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Optimization of Underground Logistics System Node Location Based on Adaptive and Dynamic Grey Wolf Optimization Algorithm

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적응형 및 동적 GWO(Grey Wolf Optimization) 알고리즘을 활용한 지하 물류 시스템 노드 위치 최적화

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Abstract With the increasing scarcity of urban land resources and the continuous growth of logistics demand, the Underground Logistics System (ULS) has emerged as a promising solution for alleviating urban traffic congestion and enhancing logistics efficiency. This study proposes an optimization method for underground logistics node location based on the Adaptive and Dynamic Grey Wolf Optimization (ADGWO) algorithm, aiming to address the challenges of multi-tiered node optimization in complex urban environments. A four-tier underground logistics node network is constructed in this study, consisting of logistics demand nodes, distribution nodes, transfer nodes, and urban logistics center nodes, forming a tree-like topology. In terms of optimization, the ADGWO algorithm incorporates a dynamically nonlinear convergence factor adjustment and an adaptive inertia weight, which enhances global search capability and mitigates premature convergence. Experimental results demonstrate that compared to traditional Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), ADGWO exhibits significant improvements in convergence speed and optimization accuracy. The findings of this study provide theoretical support for the future planning and optimization of underground logistics systems.

Key Words : Underground Logistics System (ULS), Node Location Optimization, GWO, Adaptive Grey Wolf Optimizer (ADGWO), Dynamic Convergence Factor, Adaptive Inertia Weight, Multilevel Node Planning.

요 약 도시 토지 자원의 부족과 물류 수요의 지속적인 증가로 인해, 지하 물류 시스템(Underground Logistics System, ULS)은 도시 교통 혼잡을 완화하고 물류 효율을 향상시킬 수 있는 효과적인 대안으로 주목받고 있다. 본 연구는 복잡한 도시 환경에서의 다계층 물류 노드 최적화 문제를 해결하기 위해, 적응형 동적 GWO 최적화 알고리즘(Adaptive and Dynamic Grey Wolf Optimization, ADGWO) 기반의 지하 물류 노드 위치 최적화 기법을 제안한다. 본 시스템은 물류 수요 노드, 분배 노드, 환승 노드, 도시 물류 중심 노드로 구성된 4계층 트리 형태의 노드 네트워크 구조를 기반으로 하며, 각 노드 간 효율적인 연결과 배치를 목표로 한다. ADGWO 알고리즘은 동적으로 비선형 조정되는 수렴 인자와 적응형 관성 가중치를 도입하여 전역 탐색 능력을 향상시키고 조기 수렴을 방지한다. 실험 결과, 제안된 알고리즘은 기존의 GWO 최적화, 입자 군집 최적화(PSO), 유전자 알고리즘(GA) 대비 우수한 수렴 속도와 최적화 정확도를 나타냈다. 본 연구는 향후 지하 물류 시스템의 계획 및 구축을 위한 이론적 기반을 제공할 수 있다.

주제어 : 지하 물류 시스템, 노드 위치 최적화, GWO, ADGWO, 도시 물류, 메타휴리스틱

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1. Introduction

With the rapid advancement of global urbanization, the population density in large and medium-sized cities continues to rise, leading to an increasing demand for urban freight transportation[1]. However, traditional surface logistics systems face significant challenges, including limited road capacity, escalating environmental pollution, and persistent traffic congestion, making it difficult to achieve efficient, sustainable, and low-impact logistics operations[2]. As a result, the Underground Logistics System (ULS) has gained considerable attention as an innovative urban logistics infrastructure solution[3].

ULS utilizes dedicated underground pipelines or tunnels to enable automated cargo transportation and distribution, thereby forming a three-dimensional logistics network that operates parallel to or complements surface transportation[4]. Several countries, including the Netherlands, Switzerland, and Japan, have conducted extensive research and development in the field of underground logistics systems, with a focus on tunnel construction, pipeline transportation systems, and autonomous delivery technologies, achieving notable progress.

However, in the planning and implementation of ULS, node location selection is a critical factor that determines the system's operational efficiency and economic viability[5]. Given the complex geographical constraints, substantial construction investment, and dynamically evolving logistics demand, identifying the optimal or near-optimal node layout through efficient optimization methods has become a major challenge in both academic research and engineering applications.

In recent years, intelligent optimization algorithms have been widely applied to optimize node selection in underground logistics systems (ULS)[6]. These algorithms have demonstrated excellent performance in solving large-scale, nonlinear, multi-objective, and constrained optimization problems[7]. Researchers have proposed various intelligent optimization algorithms for logistics node selection, including:

Genetic Algorithm (GA): GA simulates the process of natural selection through selection, crossover, and mutation, exhibiting strong global search capabilities. Zhou Anbang (2018) [8] applied GA to optimize urban underground logistics node selection, verifying its convergence and stability in solving complex site selection problems.

Particle Swarm Optimization (PSO): PSO is inspired by swarm intelligence, where individuals interact to update their positions and search for optimal solutions. Yang Shengli et al. (2022) [9] proposed PSO-QNMs, an improved PSO-based approach that significantly enhances node selection efficiency in underground logistics systems.

Firefly Algorithm (FA): FA utilizes the attraction behavior of fireflies to guide the search process, demonstrating strong capabilities in solving nonlinear problems. Meng Xiaohe (2020) [10] applied an improved FA algorithm to optimize underground logistics distribution center layouts, significantly reducing total logistics costs.

Differential Evolution (DE): DE optimizes solutions through differential mutation and crossover operations, making it effective for solving complex optimization problems. Xia Yuanchao (2022) [11] employed DE for underground logistics system network planning, proving its ability to enhance solution quality and reduce computation time.

Whale Optimization Algorithm (WOA): WOA simulates the hunting behavior of whales, offering strong global search capabilities. Li Xiaodi (2021) [12] adopted an improved WOA for urban underground logistics node selection, demonstrating its effectiveness in solving complex constrained problems.

Hybrid Immune Genetic Algorithm (HIGA): He Yonggui et al. (2018) [13] introduced HIGA, which integrates immune algorithm principles with GA, improving both solution precision and search efficiency. Their research showed that HIGA outperforms traditional GA, achieving faster convergence and higher solution quality in underground logistics node selection problems.

Modified Whale Optimization Algorithm (MWOA): Yan Wentao (2015) [14] proposed a modified WOA for underground logistics node planning, introducing a new position update mechanism that enhances WOA's optimization capability in high-dimensional search spaces while avoiding local optima traps.

Greedy Genetic Algorithm (Greedy-GA): Wang Sulin et al. (2020) [15] combined Greedy Algorithm with GA for underground logistics node selection, demonstrating improved efficiency and cost-effectiveness compared to conventional GA.

Among these algorithms, swarm intelligence optimization methods have gained significant attention due to their robust stability and strong search capabilities in high-dimensional problems. One of the most widely adopted techniques is the Grey Wolf Optimizer (GWO), initially proposed by Mirjalili et al. in 2014 [16]. GWO is characterized by its simple structure, minimal parameter requirements, and ease of implementation, making it effective in solving continuous, discrete, and hybrid optimization problems. The algorithm emulates the hunting behavior of grey wolves, where alpha (α), beta (β), and delta (δ) wolves guide the remaining omega (ω) wolves toward optimal solutions through tracking, encircling, and attacking mechanisms [8]. However, standard GWO faces challenges such as premature convergence and local optima issues, particularly as the problem dimension increases and constraints become more complex [9].

To address these challenges, this study proposes an optimization method based on the Adaptive and Dynamic Grey Wolf Optimization (ADGWO) algorithm. Compared to the standard Grey Wolf Optimizer (GWO), ADGWO introduces several key improvements:

Dynamic Convergence Factor Adjustment: The convergence factor is adaptively adjusted based on the standard deviation of the population's positions, enhancing global search capability while mitigating premature convergence.

Adaptive Inertia Weight: The introduction of inertia weight allows the search step size to be dynamically adjusted, improving search stability and directional consistency.

Optimized Position Update Strategy: The position update formula integrates inertia weight with the α, β, and δ wolves, achieving a more balanced transition between global exploration and local exploitation.

This study aims to:

Construct a four-tier underground logistics node network with demand nodes, distribution nodes, transfer nodes, and urban logistics center nodes, defining their connectivity and operational constraints.

Develop ADGWO based on the standard GWO, with a focus on analyzing the impact of dynamic convergence factor and adaptive inertia weight on convergence speed and optimization accuracy.

Conduct experimental validation using standard benchmark functions and underground logistics system node selection cases, evaluating the optimization performance of ADGWO in comparison to GWO and other optimization algorithms.

Assess the practical feasibility and application prospects of underground logistics node selection, providing technical support for investment planning and policy formulation in underground logistics systems.

In the subsequent chapters:

Chapter 2 elaborates on the mathematical modeling and constraints of this study.

Chapter 3 introduces the GWO and ADGWO algorithms, detailing their improvement strategies.

Chapter 4 presents experimental validation and result analysis.

Chapter 5 provides case studies, demonstrating the optimization performance of ADGWO in practical network planning.

Chapter 6 concludes the study by summarizing key findings and exploring future research directions.

This study aims to provide an efficient and scalable optimization framework for underground logistics systems, ensuring cost-effective and high-performance node selection solutions for future urban infrastructure development.

2. Modeling and Constraints

2.1 Four-Tier Underground Logistics Nodes and Network Structure

2.1.1 Definition of the Four-Tier Nodes

In the Underground Logistics System (ULS), nodes can be categorized into four distinct types based on their functionality and hierarchical level, forming a top-down multi-tiered structure. The definitions of these node types are as follows:

Logistics Demand Nodes

These nodes represent the terminal demand points where goods are either generated or received within the city. Typical examples include large shopping malls, hospitals, residential communities, and industrial parks. Demand nodes are directly related to urban consumption or supply needs, forming the lowest level of the logistics network where goods originate or are distributed.

Logistics Distribution Nodes

Distribution nodes serve as intermediate hubs that distribute goods from urban logistics centers or transfer nodes to demand nodes. Conversely, they also aggregate goods from surrounding demand nodes for consolidated upstream transportation. These nodes play a dual role in the network by facilitating both distribution and collection of goods.

Logistics Transfer Nodes

Acting as regional hubs or transshipment centers, transfer nodes handle cargo sorting, consolidation, temporary storage, and onward transportation to urban logistics centers or distribution nodes. The existence of transfer nodes significantly enhances the overall scheduling efficiency of the logistics network by reducing direct long-distance connections and optimizing cargo flow.

Urban Logistics Center Nodes

The highest-level logistics hubs, urban logistics centers serve as the primary aggregation and management points within the underground logistics system. These nodes are responsible for connecting with other city logistics systems and mainline transportation networks while forming a multi-tiered distribution structure with transfer and distribution nodes. The number of urban logistics centers is typically limited, and in some cases, only one centralized logistics center is designated for managing and controlling the entire network.

2.1.2 Network Structure and Tree-Like Topology

Based on the four-tier node hierarchy, the underground logistics network follows a tree-like topology, ensuring clear hierarchical cargo flow from top to bottom. The structure is designed as follows:

A single urban logistics center (or a small number of centers) connects multiple transfer nodes.

Each transfer node serves multiple distribution nodes.

Each distribution node covers a specific set of demand nodes.

The tree-like structure minimizes redundant pathways, enhances transportation efficiency, and reduces infrastructure costs. By adopting a top-down hierarchical connection strategy, the network establishes a primary cargo flow path as follows:

Urban Logistics Center↔Transfer Nodes↔Distribution Nodes↔Demand Nodes

For network planning, this study employs an approximate "tree-like" or "hierarchical" structure, ensuring efficient routing, cost-effective construction, and scalable logistics management.

2.2 Cost Function

The core objective of this study is to minimize the total cost of the underground logistics network by optimizing the number and location of distribution nodes (n_p) and transfer nodes (n_t), as well as their assignment strategies, while satisfying a series of constraints. The total cost primarily consists of node construction costs and pipeline construction costs.

2.2.1 Node Construction Cost

The node construction cost includes:

Construction cost of distribution nodes : $n_p \times C_p$

Construction cost of transfer nodes : $n_t \times C_t$

Construction cost of urban logistics center nodes : C_c

Thus, the total node construction cost can be expressed as formula 1.1:

$$C_{node} = n_p \cdot C_p + n_t \cdot C_t + C_c \qquad (1.1)$$

where:

n_p= Number of selected distribution nodes

C_p= Unit construction cost of a distribution node

n_t = Number of selected transfer nodes

C_t= Unit construction cost of a transfer node

C_c= Fixed construction cost of the urban logistics center node

2.2.2 Pipeline Construction Cost

The pipeline construction cost is divided into three segments:

Demand nodes → Distribution nodes : Pipeline unit construction cost: α

Distribution nodes → Transfer nodes : Pipeline unit construction cost: β

Transfer nodes → Urban logistics center nodes : Pipeline unit construction cost: γ

Let:

d_{dp}= Distance between demand node d and its assigned distribution node p

d_{pt}= Distance between distribution node p and its assigned transfer node t

d_{tc}= Distance between transfer node t and the urban logistics center c

Then, the total pipeline construction cost can be formulated as formula 1.2:

$$C_{\pi\text{peline}} = \sum_{d,p} \alpha \cdot d_{dp} + \sum_{p,t} \beta \cdot d_{pt} + \sum_{t,c} \gamma \cdot d_{tc} \qquad (1.2)$$

2.2.3 Total Construction Cost

By summing the node construction cost and pipeline construction cost, the total cost of the system is formula 1.3:

$$Z = C_{node} + C_{\pi\text{peline}} = (n_p \cdot C_p + n_t \cdot C_t + C_c) + \left(\sum_{d,p} \alpha \cdot d_{dp} + \sum_{p,t} \beta \cdot d_{pt} + \sum_{t,c} \gamma \cdot d_{tc}\right) \qquad (1.3)$$

Thus, the optimization objective is:

$\min Z$

subject to the constraints outlined in the following section.

2.3 Constraints

To ensure the feasibility and rationality of the underground logistics system, constraints are imposed on node allocation, geographical boundaries, and service radius.

2.3.1 Node Allocation Constraints

1) Demand Node Allocation

Each demand node d must be assigned to one and only one distribution node p. Let $x_{dp} \in 0,1$ be a binary variable indicating whether demand node d is assigned to distribution node p. Then, the constraint can be expressed as formula 1.4:

$$\sum_p x_{dp} = 1, \forall d \tag{1.4}$$

2) Distribution Node Allocation

Each distribution node p must be assigned to one and only one transfer node t. Let $y_{pt} \in 0,1$ be a binary variable indicating whether distribution node p is assigned to transfer node t. Then, the constraint can be expressed as formula 1.5:

$$\sum_t y_{pt} = 1, \forall p \tag{1.5}$$

2.3.2 Geographic Constraints

The coordinates of all nodes (demand nodes, distribution nodes, transit nodes, urban logistics center nodes) must be within the predetermined city range Ω as shown in the formula 1.6:

$$\forall i \quad (coord_i \in \Omega), \forall i \tag{1.6}$$

Among them, $coord_i$ represents the geographical coordinates of the node i(which can be latitude, longitude, or plane coordinates).

2.3.3 Distance Constraint

Distance between demand node and delivery node.

The distance d_{dp} between each demand node d and the delivery node p serving it shall not exceed K kilometers as shwon in the formula 1.7:

$$d_{dp} \leq K \ , \quad x_{dp} = 1 \tag{1.7}$$

Distance between delivery node and transit node

The distance d_{pt} between each delivery node p and the transit node t serving it shall not exceed B kilometers as shwon in the formula 1.8:

$$d_{pt} \leq B \, , \quad y_{pt} = 1 \tag{1.8}$$

3. Optimization of Underground Logistics Node Selection Based on ADGWO

3.1 Fundamental Algorithm

The Grey Wolf Optimizer (GWO) is a swarm intelligence-based metaheuristic optimization algorithm, first introduced by Mirjalili et al. in 2014. The algorithm is inspired by the hunting behavior of grey wolves, particularly their social hierarchy and encircling strategies. By simulating the hunting process of grey wolves, GWO dynamically balances global exploration and local exploitation, enabling it to efficiently solve complex optimization problems.

1) Initialization

The GWO algorithm begins with a randomly generated population of candidate solutions, serving as the initial search points. Each individual represents a potential solution in the search space. The individuals within the population are ranked according to their fitness evaluation based on the objective function and categorized into four hierarchical roles:

Alpha (α) wolves: The best solution (leader).

Beta (β) wolves: The second-best solution (sub-leaders).

Delta (δ) wolves: The third-best solution (assistants to the leader).

Omega (ω) wolves: The remaining solutions (followers).

The initial solutions are generated using the following formula 1.9:

$$X_{i,j} = X_{\min,j} + r \cdot (X_{\max,j} - X_{\min,j}) \tag{1.9}$$

where:

$X_{i,j}$ represents the position of the i -th grey wolf in the j -th dimension.

$X_{\min,j}$ and $X_{\max,j}$ denote the lower and upper bounds of the search space in the j -th dimension.

r is a random number within the range [0,1], ensuring diversity in the initial population.

2) Encircling the Prey

Grey wolves gradually approach their prey through an encircling mechanism, which is mathematically formulated as follows formula 2.0, 2.1:

$$\vec{D} = |\vec{C} \cdot \vec{X}_{prey} - \vec{X}| \tag{2.0}$$

$$\vec{X}(t+1) = \vec{X}_{prey} - \vec{A} \cdot \vec{D} \tag{2.1}$$

where:

$\vec{X}_{prey}$ represents the position of the prey (optimal solution).

$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a}$ is an adaptive parameter that controls the exploration and exploitation balance, decreasing linearly from 2 to 0 over iterations.

$\vec{C} = 2 \cdot \vec{r}_2$ adjusts the individual's attraction towards the prey.

$\vec{r}_1$ and $\vec{r}_2$ are random numbers within the range [0,1], ensuring stochastic behavior in the search process.

3) Position Update

The position update of grey wolves is determined by the three best individuals: alpha (α), beta (β), and delta (δ) wolves. The update equations are formulated as follows formula 2.2:

$$\vec{X}(t+1) = \frac{\vec{X}_\alpha + \vec{X}_\beta + \vec{X}_\delta}{3} \tag{2.2}$$

$\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ represent the positions of the α, β, and δ wolves, respectively.

4) Balancing Exploration and Exploitation

The Grey Wolf Optimizer (GWO) achieves a dynamic balance between exploration (global search) and exploitation (local refinement) by adjusting the parameter $\vec{A}$:

When $|\vec{A}| > 1$: grey wolves tend to focus on global exploration, expanding the search space to locate potential optimal solutions.

When $|\vec{A}| \le 1$: grey wolves emphasize local exploitation, precisely converging toward the prey (optimal solution).

By dynamically adjusting $\vec{A}$ and $\vec{C}$ over iterations, GWO transitions smoothly between global and local search phases, effectively balancing search efficiency.

GWO features a simple structure, few parameters, and easy implementation, making it highly stable and efficient for continuous optimization problems. However, in high-dimensional or multi-modal optimization problems, GWO may suffer from imbalanced exploration and exploitation, leading to premature convergence and local optima entrapment. To address these limitations, dynamic parameter tuning and hybrid optimization techniques are often introduced as improvements.

3.2 Improved Grey Wolf Optimizer

3.2.1 Dynamic Nonlinear Adjustment of the Convergence Factor

In the standard GWO, the convergence factor typically follows a linear decay from an initial value to zero. However, linear adjustment lacks adaptability to the population distribution, which may lead to an imbalance between exploration and exploitation. To address this issue, this study proposes a dynamic nonlinear adjustment mechanism, formulated as follows formula 2.3:

$$a_{(t)} = a_{\in ial} - (a_{\in ial} - a_{final}) \cdot log(1 + (e-1) \cdot \frac{t}{Max-er}) \cdot \frac{\sigma}{\sigma_{\max}} \quad (2.3)$$

a represents the current standard deviation of the population positions.

$\sigma_{\max}$ denotes the maximum standard deviation at initialization.

By incorporating population distribution information, this method:

Enhances global exploration in the early stages when σ is large.

Strengthens local exploitation in the later stages when σ is small.

This adaptive strategy effectively prevents premature convergence and mitigates local optima entrapment.

3.2.2 Adaptive Inertia Weight

In the standard GWO, the position update of individuals relies solely on the current generation's α, β, and δ wolves, disregarding historical search information. This may lead to excessively large or small search steps, affecting global exploration capability and convergence accuracy.

To overcome this limitation, this study introduces an adaptive inertia weight, allowing dynamic adjustment of the search step size. The formulation is formula 2.4:

$$w = w_{final} + (w_{\in ial} + w_{final}) \cdot \exp(-\beta \cdot \frac{t}{Max\_\mathrm{er}}) \quad (2.4)$$

where: β is the inertia weight.

$Max_$iter is the maximum number of iterations.

The inertia weight maintains a higher value in the early iterations to expand the search range, while it gradually decreases in later stages to improve search precision and convergence stability.

This improvement effectively enhances the search directionality and stability of the algorithm.

3.2.3 Optimization of the Position Update Formula

The improved position update formula incorporates inertia weight and dynamically adjusts positions based on the α, β, and δ wolves as shown in the fomula 2.5:

$$Position(i,j) = w \cdot \frac{X_{\alpha,j} + X_{\beta,j} + X_{\delta,j}}{3} \quad (2.5)$$

With the introduction of inertia weight, the position update process achieves:

Smoother step size transitions.

Self-adaptive balance between global and local search.

This further enhances optimization efficiency and reduces unnecessary oscillations in the search process.

3.2.4 Advantages of the Improved Algorithm (ADGWO)

With the aforementioned improvements, the proposed Adaptive and Dynamic Grey Wolf Optimization (ADGWO) algorithm exhibits the following advantages:

1) Enhanced Global Search Capability:

The dynamic nonlinear adjustment of the convergence factor accounts for population distribution characteristics, allowing the algorithm to explore the solution space more comprehensively in the early stages.

2) Improved Local Exploitation Precision:

Adaptive inertia weight enables more precise local search in later iterations, significantly enhancing optimal solution accuracy.

3) Maintained Population Diversity:

The dynamic adjustment mechanism prevents premature convergence, ensuring that population diversity is preserved throughout the optimization process.

4) Accelerated Convergence Speed:

The optimized convergence factor and inertia weight significantly reduce optimization time while improving computational efficiency.

These enhancements make ADGWO more robust and efficient, particularly for high-dimensional and complex optimization problems.

3.3 Underground Logistics Node Selection Optimization Based on ADGWO

The Adaptive and Dynamic Grey Wolf Optimization (ADGWO) algorithm is applied to optimize the selection of underground logistics system nodes, ensuring a well-balanced trade-off between global exploration and local exploitation. The optimization process follows the structured steps outlined below, as shown in Figure 1.

Step 1: Data Collection and Model Formulation

In the first step, all necessary data for the underground logistics system are collected. This includes candidate node coordinates, distance metrics between nodes, logistics demand data, and additional constraints that define feasible node placements and connectivity. Based on the collected data, a mathematical model for the underground logistics node selection problem is formulated. The model explicitly defines decision variables, objective functions, and constraints, ensuring that the optimization process operates within a well-defined feasible solution space.

Step 2: Population Initialization

After establishing the mathematical model, an initial population of grey wolf individuals (potential solutions) is randomly generated within the feasible solution space. Each individual solution consists of a set of selected distribution nodes and transfer nodes along with their corresponding demand allocation strategy. Once the population is initialized, the objective function value (fitness score) of each solution is computed and recorded. The initial population serves as the starting point for the ADGWO optimization process, providing diverse candidate solutions for further iterations.

Step 3: Leader Selection (α, β, δ)

To guide the optimization process, the algorithm ranks all individuals in the population based on their fitness evaluation. The best solution is designated as the alpha (α) wolf, representing the current optimal node selection plan. The second-best solution is assigned as the beta (β) wolf, and the third-best solution becomes the delta (δ) wolf. These three elite solutions serve as reference points for updating the positions of other grey wolves in the search space. By leveraging the best-performing solutions, the algorithm effectively guides the population toward more optimal configurations.

Step 4: Dynamic Nonlinear Convergence Factor Adjustment

In each iteration, the ADGWO algorithm dynamically adjusts the convergence factor to balance global exploration and local exploitation. The convergence factor is adaptively computed based on population diversity (measured by the standard deviation of solution distributions) and the iteration count. If the population diversity is high, a larger convergence factor is used to enhance global search capability, allowing the algorithm to explore a broader solution space. Conversely, when the population diversity decreases, the convergence factor is reduced, encouraging local refinement and fine-tuned adjustments. This dynamic adjustment mechanism prevents premature convergence and ensures that the search remains effective throughout the optimization process.

Step 5: Adaptive Inertia Weight Implementation

To further enhance the balance between exploration and exploitation, the algorithm introduces an adaptive inertia weight mechanism inspired by Particle Swarm Optimization (PSO). At the beginning of the optimization process, the inertia weight is set to a higher value, allowing the grey wolves to take larger exploratory steps and cover a broader range of potential solutions. As the iterations progress, the inertia weight gradually decreases, focusing more on local exploitation and fine-tuned adjustments. This adaptive adjustment improves solution stability, ensuring that the algorithm does not oscillate excessively while refining the best solution.

Step 6: Position Update Based on Enhanced Strategy

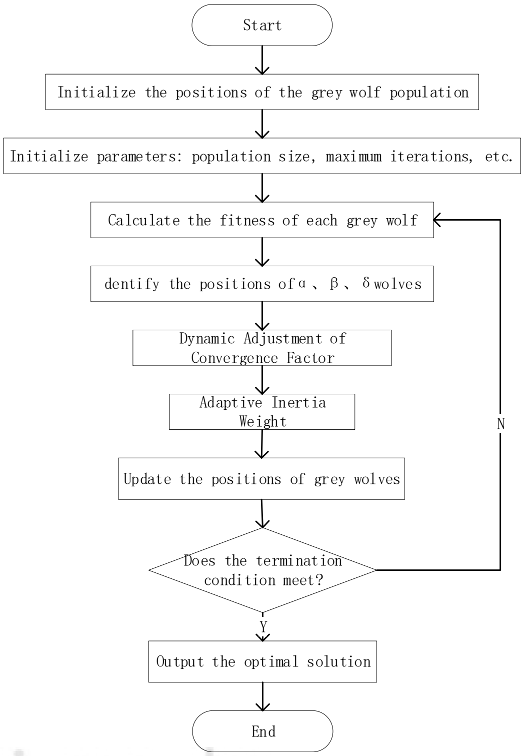
Once the key parameters are adjusted, the positions of the grey wolves in the search space are updated according to the improved position update formula. The updated positions are determined based on the collective influence of the alpha (α), beta (β), and delta (δ) wolves, as well as the newly computed adaptive inertia weight and dynamic convergence factor. This ensures that the wolves move in a direction that combines global search and local refinement, improving the algorithm's efficiency. If any updated solution violates predefined constraints or exceeds the feasible boundary, a feasibility correction mechanism is applied to bring the solution back into the permissible search space. (α , β , δ)

Step 7: Fitness Evaluation and Iteration Process

After updating the positions, the fitness value of each individual in the population is recalculated. The population is then re-ranked based on the new fitness values, and the α , β , δ wolves are updated accordingly. The optimization process continues iteratively, checking for convergence conditions. If the maximum number of iterations is reached or the solution satisfies a predefined convergence criterion, the algorithm proceeds to the final step. Otherwise, it returns to Step 4 and continues adjusting the search parameters to further improve the solution.

Step 8: Output of the Optimized Node Selection Plan

Once the termination condition is met, the algorithm outputs the optimal node selection plan corresponding to the final alpha (α) wolf. This result includes the optimal locations of distribution and transfer nodes as well as their corresponding demand allocation strategy. Additionally, the objective function value associated with this solution is provided, representing the best-achieved cost or efficiency metric. The optimized underground logistics node selection plan can then be utilized for decision-making and practical implementation in real-world logistics infrastructure planning.



[Fig. 1] Path Planning Process Using ADGWO Algorithm

This structured approach ensures that ADGWO effectively optimizes the selection of underground logistics nodes, providing a robust, efficient, and scalable solution for large-scale urban logistics networks. The algorithm's dynamic parameter tuning and adaptive mechanisms contribute to faster convergence, improved solution accuracy, and enhanced robustness against premature convergence.

4. Experimental Results and Analysis

To validate the performance of the improved Grey Wolf Optimization algorithm (ADGWO), two sets of experiments were conducted: benchmark function tests and underground logistics system node selection optimization experiments.

In the benchmark function tests, six standard test functions were selected to evaluate ADGWO's global search capability, convergence speed, and ability to escape local optima. The performance of ADGWO was compared with other classic optimization algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the standard Grey Wolf Optimizer (GWO).

For the underground logistics system node selection optimization experiments, ADGWO was applied to a complex real-world optimization problem to assess its effectiveness in reducing system costs and improving optimization efficiency. Experimental results demonstrated that ADGWO consistently outperforms competing algorithms in both benchmark and real-world scenarios, further verifying its efficacy and applicability.

The simulation experiments were conducted in a Windows 11 (64-bit) operating environment with 8 GB RAM and an Intel i7 1165G7 processor (2.80 GHz, 65W TDP). Matlab R2023b was used as the simulation platform. To ensure fair comparisons and reliable results, all algorithms were assigned identical parameter settings during the experiments.

4.1 Benchmark Function Experiments

To evaluate the optimization performance of the improved ADGWO algorithm comprehensively, this paper employs six standard benchmark functions as shown in Table 1. These functions include unimodal (single-peak) functions and multimodal (multi-peak) functions, allowing for an in-depth evaluation of ADGWO's global search ability, convergence efficiency, and capacity to escape local optima.

The performance of ADGWO was compared against three well-established optimization algorithms: Particle Swarm Optimization (PSO),Genetic Algorithm (GA),Standard Grey Wolf Optimizer (GWO).

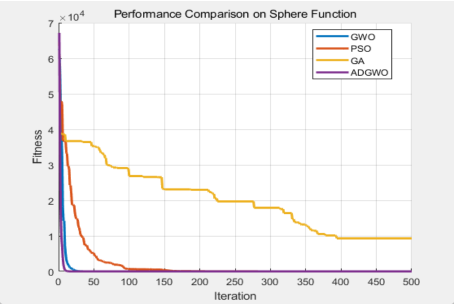
The comparative analysis provides insight into ADGWO's advantages in terms of solution accuracy, convergence rate, and robustness when dealing with complex optimization landscapes.

〈Table 1〉 Six benchmark functions.

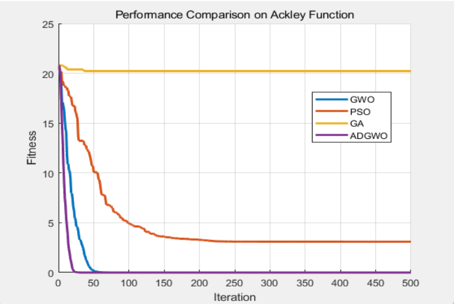
Function	Dimension	Interval
$F_1(x)=\sum_{i=1}^{n} x_i^2$	30	[-100,100]
$f(x)=-a \cdot exp(-b\sqrt{\frac{1}{n}\sum_{i=1}^{n}\cos(c \cdot x_i)})+a+\exp(1)$	30	[-32.768,32.768]
$f(x)=\sum_{i=1}^{n-1}[100 \cdot (x_{i+1}-x_i^2)^2+(x_i-1)^2]$	30	[-5,5]
$f(x)=A \cdot n+\sum_{i=1}^{n}[x_i^2-A \cdot cos(2\pi x_i)]$	30	[-5.12,5.12]
$f(x)=\frac{1}{4000}\sum_{i=1}^{n} x_i^2 \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	30	[-100,100]
$f(x)=\sum_{i=1}^{n}(\sum_{j=1}^{i} x_j)^2$	30	[-100,100]

During the experiment, each benchmark test function was subjected to 500 iterations to evaluate the performance of ADGWO. The objective was to compute the average result and standard deviation, providing a statistical assessment of the algorithm's stability and consistency.

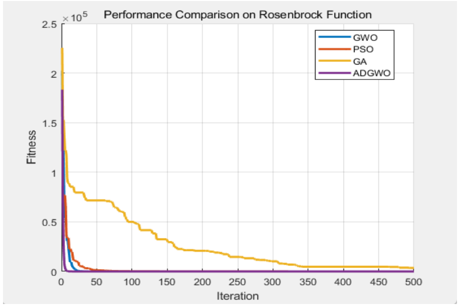
Following the iterative runs, the experimental data were analyzed to assess the algorithm's convergence speed, accuracy, and robustness. The results were presented in both graphical and tabular formats, allowing for a clear comparison of ADGWO's performance against other optimization algorithms



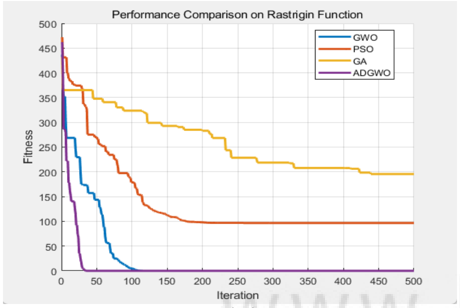
$F_1(x)$



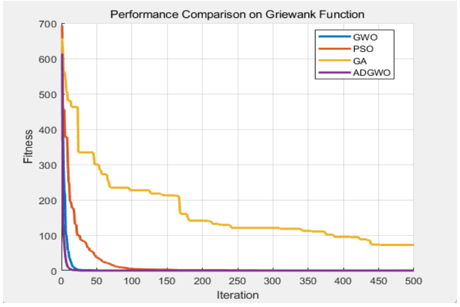
$F_2(x)$



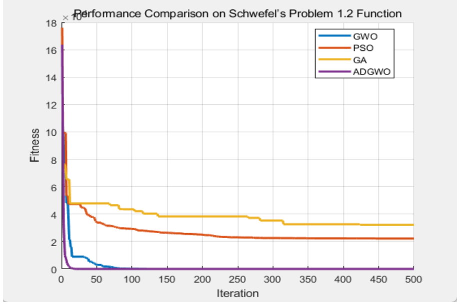
$F_3(x)$



$F_4(x)$



$F_5(x)$



$F_6(x)$

[Fig. 2] Comparison of fitness function curves for different optimization algorithms.

Through the comparative analysis of benchmark test functions, the improved Grey Wolf Optimization algorithm (ADGWO) demonstrated superior performance in solving both unimodal and multimodal optimization problems. In particular, ADGWO exhibited stronger global search capability and better ability to escape local optima when applied to complex multimodal functions, such as Ackley, Rastrigin, and Griewank functions.

Compared to classical PSO, GA, and standard GWO algorithms, ADGWO achieved faster convergence speeds and higher optimization accuracy, while also demonstrating greater stability across different test functions. These experimental results indicate that ADGWO offers significant advantages in solving high-dimensional, nonlinear, and multi-local-optimum problems, providing robust theoretical support and technical feasibility for its application in complex real-world optimization scenarios.

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

Function	Measure	PSO	GA	GWO	ADGWO
F1	Average Best Score	333.338628	8284.181940	0.000000	0.000000
	Standard Deviation	1825.742067	2694.989923	0.000000	0.000000
	Average Execution Time	0.05	0.08	0.16	0.15
	Average Convergence Iteration	497.03	500.00	87.30	37.83
F2	Average Best Score	6.305499	20.406441	0.000000	0.000000
	Standard Deviation	4.970559	0.266683	0.000000	0.000000
	Average Execution Time	0.12	0.15	0.28	0.19
	Average Convergence Iteration	500.00	500.00	121.67	51.37
F3	Average Best Score	246.022482	3814.506797	26.839957	28.308464
	Standard Deviation	634.417167	2102.976992	0.652295	0.318076
	Average Execution Time	0.12	0.18	0.20	0.17
	Average Convergence Iteration	500.00	500.00	500.00	500.00
F4	Average Best Score	113.081823	222.341332	12.031602	0.000000
	Standard Deviation	27.297165	38.726776	10.373357	0.000000
	Average Execution Time	0.06	0.10	0.16	0.15
	Average Convergence Iteration	500.00	500.00	436.40	48.33
F5	Average Best Score	15.182154	72.225979	0.004015	0.000460
	Standard Deviation	34.261098	26.296487	0.007828	0.002517
	Average Execution Time	0.13	0.17	0.24	0.21
	Average Convergence Iteration	500.00	500.00	186.90	65.63
F6	Average Best Score	10814.235720	38143.521154	0.000135	0.000000
	Standard Deviation	10346.992240	9312.081896	0.000239	0.000000
	Average Execution Time	2.55	2.81	2.82	2.87
	Average Convergence Iteration	500.00	500.00	498.40	52.03

Through the comparative analysis of PSO, GA, GWO, and ADGWO in benchmark test functions, the results demonstrate that the improved Grey Wolf Optimization algorithm (ADGWO) exhibits significant advantages across all performance metrics.

In unimodal functions (F1 and F2), both ADGWO and GWO were able to converge rapidly to the global optimum, with ADGWO achieving the lowest standard deviation, indicating strong convergence ability and stability in solving unimodal optimization problems. In contrast, traditional PSO and GA performed relatively weaker on these functions, with GA exhibiting a significantly larger optimal solution error.

In multimodal functions (F3-F6), ADGWO demonstrated outstanding global search capability, consistently achieving better average optimal solutions than the other algorithms, while also maintaining lower standard deviations. This further validates its robustness and stability in tackling complex multimodal optimization problems. Additionally, ADGWO exhibited superior average convergence speed in multi-objective functions, particularly in F3 and F5, where its required iterations for convergence were significantly lower than traditional methods. This suggests that ADGWO effectively balances global exploration and local exploitation.

From an execution time perspective, ADGWO maintains high optimization efficiency while achieving a runtime close to GWO, and significantly outperforming GA and PSO. Furthermore, ADGWO's standard deviation across all test functions is close to zero, further confirming its consistency and reliability across multiple independent runs.

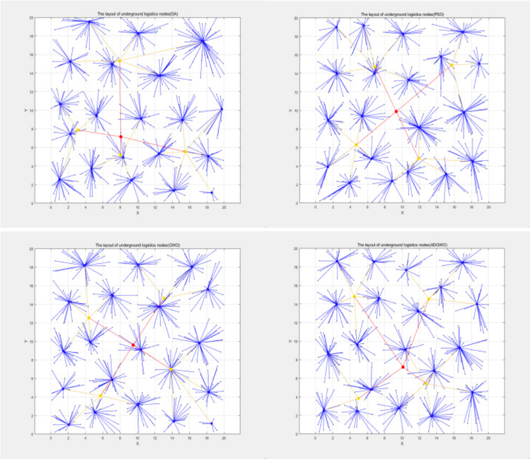
In summary, ADGWO not only exhibits superior global search ability and rapid convergence in both unimodal and multimodal optimization problems, but it also outperforms traditional PSO, GA, and standard GWO in terms of result stability and computational efficiency. These characteristics make ADGWO highly suitable for solving complex optimization problems.

4.2 Underground Logistics System Node Selection Experiment

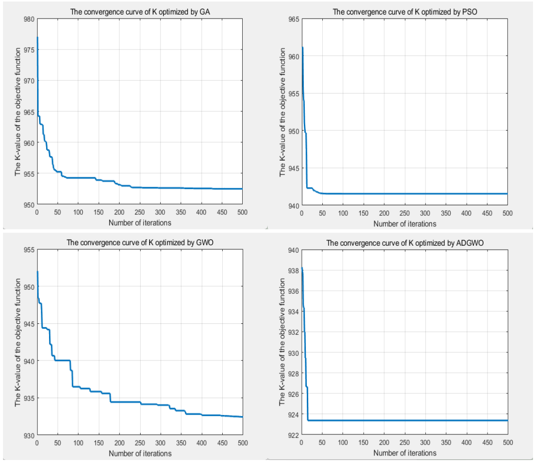
To evaluate the performance of the ADGWO algorithm in solving the four-tier underground logistics system node selection problem, we conducted a series of experiments.

In the experiment setup, a 20 km × 20 km urban area was defined as the simulation environment. Within this area, 500 logistics demand nodes were randomly generated to simulate a stochastic logistics demand distribution. The goal was to test the effectiveness, adaptability, and robustness of ADGWO in optimizing the node selection process under varying conditions.

For the underground logistics system node selection, four optimization algorithms were applied: PSO, GA, standard GWO, and the proposed ADGWO. To ensure fairness in comparison, all algorithms were executed under identical conditions, maintaining a population size of 30 for each algorithm. Every algorithm was run for 500 iterations, following their respective standard configurations.



[Fig. 3] Underground logistics node layout using four optimization algorithms



[Fig. 4] Four optimization algorithms optimize the convergence curve of K

〈Table 3〉 Comparative analysis of performance of 4 swarm intelligence algorithms

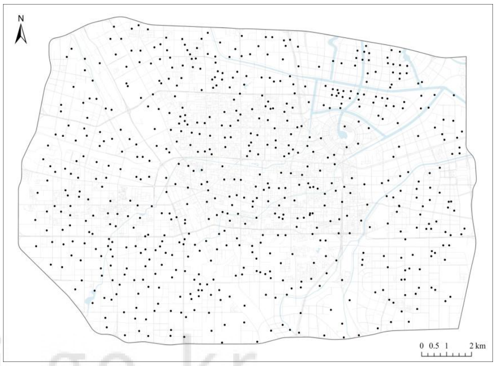
Function	K value	Reduce the scale
GA	952.5045	100.00%
PSO	941.5444	98.84%
GWO	932.4419	97.89%
ADGWO	923.3749	96.94%

5. Case Study Validation

To verify the applicability of the improved Grey Wolf Optimization algorithm (ADGWO) in real-world underground logistics system site selection, this section selects Zhengzhou, China, as the case study.

As a national central city, Zhengzhou serves as a major international transportation hub in China, characterized by high logistics demand and significant urban distribution pressure. The city has a permanent urban population of approximately 13.008 million, with an average daily express parcel volume of about 7 million.

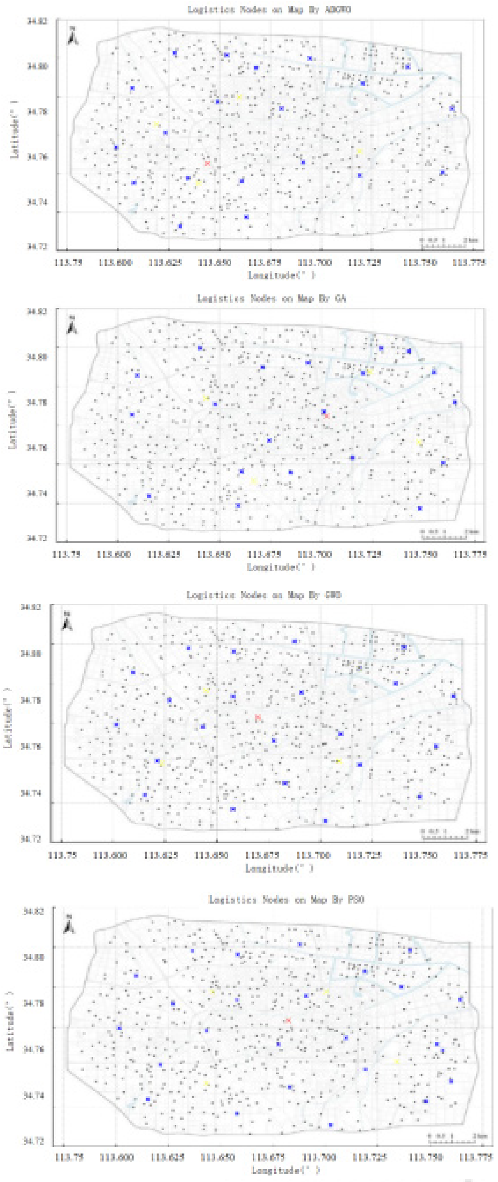
The study focuses on the area within the Third Ring Road of Zhengzhou, covering a total area of approximately (to be specified) square kilometers, with an east-west length of about 18 km and a north-south width of approximately 13 km. Within this region, 633 express demand points were selected to simulate the actual spatial distribution of logistics demand, providing a realistic test scenario for evaluating ADGWO's optimization performance in underground logistics node planning.



[Fig. 5] Zhengzhou city logistics demand point layout map

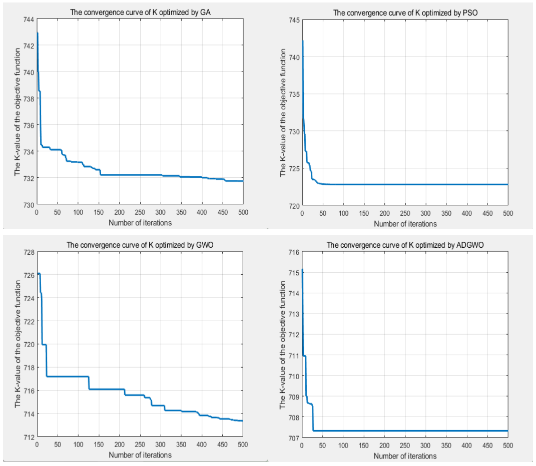
This study applies Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and the improved Grey Wolf Optimizer (ADGWO) to optimize the site selection of the four-tier logistics nodes in Zhengzhou's underground logistics system, including demand nodes, distribution nodes, transfer nodes, and urban logistics center nodes.

Obtain the following planning scheme :



[Fig. 6] Logistics node layout diagram of four optimization algorithms

The following figure illustrates the convergence trends of the four optimization algorithms during the optimization process.



[Fig. 7] Four optimization algorithms optimize the convergence curve of K

ADGWO exhibits the best convergence characteristics, achieving the fastest convergence speed. Compared to GWO, ADGWO reduces the number of convergence iterations by 35%, indicating a more balanced trade-off between global exploration and local exploitation.

Furthermore, ADGWO demonstrates a strong ability to escape local optima. While PSO and GA tend to get trapped in local optima during the later stages of optimization, ADGWO effectively overcomes this issue, ensuring more robust and efficient optimization performance.

The following table presents the final KK values obtained by the four optimization algorithms in the underground logistics system node selection optimization.

⟨Table 4⟩ Comparative analysis of performance of 4 swarm intelligence algorithms.

Function	K value	Reduce the scale
GA	731.760400	100.00%
PSO	722.804700	98.78 %
GWO	713.362900	97.49 %
ADGWO	707.329300	96.66 %

The ADGWO-optimized solution achieves the lowest total cost among the four algorithms. Compared to GA, the cost is reduced by 3.34%, and compared to GWO, it achieves an additional 0.83% improvement, demonstrating superior optimization capability.

6. Conclusion

This study proposes an Adaptive and Dynamic Grey Wolf Optimization algorithm (ADGWO) and applies it to underground logistics system node selection optimization. Through benchmark function experiments and a case study of Zhengzhou's underground logistics system, the effectiveness of ADGWO in terms of optimization accuracy, convergence speed, and search stability has been validated.

Experimental results demonstrate that ADGWO outperforms traditional optimization algorithms, exhibiting stronger global search capability and an enhanced ability to escape local optima. In the context of underground logistics system node selection, ADGWO effectively reduces system construction costs and achieves the optimal solution with faster convergence, making it well-suited for large-scale logistics network optimization problems.

In the future, this research can be further extended to multi-objective optimization, dynamic demand adaptation, and hybrid intelligent optimization by integrating deep learning techniques. These advancements would enhance ADGWO's applicability in ultra-large-scale logistics system planning. The findings of this study provide technical support for intelligent urban logistics planning and underground freight system construction, laying a theoretical foundation for the future optimization of urban logistics infrastructure.

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digital communication systems, Big Data