr = N/2
16	Brain Storm Optimization (BSO)	m = 5, $P_{5a} = 0.2$, $P_{6b} = 0.8$, $P_{6bi} = 0.4$, $P_{6c} = 0.5$, k = 20, $\mu = 0$, $\sigma = 1$
17	Teaching-Learning-Based Optimization (TLBO)	$T_F = 1$ or 2
18	Differential Search (DS) [11]	$P_1 = 0.3 \times$ rand, $P_2 = 0.3 \times rand$
19	Flower Pollination Algorithm (FPA)	p = 0.8
20	Ali Baba And The Forty Thieves Algorithm (AFT)	a = ceil((nnoThieve-1).*rand(noThieves,1))‘
21	Grey Wolf Optimizer (GWO)	$\alpha = 2–2 \times (FEs/MaxFEs)$
22	Moth-Flame Optimization (MFO)	r = -l-$(FEs/MaxFEs)$, t = r + (l-r) $\times rand$, b = 1
23	Lightning Search Algorithm (LSA)	maxchtime = 10, direct = $sign(unifrnd(-1,1))$
24	Stochastic Fractal Search (SFS) [12]	MDN = 2, Walk = 1

(*continued*)

Table 1. (*continued*)

NO.	Algorithms	Parameters Settings
25	Whale Optimization Algorithm (WOA)	b = 1, a1 = 2-(2 × FEs/MaxFEs), a2 = -l-(FEs/MaxFEs)
26	Jaya	No parameters
27	Sine Casine Algorithm (SCA)	a = 2
28	Multi-Verse Optimizer (MVO)	$WEP_{max} = 1$, $WEP_{min} = 0.2$
29	Salp Swarm Algorithm (SSA)	$c_1 = 2 \times exp((4 \times FEs/MaxFEs)2)$
30	Coyote Optimization Algorithm (COA)	$N_c = 5$, $N_p = 8$
31	Atom Search Optimization (ASO)	$\alpha = 50$, $\beta = 0.2$
32	Artificial Electric Field Algorithm (AEFA) [13]	$K_0 = 500$, $\alpha = 30$
33	Harris Hawks Optimization (HHO)	$E_0 = 2 \times rand\text{-}1$, $E_1 = 2–2 \times (FEs/MaxFEs)$
34	Artificial Ecosystem-based Optimization (AEO)	$a = rand \times (FEs/MaxFEs)$, $c = randn/2 \times \|randn\|$
35	Supply-Demand-Based Optimization (SDO)	$a_1 = 2 \times ((MaxFEs - FEs + 1)/MaxFEs)$
36	Manta Ray Foraging Optimization (MRFO)	$S = 2$, $r_1 = rand$, $Coef = FEs/MaxFEs$
37	Gaining Sharing Knowledge (GSK) [14]	$p = 0.1$, $k_r = 0.9$, $k_f = 0.5$
38	Equilibrium Optimizer (EO) [15]	$V = 1$, $a_1 = 2$, $a_2 = 1$, $GP = 0.5$
39	Coronavirus Herd Immunity Optimizer (CHIO)	MaxAge = 100, CO = 1, BRr = 0.05
40	Heap- Based Optimizer (HBO)	cycles = $\lfloor MaxIt/25 \rfloor$, degree = 3
41	Marine Predators Algorithm (MPA) [16]	FADs = 0.2, P = 0.5
42	Arithmetic Optimization Algorithm (AOA)	$MOP_{Max} = 1$, $MOP_{Min} = 0.2$, $\alpha = 5$, $\mu = 0.499$
43	Runge kutta optimizer (RUN)	a = 20, b = 12
44	weighted mean of vector (INFO)	I = *randi* ([2.5])
45	White Shark Optimizer (WSO)	f = [0.07,0.75], $\tau = 4.11$, p = [0.5,1.5], $a_0 = 6.25$, $a_1 = 100$, $a_2 = 0.0005$
46	Honey Badger Algorithm (HBA)	$\beta = 6$, c = 2, *flag*= -1 or 1
47	Dwarf Mongoose Optimization Algorithm (DMOA)	b = 3, $L_p = 0.6$, peep = 2
48	Snake Optimizer (SO)	$T_1 = 0.25$, $T_2 = 0.6$, $C_1 = 0.5$, $C_2 = 0.05$, $C_3 = 2$

(*continued*)

Table 1. (*continued*)

NO.	Algorithms	Parameters Settings
49	Growth Optimizer (GO) [7]	$P_1 = 5, P_2 = 0.001, P_3 = 0.3$
50	Improved Growth Optimizer (ASGO)	$V_{ld} = 0.9, V_{rd} = 0.8, P_1 = 5, P_2 = 0.001, P_3 = 0.3, P_4 = 0.5$

likelihood of falling into a local optimum and effectively balancing between exploitation and exploration, and thus is more competitive than most comparative algorithms, which proves the excellence of the technique in terms of search performance.

The search performance of ASGO outperforms other algorithms in functions F1, F12, F17, F18, F20, F21, and F30. Although ASGO is not ranked first in F5, F6, F7, F9, F10, F14, F19, F22, F23, F24, F26, F27, and F28, this improvement is still significant com-pared to the traditional GO algorithm. For F2, F3 and F16, the performance of ASGO is slightly lower than GO, but still better than other algorithms. Such obvious optimization effect is achieved mainly because the adaptive parameter and targeted random mutation strategies proposed in this paper can further enhance the search efficiency and the discovery ability of the global optimal solution, and increase the population diversity, so as to achieve the purpose of avoiding premature convergence and improving the algorithm's search performance.

4.3 Convergence Results and Analysis

Figure 1 shows the convergence curves of the top ten ranked algorithms among all competing algorithms on four different groups of problems.

For the unimodal function F1, at D = 30, 50 and 100, ASGO shows excellent performance, not only the optimal solution accuracy is higher than other algorithms, but also the convergence speed is especially significant, and there is no tendency to fall into local optimization. On the simple multimodal function F5, due to the complexity of the problem, the performance of various algorithms varies greatly. At D = 30 and D = 50, ASGO's performance is second only to the AEFA algorithm, with significant improvement compared to GO. And at D = 100, the convergence curve of ASGO gradually surpasses that of AEFA algorithm and becomes the most outstanding performance algorithm. On the hybrid function F19, the convergence accuracy of ASGO is significantly better than GO algorithm and other algorithms. As for the composition function F23, at D = 30, although the performance of ASGO is slightly inferior to that of AEFA and GSK algorithms, with the in-crease of the problem dimension, ASGO gradually surpasses these two algorithms, and finally becomes the most outstanding algorithm.

The total experimental results show that the improved growth optimizer ASGO proposed in this paper has better convergence and optimization performance both in low-dimensional and high-dimensional conditions, and the solution accuracy, convergence speed and stability of ASGO are all optimal. This is due to the use of adaptive adjustment mechanism, which makes the algorithm pay more attention to exploration in the early search process, and on exploiting known best solutions in the later phase,

Table 2. Results of CEC2017 benchmark test functions of ASGO with top ten ranked algorithms at D = 30.

No.	Item	GO	GSK	SFS	DE	ASO	AEFA	MPA	EO	COA	DS	ASGO
F1	mean	1.89E-23	1.01E-21	5.61E-03	1.90E + 03	2.99E + 03	3.90E + 03	6.25E + 03	6.77E + 03	7.20E-01	1.78E + 02	**4.73E-24**
	std	2.84E-23	7.36E-22	5.12E-03	1.85E + 03	3.36E + 03	4.48E + 03	6.45E + 03	3.74E + 03	5.53E-01	1.26E + 02	**1.06E-23**
	h	≈	+	+	+	+	+	+	+	+	+	≈
F2	mean	4.21E-09	1.34E-07	6.16E + 10	4.15E + 11	1.31E-05	6.21E + 11	4.63E + 03	1.36E + 07	1.02E + 07	9.91E + 09	1.06E-08
	std	7.20E-09	2.19E-07	9.61E + 10	8.77E + 11	2.13E-05	9.51E + 11	7.88E + 03	2.12E + 07	1.86E + 07	1.01E + 10	2.14E-08
	h	≈	≈	+	+	+	+	+	+	+	+	≈
F3	mean	2.17E-28	2.75E-27	8.68E-03	1.00E-04	1.13E + 00	9.53E + 04	1.39E-02	8.51E + 00	1.85E + 04	4.35E + 04	5.99E-28
	std	1.38E-28	1.03E-27	1.78E-02	1.59E-04	1.79E + 00	1.25E + 04	2.06E-02	9.79E + 00	7.81E + 03	1.01E + 04	4.29E-28
	h	≈	+	+	+	+	+	+	+	+	+	≈
F4	mean	1.33E + 01	2.54E + 01	5.13E + 01	6.96E + 01	9.61E + 01	8.78E + 01	6.80E + 01	4.44E + 01	7.49E + 01	6.74E + 01	2.72E + 01
	std	2.54E + 01	2.92E + 01	4.64E + 01	1.08E + 01	4.95E + 01	1.80E + 00	3.60E + 01	4.01E + 01	4.59E + 01	3.75E + 01	3.37E + 01
	h	≈	≈	≈	+	+	+	+	≈	≈	+	≈
F5	mean	2.41E + 01	2.19E + 01	9.13E + 01	2.50E + 01	5.03E + 01	1.85E + 01	5.59E + 01	6.79E + 01	5.73E + 01	1.04E + 02	1.93E + 01
	std	5.82E + 00	4.16E + 00	2.65E + 01	9.71E + 00	2.11E + 01	2.50E + 00	9.66E + 00	1.80E + 01	2.13E + 01	1.44E + 01	4.70E + 00
	h	≈	≈	+	≈	+	≈	+	+	+	+	≈
F6	mean	5.53E-03	4.31E-02	2.38E-02	1.64E-02	8.98E-08	1.60E-06	5.30E-01	8.78E-02	7.08E-02	1.78E-02	2.49E-03
	std	5.01E-03	9.64E-02	5.33E-02	3.20E-02	1.18E-07	1.30E-06	4.11E-01	1.81E-01	5.44E-02	6.91E-03	2.40E-03
	h	≈	≈	≈	≈	-	-	+	≈	+	+	≈
F7	mean	5.73E + 01	1.37E + 02	1.34E + 02	1.34E + 02	5.43E + 01	4.88E + 01	9.96E + 01	9.87E + 01	1.18E + 02	1.25E + 02	5.13E + 01
	std	6.13E + 00	6.88E + 01	3.78E + 01	6.95E + 01	7.65E + 00	2.95E + 00	9.31E + 00	1.59E + 01	2.56E + 01	8.72E + 00	1.86E + 00
	h	≈	+	+	+	≈	≈	+	+	+	+	≈
F8	mean	2.57E + 01	3.18E + 01	9.21E + 01	2.43E + 01	4.26E + 01	1.79E + 01	7.34E + 01	6.38E + 01	8.15E + 01	8.59E + 01	2.77E + 01
	std	6.03E + 00	9.92E + 00	2.85E + 01	4.43E + 00	9.81E + 00	3.07E + 00	1.75E + 01	1.38E + 01	1.79E + 01	2.34E + 01	1.04E + 01

(*continued*)

Table 2. (*continued*)

No.	Item	GO	GSK	SFS	DE	ASO	AEFA	MPA	EO	COA	DS	ASGO
	h	≈	≈	+	≈	≈	≈	+	+	+	+	≈
F9	mean	1.92E + 00	4.96E + 00	2.83E + 02	1.47E + 00	4.88E-27	4.83E-25	5.38E + 01	8.93E + 00	2.80E + 02	1.92E + 03	1.89E + 00
	std	1.01E + 00	1.04E + 01	2.94E + 02	1.17E + 00	6.11E-27	1.12E-25	5.62E + 01	8.43E + 00	1.29E + 02v	5.40E + 02	1.03E + 00
	h	≈	≈	+	≈	-	-	+	+	+	+	≈
F10	mean	2.74E + 03	6.75E + 03	2.49E + 03	2.83E + 03	3.02E + 03	1.53E + 03	2.53E + 03	3.88E + 03	2.39E + 03	2.44E + 03	1.71E + 03
	std	1.58E + 03	3.36E + 02	8.12E + 02	1.12E + 03	9.52E + 02	4.46E + 02	2.25E + 02	7.68E + 02	2.83E + 01	3.03E + 02	5.46E + 02
	h	≈	+	≈	+	≈	≈	≈	+	≈	≈	≈
F11	mean	2.35E + 01	1.26E + 01	3.28E + 01	2.74E + 01	4.55E + 01	1.77E + 02	4.38E + 01	2.63E + 01	3.97E + 01	3.69E + 01	3.53E + 01
	std	2.40E + 01	4.19E + 00	1.45E + 01	1.43E + 01	1.13E + 01	1.90E + 01	1.42E + 01	1.27E + 01	2.17E + 01	3.68E + 00	3.15E + 01
	h	≈	≈	≈	≈	≈	+	≈	≈	≈	≈	≈
F12	mean	1.23E + 03	5.02E + 03	1.83E + 04	2.97E + 04	3.51E + 04	4.89E + 05	1.44E + 04	1.20E + 05	1.99E + 04	3.07E + 05	**9.22E + 02**
	std	1.68E + 02	4.06E + 03	4.97E + 03	7.30E + 03	2.32E + 04	1.92E + 05	1.05E + 04	7.27E + 04	9.96E + 03	2.61E + 05	**3.52E + 02**
	h	≈	≈	+	+	+	+	+	+	+	+	≈
F13	mean	1.12E + 02	5.37E + 02	2.60E + 02	9.54E + 03	6.44E + 03	6.58E + 04	9.82E + 01	3.66E + 04	2.07E + 04	4.04E + 03	1.37E + 03
	std	5.00E + 01	9.10E + 02	2.29E + 02	1.42E + 04	3.08E + 03	2.28E + 04	4.36E + 01	3.15E + 04	1.88E + 04	2.84E + 03	2.85E + 03
	h	≈	≈	≈	≈	+	+	≈	+	+	≈	≈
F14	mean	3.42E + 01	3.21E + 01	1.64E + 01	5.09E + 01	1.06E + 04	2.78E + 05	2.86E + 01	4.02E + 03	6.45E + 01	3.19E + 02	2.29E + 01
	std	1.04E + 01	5.39E + 00	5.85E + 00	2.99E + 01	4.63E + 03	3.88E + 05	2.14E + 00	2.57E + 03	1.55E + 01	2.57E + 02	1.29E + 01
	h	≈	≈	≈	≈	+	+	≈	+	+	+	≈
F15	mean	1.21E + 01	1.05E + 01	1.75E + 01	6.23E + 01	2.48E + 03	1.63E + 04	2.51E + 01	1.34E + 04	9.40E + 01	6.49E + 01	1.23E + 01
	std	3.70E + 00	4.77E + 00	4.87E + 00	5.81E + 01	3.38E + 03	1.45E + 04	7.49E + 00	1.27E + 04	7.01E + 01	3.15E + 01	4.24E + 00

(*continued*)

Table 2. (*continued*)

No.	Item	GO	GSK	SFS	DE	ASO	AEFA	MPA	EO	COA	DS	ASGO
	h	≈	≈	≈	≈	+	+	+	+	+	+	≈
F16	mean	2.23E + 02	5.06E + 02	6.04E + 02	5.11E + 02	6.98E + 02	5.98E + 02	4.35E + 02	5.37E + 02	8.90E + 02	5.99E + 02	2.70E + 02
	std	1.68E + 02	4.43E + 02	3.04E + 02	2.74E + 02	2.10E + 02	2.70E + 02	1.86E + 02	1.73E + 02	4.01E + 02	1.80E + 02	1.78E + 02
	h	≈	≈	≈	≈	+	≈	≈	≈	+	+	≈
F17	mean	9.88E + 01	9.49E + 01	8.71E + 01	1.12E + 02	1.64E + 02	5.25E + 02	6.71E + 01	2.68E + 02	3.23E + 02	1.03E + 02	**4.29E + 01**
	std	5.85E + 01	7.57E + 01	5.96E + 01	1.54E + 02	6.36E + 01	1.95E + 02	1.20E + 01	2.30E + 02	1.49E + 02	4.32E + 01	**1.59E + 01**
	h	≈	≈	≈	≈	+	+	+	+	+	+	≈
F18	mean	3.80E + 01	1.92E + 02	3.96E + 01	3.72E + 03	9.90E + 04	3.55E + 05	3.03E + 01	1.18E + 05	2.94E + 04	3.96E + 04	**3.02E + 01**
	std	6.16E + 00	9.77E + 01	4.53E + 00	4.25E + 03	8.87E + 04	3.51E + 05	4.44E + 00	8.58E + 04	4.21E + 04	1.42E + 04	**1.36E + 00**
	h	+	+	+	+	+	+	≈	+	+	+	≈
F19	mean	1.50E + 01	1.13E + 01	1.66E + 01	4.56E + 01	5.11E + 03	4.86E + 03	1.18E + 01	8.36E + 03	1.11E + 02	3.05E + 01	1.32E + 01
	std	1.72E + 00	3.47E + 00	1.12E + 01	6.90E + 01	5.11E + 03	4.13E + 03	3.07E + 00	1.32E + 04	1.66E + 02	4.68E + 00	5.57E + 00
	h	≈	≈	≈	≈	+	+	≈	+	+	+	≈
F20	mean	1.01E + 02	7.07E + 01	1.72E + 02	1.56E + 02	2.79E + 02	4.09E + 02	1.30E + 02	2.78E + 02	3.05E + 02	2.42E + 02	**6.20E + 01**
	std	8.38E + 01	6.12E + 01	1.27E + 02	1.14E + 02	1.21E + 02	1.31E + 02	6.53E + 01	1.56E + 02	8.07E + 01	1.13E + 02	**6.00E + 01**
	h	≈	≈	≈	≈	+	+	≈	+	+	+	≈
F21	mean	2.27E + 02	2.26E + 02	2.61E + 02	2.32E + 02	2.52E + 02	2.27E + 02	2.52E + 02	2.70E + 02	2.75E + 02	2.31E + 02	**2.24E + 02**
	std	5.97E + 00	7.53E + 00	2.15E + 01	4.82E + 00	2.36E + 01	8.82E + 00	7.73E + 00	2.69E + 01	1.92E + 01	1.03E + 02	**8.73E + 00**
	h	≈	≈	+	≈	≈	≈	+	+	+	≈	≈
F22	mean	6.80E + 02	1.00E + 02	1.00E + 02	3.11E + 03	1.00E + 02	1.00E + 02	1.03E + 02	1.34E + 03	2.78E + 03	6.79E + 02	1.00E + 02
	std	1.30E + 03	1.10E + 00	0.00E + 00	2.35E + 03	1.46E-13	4.71E-13	1.94E + 00	1.72E + 03	1.54E + 03	1.29E + 03	1.00E-14

(*continued*)

Table 2. (*continued*)

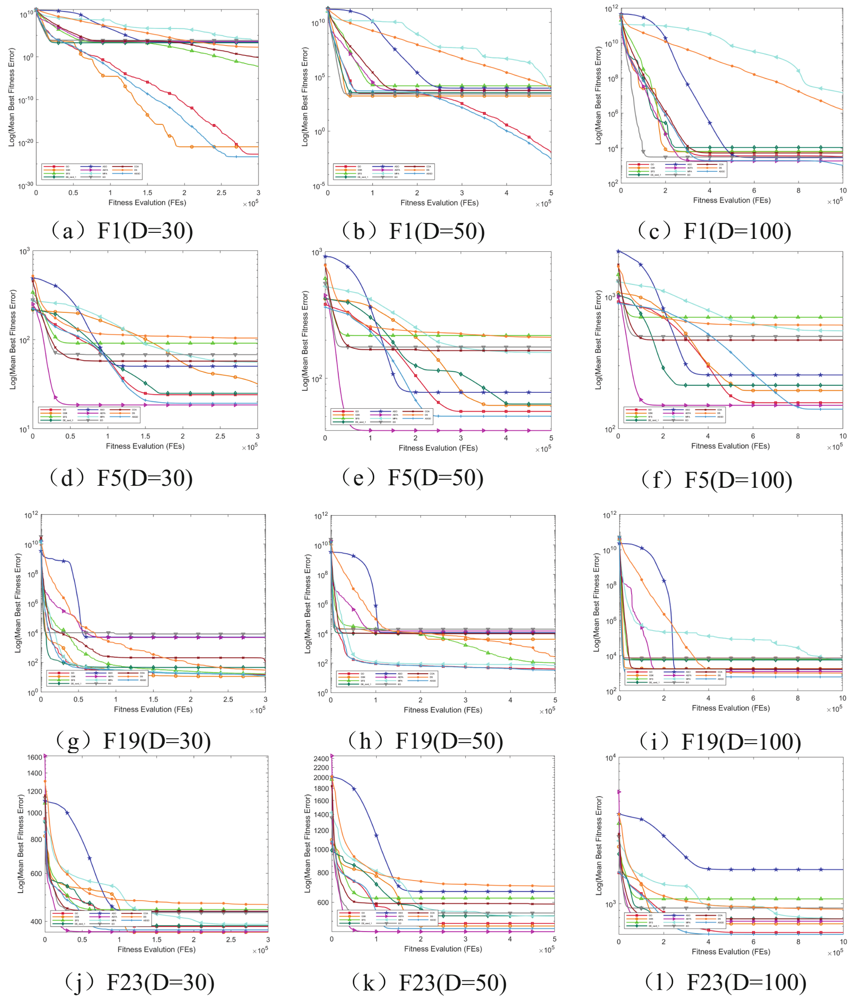
No.	Item	GO	GSK	SFS	DE	ASO	AEFA	MPA	EO	COA	DS	ASGO
	h	≈	+	≈	+	+	+	+	+	+	+	≈
F23	mean	3.83E + 02	3.65E + 02	4.42E + 02	3.86E + 02	4.35E + 02	3.67E + 02	3.90E + 02	4.31E + 02	4.36E + 02	4.61E + 02	3.72E + 02
	std	1.00E + 01	8.47E + 00	1.95E + 01	9.89E + 00	1.32E + 01	8.10E + 00	1.85E + 01	3.82E + 01	2.60E + 01	1.45E + 01	7.49E + 00
	h	≈	≈	+	≈	+	≈	≈	+	+	+	≈
F24	mean	4.57E + 02	4.34E + 02	4.99E + 02	4.73E + 02	4.39E + 02	4.26E + 02	4.57E + 02	4.79E + 02	5.05E + 02	5.65E + 02	4.45E + 02
	std	7.32E + 00	3.69E + 00	3.67E + 01	2.81E + 01	1.14E + 01	8.42E + 00	1.45E + 01	3.17E + 01	1.61E + 01	3.36E + 01	5.92E + 00
	h	+	-	+	≈	≈	-	≈	≈	+	+	≈
F25	mean	3.86E + 02	4.07E + 02	3.88E + 02	3.96E + 02	3.87E + 02	3.87E + 02	3.86E + 02	3.87E + 02	3.87E + 02	3.85E + 02	3.86E + 02
	std	1.86E + 00	2.98E + 01	5.55E + 00	1.88E + 01	3.53E-01	3.87E-02	1.63E + 00	1.76E + 00	2.39E + 00	2.18E + 00	1.56E + 00
	h	≈	≈	≈	+	+	≈	≈	≈	≈	≈	≈
F26	mean	1.37E + 03	8.26E + 02	1.58E + 03	1.33E + 03	9.24E + 02	2.40E + 02	3.00E + 02	1.43E + 03	2.01E + 03	2.12E + 02	1.32E + 03
	std	1.56E + 02	5.28E + 02	1.25E + 03	2.60E + 02	6.81E + 02	5.48E + 01	2.50E-03	6.57E + 02	2.37E + 02	2.34E + 01	1.35E + 02
	h	≈	-	≈	≈	≈	-	-	≈	+	-	≈
F27	mean	5.08E + 02	5.05E + 02	5.19E + 02	5.27E + 02	5.84E + 02	5.07E + 02	5.03E + 02	5.28E + 02	5.16E + 02	5.38E + 02	5.04E + 02
	std	6.68E + 00	1.67E + 01	1.40E + 01	1.25E + 01	5.79E + 01	2.88E + 00	7.25E + 00	1.41E + 01	1.13E + 01	6.86E + 00	9.63E + 00
	h	≈	≈	≈	+	≈	≈	≈	+	≈	+	≈
F28	mean	3.56E + 02	3.32E + 02	3.02E + 02	3.48E + 02	3.21E + 02	4.17E + 02	3.38E + 02	3.23E + 02	4.07E + 02	4.06E + 02	3.21E + 02
	std	7.91E + 01	7.16E + 01	3.91E + 00	5.66E + 01	4.62E + 01	2.34E + 01	5.33E + 01	5.09E + 01	9.05E + 00	9.03E + 00	4.62E + 01
	h	≈	≈	≈	≈	≈	+	≈	≈	+	+	≈
F29	mean	5.20E + 02	4.78E + 02	6.60E + 02	5.05E + 02	5.37E + 02	8.34E + 02	5.27E + 02	7.76E + 02	9.21E + 02	6.44E + 02	5.22E + 02
	std	7.76E + 01	4.16E + 01	7.93E + 01	1.82E + 02	8.78E + 01	1.67E + 02	6.89E + 01	2.86E + 02	1.27E + 02	1.10E + 02	8.88E + 01

(*continued*)

Table 2. *(continued)*

No.	Item	GO	GSK	SFS	DE	ASO	AEFA	MPA	EO	COA	DS	ASGO
	h	≈	≈	+	≈	≈	+	≈	+	+	≈	≈
F30	mean	2.05E + 03	2.02E + 03	3.11E + 03	4.25E + 03	6.23E + 03	1.38E + 05	2.09E + 03	8.04E + 03	2.59E + 03	3.80E + 03	**2.00E + 03**
	std	9.83E + 01	4.62E + 01	8.73E + 02	3.83E + 03	1.63E + 03	7.93E + 04	9.60E + 01	4.82E + 03	5.06E + 02	6.80E + 02	**3.91E + 01**
	h	≈	≈	+	+	+	+	≈	+	+	+	≈
w/l/t	2/28/0	6/22/2	14/16/0	12/18/0	18/10/2	17/9/4	14/15/1	22/8/0	25/5/0	23/6/1	0/30/0	
median F	3.82	4.08	6.01	5.91	6.64	6.88	5.74	7.94	8	7.82	3.16	

which improves the search efficiency, adaptability and ability to find the global optimal solution of the algorithm; and in the reflection phase introduces the targeting stochastic mutation strategies, which increases the diversity of the population, avoids premature convergence to local optimal solution, and enhances the search performance of the algorithm. It is proved that the improved ASGO algorithm has feasibility and effectiveness, and the search performance is high.



（a） F1(D=30) （b） F1(D=50) （c） F1(D=100)

（d） F5(D=30) （e） F5(D=50) （f） F5(D=100)

（g） F19(D=30) （h） F19(D=50) （i） F19(D=100)

（j） F23(D=30) （k） F23(D=50) （l） F23(D=100)

Fig. 1. The convergence curves of ASGO with top ten ranked algorithms on four groups of problems.

4.4 Statistical Results and Analysis

The statistical results shown in Table 3 were obtained by performing the Friedman test on the mean fitness values of 50 metaheuristic algorithms. As can be seen from the table, ASGO ranks first with a mean ranking of 5.470, which is significantly ahead of the traditional GO algorithm. These results show that the modifications made to the standard GO algorithm can significantly improve its performance and overcome its limitations.

Table 3. The Friedman test ranks for ASGO and the compared algorithms.

id	Algorithms	D = 30	D = 50	D = 100	Mean rank
1	ASGO	4.950	4.840	6.620	5.470
2	GO	6.300	5.130	5.950	5.793
3	GSK	8.100	10.110	11.450	9.887
4	MPA	11.110	11.410	16.390	12.970
5	DE	12.750	15.360	14.180	14.097
6	SFS	12.200	15.290	15.820	14.437
7	ASO	14.940	15.530	14.960	15.143
8	AEFA	19.720	15.840	12.430	15.997
9	COA	17.790	18.410	14.890	17.030
10	SDO	17.020	18.840	17.040	17.633
11	EO	19.110	18.930	16.440	18.160
12	FA	20.320	18.280	17.300	18.633
13	DS	17.610	19.870	21.080	19.520
14	SO	22.030	20.610	18.700	20.447
15	HBA	22.730	23.110	18.000	21.280
16	INFO	22.110	23.920	20.830	22.287
17	SA	21.450	22.110	24.180	22.580
18	MVO	25.570	23.250	19.610	22.810
19	AEO	24.280	23.690	20.580	22.850
20	TLBO	21.970	22.940	23.810	22.907
21	CS	20.920	23.430	25.630	23.327
22	FPA	21.910	24.560	23.750	23.407
23	PSO	24.710	23.250	22.370	23.443
24	HBO	23.260	23.540	23.540	23.447
25	MRFO	24.910	25.310	20.410	23.543

(*continued*)

Table 3. (*continued*)

id	Algorithms	D = 30	D = 50	D = 100	Mean rank
26	BBO	25.440	23.680	23.100	24.073
27	CHIO	25.300	23.190	24.190	24.227
28	AFT	26.030	24.090	23.420	24.513
29	GA	28.830	25.250	21.260	25.113
30	RUN	25.890	26.880	24.320	25.697
31	SSA	28.940	25.390	22.920	25.750
32	WSO	26.010	27.180	26.790	26.660
33	HS	22.800	25.970	31.230	26.667
34	CMA_ES	26.850	26.240	27.350	26.813
35	SFLA	18.630	17.820	45.290	27.247
36	GSA	30.940	28.350	23.470	27.587
37	LSA	32.190	31.330	28.630	30.717
38	GWO	31.320	30.330	31.710	31.120
39	DMOA	29.870	30.610	33.390	31.290
40	ABC	29.590	30.750	33.900	31.413
41	ACO	30.040	31.640	36.470	32.717
42	BSO	36.390	35.130	31.540	34.353
43	HHO	40.140	39.710	35.850	38.567
44	CA	38.090	39.210	42.600	39.967
45	MFO	40.490	41.430	40.720	40.880
46	Jaya	40.100	41.010	42.600	41.237
47	WOA	43.680	41.870	39.670	41.740
48	SCA	45.380	46.070	45.790	45.747
49	AOA	45.580	46.980	47.190	46.583
50	BFO	48.690	47.290	45.630	47.203

The Wilcoxon signed-rank test is a pairwise comparison of ASGO with all competing algorithms to verify whether there is a significant difference between the algorithms at a significance level α of 0.05.

In Table 4, the indicator "$+/=/-$" is based on the Wilcoxon signed-rank test, which indicates whether the competing algorithms perform better, comparable, or worse relative to ASGO at $\alpha = 0.05$.

Since the test involves more algorithms, only the statistics of the first six algorithms are counted, which are listed in Table 4. In the indicator "$+/=/-$", the number of times that GO and GSK outperform ASGO decreases significantly as the dimensionality increases. The indicators "$+/=/-$" for MPA, DE, and SFS remain stable.

Table 4. The Wilcoxon signed-rank test results of the algorithms.

vs. ASGO		D = 30	D = 50	D = 100
GO	+/= /−	0/28/2	0/28/2	3/24/3
GSK	+/=/−	2/22/6	1/22/7	1/16/13
MPA	+/=/−	1/15/14	0/11/19	1/8/21
DE	+/=/−	0/18/12	0/12/18	0/13/17
SFS	+/=/−	0/16/14	0/9/21	1/10/19

5 Conclusion

In order to enhance the performance of the growth optimizer (GO), this paper proposes an improved growth optimizer (ASGO) based on adaptive parameter and targeted stochastic mutation strategies. The algorithm combines the adaptive adjustment mechanism and the targeted stochastic mutation strategies, which significantly reduces the possibility of the algorithm falling into a local optimum. In the learning phase, ASGO achieves dynamic adaptive adjustment of the learning and reflection speeds through the decay factor, while in the reflection phase, it adopts the targeted stochastic mutation strategies to optimize and adjust the specific dimensions in a targeted manner, thus improving the algorithm's search efficiency and the ability to find the globally optimal solution, and effectively avoiding premature convergence. The algorithm is validated on 30 test functions of the CEC2017 test suite and compared with nearly 50 state-of-the-art meta-heuristics as competing algorithms. The results show that ASGO effectively improves the convergence speed and global optimal search performance of the GO algorithm. Its innovative approach to dynamically adjusting search strategies and enhancing diversity through targeted mutation holds significant promise for both theoretical re-search and practical applications. Nevertheless, we also realize that the algorithm still has some limitations. For example, further research is needed to investigate the performance of the algorithm when dealing with specific types of problems, and to explore more adaptive parameter tuning strategies to further enhance the performance. Future work will focus on these aspects to drive further development in the field of optimization and lay the foundation for more efficient, adaptive and robust solutions.

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