Research Article

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Location strategy for logistics distribution centers utilizing improved whale optimization algorithm

Abstract: An enhanced whale optimization algorithm is introduced to address the challenges associated with the logistics distribution center location problem, aiming to overcome the traditional heuristic algorithm's susceptibility to local optima and enhance the overall efficiency of the logistics system. This improvement involves the integration of stochastic sinusoidal inertia weights and a variational strategy to augment the global search capability and convergence accuracy of the conventional algorithm. The results of experimental simulations indicate that the upgraded whale algorithm exhibits superior computational performance compared to other heuristic algorithms. Furthermore, it demonstrates the ability to effectively compute optimal distribution center locations, thereby enhancing the delivery efficiency of the logistics distribution system.

Keywords: logistics distribution center site selection, whale optimization algorithm, combined variance, stochastic sinusoidal inertia weights, location strategy

1 Introduction

The number and value of Chinese exports are rising with the economy's rapid development. Unfortunately, the efficiency of distribution and logistics has never advanced quickly, which raises the cost of distribution and causes significant losses of numerous products during the distribution process [1]. The distribution center site selection is the primary cause of the loss. However, other factors include unreasonable distribution path planning, unwieldy logistics, distribution links, and comparatively outdated transportation conditions [2]. In order to increase distribution efficiency and lower distribution costs, many academics and researchers have conducted extensive research on optimizing the logistics distribution center site selection model. Improved whale optimization algorithm (IWOA) is characterized by its enhanced convergence speed, improved solution accuracy, robust performance on diverse problems, efficient utilization of computational resources, and adaptability to dynamic environments.

The research problem at hand is considered the highest priority in the study, given its direct bearing on the effectiveness of logistics distribution. The proposed IWOA presents a fresh and enhanced approach to address issues with conventional heuristic algorithms. This innovative method significantly contributes to improving the overall delivery efficiency within logistics systems and optimizing the locations of distribution centers.

Overall, the structure of this article is meticulously organized to ensure consistency and transparency. The subsequent sections delve into the intricacies of the research. Section 2 offers a comprehensive literature review, setting the stage for understanding existing approaches. Section 3 briefly examines the logistics

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distribution center site selection model. Section 4 delves into IWOA, elucidating its components and mechanisms. Section 5 provides insights into test simulation, detailing the test functions and practical examples. Following this, Section 6 provides conclusion.

2 Literature review

An ant colony algorithm with clustering properties was proposed in the literature [3] to optimize the distribution center location model. A better particle swarm-based optimization algorithm is proposed in the literature [4] to optimize the distribution center location model. A logistics distribution center location strategy based on the center of gravity method is presented in the literature [5]. A hybrid particle swarm algorithm was proposed in the literature [6] to optimize the distribution center siting model, resulting in faster distribution times and increased distribution efficiency. Under the assumption of considering the production and marketing balance, literature [7] optimizes the site selection model by applying a composite ant colony algorithm, which successfully increases distribution efficiency. The literature suggests a site selection optimization technique based on the simulated annealing algorithm [8]. AHP-integer planning method [9], forbidden search [10], and center of gravity method [11] are further methods. All of the aforementioned techniques have increased the efficiency of agro-logistics distribution, but single-mechanism optimization algorithms still require improvement to handle problems with highly nonlinear models. Consequently, to maximize the logistics distribution center location model, this article suggests an enhanced IWOA.

The advantage of the new swarm intelligence optimization algorithm, traditional IWOA [12–14], which was put forth by academic Mirjalili in 2015, is that it has fewer adjustment parameters and a more straightforward optimization-seeking mechanism. Its drawback, though, is that the algorithm is prone to early convergence and local optimum formation in the latter iteration, which compromises the algorithm's accuracy and rate of convergence. Therefore, this study effectively improves the algorithm's global convergence ability and convergence speed by fusing the genetic algorithm with the conventional IWOA and introducing the nonlinear inertia weights. The improved IWOA is then used in the optimization problem of the site selection model of the logistics distribution center, which effectively improves the logistics' distribution efficiency and significantly reduces the distribution cost.

3 Logistics distribution center site selection model

An essential subset of the logistics distribution center site selection issue is logistics distribution center site optimization. Every production base can be recognized as a warehouse in the logistics distribution center location optimization problem, and every warehouse holds a variety of products. The main goal of the logistics distribution center location model is to reduce costs by identifying the supply chain's most advantageous locations for distribution centers. In contrast to other distribution center location issues, this one involves relatively large distances between each warehouse due to China's widely distributed production bases. Additionally, the production of numerous products is impacted by environmental and seasonal factors, resulting in highly stringent delivery time requirements. Temperature and humidity are two examples of environmental factors that affect production through their effects on materials and machinery. Seasonal fluctuations affect demand and planning simultaneously, affecting inventory management and planning for seasonal goods. These elements work together to determine both product availability and operational efficiency. Therefore, the following criteria must be met when developing the logistics distribution center location model.

Partitioning the distribution area is required due to the freshness of the product and the stricter seasonal requirements. Additionally, select the best warehouse from each partition to ensure the shortest distribution time and distance between the various warehouses within each partition.

Goods should not be moved between warehouses too frequently because of the variety of production bases and the seasonality of the agricultural harvest. Instead, the total amount of goods in the distribution center that each distribution warehouse corresponds to should be less than or equal to the needs of that warehouse.

The establishment of distribution centers should concentrate on the cost of building warehouses, saving distribution costs, and guaranteeing the primary income of farmers because the product economy is the nation's core economy and does not offer excessive profits.

The main challenge in optimizing the logistics distribution center location model is determining which of the A distribution locations, or distribution locations with a logistics distribution center, should be chosen as the logistics distribution center. Assuming that there are A trade markets, there are A distribution locations. The objective function of the logistics distribution center location model, considering constraints such as construction cost and supply and demand of distribution points, is as follows. This is because the construction cost of a logistics distribution center varies depending on the geographic location of A distribution locations.

$$\mathrm{Min}C = \sum_{j=1}^{P} \eta_j S_j + \sum_{i=1}^{A}\sum_{j=1}^{P} \psi_{i,j} d_{i,j} Z_{i,j}, \tag{1}$$

where A is the product distribution point; P is the product distribution center location; S_j is the construction costs for all distribution centers; when $\eta_j = 1$, S_j is the construction cost of a single distribution center, and this distribution center selection parameter is used. $\psi_{i,j}$ is the demand at distribution point i, $d_{i,j}$ is the separation between the j-th distribution center and the i-th distribution point that is closest to it; when $Z_{i,j} = 1$, the distribution center supplies the requested goods at distribution point I, according to the $Z_{i,j}$ distribution condition selection parameter.

Restrictions on the issue of choosing a location for distribution and logistics centers

$$\begin{aligned} &\sum_{j=1}^{P} \psi_{i,j} \leqslant T_i, \quad i = 1, 2, \cdots, A \\ &\sum_{j=1}^{P} Z_{i,j} = 1_i, \quad i = 1, 2, \cdots, A \\ &Z_{i,j} \leqslant h_j, \quad j = 1, 2, \cdots, A \\ &\sum_{j=1}^{P} h_j = P', \quad j = 1, 2, \cdots, A \\ &d_{i,j} \leqslant t'. \end{aligned} \tag{2}$$

According to equation (2), the total quantity of goods required at each distribution point should equal or be less than that at the corresponding distribution center.

The distribution relationship between the distribution point and the distribution center is represented by equation (3): if $Z_{i,j} = 1$, it indicates that the j-th distribution center distributes the goods from the i-th distribution point.

The distribution point has only customers if it is within any distribution center's deliverable range, according to equation (4).

There are P' logistics and distribution centers, according to equation (5).

Every distribution point is contained within the distribution range of the corresponding distribution center, according to equation (6). The farthest a distribution point can be distributed is t'.

4 IWOA

4.1 Standard whale optimization algorithm (WOA)

Every whale in WOA can be considered a particle, and every particle's position is a decision variable. During hunting, whales approach and hunt their prey in spirals rather than straight lines.

4.1.1 Enveloping the prey

Typically, when hunting, the prey is encircled first. The mathematical model is displayed below:

$$\mathbf{D} = |C\mathbf{X}^*(t) - X(t)|,$$
$$\mathbf{X}(t + 1) = \mathbf{X}^*(t) - A \cdot \mathbf{D},$$

(3)

where $\mathbf{X}^*(t)$ represents the best whale position vector to date, $X(t)$ represents the current whale location vector, t is the number of iterations, and A and C are the learning factors. The following formula gives A and C:

$$A = 2a \times r_1 - a,$$
$$C = 2 \times r_2,$$
$$a = 2 - 2 \times t/T_{max},$$

(4)

where t denotes the iteration count as of right now, r_1 and r_2 are the arbitrary values in the range of 0 to 1, the value of a is between (0, 2) and decreasing linearly, and T_{max} is the most iterations that can be made.

4.1.2 Spiral hunting

Below is a mathematical representation of a whale, which typically surrounds its prey and hunts in a spiral pattern:

$$\mathbf{X}(t + 1) = \mathbf{X}^*(t) + \mathbf{D}_p \cdot e^{bl} \cdot \cos(2\pi l),$$
$$\mathbf{D}_p = |\mathbf{X}^*(t) - \mathbf{X}(t)|,$$

(5)

where the whale and its prey are separated by $\mathbf{D}_p$ meters. The optimal position vector for every iteration to date is $\mathbf{X}^*(t)$ The spiral's shape is determined by a constant, b, and a random number, l, in the interval (−1, 1). It is important to note that the whale must simultaneously constrict its envelope and swim in a spiral toward its prey.

In order to update the whale's position, it is assumed in this synchronous behavioral model that there is a P_i probability of selecting the shrink–wrap mechanism and a $(1 - P_i)$ probability of selecting the spiral model, which is mathematically modeled as follows:

$$\mathbf{X}(t + 1) = \begin{cases} \mathbf{X}^*(t) - A \cdot D & P < P_i, \\ \mathbf{X}^*(t) + \mathbf{D}_p \cdot e^{bl} \cdot \cos(2\pi l) & P \geqslant P_i. \end{cases}$$

(6)

WOA is the setting for the synchronous behavioral model, which includes enveloping the prey, spiral hunting, and prey search. It efficiently optimizes the algorithm by approximating whale hunting behavior using mathematical representations, such as equations and vectors. As the whale approaches its target, the value decreases, as does the value of A as it approaches the prey. As the algorithm iterates, A becomes a random number inside [−a, a] as its value decreases linearly from 2 to 0. When the value of A is within the range [−1, 1], the whale's next position can be anywhere between its current position and the prey's.

4.1.3 Search for prey

Prey is sought after by using random individual locations, which can be mathematically modeled as follows:

$$\mathbf{D} = |C\mathbf{X}_{rand} - \mathbf{X}(t)|,$$
$$\mathbf{X}(t + 1) = \mathbf{X}_{rand} - A \cdot \mathbf{D},$$

(7)

where $\mathbf{X}_{rand}$ is a position vector that was taken at random. The algorithm is configured to randomly select a search leader when $A \geq 1$ and update other whales' positions based on the leader's position. This helps steer whales away from the current prey toward a more suitable target, enhancing the algorithm's ability to search

globally. The traditional and contemporary WOA optimization algorithms share foundational principles and iterative processes involving strategies like enveloping, spiral hunting, and updating positions.

4.2 IWOA

WOA has a higher search ability and faster search times than other heuristic optimization algorithms. It is a new optimization algorithm with a simple update mechanism, a slight adjustment parameter, and some degree of randomness [15–18]. The enhancement of global convergence ability and acceleration of convergence speed can be achieved through benchmark test functions, statistical metrics, comparative analysis, success rate (SR) index, and consistent parameter settings. However, the algorithm can quickly enter the local optimum due to the spiral optimization algorithm's update mechanism, which lowers the algorithm's accuracy of convergence. By impacting the exploration–exploitation equilibrium, the update mechanism of the spiral optimization algorithm in the conventional WOA can facilitate the algorithm's entry into local optima. Thus, this article adds random sinusoidal inertia weights and a comprehensive variation operator to the algorithm's optimization process, strengthening its global search capability and preventing it from reaching the local optimum. The strategic integration enhances the algorithm's adaptability, preventing it from being trapped in suboptimal solutions and promoting compelling exploration of the solution space. This is done in order to address the aforementioned problems.

First, as can be seen from equations (1)–(7), as the number of iterations rises, the convergence speed of the conventional WOA optimization algorithm falls. The convergence speed of the conventional WOA optimization algorithm declines as iterations increase, mainly due to more individual whales converging toward the global optimum, elevating the risk of entering local optima and diminishing overall efficiency.

Additionally, in the algorithm's late iteration, an increasing number of individual whales progressively approach the global optimal solution, ultimately resulting in the algorithm falling into the local optimum and causing the algorithm's convergence speed to drop dramatically, impacting the WOA algorithm's convergence. Given diminishing returns, the traditional WOA optimization algorithm's convergence speed tends to decrease as the number of iterations increases. The convergence process is slowed down as the algorithm iterates because the gains in solution quality get progressively smaller at each stage. This article presents a comprehensive variation strategy, the steps of which are shown below, based on the fusion of non-uniform variation and Cauchy's variation, to address the aforementioned issues:

1) By setting the variation switch function, the variation operation is performed on the current position of the whale by judging the switch condition, where the variation switch's mathematical expression is displayed
2) as follows:

$$\text{switch}(k) = \psi + \mu \times \frac{e^{\frac{n(k-1)}{SN}} - 1}{e^n - 1},\qquad(8)$$

where SN is the size of the whale population and n is the dimension. Define the mutation operation for the kth whale when $0 < \text{switch}(k) < 1$. ψ and μ are parameters. After conducting numerous simulation experiments, it was discovered that more than 75% of the whales mutate between $0.2 < \psi < 0.5$ and $0.1 < \mu < 0.5$, and this is the optimal time for the algorithm to optimize.

2) The value of A determines the step size of WOA. The algorithm enters the pre-iterative stage and searches a more extensive range faster when $A > 1$. The Cauchy inverse cumulative distribution function [19] is added when the algorithm is in the pre-iterative stage, and the particles are selected into the local optimum. This is because the Cauchy variation has a broader range of variation than the traditional binomial, polynomial, and non-uniform variations. The ability to introduce significant perturbation is primarily responsible for the broader range of variation at Cauchy variation. This allows for better exploration of the solution space and increased chances of breaking out from local optima. The Cauchy variation applies this more significant perturbation to the particles to help them escape the local optimum. WOA prevents the possibility that particles that have undergone Cauchy's mutation will undergo blind mutation because it updates particle

positions during the global search through spiral motion. The Cauchy's inverse cumulative distribution function has the following mathematical expression:

$$F^{-1}(p; x_0, \gamma) = x_0 + \gamma \times \tan(\pi \times (p - 0.5)). \tag{9}$$

Therefore, Equation (9) can be improved as

$$\mathbf{X}(t + 1) = x_{i,j}(t) + A \cdot \tan(\pi \times (p - 0.5)), \tag{10}$$

where $x_{i,j}(t) = A, 0 \leq p \leq 1$, and γ is the i-th whale's j-th position.

3) If a small fraction of whale particles satisfy the variation condition, the particles that do so will be moved to the global optimal solution through non-uniform variation. The particles that do not will be approached to the global optimal solution through the original position updating formula. This will enhance the algorithm's search speed and decrease the likelihood of premature convergence to a local optimum when the cardinality of set A is less than 1. Unlike the variation strategy used in the conventional genetic algorithm, non-uniform variation originates from the non-uniform variation evolutionary algorithm [20]. Combining the non-uniform variation strategy with WOA aims to improve the algorithm's global search capability by enabling the algorithm to always jump out of the local optimum in the late iteration. Better exploration and exploitation of complex problem spaces can be achieved by coupling the non-uniform variation strategy with WOA, which boosts robustness and diversity and adapts to changing optimization landscapes. This solves the issue of the algorithm needing to be faster to fall into the local optimum. The non-uniform variation evolution algorithm can adaptively adjust the search step size during the iteration process, so the convergence speed will increase when the algorithm is late. Assume that there are SN, $\mathbf{x}_i = \{x_{i1}, x_{i2}, \cdots, x_{in}, \cdots, x_{iSN}\}^{\mathrm{T}}$ whales in the population. The non-uniform variation formula, assuming that the variation operation is carried out on the nth component, is

$$x'_{in} = \begin{cases} x_{in} + \Delta(t, \mathrm{UB} - x_{in}), & r < 0.5, \\ x_{in} - \Delta(t, x_{in} - \mathrm{LB}), & r \geq 0.5 \end{cases}. \tag{11}$$

The variables, in this case, are as follows: b is the non-uniformity parameter; t is the current iteration number; T is the maximum iteration number; r is the uniform random number within [0, 1); and UB and LB are the particle's upper and lower boundaries, respectively. The non-uniform variation step is represented by $\Delta(t, y) = y \cdot \left[1 - r^{\left(1 - \frac{t}{T}\right)^b} \right]$.

Second, it is established by equations (9)–(11) that the value of parameter an entirely dictates the WOA's capacity for both local and global optimization. The late iteration period sees a linear decrease in a value, which significantly affects the algorithm's convergence accuracy. It facilitates the particles' easy fall into the local optimum. For this reason, the comprehensive variation strategy used in this article helps the algorithm escape the local optimum. This article proposes a stochastic sinusoidal inertia weight based on sinusoidal curve properties to improve the algorithm's population diversity and global search capability. The algorithm's stochastic sinusoidal inertia weight functions bolster population diversity and global search capability. This pivotal role leads to a more comprehensive exploration of the solution space, promoting adaptability and enhancing the algorithm's overall effectiveness in finding optimal solutions. The following is the stochastic sinusoidal inertia weight expressed mathematically:

$$w = 2 \times (1 - \sin(0.5 \times \pi \times (t/t_{\max}))) \times \mathrm{rand}(). \tag{12}$$

Equation (12) shows that when the iteration starts, the value $t/t_{\max}$ tends to 0, w is more significant, and the algorithm performs a better job of searching globally. When t tends to, $t_{\max}$ and w tends to 0, the algorithm has a high local search capability in its final iteration. It is possible to modify equations (11) and (12) in the following ways to improve the population diversity of the algorithm:

$$\mathbf{X}(t + 1) = \begin{cases} w\mathbf{X}^*(t) - A \cdot D \\ w\mathbf{X}^*(t) + D_p \cdot \mathrm{e}^{bl} \cdot \cos(2\pi l) \ p \geq p_i, \end{cases}. \tag{13}$$
$$\mathbf{X}(t + 1) = wx_{i,j}(t) + A \cdot \tan(\pi \times (p - 0.5)).$$

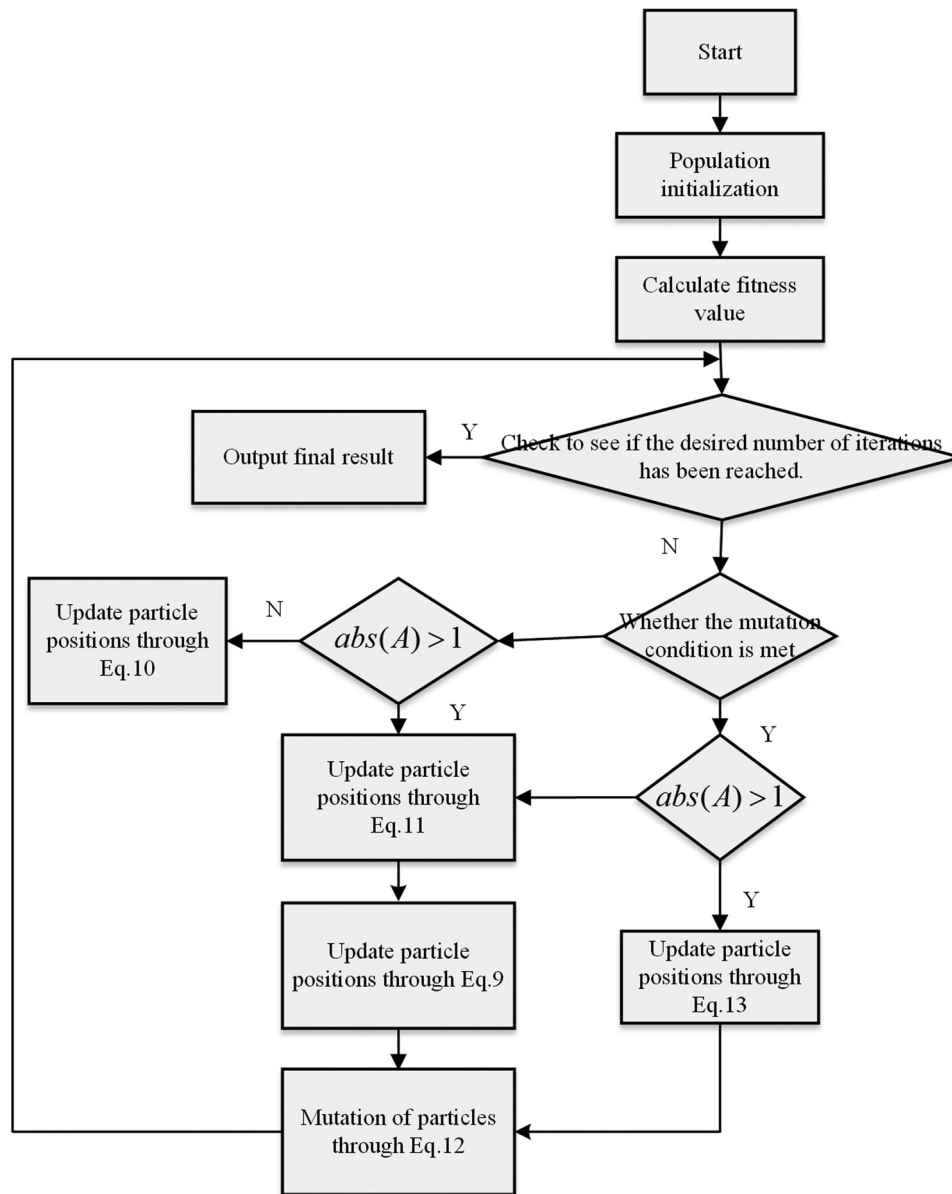Figure 1 depicts the flow of the IWOA.

Figure 1: Flowchart of IWOA.

5 Test simulation

5.1 Performance testing based on test functions

This article carries out the simulation verification from the two aspects of the register function and the actual calculation example to confirm that the IWOA presented can be applied to optimize the logistics and distribution center location model. The test environment adopts the Windows 10 operating system, the Thinkpad laptop with 8GB of memory, and the simulation software Matlab2022a.

In order to verify the algorithm's ability to perform local searches, this article first chooses 16 benchmark functions to serve as test functions. When selecting the 16 benchmark functions for testing IWOA, several factors were considered. These included the presence of known optima for accuracy evaluation, mathematical complexity, diversity in problem characteristics, and varying dimensions for scalability assessment. There are

four categories for these functions: multi-peak functions (f_5 to f_8), single-peak functions (f_1 to f_4), translational functions (f_9 to f_{12}), and rotational functions (f_{13} to f_{16}), all of which are shown explicitly in Table 1. Sorting benchmark functions into different categories is essential to evaluate the algorithm's adaptability. Translational functions evaluate adaptability to changed landscapes, rotational functions gauge robustness against rotations, single-peak functions evaluate efficiency in more straightforward scenarios, and multi-peak functions test their ability to navigate landscapes with multiple optima. Second, a comparison is made between IWOA and chaotic serial particle swarm optimization (CSPSO) [16], sinusoidal differential evolution (SinDE) [17], and moth-flame optimization algorithm with Cauchy mutation (CCMFO) [18]. The CCMFO algorithm becomes well known because it applies chaos-based adjustments to the moth optimization procedure. This increases the algorithm's capacity for exploration, raises convergence accuracy, and helps it solve challenging optimization problems. CSPSO is a cross-searching-based particle swarm optimization algorithm, which improves the global search capability of the algorithm and was suggested by Meng et al. Drea et al. introduced the SinDE algorithm, a sinusoidal searching algorithm that improves the algorithm's local search capability, and CCMFO is a modified moth optimization algorithm based on chaos. Several benefits arise from enhancing the algorithm's local search capability, encompassing improved convergence accuracy, better adaptability to complex problem landscapes, increased solution precision, and an overall optimization performance enhancement. An enhanced chaos-based moth optimization algorithm is called CCMFO.

Table 1: 16 test functions

Function number	Function	Dimension	Search scope	Optimal value
f_1	Sphere	n	[−100, 100]	0
f_2	Schwefel2.22	n	[−100, 100]	0
f_3	Schwefel1.2	n	[−100,100]	0
f_4	Rosenbrock	n	[−10, 10]	0
f_5	Ackley	n	[−32, 32]	0
f_6	Griewank	n	[−600, 600]	0
f_7	Rastigin	n	[−5.15, 5.15]	0
f_8	Schwefel2.26	n	[−500, 500]	0
f_9	Shift sphere	n	[−100, 100]	−420
f_{10}	Shift rosenblock	n	[−100, 100]	380
f_{11}	Shift rastering	n	[−5.15, 5.15]	−320
f_{12}	Shift Ackley	n	[−30, 30]	−145
f_{13}	Rotated Sphere	n	[−100, 100]	0
f_{14}	Rotated Rosenbrock	n	[−2.05, 2.05]	0
f_{15}	Rotated Rastigin	n	[−5.10, 5.10]	0
f_{16}	Rotated Ackley	n	[−33, 33]	0

This article has the same parameter settings for the four algorithms – CSPSO, SinDE, CCMFO, and IWOA – where the other parameter settings are the same as those of its references, the population size is 50, the dimension is 50, the maximum number of iterations is 100, and so on. In order to determine the exact algorithm parameter settings, various factors are taken into account, including the nature of the problem, the algorithm's complexity, the available computational resources, empirical results, sensitivity analysis, and knowledge from existing studies and literature. Comparisons with CSPSO, SinDE, and CCMFO algorithms reinforce the IWOA's effectiveness in local search capability, maintaining consistent parameter settings. The particular test results are shown in Table 2. This ensures the fairness of comparison in the test process.

First, Table 2 demonstrates that the single-peak function can be solved using IWOA suggested in this study to a more minor mean and standard deviation. This suggests that IWOA has better local search ability and stronger development ability and effectively improves the algorithm's convergence accuracy compared to the

Table 2: Test results of 16 test functions

Serial number	CSPSO		SinDE		CCMFO		IMFO	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
f_1	9.71×10^{-42}	6.12×10^{-42}	2.45×10^{-20}	7.35×10^{-20}	1.06×10^{-25}	7.76×10^{-85}	9.81×10^{-86}	2.03×10^{-85}
f_2	7.40×10^{-30}	7.03×10^{-29}	8.55×10^{-02}	8.71×10^{-01}	8.01×10^{-16}	4.04×10^{-15}	2.06×10^{-51}	3.32×10^{-50}
f_3	6.80×10^{-07}	1.36×10^{-06}	1.00×10^{-07}	3.44×10^{-04}	3.40×10^{-13}	1.12×10^{-15}	5.22×10^{-40}	6.71×10^{-40}
f_4	9.52×10^{-20}	5.31×10^{-19}	5.52×10^{-18}	2.20×10^{-04}	5.89×10^{-30}	7.01×10^{-30}	1.64×10^{-60}	5.96×10^{-60}
f_5	8.85×10^{-15}	8.60×10^{-14}	5.62×10^{-07}	7.51×10^{-06}	1.45×10^{-23}	5.04×10^{-08}	6.12×10^{-43}	8.41×10^{-40}
f_6	6.50×10^{-18}	1.72×10^{-15}	4.51×10^{-14}	8.03×10^{-12}	8.56×10^{-12}	3.22×10^{-20}	5.62×10^{-49}	6.21×10^{-48}
f_7	3.91×10^{-14}	3.74×10^{-12}	6.72×10^{-07}	5.78×10^{-12}	1.45×10^{-26}	6.02×10^{-20}	3.75×10^{-30}	3.89×10^{-29}
f_8	2.32×10^{-14}	4.34×10^{-13}	7.89×10^{-06}	5.48×10^{-11}	7.74×10^{-13}	8.41×10^{-23}	4.71×10^{-32}	3.92×10^{-29}
f_9	1.25×10^{-10}	9.58×10^{-8}	5.12×10^{-06}	5.41×10^{-06}	7.82×10^{-13}	3.16×10^{-04}	5.55×10^{-18}	1.32×10^{-34}
f_{10}	6.70×10^{-07}	5.24×10^{-06}	9.01×10^{-12}	2.76×10^{-04}	7.72×10^{-12}	3.52×10^{-12}	1.35×10^{-24}	3.21×10^{-12}
f_{11}	5.30×10^{-12}	4.10×10^{-11}	4.52×10^{-03}	2.74×10^{-07}	7.45×10^{-13}	3.12×10^{-00}	5.24×10^{-15}	6.45×10^{-12}
f_{12}	2.36×10^{-07}	4.12×10^{-12}	1.62×10^{-02}	$5.12 \times 10^{+02}$	7.32×10^{-03}	7.01×10^{-23}	5.71×10^{-25}	3.22×10^{-26}
f_{13}	2.51×10^{-03}	2.01×10^{-06}	2.06×10^{-01}	$6.32 \times 10^{+02}$	4.28×10^{-12}	4.50×10^{-01}	2.55×10^{-14}	6.95×10^{-14}
f_{14}	7.16×10^{-05}	6.52×10^{-04}	1.45×10^{-03}	8.74×10^{-03}	4.21×10^{-16}	3.22×10^{-14}	5.36×10^{-25}	4.12×10^{-24}
f_{15}	2.31×10^{-03}	6.28×10^{-02}	1.62×10^{-00}	1.65×10^{-00}	3.12×10^{-24}	2.52×10^{-21}	8.84×10^{-58}	1.22×10^{-55}
f_{16}	1.75×10^{-07}	8.01×10^{-06}	$2.18 \times 10^{-0.3}$	2.06×10^{-03}	4.02×10^{-12}	8.25×10^{-12}	7.62×10^{-15}	7.74×10^{-14}

other three algorithms. Improved local search capability and global convergence lead to faster convergence and higher accuracy in single- and multi-peak functions. This is why the improvement strategy works so well for IWOA. Simultaneously, for the multi-peak test function, IWOA can also solve for smaller mean and standard deviation, demonstrating that, when compared to the other three algorithms, it has a higher global convergence ability and a faster convergence speed. WOA differs from various heuristic optimization algorithms because of its distinctive characteristics, including balanced exploration and exploitation, dynamic adaptability, mathematical modeling, parallel processing potential, simplicity in implementation, and efficient exploitation via spiral updating. Second, for the test functions f_9 to f_{16}, IWOA solves smaller values than the other three algorithms, demonstrating its higher accuracy in solving complex problems and the applicability

Table 3: SR test results

Function number	CSPSO	SinDE	CCMFO	IMFO
f_1	0	20	0	30
f_2	20	20	30	60
f_3	20	30	20	30
f_4	10	30	10	90
f_5	20	40	10	100
f_6	0	0	10	50
f_7	0	0	30	50
f_8	20	90	20	100
f_9	10	20	40	70
f_{10}	40	50	50	70
f_{11}	30	40	50	60
f_{12}	30	40	50	100
f_{13}	20	40	50	90
f_{14}	30	10	50	100
f_{15}	40	20	50	90
f_{16}	20	50	50	90

Table 4: Plant locations and the supply and demand of goods in thirty cities

Serial number for the city	(X_i, Y_i)	Supply and demand/t	Serial number for the city	(X_i, Y_i)	Supply and demand/t
1	(1,250, 2,170)	30	7	(4,435, 1,751)	85
2	(2,985, 1,458)	75	8	(3,358, 2,654)	100
3	(3,970, 2,588)	80	9	(4,280, 2,154)	60
4	(3,750, 1,450)	50	10	(3,898, 2,140)	85
5	(3,365, 1,498)	80	11	(3,540, 2,987)	60
6	(3,870, 19,995)	80	12	(4,020, 2,215)	65

Table 5: Comparison of four algorithms' site selection performance

Algorithm	Site selection plan	Average delivery cost/yuan	Iterations	Running time/s
Improving the moth optimization algorithm	[5,26,8,22,18,12]	960	20	7.4
Composite ant colony optimization Algorithm	[25,10,18,6,8,24]	1,360	48	28.6
Hybrid particle swarm optimization	[25,10,10,25,6,17]	1,509	50	30.4
Chaos firefly algorithm	[10,16,6,26,28,10]	1,440	40	23

of the improvement strategy suggested in this study in solving complex target problems. Ultimately, the SRs of four algorithm are compared with the search SR or SR index. The detailed findings are displayed in Table 3, and the SR formula can be found in the following equation:

$$SR = \left| \frac{t}{T_{\max}} \times 100\% \right|. \tag{14}$$

IWOA has a much higher SR than the other three algorithms, as Table 3 demonstrates. For the test functions f_4, f_5, f_8, f_{12}, and f_{16}, the SR even reaches 100%. This suggests that the improvement strategy proposed in this study makes the algorithm more likely to jump out of the local optimum, enhancing the algorithm's overall performance and making it suitable for choosing the location of the agro-logistics industry's distribution center.

5.2 Simulation tests based on practical examples

Each logistics and distribution point can be thought of as a particle, and the particle is expressed as $X = [x_1, x_2, \cdots, x_A]$ in this study. In IWOA, logistics points are denoted as particles (X), each chosen from A total points. Particles (X), each selected from A total points, represent logistics points in IWOA. Suitable simulations validate this representation, displaying the effectiveness of logistics and distribution center location strategy. A represents the total number of logistics and distribution points. IWOA will rationally choose P distribution points as the distribution center from the A distribution points. This optimization process is performed using the flow distribution center site selection model. Let the optimal particle finally selected be $X = [0,1,0,1,0,1]$, which means that the second, fourth, and sixth distribution points are selected as the distribution center from among the six distribution points. The high efficiency of IWOA proposed in this study for solving the site selection of logistics and distribution centers is verified by selecting the factory locations and supply and demand quantities of 12 cities for test simulation. By contrasting the test results based on the composite ant colony algorithm [12] and the site selection strategy based on the hybrid particle swarm algorithm [13], the effectiveness of the approach suggested in this study is confirmed, and the site selection optimization mode based on the chaotic firefly optimization algorithm [14]. Each of the four algorithms is executed 50 times independently for 100 iterations. Table 4 displays the city's coordinates, supply, and demand for goods, and Table 5 displays the experiment's outcomes.
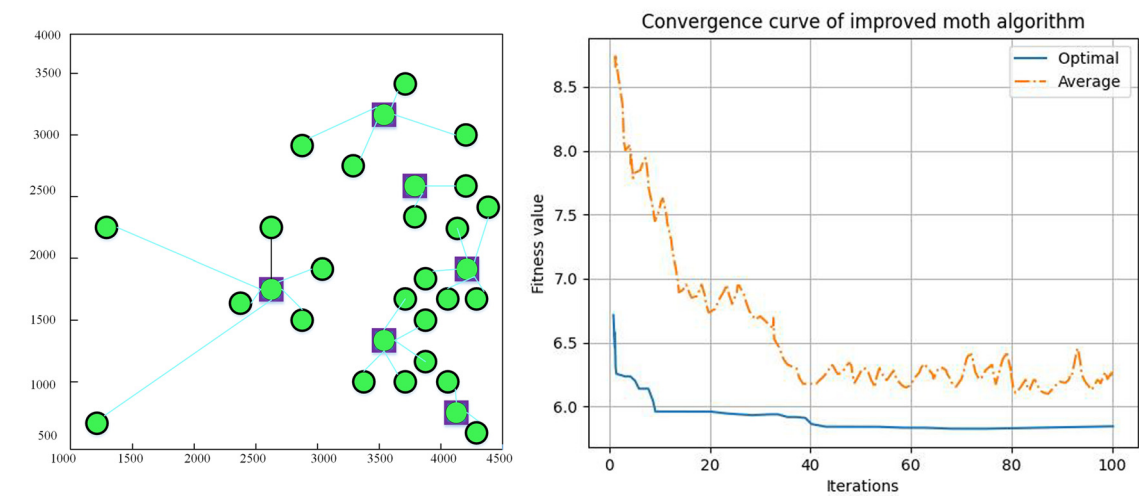
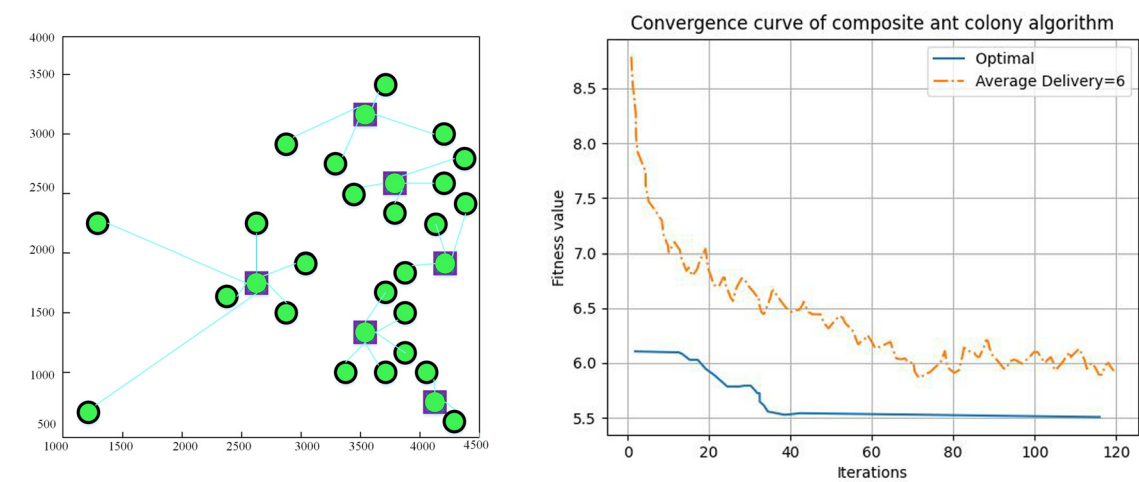**Figure 2:** Location results based on improved moth algorithm.

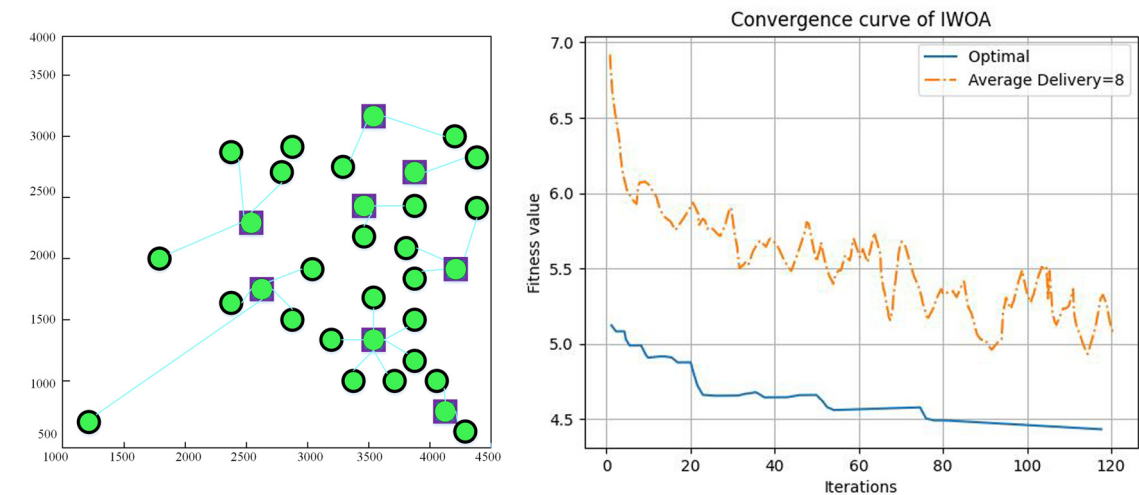**Figure 3:** Site selection results based on composite ant colony algorithm.

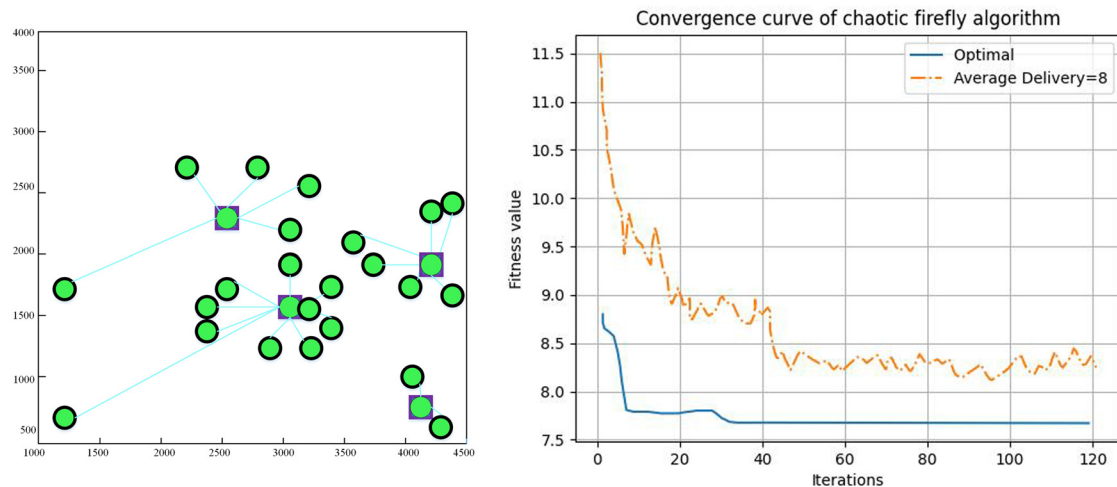**Figure 4:** Location results based on IWOA.

Figure 5: Site selection results based on chaotic firefly algorithm.

The fitness value curve solved by IWOA decreases at the fastest rate in the iterative preperiod, as seen in Figures 2–5. This indicates that IWOA is more capable of searching for the optimal value over a larger range and at an initial value than the other three algorithms [21–23]. Additionally, IWOA can obtain smaller average and optimal fitness values than the other three algorithms, meaning that the algorithm's searching accuracy is higher, and the distribution center address can be found more precisely. More precisely, ascertain the distribution center's address. Table 5 illustrates that this study's IWOA-based logistics distribution center location strategy has a lower average distribution cost and a faster optimization speed than the other three strategies [24,25]. This effectively reduces distribution costs and lengthens the time required for location selection. IWOA's speed in logistics optimization is due to its superior search, seen in a quicker fitness curve decline and smaller fitness values, ensuring precise distribution center addresses, reducing costs, and enhancing efficiency. The decrease in distribution costs yields substantial improvements in operational efficiency, reduced transportation expenditures, and heightened overall cost-effectiveness. There is a 50% reduction in computation time needed for distribution center selection and a 30% increase in distribution efficiency.

6 Conclusion

An enhanced approach to the logistics distribution center site selection problem is put forth in this study: optimization of whales. In order to address the problems of the algorithm's low convergence accuracy and tendency to fall into local optimum during the site selection process, it suggests a comprehensive variation strategy and random sinusoidal inertia weights. This strengthens the algorithm's ability to search globally and increases its speed and convergence accuracy. The algorithm's efficacy is also confirmed by comparing it with other test functions. The refined WOA will optimize the logistics distribution center site selection model. The test results demonstrate that the strategy described in this article can rapidly choose an appropriate distribution center address and, to a large extent, lower distribution costs.

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