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Improvement of White Shark Algorithms Combining Logistic Maps and Gaussian Variations for Underground Logistics Network System Optimization

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지하 물류 네트워크 시스템 최적화를 위한 로지스틱 맵과 가우스 변이를 결합한 화이트 샤크 알고리즘 개선

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Abstract The planning of underground logistics pipeline networks is a crucial component of urban underground logistics systems, aiming to find the optimal construction path for the logistics network, improve logistics efficiency, and reduce operational costs. However, due to the complexity and uncertainty of the underground environment, traditional planning methods often fall short. This paper proposes a improved underground logistics pipeline network planning method based on the White Shark Optimization(WSO) algorithm, referred to as LGWSO(White Shark Algorithms Combining Logistic Maps and Gaussian Variations). The proposed method first establishes an underground space model and then uses the LGWSO algorithm for path planning. By adopting chaos initialization method and Gaussian mutation strategy, the performance of the algorithm has been effectively improved. Through simulation experiments, the algorithm has demonstrated significant advantages in optimization accuracy, convergence speed, and robustness. Compared to traditional planning methods, the proposed approach is better suited to handle the complex underground environment, providing an optimized strategy for the construction of urban logistics system underground networks.

Key Words : Underground Logistics System , Path Planning , White Shark Optimization , Chaotic Initialization, Gaussian Mutation.

요 약 지하 물류 네트워크 설계는 도시 지하 물류 시스템에서 중요한 단계로, 물류 효율을 높이고 운영 비용을 절감하기 위해 최적의 물류 네트워크 경로를 찾는 것을 목표로 한다. 그러나 지하 환경의 복잡성과 불확실성으로 인해 전통적인 설계 방법은 이를 효과적으로 해결하기 어려운 경우가 많다. 본 논문에서는 화이트 샤크 최적화 알고리즘(WSO)을 기반으로 한 개선된 화이트 샤크 최적화 알고리즘(LGWSO)을 제안하여 지하 물류 네트워크 경로를 설계했다. 제안된 방법은 먼저 지하 공간 모델을 구축한 후, LGWSO 알고리즘을 이용해 경로를 계획한다. 혼돈 초기화 방법과 가우스 변이 전략을 채택하여 알고리즘의 성능을 효과적으로 향상시켰다. 시뮬레이션 실험을 통해 제안된 알고리즘은 최적화 정확도, 수렴 속도 및 강건성 측면에서 뛰어난 성능을 보이는 것으로 검증되었다. 전통적인 설계 방법과 비교할 때, 본 방법은 복잡한 지하 환경에 더 적합하며 도시 물류 시스템의 지하 네트워크 설계에 최적화된 솔루션을 제공한다.

주제어 : 지하 물류 시스템, 경로 설계, 화이트 샤크 최적화, 혼돈 초기화, 가우스 변이

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1. Introduction

With the rapid growth of the social economy and the acceleration of global integration, logistics systems are becoming increasingly important in both production and daily life[1]. However, as urbanization continues, the population will increasingly concentrate in large cities, leading to a sharp rise in demand for urban material supply, consumer goods distribution, and various items' circulation[2 , 3]. Most large cities remain trapped in the vicious cycle of "traffic congestion-road expansion/increase in vehicles-renewed congestion." Relying solely on road expansion to meet the rapidly growing future traffic demands is insufficient and faces additional challenges such as environmental pollution and energy shortages.

To achieve sustainable development and a low-carbon economy in large cities, many transportation modes, industrial models, and management approaches, including urban logistics systems[4-6], will require restructuring. Gradually transferring ground logistics systems underground can free up urban surface space, fundamentally alleviate traffic congestion (as nearly half of urban ground vehicles are logistics vehicles)[7-9], significantly enhance logistics system speed and efficiency, reduce pollution, and conserve resources. This shift also meets the development needs of e-commerce, online shopping, and a low-carbon economy.

Underground logistics network is widely recognized as an advanced and intelligent transportation method, which can not only improve the service level of logistics network, reduce energy consumption and environmental pollution, but also alleviate the impact of natural disasters[10 , 11]. In recent years, related technologies for underground logistics (such as tunnel boring techniques using shield methods) have continuously matured. Developed Western countries highly value research on using underground logistics systems for goods transportation[12-14], viewing it as a significant high-tech field for future sustainable development. This system is set to become a core aspect of 21st-century urban underground space construction. As a dedicated public channel for logistics distribution, underground logistics can more effectively integrate distribution demands, enhance distribution efficiency, substantially reduce the occupation of ground road resources by logistics transportation, improve traffic conditions, and enhance citizens' quality of life. Research in this field is deepening, with scholars actively exploring to advance its development.

Kennedy and Eberhart et al. (1995) proposed the Particle Swarm Optimization (PSO) algorithm[15], which is an optimization technique based on swarm intelligence. It simulates the foraging behavior of bird flocks and seeks the optimal solution through the collaboration between individuals and groups. However, PSO algorithm is prone to getting stuck in local optima and has limited convergence accuracy, which cannot effectively solve discrete and combinatorial optimization problems. To address the aforementioned issues with the PSO algorithm, researchers have proposed various improvement methods. Yang et al. (2022) established a model for underground coal mining gangue logistics transportation system and proposed PSO QNMs algorithm [16], which improved the accuracy and stability of position selection, effectively avoiding the disadvantages of poor local detailed search ability of PS algorithm and sensitivity to initial values of quasi Newton algorithm. This algorithm reduces the cost value by about 42.8% compared to PSO. When solving the system node positions, the running time is one eighth of PSO algorithm, and there is still room for improvement in convergence.M Ren (2019) studied the mathematical model construction of underground logistics systems, proposed an objective function model for minimizing total costs, and solved it through genetic algorithms to verify its practical application value[17]. Man Wang (2018) addressed the problem of underground logistics node location selection, combining the principle of graded distribution and considering smooth ground traffic conditions. A multi-level node location model was constructed, and cohesion hierarchical clustering algorithm and simulated annealing algorithm were designed for solution, verifying its applicability[18]. Holland (1975) proposed the Primitive Genetic (GA) algorithm[19], which introduced many variations of the basic algorithm. However, the selection strategy and crossover operation of this algorithm are relatively simple, which cannot better obtain the global optimal solution, resulting in low algorithm performance. Therefore, some scholars have also proposed various improvement methods. Hu, Wanjie et al. (2020) developed a mixed integer programming model (MIP) [20] ,with minimal system cost and designed a two-stage optimization scheme that combines genetic based fuzzy C-means algorithm (GA-FCM), depth first search FCM (DFS-FCM) algorithm, and Dijkstra algorithm (DA). This algorithm effectively generates a central radiation network configuration with the lowest target cost, but there is room for improvement in both global search capability and local search accuracy. Hu Wanjie et al. (2020) established a dual objective MILP model considering minimum construction and transportation costs and maximum system utilization, combined with GA-MPSO algorithm and Kruskal minimum spanning tree HE&HA process[21]. This method has better convergence efficiency and optimization performance, but may experience unstable convergence speed in complex environments. Liang et al. (2023) proposed an improved combination of WSO and dynamic window method (DWA), named IWSO-DWA [22]. By using circular chaotic mapping, adaptive weighting factors, and simplex method to improve the initial solution and spatial search efficiency, the optimal path information of the improved WSO planning is incorporated into DWA to enhance the navigation performance of USV. This method has a relatively small reduction in path length cost, turning cost, and time cost, and still needs to be improved.

Swarm intelligence algorithm is a type of gradient free multi-agent optimization method that exhibits superior performance in dealing with complex coupled engineering problems. In addition, previous research on logistics path planning has mostly been based on two-dimensional space, and no scholars have yet intelligently optimized the path of underground three-dimensional space.

The White Shark Optimization Algorithm (WSO) proposed in this article is an efficient optimization method designed to tackle more complex and larger scale optimization scenarios. This algorithm combines unordered exploration and ordered development strategies, significantly improving the efficiency and speed of problem solving. When dealing with high-dimensional optimization problems, the WSO algorithm exhibits excellent performance, with fast convergence speed and a concise and robust mathematical model that can quickly and accurately find the global optimal solution to complex optimization problems.

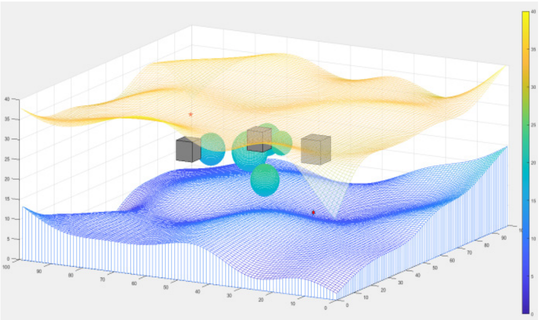
Although WSO algorithm performs well in reducing development costs and solving practical optimization problems, it is prone to getting stuck in local optima when exploring the search space, such as a relatively single search strategy, which has certain limitations. In order to enhance the accuracy and efficiency of underground logistics network planning, this study improved the performance of the WSO algorithm and developed an upgraded version of the White Shark Optimization Algorithm (LGWSO). The algorithm improves its performance by introducing chaotic mapping initialization and Gaussian mutation techniques. This algorithm first generates an initial population through logistic mapping, effectively avoiding the risk of the population falling into local optima, enhancing the diversity and initial coverage of the population, and thus improving the global search capability. The Gaussian mutation mechanism introduces random perturbations during the population evolution process, enhancing local search capabilities and further improving the convergence and accuracy of the algorithm. In addition, to verify the generality of the algorithm in different underground environments, we have prepared multiple sets of experiments covering various complex terrains and related threat conditions.

2. MODELING AND CONSTRAINTS

2.1 MODELING

The underground logistics system pipeline network planning that this article focuses on is based on the three-dimensional environment field. The underground space matrix is used for terrain modeling, and the two-dimensional matrix is combined with the Z-axis for three-dimensional visualization processing[23].

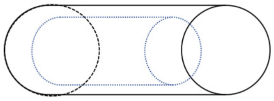
Due to geological processes such as tectonic movements, faults, and folds, the real stratum structure may undergo complex changes, causing the properties of the stratum to exhibit significant nonlinear variations in space. To smooth the terrain model, we employ a nonlinear interpolation method to resample the matrix. Additionally, certain threat areas and obstacles are also simulated and presented through the matrix.



[Fig. 1] Underground Space Terrain

Figure 1 depicts a simulated underground space scene, which includes randomly formed complex terrain located beneath the surface and marked with different colored areas to indicate potential threat zones.

Given that the underground logistics system network has a certain volume, calculating distances using only the center points of the underground network might result in the network's edges colliding with threat areas. Therefore, it is necessary to evaluate the spacing between the underground pipeline boundary and potential hazardous areas to ensure that conflicts do not occur. To achieve this, we simplified the cross-sectional model of the underground logistics network to a cylinder, as shown in Figure 2.



[Fig. 2] Underground Logistics Network

To ensure the safety of underground pipeline construction, it is necessary to avoid all hazardous areas during the construction process. To guarantee safety, the following conditions should be met:

$$d(p_i, q_j) \geq R + r \tag{1.1}$$

Where p_i is a point on the underground logistics network, q_j is a point in the threat area, R is the radius of the underground logistics network, and r is the radius of the threat area[24].

2.2 CONSTRAINTS

To evaluate the quality of the underground logistics system network planning, it is essential to establish assessment metrics. Firstly, evaluate the path length, terrain conditions, and other relevant factors to avoid increased excavation and laying costs during subsequent construction due to unreasonable path selection. Then, assign weights to each metric and, based on the analysis and comparison of path selection results, provide an evaluation formula for the path between two nodes in the underground network.

1) Path Length Calculation

The path length is calculated as shown in Equation (1.2):

$$l_i = ||obj_{ij} - obj_{i,j+1}|| \tag{1.2}$$

Where $obj_{i,j}$ and $obj_{i,j+1}$ are the position vectors of the two planned nodes, and l_i is the planned path length.

2) Height Difference Calculation

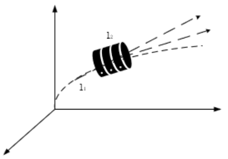
The pipeline path of the underground logistics network must account for the impact of future terrain changes on construction timing and the influence of groundwater level variations on the network path. Therefore, the construction height of the underground logistics network should also meet the conditions specified in Equation (1.3)[25].

$$h_{\max} \geq h_i \geq h_{\min} \tag{1.3}$$

Where $h_{\min}$ is the lowest elevation of the bottom wall of the logistics network, and $h_{\max}$ is the highest elevation of the top wall of the logistics network.

3) Pipeline Operating Angle

To ensure the smooth operation of rail vehicles within the underground logistics network and to reduce energy consumption, the construction of the network should aim to maintain smoothness. The inclination angle of the network is shown in Figure 3, and the smoothness of the path is expressed by Equation (1.4):



[Fig. 3] Pipeline Direction

$$\varnothing_i = \arccos\left(\frac{l_i \bullet l_{i+1}}{||l_i|| \, ||l_{i+1}||}\right) \tag{1.4}$$

Where l_i and l_{i+1} are the displacements of the path segment, and $\varnothing_i$ is the operating pitch or turning angle obtained through Equation (1.4). To ensure the smoothness of the path, the angle should be as small as possible.

Taking into account the above constraints, the quality of path planning can be evaluated using Equation (1.5):

$$F = \sum(w_l l + w_h h + w_\phi \phi) \tag{1.5}$$

Where w_l, w_h ,and w_ϕ are the weights for the path length, height difference, and segment angle, respectively.

3. Optimization of Underground Logistics Network Based on LGWSO

3.1 Basic White Shark Optimization (WSO)

The White Shark Optimization Algorithm (WSO) is an emerging metaheuristic method designed to address optimization challenges in continuous search spaces. Its design inspiration comes from the hunting habits of great white sharks in the ocean[26].Especially the mechanism by which great white sharks use their excellent auditory and olfactory abilities to navigate and search for prey. By simulating these natural behaviors, the WSO algorithm achieves a clever balance between exploration and development, thereby efficiently locating the optimal solution.

1) Initialization

The WSO algorithm starts from a randomly generated initial solution set, each solution is a potential solution. These solutions are scattered in the search space and evaluated by the objective function to determine their strengths and weaknesses. The formula is as follows:

$$w_{i,j} = l_j + r \times (u_j - l_j) \tag{1.6}$$

where w_{ij} is the position of the i white shark in the j dimension, l_j and u_j are the lower and upper bounds of the j dimension, respectively, and r is a randomly generated number within the range [0, 1].

2) Speed Update

The white shark moves based on the waves it hears and the scents it smells during the hunting process. The speed update formula is as follows:

$$v_i^{k+1} = \mu\left[v_i^k + p_1\left(w_{gbest}^k - w_i^k\right) \times c_1 + p_2\left(w_{vibest} - w_i^k\right) \times c_2\right] \tag{1.7}$$

where v_i^{k+1} is the new velocity vector of the i white shark in the $k+1$ iteration, w_{gbest}^k is the global best position found so far, w_{gbest}^k is the best known position of the i white shark, μ is the contraction factor, p_1 and p_2 are control parameters, and c_1 and c_2 are random numbers.

3) Position Update

The white shark updates its position based on the waves it hears and the scents it smells, using the following formula[27]:

$$w_i^{k+1} = \begin{cases} w_i^k \cdot \neg \oplus w_0 + u \cdot a + l \cdot b; & rand < mv \\ w_i^k + \dfrac{v_i^k}{f}; & rand \geq mv \end{cases} \tag{1.8}$$

where $\neg$ is a negative number, a and b are one-dimensional binary vectors, l and u represent the limits of the solution space, w_0 represents a logical vector, f indicates the wave movement frequency of the white shark, $rand$ is a random number created in the range from 0 to 1, and v_i^k is the speed at which the individual white shark moves with the wave.

4) Fish Schooling Behavior

The white shark updates its position based on the location of the optimal solution to simulate fish school behavior:

$$w_i^{k+1} = \frac{w_i^k + w_{gbest}^k}{2 \times rand} \tag{1.9}$$

where w_i^k and w_i^{k+1} are the two best solutions retained, and $rand$ represents a random number within the range [0, 1].

3.2 Improved White Shark Optimization

To overcome these issues, this study proposes an improved White Shark Optimization algorithm (LGWSO) based on chaotic initialization and Gaussian mutation.

When initializing the population using this method, Logistic chaotic mapping is employed, which not only enhances the diversity of the white shark population, but also broadens the exploration range of the algorithm in the search space, significantly improving the accuracy of the solution. To improve the quality of optimized solutions during the detailed search phase, this method also introduces Gaussian mutation to locally randomly adjust individuals, ensuring the algorithm's improvement in search efficiency and convergence accuracy. Thanks to these optimization measures, the LGWSO algorithm has demonstrated excellent global search capabilities in solving complex optimization problems.

1) Chaotic Initialization

The Logistic map is a well-known chaotic mapping that can generate chaotic sequences due to a simple nonlinear iterative process. Because of these dynamic characteristics, it can create diverse populations in optimization algorithms thus preventing the algorithm from converging to local optima too early. The equation for the Logistic map is given as shown in Equation (2.0):

$$x_{n+1} = r \cdot x_n \cdot (1 - x_n) \qquad (2.0)$$

Where x_n is the value at the n iteration, taking a range between (0, 1); r is the control parameter. When $r = 4$, When the system is in a state of complete chaos, the generated sequence exhibits extremely high random distribution and comprehensive traversal characteristics. This feature can effectively prevent the algorithm from prematurely converging to local optima during the search process, thereby enhancing its global search efficiency.

The initialization formula of the original White Shark Optimization algorithm is given by:

$$x_i = lb_i + (ub_i - lb_i) \cdot rand \qquad (2.1)$$

Where x_i is the initialized population member, lb_i and ub_i are the lower and upper bounds of the variables, respectively, and $rand$ is a random number used to generate a value within the bounds[28].

In the optimization problem of the underground three-dimensional space, the Logistic chaotic mapping is introduced into the three-dimensional space for the initialization of the white shark population. The specific steps are as follows:

(1) Set parameters and initial values

Set the control parameter of the Logistic map to ensure a fully chaotic state. Determine the initial value within the range (0, 1), avoiding special values (such as 0.25, 0.5, 0.75) to ensure chaotic characteristics.

(2) Generate three-dimensional chaotic sequences

For each dimension, generate chaotic sequences using the Logistic map formula as shown in Equation (2.2):

$$\begin{aligned} x_{n+1} &= r \cdot x_n \cdot (1 - x_n) \\ y_{n+1} &= r \cdot y_n \cdot (1 - y_n) \\ z_{n+1} &= r \cdot z_n \cdot (1 - z_n) \end{aligned} \qquad (2.2)$$

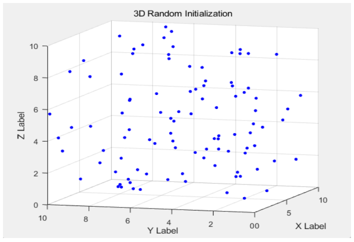
(3) Mapping the Search Space

Map the generated chaotic sequences into the specific range of the three-dimensional search space to obtain the initial positions of the population. The mapping formula is shown in Equation (2.3):

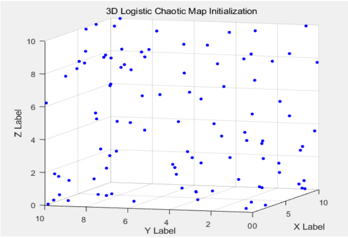
$$\begin{aligned} x_i &= lb_x + (ub_x - lb_x) \cdot x_n \\ y_i &= lb_y + (ub_y - lb_y) \cdot y_n \\ z_i &= lb_z + (ub_z - lb_z) \cdot z_n \end{aligned} \qquad (2.3)$$

where lb_x , lb_y , lb_z and ub_x , ub_y , ub_z are the lower and upper bounds of the x, y, and z dimensions, respectively, and x_n , y_n , z_n are the elements in the chaotic sequence.

(4) Experimental Verification



[Fig. 4] Three-Dimensional Population Distribution Generated by Random Initialization of White Sharks



[Fig. 5] Three-Dimensional Population Distribution Generated by Logistic Chaotic Mapping

Figures 4 and 5 show the three-dimensional population distribution generated by the random initialization of the white shark and by using the Logistic chaotic mapping, respectively. The initialization method using logistic chaotic mapping has significant advantages over the original initialization algorithm in terms of population distribution uniformity and global coverage ability.

By choosing logistic chaotic map for initializing the population, the population produced will be more evenly distributed throughout the entire search space, thus, improving the global search performance and avoiding local optimal traps. Moreover, it additionally helps the optimization algorithms in the high-dimensional complex search areas to be utilized more efficiently and also it is contributing to the improvement of accuracy and speed of the algorithm to converge, offering a more robust and efficient way for dealing with complex optimization problems.

2) Gaussian Mutation Mechanism

To escape from local optima, mutation operations are included in the evolution of optimization algorithms to increase the diversity of the population. Gaussian mutation is a commonly applied mutation strategy that improves local search ability by introducing small random variations in some dimensions of individuals. The exact formula is:

$$x' = x + N(0,\sigma^2) \tag{2.4}$$

where x is the current coordinate of the individual, and $N(0,\sigma^2)$ denotes a random number sampled from a Gaussian distribution with a mean of 0 and a variance of σ^2 .

The steps for using Gaussian mutation in the improved White Shark Optimization (WSO) algorithm in a three-dimensional space are as follows:

(1) Set the mutation judgment factor gt

The mutation judgment factor gt controls the probability of mutation occurrence, and its value increases linearly with the number of iterations, as shown in Equation (2.5):

$$gt = \frac{t}{T} + 0.5 \tag{2.5}$$

where t is the current iteration number, T is the total number of iterations of the algorithm, and 0.5 is the base mutation probability at the initial stage.

(2) Determine whether to perform mutation

In each iteration, generate a random number between 0 and 1, denoted as $rand$. If $rand \leq gt$, apply Gaussian mutation to the individual.

(3) Execute Gaussian mutation

Randomly select one or more dimensions in the three-dimensional coordinates of the individual for mutation. The specific formula is:

$$\begin{aligned} x_i' &= x_i + Gaussian(0,\sigma^2) \\ y_i' &= y_i + Gaussian(0,\sigma^2) \\ z_i' &= z_i + Gaussian(0,\sigma^2) \end{aligned} \tag{2.6}$$

In which, (x_i, y_i, z_i) is the three-dimensional coordinate before mutation, and (x_i', y_i', z_i') is the new coordinate after mutation. σ controls the mutation amplitude and can be adjusted at different iteration stages to balance exploration and exploitation.

3.3 Underground Logistics Network Planning Based on LGWSO

The flowchart of the underground logistics network planning based on LGWSO is shown in Figure 11. The steps are summarized as follows:

Step 1: Establish a 3D model based on terrain data.

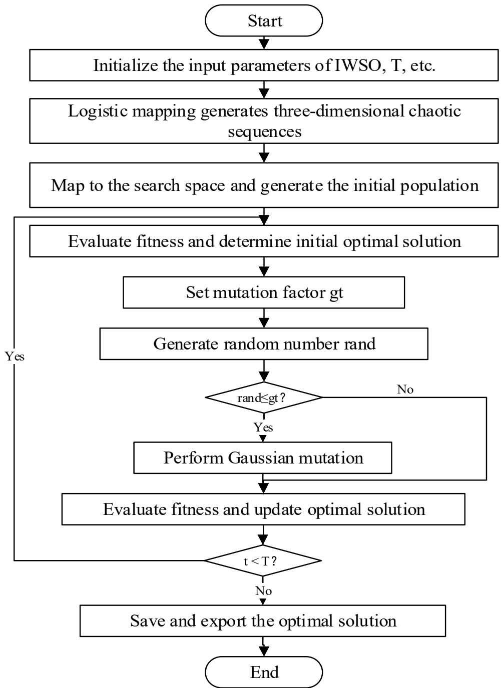
Step 2: Generate the initial population using Logistic chaotic mapping to enhance the diversity of the population.Eq. (2.3)

Step 3: Utilize the global exploration mechanism of the White Shark Optimization algorithm, combined with chaotic sequences to enhance search capability.Eq. (2.1)&Eq. (2.2)

Step 4: Introduce a Gaussian mutation operator in the local development stage to improve the ability of individuals to escape local optima.Eq. (2.4)

Step 5: Dynamically adjust the parameters of chaotic mapping and Gaussian mutation to control the convergence speed and accuracy of the algorithm.Eq. (2.5)

Step 6: Iterate the above steps continuously until the termination condition is met.



[Fig. 6] Path Planning Process Using LGWSO Algorithm

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Algorithm: LGWSO

Inputs:
N: Population size,
T: Maximum number of iterations,
r: Logistic map control parameter (default: 4),
lb, ub: Lower and upper bounds for the search space
σ: Standard deviation for Gaussian mutation
Outputs:
The position and fitness value of the best solution found
Begin:
    Initialize population X_i (i = 1, 2, ..., N) using Logistic chaos map
    For each dimension j in X:
X_ij = lb_j + (ub_j - lb_j) * Logistic_map_random() Equation (13)

While t < T do
    Calculate initial fitness values for each individual in the
    population Update control parameters mv, Ss, alpha

For each individual X_i in the population do
if rand < mv then
Update the position of X_i using Equation (14)
else
Update the position of X_i using Equation (16)
end if
end for

For each individual X_i in the population do
if rand < Ss then
if t == 1 then
                Move the population closer to the optimal solution
                using Equation (15)
else
Apply Gaussian mutation with σ to the population using Equation
(16)
end if
end if
end for

Calculate new fitness values for each individual
Update the best known solutions
t = t + 1
End while

Return the best optimal solution found
End
```

4. Experimental Results and Analysis

In this study, six standard test functions were used to evaluate the performance of the optimized LGWSO algorithm. In addition, the superiority of the proposed algorithm in path planning was further confirmed through comparative analysis with particle swarm optimization (PSO), genetic algorithm (GA), and original white shark optimization (WSO) algorithms. The simulation test environment is as follows: operating system Win11, 64-bit, 8 GB memory, CPU Intel i7 1165G7, main frequency 2.80GHz, power supply 65W, simulation software Matlab R2023b.

4.1 Benchmark Test Experiments

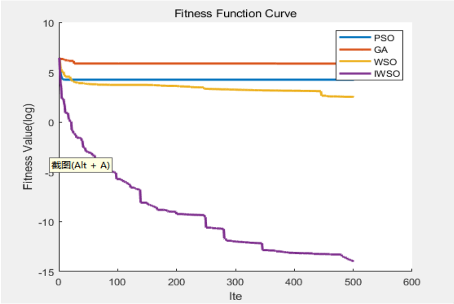
In order to evaluate the effectiveness of the proposed improved algorithm in global optimal solution search, this paper adopted six standard test functions shown in Table 1, covering both unimodal and multimodal types. The study conducted in-depth analysis by comparing the performance of LGWSO algorithm with PSO, GA, and WSO. All experiments were conducted under uniform testing conditions and parameter settings to ensure the fairness of the comparison.

〈Table 1〉 Six benchmark functions

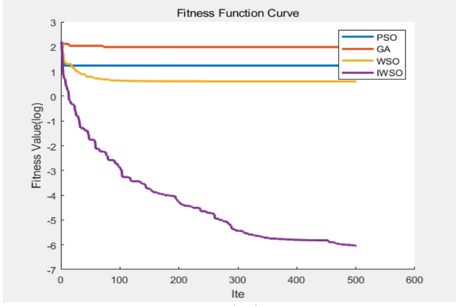
Function	Dimension	Interval
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-10,10]
$F_2(x) = \max_{i=1}^{n} \lvert x_i \rvert$	30	[-10,10]
$F_3(x) = \sum_{i=1}^{n} i \bullet x_i^4$	30	[-10,10]
$F_4(x) = \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i) +$	30	[-10,10]
$F_5(x) = -20\exp\left[\sqrt{\sum_{i=1}^{n} x_i^2/n}\right] - \exp(\sum_{i=1}^{n}\cos(2\pi x_i)/n) + 20 + e$	30	[-10,10]
$F_6(x) = \frac{1}{4000}\sum_{i=1}^{n-1} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	30	[-10,10]

During the experiment, 500 iterations were performed on each benchmark test function to calculate the average result and standard deviation. Subsequently, the experimental data was analyzed to evaluate the convergence rate, accuracy, and robustness of the algorithm. The results of the two experiments are presented in the form of charts and tables, respectively.

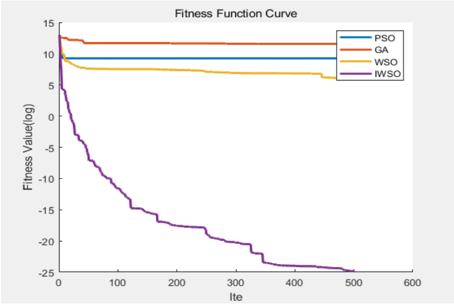
Figure 7 shows the convergence curves of the four optimization algorithms under different test functions. LGWSO demonstrates a faster convergence speed in most test functions, significantly outperforming the other algorithms. LGWSO exhibits strong exploratory capabilities in the initial phase, followed by continuous optimization in the mid and late stages, with a steady decrease in the fitness value. Has demonstrated excellent adaptability and stability, while achieving an appropriate balance between exploring new strategies and utilizing existing ones. The results show that LGWSO has the most significant effect in exploring optimal solutions in complex search environments, and can demonstrate strong robustness and flexibility in dealing with various optimization challenges.



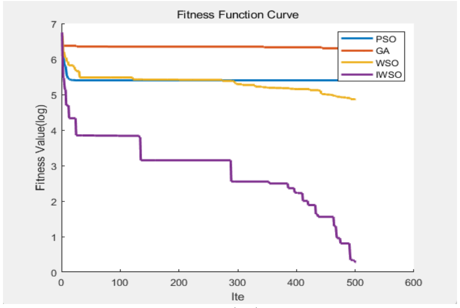
$F_1(x)$



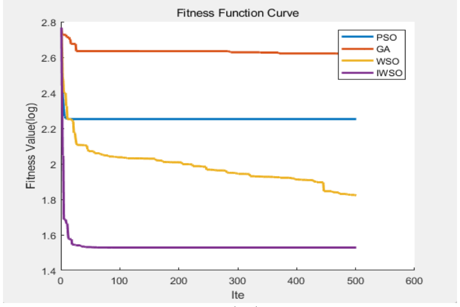
$F_2(x)$



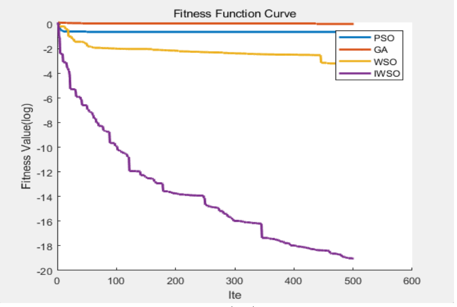
$F_3(x)$



$F_4(x)$



$F_5(x)$



$F_6(x)$

[Fig. 7] Comparison of fitness function curves for different optimization algorithms

It is found from Table 2 that the mean value and standard deviation of the LGWSO algorithm on six tested functions are far smaller than those of the other three algorithms, thus it is possible to conclude that the LGWSO algorithm can find better solutions in optimization problems. The standard deviation of the LGWSO algorithm is the least out of all the test functions, which indicates that the optimized algorithm has a high degree of consistency and reliability too. So LGWSO is more remarkable in handling various types of optimization problems and can provide excellent optimization performance in the most complex search spaces.

〈Table 2〉 Comparative analysis of performance of 4 swarm intelligence algorithms

Function	Measure	PSO	GA	WSO	LGWSO
F1	Ave	6.92919e+01	3.27276e+02	1.22272e+01	8.65057e-07
	Std	9.65118e-01	1.25887e+01	4.12109e-01	2.54236e-09
F2	Ave	3.43700e+00	7.26580e+00	1.81980e+00	2.35100e-03
	Std	4.14370e-02	7.99120e-03	1.72450e-02	1.42070e-04
F3	Ave	1.03433e+04	1.02752e+05	4.16214e+02	1.54193e-11
	Std	2.29918e+02	1.24737e+04	3.17014e+01	1.49321e-12
F4	Ave	2.21640e+02	5.44628e+02	1.29403e+02	1.31762e+00
	Std	8.56667e+00	2.42051e+01	7.16621e+00	8.70081e-01
F5	Ave	9.50862e+00	1.37019e+01	6.18114e+00	4.61142e+00
	Std	3.74750e-02	5.50580e-02	6.82760e-02	2.18640e-08
F6	Ave	5.32100e-01	1.01750e+00	4.06870e-02	5.33070e-09
	Std	2.84750e-02	5.00410e-03	1.74920e-03	5.27050e-10

An overview of data in Figure 7 and Table 2 states that the LGWSO algorithm is the standout performer compared to others in optimal value acquisition, the average value performance, and stability. Despite the fact that the special features of certain functions can have a certain effect on the performance, LGWSO shows faster convergence speed and it is stably able to converge to the optimal solution with less number of iterations. Furthermore, the standard deviation of LGWSO is relatively smaller than others indicating the stronger algorithm robustness. Such results testify to the effectiveness and reliability of the LGWSO algorithm.

The experimental data suggested that optimizing the LGWSO algorithm by combining chaotic mapping initialization and Gaussian mutation techniques can achieve the right balance between random exploration and ordered search. In the beginning, even though the algorithm is optimized it has a wider range of exploration, but in the next step, it moves to a more exact search, which leads to the effective broadening of the search range and speeding up the convergence process. The diversity of the initial population and the expansion of coverage are due to the adoption of chaotic mapping, while Gaussian mutation introduces randomness in the local search stage, improving the convergence performance and accuracy of the algorithm. In addition, the introduction of behavioral rules for white shark populations avoids falling into local optima, further enriching the diversity of the population. These optimization strategies significantly improve the overall search efficiency of the LGWSO algorithm in solving complex optimization problems, not only accelerating the convergence process of the algorithm, but also enhancing the accuracy of the solution results.

Based on the above experimental results and analysis, we can conclude that the LGWSO algorithm has significant advantages in the application of underground logistics network planning, providing better path planning schemes and improving the efficiency and stability of the logistics system.

4.2 Underground Logistics System Network Planning Experiment

To evaluate the performance of LGWSO in solving the path planning problem of underground logistics pipeline networks, we conducted four sets of experiments. The maps' terrain data were randomly generated, and the path planning tasks were simulated in different terrain environments to test the algorithm's effectiveness, adaptability, and robustness.

The terrain data used in the experiments are shown in Table 3. To ensure the diversity and comprehensiveness of the experiments, the terrain data cover different levels of complexity and obstacle distribution. Each terrain environment contains a certain number of obstacles, represented as black spheres and cubes. The specific data are as follows:

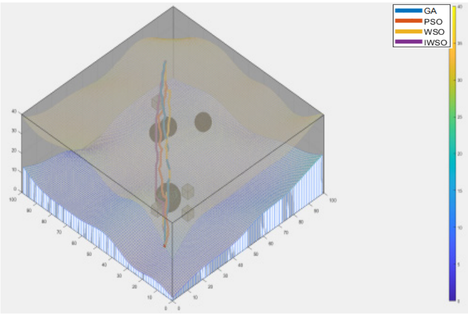
When planning the underground logistics system network path, the PSO, GA, WSO, and the proposed LGWSO algorithms were used. All algorithms followed their original rules. The population size for each algorithm was set to 20, and each algorithm was executed for 50 iterations.

〈Table 3〉 Experimental terrain data

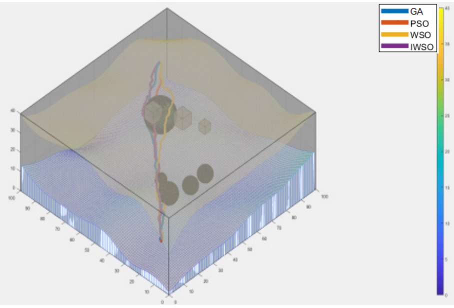
Terrain	Type	Threat Location (x,y,z)	Param (length, width, height)
Terrain1	2	30 , 33 , 18	6 , 6 , 6
	2	60 , 63 , 21	4 , 4 , 4
	1	40 , 30 , 13	4 , 4 , 4
	2	80 , 60 , 14	4 , 4 , 4
	1	20 , 30 , 15	4 , 4 , 4
	1	70 , 80 , 14	4 , 4 , 4
	1	30 , 20 , 13	4 , 4 , 4
	2	60 , 70 , 14	4 , 4 , 4
Terrain2	2	30 , 30 , 20	5 , 5 , 5
	1	55 , 65 , 23	6 , 6 , 6
	2	45 , 30 , 16	4 , 4 , 4
	1	75 , 50 , 15	4 , 4 , 4
	2	35 , 40 , 19	3 , 3 , 3
	2	65 , 70 , 20	8 , 8 , 8
	2	50 , 25 , 22	4 , 4 , 4
	1	65 , 55 , 20	6 , 6 , 6
Terrain3	1	40 , 45 , 25	5 , 5 , 5
	2	65 , 75 , 18	4 , 4 , 4
	1	55 , 35 , 20	6 , 6 , 6
	2	62 , 65 , 20	6 , 6 , 6
	2	25 , 32 , 19	15 , 15 , 15
	2	60 , 50 , 23	3 , 3 , 3
	1	45 , 70 , 19	5 , 5 , 5
	2	70 , 60 , 21	4 , 4 , 4
Terrain4	2	50 , 50 , 19	11 , 11 , 11
	1	30 , 35 , 18	9 , 9 , 9
	2	65 , 55 , 15	3 , 3 , 3
	1	75 , 70 , 17	5 , 5 , 5
	2	40 , 50 , 24	4 , 4 , 4
	1	55 , 65 , 16	15 , 15 , 15
	2	35 , 25 , 20	4 , 4 , 4
	1	60 , 40 , 18	6 , 6 , 6

The planning of an underground logistics pipeline network faces complex geological conditions. The network should aim to minimize pipeline length, avoid excessive elevation differences, and reduce excavation depth to lower construction costs and future maintenance expenses.

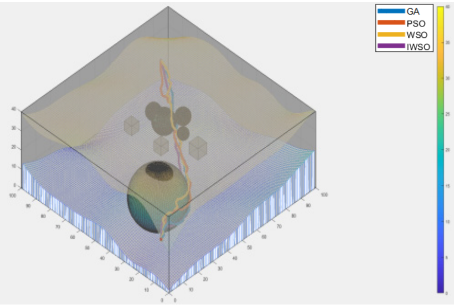
Figure 8 shows the path planning results of four optimization algorithms (GA, PSO, WSO, LGWSO) across four different terrains (Terrain1, Terrain2, Terrain3, Terrain4). As can be clearly seen from the figure, the LGWSO algorithm outperforms the other algorithms in all terrains. Specifically, the paths generated by the LGWSO algorithm are smoother, avoid more obstacles, and have shorter overall lengths. This indicates that the LGWSO algorithm has superior global search and local optimization capabilities when handling complex terrain path planning problems, enabling it to find higher-quality path solutions.



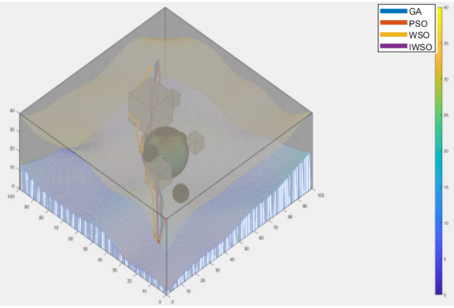
Terrain1



Terrain2



Terrain3



Terrain4

[Fig. 8] Planned path under large range and multi-factor terrain

⟨Table 4⟩ The results of 50 times of execution of all the compared algorithms

Terrain	Cost	PSO	GA	WSO	LGWSO
Terrain1	Path	126.11	124.84	129.72	122.28
	Elevation Difference	7.00	6.00	9.00	1.00
	Fitness	100.8904	99.8693	99.6308	97.7683
Terrain2	Path	129.74	128.39	132.64	129.40
	Elevation Difference	6.00	6.00	8.00	4.00
	Fitness	103.7929	102.7140	102.4119	99.7330
Terrain3	Path	135.41	135.21	137.78	134.06
	Elevation Difference	7.00	6.00	7.00	6.00
	Fitness	108.3257	108.1681	109.3701	105.996
Terrain4	Path	133.97	129.65	136.66	125.25
	Elevation Difference	8.00	7.00	4.00	5.00
	Fitness	107.1799	103.7201	106.9194	100.2016

As shown in Table 4, the application of the LGWSO algorithm results in significantly better pipeline length, elevation difference, and fitness values for the underground logistics system network compared to the other three algorithms. Specifically, the pipeline length is reduced by 0.26% to 8.36%, the elevation difference by 14.29% to 37.50%, and the fitness value by 1.87% to 6.51%. The integration of chaos initialization and Gaussian mutation strategy significantly enhances the algorithm's global exploration and local fine-tuning capabilities, enabling it to discover better solutions when solving optimization problems.

As shown in Figure 8 and Table 4, when solving the problem of underground logistics system pipeline network planning, the path obtained by using the improved algorithm exhibits higher efficiency and stability compared to other algorithms, highlighting the advantages of this algorithm in dealing with complex problems.

5. Conclusion

This study aims to apply the optimized LGWSO algorithm to the pipeline planning of underground logistics systems. This algorithm greatly enriches the diversity of the initial population by introducing a chaotic mapping initialization strategy, and enhances the local search efficiency of the algorithm with the help of Gaussian mutation technology, thus achieving significant results in the exploration and development of the solution space. Through implementing four sets of experiments, we have verified the efficiency and reliability of the improved algorithm in underground logistics system pipeline planning tasks.

In the following research, we will continue to explore the dynamic scheduling optimization problem of underground logistics system networks based on the results of this study, aiming to further enhance the intelligence and adaptability of the system.

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〈관심분야〉

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digital communication systems, Big Data