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Performance of Multi-strategy Optimized Mayfly Optimization Algorithm for Location Selection of University Reimbursement Form Submission Terminals

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ABSTRACT

The Mayfly Optimization Algorithm(MOA) suffers from inherent drawbacks, such as susceptibility to local optima and slow convergence speed. In this study, an improved mayfly algorithm integrated with multiple strategies is proposed. Firstly, a Logistic chaotic map is adopted to generate a uniformly distributed initial population, which replaces the traditional random initialization method and enhances population diversity. Secondly, a nonlinear adaptive weight factor is introduced to improve the global search capability. Thirdly, a Lévy flight strategy is incorporated to assist the algorithm in escaping local optima and further augment population diversity. Finally, mechanisms derived from Particle Swarm Optimization (PSO) are integrated into the algorithm. This integration strengthens the directionality of the algorithm, balances global exploration and local exploitation, accelerates convergence, and directly mitigates the core flaw of premature convergence in the original MOA. The performance of the improved algorithm was evaluated using 12 benchmark functions. Comparative experiments with three other state-of-the-art algorithms demonstrate that the proposed algorithm achieves higher optimization accuracy, faster convergence rate, and enhanced ability to escape local optima. Furthermore, the applicability of the proposed algorithm to practical engineering problems was validated through a case study on the optimal placement of university reimbursement form submission terminals.

Keywords

Mayfly Optimization Algorithm, Logistic Chaotic Map, Adaptive Weight Factor, Lévy Flight, Particle Swarm Optimization, Reimbursement Form Submission Terminals

Introduction

recent years, numerous intelligent optimization algorithms have been developed, drawing inspiration from a diverse range of organisms and natural phenomena. Classic examples of such algorithms include Genetic Algorithm (GA) [1], particle swarm optimization (PSO) [2], ant colony optimization (ACO) [3], sparrow search algorithm (SSA) [4], Crested Porcupine Optimizer (CPO) [5], and Grey Wolf Optimizer (GWO) [6]. Owing to their powerful capability in solving high-dimensional complex optimization problems, these algorithms are collectively termed swarm intelligence algorithms and represent a prominent research focus within the field of artificial intelligence. Meanwhile, extended variants of these core algorithms, along with their applications across diverse engineering fields, continue to be developed at a rapid pace. The Mayfly Optimization Algorithm (MOA) was first proposed as a novel swarm intelligence algorithm by Zervoudakis in 2020 [7]. This algorithm is based on the framework of PSO and is inspired by the flight patterns and mating behaviors of mayflies. Consequently, MOA retains the advantages of PSO while simultaneously incorporating beneficial mechanisms from genetic algorithms and firefly algorithms. Despite advantages such as high solution accuracy and fast convergence relative to other swarm intelligence algorithms, the Mayfly Optimization Algorithm (MOA) still exhibits limitations in search precision and convergence speed that warrant improvement. To address these limitations, extensive research has been conducted. For instance, the Logistic chaotic map was introduced to enhance population diversity and prevent premature convergence [8]. Similarly, nonlinear adaptive weighting mechanisms have been proposed to balance exploration and exploitation capabilities, facilitating adaptive search throughout the solution space [9, 10]. The Lévy flight strategy has been incorporated into other algorithms, such as the whale and ant colony optimizers, to mitigate their tendency to converge to local optima [11, 12]. Furthermore, hybrid approaches, such as combining the whale optimization algorithm with PSO, have been developed to accelerate convergence and balance global exploration with local exploitation [13]. Building upon these concepts, this study proposes an improved MOA integrating

four key strategies: (1) using a Logistic chaotic map for initial population generation to enhance diversity; (2) introducing an adaptive nonlinear weighting factor to improve global search capability; (3) implementing a Lévy flight strategy to strengthen the ability to escape local optima; and (4) incorporating a PSO-based mechanism to accelerate convergence and refine the search for optimal solutions.

Mayfly Optimization Algorithm

The fundamental principles of the Mayfly Optimization Algorithm (MOA) are elaborated as follows [14]. Initially, the algorithm randomly initializes two disjoint populations, namely male and female mayflies. The position of each mayfly, which encodes a potential solution to the optimization problem, is denoted by a d -dimensional vector $x = (x_1, x_2, \dots, x_d)$, while its locomotion behavior is regulated by a velocity vector $v = (v_1, v_2, \dots, v_d)$. The performance (or fitness) of each position vector is quantified by a predefined objective function $f(x)$. In the iterative evolution process, each mayfly updates its position by moving toward two target positions: its own personal historical best position (pbest) and the global best position (gbest) of the entire swarm [15].

Inspired by the mating behavior in the natural life cycle of mayflies, MOA incorporates an abstraction of the mating mechanism. Specifically, male and female mayflies with optimal fitness values are preferentially paired to generate high-quality offspring. Correspondingly, individuals with relatively inferior fitness are matched sequentially to produce subsequent generations. This selective pairing process is repeated iteratively until all individuals in the population are assigned mating partners.

The Renewal of Male Mayflies

The most prominent distinguishing characteristic of male mayflies is their propensity to aggregate in large swarms. The position of each male mayfly is jointly influenced by its own historical navigation experience and the collective presence of neighboring conspecific male mayflies. Assume that at iteration t , the position of the i -th male mayfly is denoted as x_i^t . At iteration $t + 1$, its new position is determined by adding its instantaneous velocity at iteration $t + 1$ (denoted as v_i^{t+1}) to its current position x_i^t at iteration t . This position update rule at iteration $t + 1$ can be mathematically formulated as (1).

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (1)$$

Given that male mayflies are not sessile but exhibit active locomotion above the water surface to engage in courtship displays (dances), the corresponding velocity update formulation for male mayflies is mathematically defined as (2).

$$v_{i,j}^{t+1} = v_{i,j}^t + a_1 e^{-\beta r_p^2} (pbest_{i,j}^t - x_{i,j}^t) + a_2 e^{-\beta r_g^2} (gbest_j^t - x_{i,j}^t) \quad (2)$$

Among these parameters, $v_{i,j}^t$ denotes the velocity of the i -th mayfly in the j -th dimension at the t -th iteration, while $x_{i,j}^t$ represents its corresponding position in the j -th dimension at the t -th iteration. a_1 and a_2 are defined as the ephemeral attraction coefficients; $pbest_{i,j}^t$ refers to the individual historical best position of the i -th mayfly in the j -th dimension, and $gbest_j^t$ denotes the global best position of the entire swarm in the j -th dimension. β is the visibility coefficient, which serves to regulate the perceptual range of mayflies during the optimization process. r_p and r_g respectively represent the Euclidean distances between the current position $x_{i,j}^t$ and the target positions $pbest_{i,j}^t$ and $gbest_j^t$. The mathematical formulation for calculating these distances is given by (3).

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^n (x_{i,j} - X_{i,j})^2} \quad (3)$$

Among these parameters, $x_{i,j}$ denotes the position of the i -th mayfly in the j -th dimension, while X_i (a generic target position) can be appropriately substituted with either $pbest_{i,j}$ (the individual historical best position) or $gbest_j$ (the global best position of the entire swarm).

To converge to the optimal solution (i.e., the global best position), mayflies are required to continuously update their locomotion velocity, and the corresponding velocity update formulation for mayflies is mathematically presented as Equation (4).

$$v_{i,j}^{t+1} = v_{i,j}^t + d \times r \quad (4)$$

Among these parameters, d is defined as the dance coefficient, while r denotes a random scalar uniformly distributed within the interval $[-1, 1]$.

The Renewal of Female Mayflies

Unlike male mayflies that tend to aggregate in swarms, female mayflies fly toward male swarms for mating and reproduction. Assume that the position of the i -th female mayfly in the j -th dimension at iteration t is denoted as $y_{i,j}^t$; then its position at iteration $t + 1$ is calculated by summing its velocity at iteration $t + 1$ ($v_{i,j}^{t+1}$) and its current position $y_{i,j}^t$ at iteration t . This position update rule can be mathematically expressed as (5).

$$y_{i,j}^{t+1} = y_{i,j}^t + v_{i,j}^{t+1} \quad (5)$$

The updated velocity expression for female mayflies is:

$$v_{i,j}^{t+1} = \begin{cases} v_{i,j}^t + a_3 e^{-\beta r_m^2} (x_{i,j}^t - y_{i,j}^t) & \text{if } f(y_i) > f(x_i) \\ v_{i,j}^t + f_l \times r & \text{otherwise} \end{cases} \quad (6)$$

Among these parameters, $v_{i,j}^t$ denotes the velocity of the i -th mayfly in the j -th dimension at iteration t , while $y_{i,j}^t$ denotes the position of the i -th female mayfly in the j -dimensional solution space at iteration t . a_3 is an inter-attraction coefficient representing the mutual attraction between male and female mayflies; r_m denotes the Euclidean distance between corresponding male and female mayflies; β is the visibility coefficient (consistent with the aforementioned definition); f_l is the random walk coefficient; and $f(x)$ is the fitness function.

Mating Among Mayflies

Inspired by mayfly mating behavior, the mating formula for MOA is as follows:

$$\text{offspring}_1 = L * \text{male} + (1 - L) * \text{female} \quad (7)$$

$$\text{offspring}_2 = L * \text{female} + (1 - L) * \text{male} \quad (8)$$

Among these parameters, offspring_1 denotes the offspring (next-generation) mayfly individual generated by mating, while male denotes the father mayfly, female denotes the mother mayfly. Additionally, L is a random weighting coefficient that is uniformly distributed within the interval $[-1, 1]$.

Improvements to the MOA

Compared to other swarm intelligence algorithms, MOA offers higher solution accuracy and faster convergence, but there remains potential for improvement in search precision and convergence speed. To enhance algorithm performance and enable it to escape local optima, this paper proposes four improvement measures.

Introducing the Logistic Chaotic Map into the Algorithm

The Logistic mapping[16] is a typical mapping mechanism with strong nonlinear characteristics, suitable for high-dimensional and complex optimization problems. The perturbation formula for the chaotic mechanism of the Logistic mapping is as follows [17]:

$$z_{i,j}^{t+1} = \mu z_{i,j}^t (1 - z_{i,j}^t) \quad (9)$$

Among these parameters, μ is the control parameter of the Logistic map with a value range of $\mu \in [0, 4]$. Specifically, when $\mu = 4$, the sequence generated by the Logistic map enters a state of complete chaos and exhibits the maximum degree of randomness. This characteristic ensures the highest possible level of population diversity and maximizes the perturbation effect on the mayfly swarm. Accordingly, the control parameter μ is set to 4 in this study. In addition, $z_{i,j}^t \in [0, 1]$ denotes the chaotic state value corresponding to the i -th mayfly in the j -th dimension at iteration t , which is used to characterize the chaotic position of the individual.

The formula for mapping $x_{i,j}^t \in [x_{\min}, x_{\max}]$ to $z_{i,j}^t \in [0, 1]$ is given as follows:

$$z_{i,j}^t = \frac{x_{i,j}^t - x_{\min}}{x_{\max} - x_{\min}} \quad (10)$$

The formula for mapping $z_{i,j}^t$ back to $x_{i,j}^t$ is given as follows:

$$x_{i,j}^t = x_{\min} + z_{i,j}^t \cdot (x_{\max} - x_{\min}) \quad (11)$$

Introducing nonlinear adaptive weighting factors into the algorithm

Nonlinear adaptive weighting factors significantly enhance the search accuracy and convergence speed in the solution space. When the weight factor increases, the algorithm will exhibit strong global search capabilities; when the weight factor decreases, the algorithm will demonstrate robust local search capabilities[18]. The weighting factor employed by the optimization algorithm in this paper is also nonlinearly adaptive and can be expressed as

$$\omega_t = \frac{e^{\pi(1-\frac{t}{T_{\max}})} - e^{-\pi(1-\frac{t}{T_{\max}})}}{e^{\pi(1-\frac{t}{T_{\max}})} + e^{-\pi(1-\frac{t}{T_{\max}})}} \quad (12)$$

Among these parameters, t denotes the iteration count; $T_{\max}$ denotes the maximum iteration count. As the number of iterations increases, the nonlinear adaptive weighting factor exhibits a nonlinear decrease and ultimately reaches a minimum value. By incorporating this nonlinear adaptive weighting factor into the MOA, the male mayfly position (1) will be updated to:

$$x_{i,j}^{t+1} = \omega_t x_{i,j}^t + v_{i,j}^{t+1} \quad (13)$$

Similarly, the position (5) for female mayflies will be updated to:

$$y_{i,j}^{t+1} = \omega_t y_{i,j}^t + v_{i,j}^{t+1} \quad (14)$$

Integrating the Lévy flight strategy into the algorithm

Lévy flight is a random walk strategy proposed by the French mathematician Lévy. Numerous studies indicate that the flight behavior of many animals and insects exhibits characteristics of Lévy flight[19]. Mayflies are winged insects capable of both crawling and flying. Mayflies exhibit highly random stride lengths during crawling and flight, approximating a Lévy distribution, which can be abstracted as a Lévy flight model. Applying the Lévy flight to the MOA enhances the randomness of the optimization process while simultaneously activating the search process. After incorporating the Lévy flight strategy into the speed of male mayflies in (2), the algorithm is better able to escape local optima, and search efficiency is also enhanced. The new speed expression for male mayflies is:

$$v_{i,j}^{t+1} = v_{i,j}^t + a_1 e^{-\beta r_p^2} (\text{Lévy} \oplus pbest_{i,j} - x_{i,j}^t) + a_2 e^{-\beta r_g^2} (gbest_j - x_{i,j}^t) \quad (15)$$

Among these parameters, Lévy denotes the Lévy flight factor, $\oplus$ denotes element-wise multiplication. The expression for the Lévy distribution is

$$\text{Lévy}(s, \lambda) \approx s^{-\lambda} \quad (16)$$

Among these, s is a random stride; λ is a random number from $(1, 3]$.

Integrating the PSO into the algorithm

PSO is a swarm intelligence optimization algorithm inspired by observing the foraging behavior of flocks of birds. Each individual in the swarm continuously learns and exchanges information with others, ultimately locating the optimal position[20]. The formula for updating its position and velocity is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \quad (17)$$

$$v_{i,j}^{t+1} = \omega_t v_{i,j}^t + c_1 r_1 (pbest_{i,j} - x_{i,j}^t) + c_2 r_2 (gbest_j - x_{i,j}^t) \quad (18)$$

Among these parameters, t represents the iteration count, ω denotes the inertia weight coefficient, c_1 and c_2 are learning factors (non-negative constants), and r_1 and r_2 are random numbers between 0 and 1.

To address the shortcomings of MOA, such as slow convergence speed and poor stability in later stages, integrating PSO with MOA can enhance the algorithm's speed in searching for optimal solutions. The new speed expression for male mayflies is

$$v_{i,j}^{t+1} = v_{i,j}^t + a_1 e^{-\beta r_p^2} (\text{Lévy} \oplus pbest_{i,j} - x_{i,j}^t) + a_2 e^{-\beta r_g^2} (gbest_j - x_{i,j}^t) + c_1 r_1 (pbest_{i,j} - x_{i,j}^t) + c_2 r_2 (gbest_j - x_{i,j}^t) \quad (19)$$

The new speed expression for female mayflies when $f(y_i) > f(x_i)$ is

$$v_{i,j}^{t+1} = v_{i,j}^t + a_3 e^{-\beta r_m^2} (x_{i,j}^t - y_{i,j}^t) + c_1 r_1 (pbest_i - y_{i,j}^t) + c_2 r_2 (gbest_j - y_{i,j}^t) \quad (20)$$

The new speed expression for female mayflies when $f(y_i) \leq f(x_i)$ is

$$v_{i,j}^{t+1} = v_{i,j}^t + f_l \cdot r \quad (21)$$

Algorithm Flowchart

The MSMOA operational flowchart is shown in Fig. 1.

Simulation Experiments and Comparative Analysis

Test Function Selection and Algorithm Parameter Configuration

The mayfly algorithm simultaneously incorporating the Logistic chaotic mapping, Lévy flight, nonlinear adaptive weighting factor, and fusion PSO, is denoted as MSMOA. The mayfly algorithm only employing the Lévy flight strategy is denoted as LMOA, while the mayfly algorithm solely utilizing the nonlinear adaptive weighting factor is denoted as GMOA. To validate the effectiveness and stability of the multi-strategy improved mayfly optimization algorithm, this experiment was conducted with a maximum iteration count of 500, and both male and female mayfly populations set to 20. In the experiment, the four algorithms: MOA, LMOA, GMOA, and MSMOA were each run independently 30 times. The results of these 30 experiments were statistically analyzed to calculate the best, mean, and standard deviation values for the four algorithms across all test functions. The final results are presented in Table 3. The optimization capability of an algorithm is reflected through its best value and mean value, while its stability is demonstrated by its standard deviation.

Table 1 lists the names, dimensions, and ranges of the 12 benchmark functions. The first eight of the twelve test functions are unimodal, while the last four are multimodal. Table 2 lists the parameters required for each algorithm.

Table 1. Introduction of about 12 test functions

Function	Function Name	Dim	Range
f_1	Sphere	30	$[-100, 100]$
f_2	Schwefel's 2.22	30	$[-10, 10]$
f_3	Schwefel's 1.2	30	$[-100, 100]$
f_4	Schwefel's 2.21	30	$[-100, 100]$
f_5	Rosenbrock's	30	$[-30, 30]$
f_6	step	30	$[-100, 100]$
f_7	quartic	30	$[-1.28, 1.28]$
f_8	Ackley's	30	$[-32, 32]$
f_9	penalized 1	30	$[-50, 50]$
f_{10}	penalized 2	30	$[-50, 50]$
f_{11}	Branin	2	$[-5, 0] \cup [0, 5]$
f_{12}	Goldstein-Price	2	$[-2, 2]$

Table 2. Basic parameters of 4 Algorithms

Algorithm	Parameter
MOA	$a_1 = 1, a_2 = a_3 = 1.5, \beta = 2, d = 5$
LMOA	$a_1 = 1, a_2 = a_3 = 1.5, \beta = 2, d = 5, \lambda = 1.5$
GMOA	$a_1 = 1, a_2 = a_3 = 1.5, \beta = 2, d = 5, \omega_{\max} = 0.9963$
MSMOA	$a_1 = 1, a_2 = a_3 = 1.5, \beta = 2, d = 5, \omega_{\max} = 0.9963, c_1 = c_2 = 1.5$

Experimental Results and Analysis

As shown in Table 3, analysis of the best value results shows that MSMOA achieves or comes extremely close to the theoretical values for all four test functions f_1, f_2, f_3 and f_4 , demonstrating that the improved algorithm enhances search capabilities. MSMOA achieved better best values than other algorithms at $f_5, f_8, f_9, f_{10}, f_{11}$ and f_{12} , demonstrating its high computational accuracy and strong search capabilities. Under test functions f_6 and f_7 , MSMOA did not achieve the best results but came very close to the optimal values obtained by other algorithms.

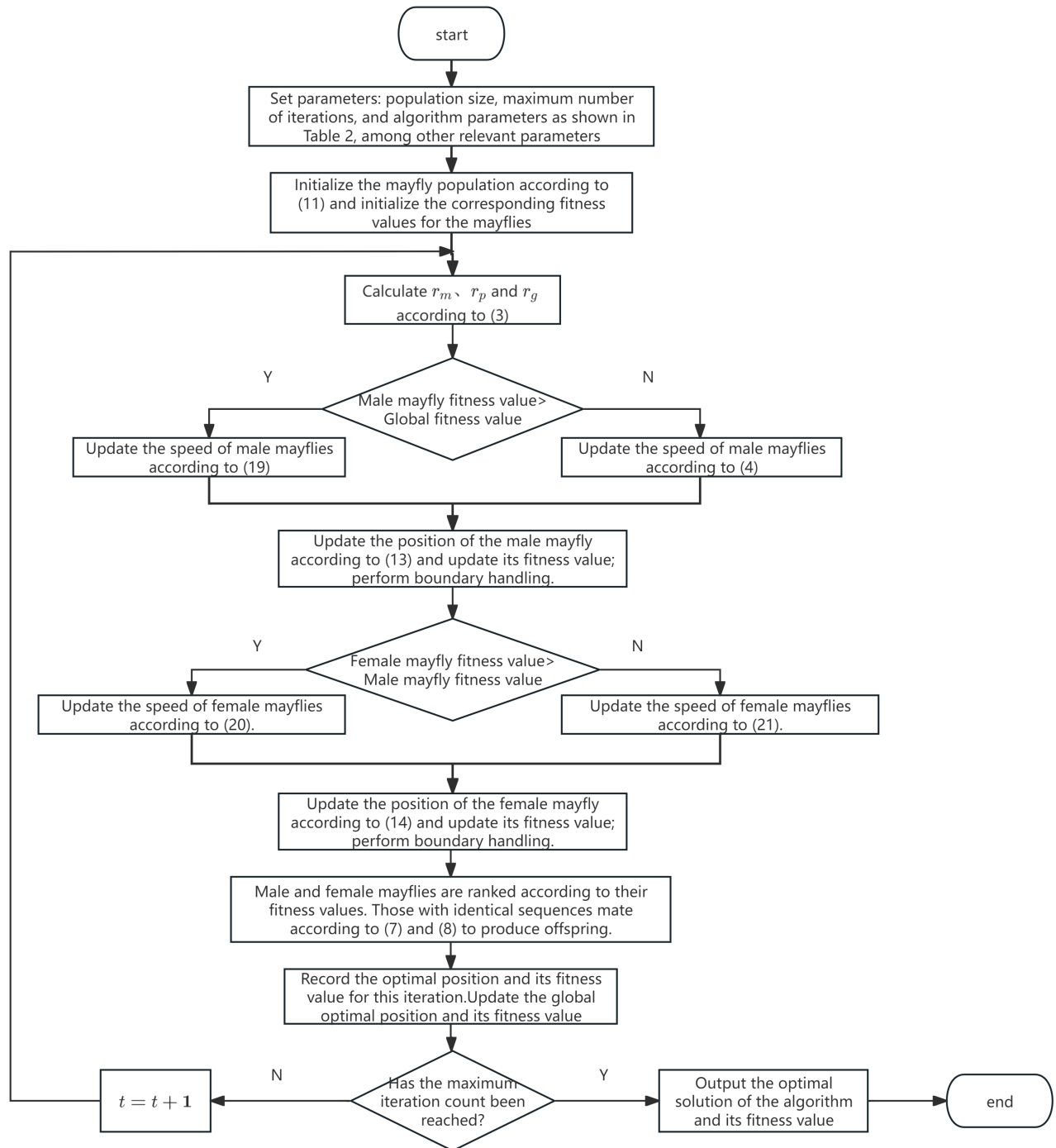


Figure 1. MSMOA Operational Flowchart.

Analysis of the mean results indicates that MSMOA achieves the theoretical value in both test functions f_1 and f_3 , demonstrating that the MSMOA mean converges to the optimal value over 30 independent runs. MSMOA achieved better mean values than other algorithms at $f_2, f_4, f_5, f_7, f_9, f_{10}$ and f_{12} . Although the test functions f_6 and f_{11} did not outperform other algorithms in terms of mean values, the differences were negligible. Overall, the MSMOA algorithm demonstrates better optimization capability.

From the perspective of standard deviation, the MSMOA algorithm achieved smaller standard deviations than other algorithms in all test functions except f_6, f_{11} and f_{12} , indicating its high stability and strong reliability.

In summary, on the test function, MSMOA demonstrates superior convergence accuracy compared to LMOA, GMOA, and MOA, while also exhibiting stronger optimization capabilities and greater ability to escape local optima. Figure 2 displays the convergence curves of the four algorithms across 12 test functions, demonstrating that MSMOA exhibits superior robustness and convergence, indicating that the improved algorithm achieves enhanced search performance.

Table 3. Results of different algorithms on test functions

Function	Algorithm	Best	Mean	Std	Function	Algorithm	Best	Mean	Std
f_1	MOA	3.85E-01	7.17E-01	1.86E-01	f_7	MOA	4.86E-02	1.69E+00	3.99E+00
	LMOA	3.30E-11	1.90E-08	4.43E-08		LMOA	8.64E-03	2.22E-02	9.50E-03
	GMOA	0.00E+00	1.92E-238	0.00E+00		GMOA	1.10E-06	1.44E-04	1.59E-04
	MSMOA	0.00E+00	0.00E+00	0.00E+00		MSMOA	1.63E-06	1.26E-04	1.11E-04
f_2	MOA	3.06E+00	5.30E+00	1.66E+00	f_8	MOA	2.22E+00	3.01E+00	4.34E-01
	LMOA	1.26E-07	7.15E-05	1.45E-04		LMOA	2.66E+00	3.71E+00	7.01E-01
	GMOA	8.15E-167	2.37E-125	1.30E-124		GMOA	8.88E-16	8.88E-16	0.00E+00
	MSMOA	4.05E-292	1.06E-254	0.00E+00		MSMOA	8.88E-16	8.88E-16	0.00E+00
f_3	MOA	2.98E+01	4.97E+01	1.30E+01	f_9	MOA	6.01E-01	3.89E+00	1.72E+00
	LMOA	8.79E-03	4.81E-01	1.76E+00		LMOA	1.01E-06	6.11E-01	7.04E-01
	GMOA	0.00E+00	1.63E-219	0.00E+00		GMOA	9.48E-06	3.68E-03	2.85E-03
	MSMOA	0.00E+00	0.00E+00	0.00E+00		MSMOA	3.56E-09	1.30E-05	4.17E-05
f_4	MOA	1.16E+00	3.23E+00	1.39E+00	f_{10}	MOA	1.48E-01	3.17E-01	1.32E-01
	LMOA	2.00E-01	1.24E+00	1.01E+00		LMOA	3.79E-07	2.13E+00	2.98E+00
	GMOA	2.17E-179	2.92E-123	1.60E-122		GMOA	1.39E-04	3.74E-03	8.81E-03
	MSMOA	5.30E-293	4.93E-258	0.00E+00		MSMOA	1.39E-08	2.00E-05	2.90E-05
f_5	MOA	9.04E+01	3.30E+02	1.81E+02	f_{11}	MOA	3.98E-01	3.98E-01	3.99E-05
	LMOA	6.41E+00	3.98E+01	2.71E+01		LMOA	3.98E-01	3.98E-01	0.00E+00
	GMOA	2.78E+01	2.82E+01	2.08E-01		GMOA	3.98E-01	3.99E-01	1.16E-03
	MSMOA	1.45E-06	4.23E-03	5.89E-03		MSMOA	3.98E-01	4.00E-01	1.57E-03
f_6	MOA	4.21E-01	7.89E-01	2.26E-01	f_{12}	MOA	3.00E+00	3.00E+00	1.86E-03
	LMOA	2.05E-12	3.13E-06	1.64E-05		LMOA	3.00E+00	3.00E+00	2.26E-15
	GMOA	8.10E-06	2.21E-04	2.24E-04		GMOA	3.00E+00	3.00E+00	1.13E+01
	MSMOA	3.24E-07	1.21E-04	1.80E-04		MSMOA	3.00E+00	3.00E+00	2.64E-03

MSMOA-Based Location Selection for Reimbursement Form Submission Terminals

In recent years, China's economic growth and heightened emphasis on science, technology, and education have led to a sustained increase in government funding for scientific innovation and higher education. This growth in funding has correspondingly increased the volume of advance reimbursement requests processed by universities. However, the large scale of university campuses, which accommodate tens of thousands of individuals, means that academic and administrative units are often dispersed across wide areas. Furthermore, the presence of multiple satellite campuses at some institutions adds another layer of geographical complexity. To address this, strategically placed reimbursement form drop boxes, collected regularly by the university finance office, can significantly improve the convenience and efficiency of the reimbursement process for the university community. This paper addresses the optimal placement problem for reimbursement form submission terminals on university campuses by applying the proposed MSMOA. This approach is shown to minimize overall infrastructure costs while ensuring full coverage of all required campus units.

Fig. 3 shows the floor plan of a university along with the locations of all school departments and colleges requiring reimbursement services. Table 4 shows the location coordinates of departments/schools with reimbursement service requests as simulation points, with the size of the demand representing the number of appointment requests for that department.

Model Establishment: Considering the university's need for comprehensive coverage of reimbursement services while minimizing costs, the variables are the volume of service demand at each marked point and the distance from the coverage point to the submission machine. The objective function is as follows:

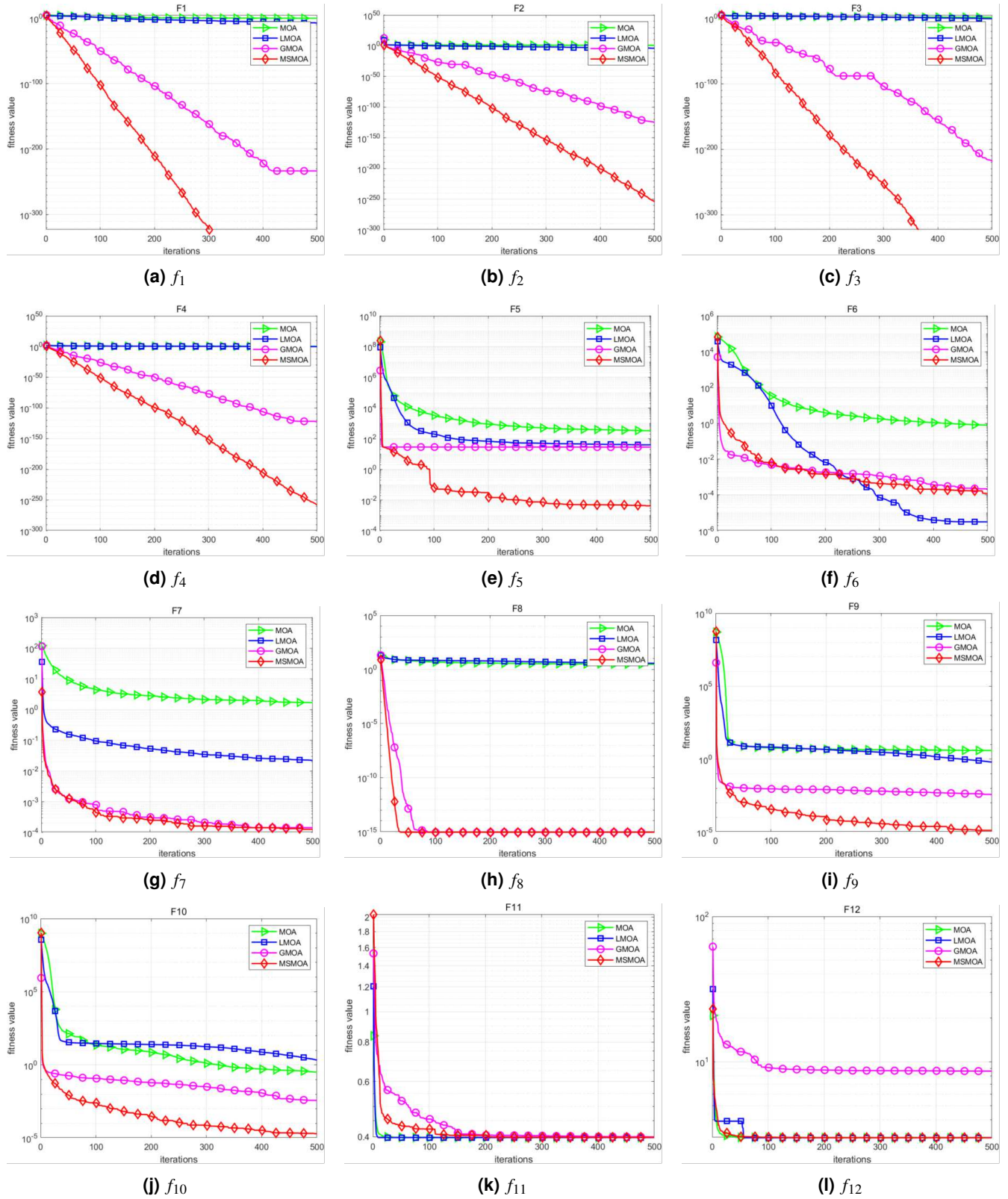


Figure 2. Convergence curves for each test function.



Figure 3. Floor plan of a university with locations of departments/schools requiring reimbursement services marked.

$$\min f(c, d) = \sum_{i=1}^M \sum_{j=1}^N c_i d_{ij} L_{ij} \quad (22)$$

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (23)$$

$$\mathbf{d} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1N} \\ d_{21} & d_{22} & \cdots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{M1} & d_{M2} & \cdots & d_{MN} \end{bmatrix} \quad (24)$$

Among these, M represents the number of reimbursement form submission terminals, N represents the number of departments/schools requiring reimbursement services, and $M < N$. c_i represents the total reimbursement appointment demand covered by the i -th submission machine; d_{ij} is the Euclidean distance between the i -th submission machine and the j -th department/school; L_{ij} denotes the coverage relationship between the i -th submission machine and the j -th department/school. If $L_{ij} \neq 0$, it indicates coverage; otherwise, it indicates no coverage.

The number of reimbursement form submission terminals allocated is insufficient, resulting in some departments/schools being located far from the machines. This will impact the convenience of submitting reimbursement forms for students and faculty in those areas, leading to a poorer reimbursement experience. Therefore, a penalty factor variable P is added simultaneously. This factor records the number of instances where the distance from the delivery machine to certain departments/schools exceeds the threshold ($k > 500$), and calculates the P -value according to (26).

$$\min f(c, d) = \sum_{i=1}^M \sum_{j=1}^N (c_i d_{ij} L_{ij} + P) \quad (25)$$

$$P = 4e^{4k} \quad (26)$$

$$k = d_{ij} \quad (27)$$

Table 4. Location coordinates and demand volume of departments/schools requiring reimbursement services.

ID	Coordinates	cost	ID	Coordinates	cost
1	(357.5,1031.25)	3824	16	(488.125,426.25)	3919
2	(137.5,990)	3754	17	(467.5,357.5)	5474
3	(55, 893.75)	3689	18	(598.125,453.75)	1794
4	(220,893.75)	690	19	(577.5,371.25)	4268
5	(61.875,770)	1680	20	(666.875,185.625)	2105
6	(206.25,756.25)	1593	21	(639.375,82.5)	1862
7	(55,550)	5220	22	(811.25,89.375)	628
8	(68.75,254.375)	2746	23	(941.875,192.5)	585
9	(192.5,254.375)	2647	24	(969.375,398.75)	2986
10	(75.625,171.875)	2050	25	(852.5,618.75)	3124
11	(206.25,171.875)	1593	26	(783.75,653.125)	3606
12	(309.375,220)	1413	27	(783.75,735.625)	2135
13	(364.375,570.625)	345	28	(838.75,756.25)	3228
14	(405.625,543.125)	219	29	(526.25,845.625)	3513
15	(460.625,591.25)	271	30	(598.125,1031.25)	308

Experimental Parameter Settings: MSMOA, GMOA, LMOA, and MOA each employed a population size of 50 and 100 iterations, running independently 30 times. M was set to 5, 6, and 7 respectively, while N represented the number of departments/schools set at 30. The cost in Table 4 denotes demand volume. Compare the four algorithms using (25) as the objective function, and record the reimbursement form submission terminals ID corresponding to the location with the minimum fitness value. Record and compare the coverage of the submission machine across departments/schools at three M -values.

Analysis of Experimental Results: The results of running the four algorithms independently 30 times are shown in Table 5. It can be seen that the coverage achieved by the four algorithms is identical when selecting the same number of reimbursement form submission terminals. Fig. 4 illustrates the coverage of department/school locations by three different numbers of reimbursement form submission terminals. The triangles indicate the placement locations of the reimbursement form submission terminals, with different colors representing the department/school locations they cover. Fig. 5 shows the convergence curves of the four algorithms when the number of reimbursement form submission terminals M is set to 5, 6, and 7, respectively. MSMOA converges faster than other algorithms, achieving the optimal fitness value within 20 iterations; it also demonstrates greater stability during the optimization process.

Based on the combined information presented in Table 5 and Fig. 4, selecting seven reimbursement form submission terminals yields the best results. Table 5 indicates that the lowest cost occurs when the number of reimbursement form submission terminals is $M=7$, followed by $M=6$, while the highest cost is incurred when $M=5$. Figure 4 indicates that when $M=5$, departments/schools in the upper-left and lower-right quadrants are farther from the reimbursement form submission terminals covering their respective zones. Meanwhile, the delivery machine at point 19 in the lower right section serves 11 departments/schools. Both situations result in a poor reimbursement submission experience for students and faculty members. When $M=6$, the coverage distribution in the upper-left section improved. However, in the lower-right section, some departments/schools remain farther from the reimbursement form submission terminals serving that area, resulting in a persistently suboptimal experience for students and faculty. In comparison, the results for $M=7$ are more reasonable. Because increasing the number of reimbursement form submission terminals would result in a single machine covering an entire department or school, significantly reducing resource utilization efficiency.

Table 5. Coverage of departments/schools by different numbers of reimbursement form submission terminals.

Number of Reimbursement Form Submission Terminals M	Location Number of the Reimbursement Form Submission Terminals	Covered Departments/Schools Location Number	Radius	Cost
5	4	1, 2, 3, 4, 5, 6, 29, 30	420	9113966.40
	7	7		
	9	8, 9, 10, 11, 12		
	19	13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23		
	26	24, 25, 26, 27, 28		
6	3	1, 2, 3, 4, 5, 6	380	8065942.98
	7	7		
	9	8, 9, 10, 11, 12		
	17	13, 14, 15, 16, 17, 18, 19, 20, 21		
	24	22, 23, 24		
7	27	25, 26, 27, 28, 29, 30	360	6745578.64
	3	2, 3, 4, 5, 6		
	7	7		
	11	8, 9, 10, 11, 12		
	17	13, 14, 15, 16, 17, 18, 19		
	21	20, 21, 22, 23		
	25	24, 25, 26, 27, 28		
	29	1, 29, 30		

Conclusions

To address the limitations of the Mayfly Optimization Algorithm (MOA), a multi-strategy improved mayfly algorithm (MSMOA) is proposed. First, a uniformly distributed initial population generated via a Logistic chaotic map is introduced to replace random initialization, thereby enhancing population diversity. Second, a nonlinear adaptive weighting factor is proposed to enhance global search capability and better balance exploration and exploitation. Third, the Lévy flight strategy is incorporated

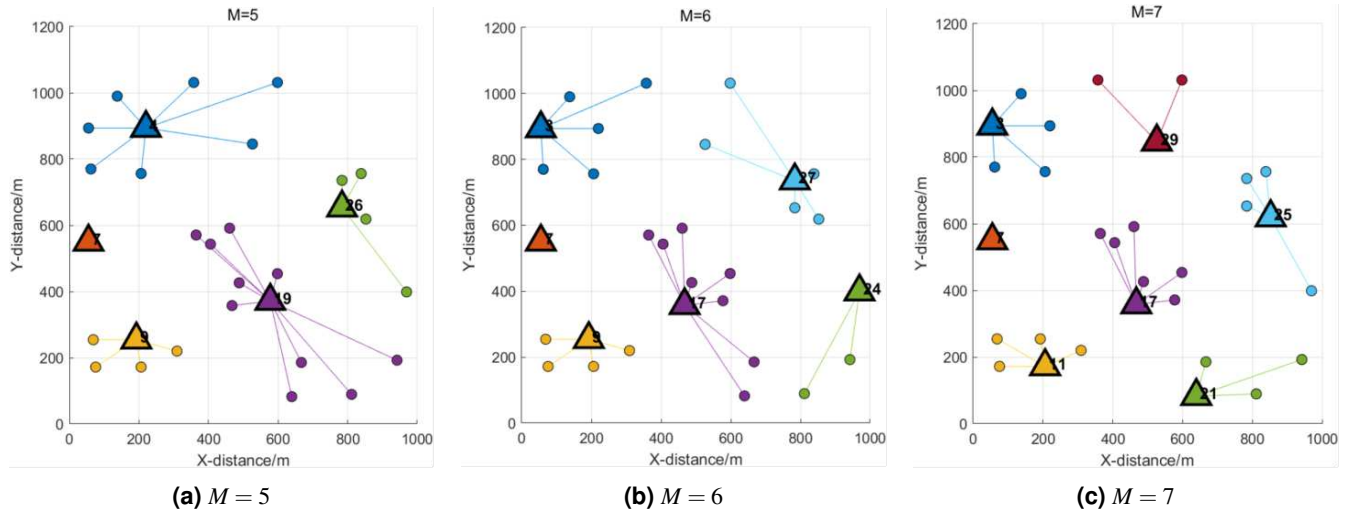


Figure 4. Coverage effect of different numbers of reimbursement form submission terminals on department/school locations.

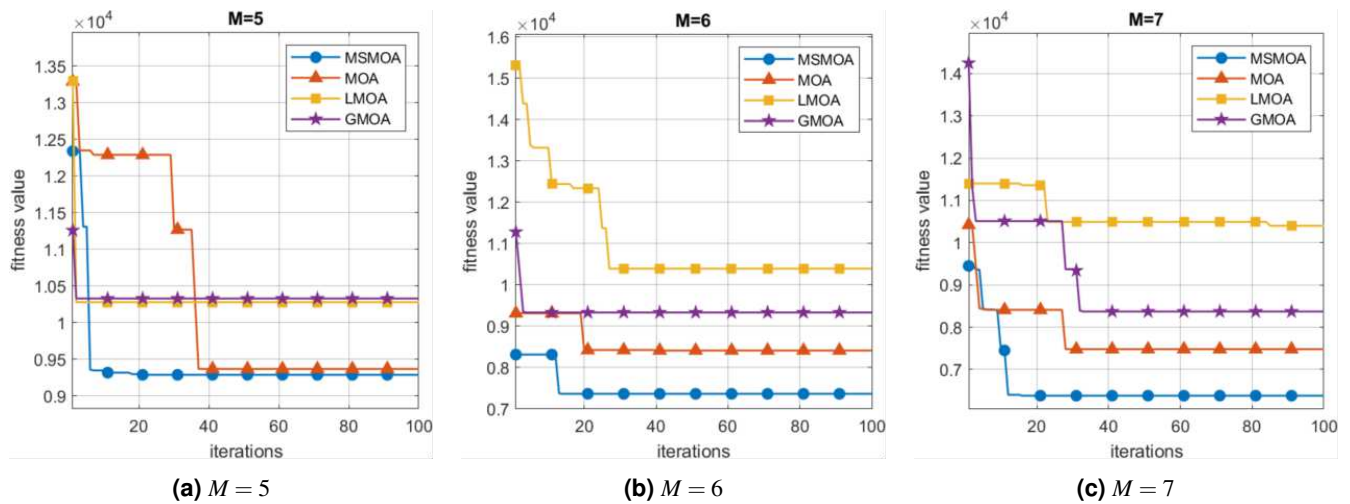


Figure 5. Convergence of different numbers of reimbursement form submission terminals.

to further augment population diversity and improve the ability to escape local optima. Finally, a Particle Swarm Optimization (PSO) mechanism is integrated. This enhancement improves the algorithm's directionality, balances global exploration and local exploitation, accelerates convergence, and directly addresses the core shortcoming of the basic MOA: premature convergence in complex optimization problems. The optimization performance and robustness of MSMOA were validated through comparative experiments against three other algorithms using 12 benchmark test functions. Furthermore, the practical feasibility of MSMOA was demonstrated through a case study on the optimal placement of university reimbursement form submission terminals. Future work will explore further refinements to MSMOA and its application to a wider range of optimization problems.

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Declarations

Competing interests

The authors declare that they have no conflict of interest.

Additional information

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