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# Cold Chain Logistics Center Layout Optimization Based on Improved Dung Beetle Algorithm

**Jinhui Li and Qing Zhou ***

College of Vehicle and Traffic Engineering, Henan University of Science and Technology, Luoyang 471003, China; jtljh@haust.edu.cn
* Correspondence: zhouqing3527@163.com

**Abstract:** To reduce the impact of the cold chain logistics center layout on economic benefits, operating efficiency and carbon emissions, a layout optimization method is proposed based on the improved dung beetle algorithm. Firstly, based on the analysis of the relationship between logistics and non-logistics, a multi-objective optimization model is established to minimize the total logistics cost, maximize the adjacency correlation and minimize the carbon emissions; secondly, based on the standard Dung Beetle Optimization (DBO) algorithm, in order to further improve the global exploration ability of the algorithm, Chebyshev chaotic mapping and an adaptive Gaussian–Cauchy hybrid mutation disturbance strategy are introduced to improve the DBO (IDBO) algorithm; finally, taking an actual cold chain logistics center as an example, the DBO algorithm and the improved DBO algorithm are applied to optimize its layout, respectively. The results show that the total logistics cost after optimization of the IDBO algorithm is reduced by 25.54% compared with the original layout, the adjacency correlation is improved by 29.93%, and the carbon emission is reduced by 6.75%, verifying the effectiveness of the proposed method and providing a reference for the layout design of cold chain logistics centers.

**Keywords:** cold chain logistics center; layout optimization; carbon emission; improved dung beetle optimization algorithm



**Citation:** Li, J.; Zhou, Q. Cold Chain Logistics Center Layout Optimization Based on Improved Dung Beetle Algorithm. *Symmetry* **2024**, *16*, 805. https://doi.org/10.3390/sym16070805

Academic Editor: Vasilis K. Oikonomou

Received: 28 May 2024
Revised: 17 June 2024
Accepted: 19 June 2024
Published: 27 June 2024



## 1. Introduction

With global trade growth and the increasing demand for food safety and pharmaceutical logistics, the efficient operation of cold chain logistics centers has become a key link in supply chain management. Optimizing the layout of cold chain logistics centers improves operational efficiency and ensures the quality and safety of goods during transportation [1]. Therefore, in the context of strengthening the cold chain logistics service system and the "dual carbon" goals, how to promote the layout planning of cold chain logistics centers is crucial for achieving green development in the logistics industry [2].

Layout optimization is a research focus in the field of logistics. Traditional layout optimization methods include process analysis and systematic layout planning [3,4]. In recent years, researchers have also employed genetic algorithms (GA), particle swarm optimization (PSO), simulated annealing (SA), and ant colony optimization (ACO) for solutions [5,6]. For example, Li et al. [7] utilized ACO to optimize layout, significantly reducing operational costs; Jiang et al. [8] designed a simulated annealing algorithm targeting material handling and transportation facility costs, and validated their method across various scale experiments; Hu et al. [9] aimed to minimize total processing costs and maximize comprehensive relationships by constructing a nonlinear programming model and solving it with a genetic algorithm, thereby reducing handling costs for enterprises.

However, current research on layout optimization mainly focuses on general logistics centers, with relatively few studies addressing the specific field of cold chain logistics centers. Compared to general logistics centers, cold chain logistics centers have unique attributes, such as stringent temperature control requirements, high energy consumption, short transportation cycles, and complex management systems. Effective temperature control necessitates that cold chain logistics centers are equipped with specialized refrigeration equipment and advanced temperature monitoring systems to ensure the quality and safety of goods during transportation and storage. The high energy consumption results from the use of refrigeration and freezing equipment, leading to increased energy costs and environmental requirements. Moreover, most existing studies have failed to simultaneously address multi-objective layout optimization and environmental sustainability. Therefore, how to optimize the layout of cold chain logistics centers while effectively reducing carbon emissions and solving it with efficient optimization algorithms is still an urgent problem to be solved.

Based on this, this paper proposes a layout optimization method for cold chain logistics centers that consider carbon emissions. The objectives are to minimize total logistics costs, maximize adjacency correlation, and minimize carbon emissions. Employing the improved dung beetle algorithm, the proposed method is applied and validated using a real-world cold chain logistics center, providing a reference for the development of cold chain logistics centers.

The paper is structured as follows: Section 2 provides a detailed review of the relevant literature, including studies on cold chain logistics centers, carbon emissions, and the improved dung beetle algorithm. Sections 3 and 4 describe the proposed optimization model and solution algorithm. Section 5 discusses the results and implications of the proposed method using a case study. Finally, Section 6 presents the discussion and conclusion, and suggests directions for future research.

## 2. Literature Review

Cold chain logistics centers play a crucial role in high-demand sectors, such as food and pharmaceuticals. However, although some studies have focused on cold chain logistics centers, they primarily carried out from relatively macro levels, such as system construction [10], sustainability [11], route optimization [12], network optimization [13], location selection [14], and evaluation [15]. These studies have significantly contributed to the development of cold chain logistics, but there is a lack of research on the layout optimization of cold chain logistics centers, especially in the comprehensive consideration of carbon emissions and other environmental factors.

Carbon emission is one of the pressing global environmental concerns today. In logistics systems, carbon emissions primarily stem from transportation processes and storage activities [16]. Although existing studies aim to reduce carbon emissions in logistics systems, most focus on transportation optimization, overlooking the impact of logistics center layout on carbon emissions [17]. For example, Wei et al. [18] proposed a method to reduce carbon emissions by optimizing transportation routes, but did not consider reducing carbon emissions by optimizing the layout of cold chain logistics centers. Therefore, this paper incorporates carbon emission factors into the layout optimization model to further reduce carbon emissions while optimizing the layout, thereby promoting the sustainable development of cold chain logistics centers.

In addressing the optimization of layout models, it is proved that layout optimization is an NP-hard problem [19], rendering traditional optimization algorithms insufficient for solving it. Therefore, in recent years, scholars have often employed intelligent optimization algorithms, as mentioned in the introduction. However, as model complexity increases and search space expands in layout problems, these algorithms tend to get stuck in local optima, exhibit slower convergence, and face exponentially increasing difficulty in finding solutions.

The Dung Beetle Optimization (DBO) algorithm [20], proposed by Xue et al. in 2023, possesses stronger optimization capabilities compared to other algorithms and has found widespread application across various domains. Zhu et al. [21] introduced an improved DBO algorithm that integrates quantum computing and multiple strategies, applying it to solve multiple practical engineering problems; Li et al. [22] employed an enhanced DBO algorithm to solve nonlinear optimization problems with multiple constraints in the manufacturing industry, and demonstrated the robustness of the improved algorithm. However, the Dung Beetle Optimization (DBO) algorithm also faces challenges, such as increased computational complexity and slow convergence rates when applied to complex optimization problems [23]. Some researchers have proposed improved versions of DBO to enhance its convergence speed and optimization performance. For example, Shen et al. [24] improved the efficiency and accuracy of DBO in solving complex problems by introducing new search mechanisms and parameters; Li et al. [25] used the improved DBO algorithm to optimize the parameters of bidirectional long short-term memory network models, improving the accuracy and stability of wind speed prediction models. However, these studies mainly focus on general optimization problems, and the applied research on optimizing the layout of cold chain logistics centers is still limited.

In addition, other optimization algorithms also perform well in solving complex optimization problems. Uniyal et al. [26] conducted an exhaustive study on the performance of nature-inspired metaheuristic algorithms in multi-objective optimization and its applications, proving the effectiveness and flexibility of these algorithms in solving complex optimization problems. However, the specific application of these algorithms to the layout of cold chain logistics centers still needs to be further explored. The enhanced Wild-Horse optimizer proposed by Kumar et al. [27] has also shown excellent performance in handling the reliability optimization problems of constrained systems. However, this research primarily focuses on system reliability optimization, and there have been insufficient studies regarding the application of layout optimization in cold chain logistics centers. Therefore, in this paper, to better solve the cold chain logistics center layout optimization problem considering the carbon emission factor, Chebyshev chaotic mapping and an adaptive Gaussian–Cauchy hybrid mutation disturbance strategy are introduced into the dung beetle algorithm, to help the algorithm to escape local optima and improve solution efficiency.

## 3. Layout Optimization Modeling

### *3.1. Problem Description*

The layout of the cold chain logistics center can be simplified by arranging the positional relationship between each functional zone in a plane to achieve the established goals and ensure the connectivity and efficiency of the operational processes. Considering the simulation solution of the model, the modeling is based on the following assumptions: ① The uniformity of the safety distance between various functional zones is maintained; ② The overall zone and each functional zone are simplified as rectangles, with the boundaries parallel to the X and Y axes; ③ Functional zone positions are denoted by the central coordinates of the rectangles.

According to the assumptions, the schematic diagram of the central plane coordinates is shown in Figure 1.

In Figure 1, the $X$-axis and $Y$-axis denote the length and width directions of the cold chain logistics center, respectively; $L$ and $H$ denote the total length and total width of the cold chain logistics center, respectively; $(x_i, y_i)$ denotes the central coordinates of the functional zone $i$; $l_i$ and $h_i$ denote the length and width of functional zone $i$, respectively; $u_{ij}$ denotes the distance to be maintained between functional zones $i$ and $j$ along the $X$-axis; $v_{jk}$ denotes the distance to be maintained between functional zones $j$ and $k$ along the $Y$-axis; $a_i$ and $b_i$ denote the safety distances from the functional zone $i$ to the boundaries of the cold chain logistics center along the $X$-axis and $Y$-axis, respectively.

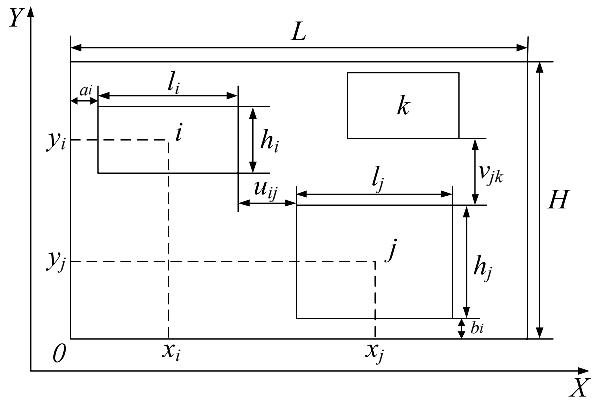



**Figure 1.** Functional zone plane coordinate diagram.

*3.2. Objective Function*

The optimization of cold chain logistics center layouts necessitates the consideration of both logistics flow and non-logistics relationships among diverse functional zones. Moreover, minimizing carbon emissions during operations is essential for realizing high efficiency and low-carbon objectives [28]. The carbon emission calculation in this paper mainly encompasses two factors: fixed-source carbon emissions and mobile-source carbon emissions.

① Fixed-source carbon emissions refer to the emissions of carbon dioxide generated by storage processes in zones of refrigeration functions in the cold chain logistics center. Therefore, the calculation of fixed-source carbon emissions is related not only to the space occupied by the functional zone but also to the amount of stored goods. The solution formula for fixed-source carbon emissions as flow is as follows:

$$T_1 = \sum_{i=1}^{N} V_i G_i^t E_c \tag{1}$$

In Equation (1), $T_1$ denotes the fixed-source carbon dioxide emissions; $V_i$ denotes the space occupied by functional zone $i$ ($m^3$); $G_i^t$ denotes the electricity consumption per cubic meter of space ($kWh/m^3$) when the inventory in the functional zone $i$ is $t$; $E_c$ denotes the carbon emission factor of electricity (kg/kWh).

② Mobile-source carbon emissions stem from the consumption of fuel or electricity during transportation, loading, and unloading activities between different functional zones. Energy consumption in these processes is influenced by a multitude of factors, such as diverse equipment, variations in operator behavior, and environmental conditions. Therefore, considering the actual operational conditions, this paper takes the influence of travel distance and vehicle load on energy consumption. The solution formula for mobile-source carbon emissions as follows:

$$T_2 = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} q_{ij} D_{ij} U E_c \tag{2}$$

$$q_{ij} = \begin{cases} 0, & there\ is\ no\ flow\ of\ goods\ between\ i\ and\ j. \\ 1, & otherwise \end{cases} \tag{3}$$

In Equation (2), $T_2$ denotes the carbon dioxide emissions from mobile sources, $q_{ij}$ is a binary variable (0–1), indicating whether there is a flow of goods between functional zones $i$ and $j$, as shown in Equation (3); $D_{ij}$ is the distance between functional zones $i$ and $j$, calculated using the Manhattan distance formula, $D_{ij} = |x_i - x_j| + |y_i - y_j|$; $U = U^* + U^0$ denotes the energy consumption of vehicles (kWh/km), where $U^*$ and $U^0$ denote the energy consumption when the forklift is fully loaded and unloaded, respectively. Each round-trip movement is regarded as one full load and one empty load.

Establish a multi-objective function that minimizes the total logistics cost, maximizes adjacency correlation, and minimizes carbon emissions, as follows:

$$\min Z1 = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} P_{ij} F_{ij} D_{ij} C_{ij} \quad (4)$$

$$\max Z2 = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} R_{ij} k_{ij} \quad (5)$$

$$\min Z3 = T_1 + T_2 \quad (6)$$

In Equation (4), $P_{ij}$ denotes the amount of logistics between functional zones $i$ and $j$; $F_{ij}$ denotes the handling frequency between functional zones $i$ and $j$; $C_{ij}$ denotes the handling cost between functional zones $i$ and $j$. In Equation (5), $R_{ij}$ denotes the comprehensive interrelationship between functional zones $i$ and $j$, determined through the System Layout Planning (SLP) method; $k_{ij}$ denotes the adjacency correlation factor between functional zones $i$ and $j$, which is related to $D_{ij}$, defined specifically as shown in Table 1.

**Table 1.** Adjacency correlation factor and distance table.

| $D_{ij}$ | $k_{ij}$ |
|---|---|
| $0 \leq D_{ij} \leq D_{\max}/6$ | 1 |
| $D_{\max}/6 < D_{ij} \leq D_{\max}/3$ | 0.8 |
| $D_{\max}/3 < D_{ij} \leq D_{\max}/2$ | 0.6 |
| $D_{\max}/2 < D_{ij} \leq 2D_{\max}/3$ | 0.4 |
| $2D_{\max}/3 < D_{ij} \leq 5D_{\max}/6$ | 0.2 |
| $5D_{\max}/6 < D_{ij} \leq D_{\max}$ | 0 |

To facilitate calculation and solution, the multi-objective function is transformed into a single-objective function. Due to the different measurement units of the three objective functions, normalization factors $\lambda_1$, $\lambda_2$, $\lambda_3$ are introduced, along with weighting coefficients $w_1$, $w_2$, $w_3$. Among them, the selection of weight coefficients can be determined by the Analytic Hierarchy Process (AHP), Delphi method, entropy weight method, etc. These three methods are classic approaches for determining weight coefficients. The AHP method has a systematic attribute, through hierarchical, pairwise comparisons to determine the relative importance of the factors [29]. It is suitable for complex, multi-level decision problems, especially when structured analysis and expert judgment are needed. However, the process is time-consuming and may also introduce subjective bias. The Delphi method [30] converges to consensus through multiple rounds of questionnaire surveys and feedback, relying on collective opinions from an expert panel and iterative feedback. It is suitable for problems requiring broad consensus, particularly in the absence of objective data. However, this process is lengthy and may lead to increased time and costs. Both the AHP and Delphi methods rely on expert judgment and belong to subjective methods. The entropy method [31] is an objective approach that determines weights based on data variability. It is suitable for decision problems with sufficient data and a desire to reduce subjective bias. The calculation process is relatively simple and fast. Therefore, researchers can choose appropriate methods based on the specific circumstances and research needs to determine weight coefficients, supporting the scientificity and reliability of the decision-making process.

In this case study, initially, each weight coefficient was assumed to be equal. However, considering the actual circumstances of the case study, and to facilitate calculation while still solving the problem effectively, combined with expert opinions, the weight coefficients of the three factors were determined to be $w_1 = 0.35,\ w_2 = 0.3,\ w_3 = 0.35$. The transformed single-objective function is as follows:

$$\min Z = \lambda_1 w_1 \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} P_{ij} F_{ij} D_{ij} C_{ij} - \lambda_2 w_2 \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} R_{ij} k_{ij} + \lambda_3 w_3 (T_1 + T_2) \tag{7}$$

where $\lambda_1 = \frac{Z_1 - Z_{1,\min}}{Z_{1,\max} - Z_{1,\min}}$, $\lambda_2 = \frac{Z_2 - Z_{2,\min}}{Z_{2,\max} - Z_{2,\min}}$, $\lambda_3 = \frac{Z_3 - Z_{3,\min}}{Z_{3,\max} - Z_{3,\min}}$.

### *3.3. Constraints*

In layout planning, the following constraints are primarily entailed:

① Boundary constraint—each functional zone can not exceed the boundaries of the planning zone and should maintain a designated safety distance from the boundaries.

$$\begin{cases} x_i + a_i + \frac{l_i}{2} \le L \\ x_i - a_i - \frac{l_i}{2} \ge 0 \end{cases} \tag{8}$$

$$\begin{cases} y_i + b_i + \frac{h_i}{2} \le H \\ y_i - b_i - \frac{h_i}{2} \ge 0 \end{cases} \tag{9}$$

② Non-overlapping constraints—each functional zone cannot overlap with each other, and the minimum spacing distance should be maintained between any two functional zones.

$$\begin{cases} \frac{l_i + l_j}{2} + u_{ij} \le \left| x_i - x_j \right| \\ \frac{h_i + h_j}{2} + v_{ij} \le \left| y_i - y_j \right| \end{cases} \tag{10}$$

## 4. Solution Algorithm of the Model

### *4.1. Standard DBO Algorithm*

The DBO algorithm is inspired by the activities of dung beetles and divides the population into four sub-populations based on the dung beetle's behaviors of rolling, dancing, reproduction, foraging, and stealing. It then executes different search methods and adopts a dynamic boundary search strategy to improve the effectiveness of algorithmic search.

(1) Rolling Behavior

Rolling behavior is divided into obstacle-free and obstacle-present scenarios. In the absence of obstacles along the rolling path, dung beetles utilize sunlight as a navigation aid. Hence, the intensity of the light source affects the beetle's path. In this case, the position update formula for rolling dung beetles is as follows:

$$x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \tag{11}$$

where, $t$ denotes the current iteration number, $x_i(t)$ denotes the position information of the $i$-th dung beetle at the $t$-th iteration, $k \in (0, 0.2]$ denotes a constant value for the deflection coefficient, $b$ is a constant value between (0,1), $\alpha$ denotes the natural coefficient, which is either $-1$ or 1, $X^w$ denotes the global worst position, and $\Delta x$ is used to simulate changes in light intensity, $\Delta x = |x_i(t) - X^w|$, with higher values indicating weaker light.

When encountering obstacles along the rolling path, dung beetles need to reorient their direction through dancing to establish a new path. In this case, the position update formula for rolling dung beetles is as follows:

$$x_i(t+1) = x_i(t) + \tan(\theta)|x_i(t) - x_i(t-1)| \tag{12}$$

where $\theta$ is the deflection angle belonging to $[0, \pi]$, and when $\theta = 0, \frac{\pi}{2}, \pi$, the position remains unchanged.

(2) Reproduction Behavior

A boundary selection strategy (as shown in Figure 2) is used to simulate the spawning zone of dung beetles:

$$\begin{aligned} Lb^* &= \max(X^* \times (1-R), Lb) \\ Ub^* &= \min(X^* \times (1+R), Ub) \end{aligned} \tag{13}$$

where $X^*$ denotes the current local optimal position, $Lb^*$ and $Ub^*$, respectively, denote the lower and upper bounds of the spawning zone, $R = 1 - t/T_{\max}$, $T_{\max}$ denotes the maximum number of iterations, and $Lb$ and $Ub$ denote the lower and upper bounds of the optimization problem, respectively.

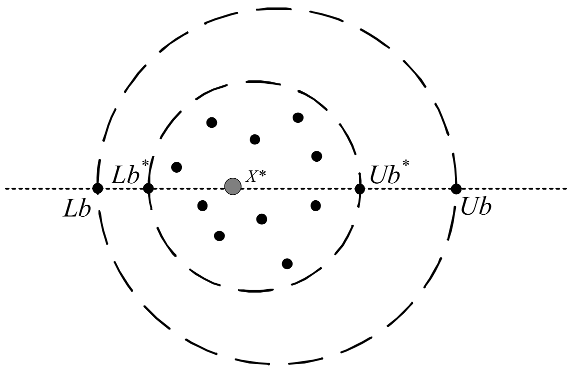



**Figure 2.** Boundary selection strategy.

The boundary range of the spawning zone is dynamically changing, mainly determined by the value of $R$. Therefore, the position of the spawning ball is also dynamic during the iteration process for:

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \tag{14}$$

where $B_i(t)$ denotes the position of the $i$-th brood ball at the $t$-th iteration, and $b_1$ and $b_2$ are two independent random vectors of size $1 \times D$, where $D$ denotes the dimension of the optimization problem.

(3) Foraging Behavior

After successful hatching, the little dung beetle needs to forage independently, with the optimal foraging zone being:

$$\begin{aligned} Lb^b &= \max\left(X^b \times (1-R), Lb\right) \\ Ub^b &= \min\left(X^b \times (1+R), Ub\right) \end{aligned} \tag{15}$$

where $X^b$ denotes the global best position, and $Lb^b$ and $Ub^b$, respectively, denote the lower and upper bounds of the optimal foraging zone, and other parameters are defined in (2).

The position update for the dung beetle is as follows:

$$x_i(t+1) = x_i(t) + C_1 \times \left(x_i(t) - Lb^b\right) + C_2 \times \left(x_i(t) - Ub^b\right) \tag{16}$$

where $x_i(t)$ denotes the position information of the $i$-th little dung beetle at the $t$-th iteration, $C_1$ is a random number following a normal distribution, and $C_2$ is a random vector belonging to (0,1).

(4) Theft Behavior

Thief dung beetles steal dung balls from other dung beetles. The position update formula for the thief dung beetle is as follows:

$$x_i(t+1) = X^b + S \times g \times \left( |x_i(t) - X^*| + \left| x_i(t) - X^b \right| \right) \tag{17}$$

where $x_i(t)$ denotes the position information of the $i$-th thief dung beetle at the $t$-th iteration, $g$ is a random vector of size $1 \times D$ following a normal distribution, and $S$ denotes a constant value.

*4.2. Improved DBO Algorithm*

In the standard DBO algorithm, although the initial population is generated randomly, it fails to ensure a high level of chaos, and in the later iterations the dung beetle population tends to cluster near the currently obtained optimal position, and the algorithm then expands the search, which easily leads to local optimal solutions. Therefore, improvements will be made to overcome the above shortcomings.

(1) Chebyshev Chaos Initialization Population

In the initial stages of the algorithm, the quality of the initial population has an important impact on the convergence speed of the algorithm. Enhancing the quality of the initial population commonly involves employing chaotic mapping functions for initialization. Among these, Chebyshev mapping stands out as a prominent representative due to its good chaotic characteristics, promoting a more uniform distribution of the population within the search space. Reference [32] tested and compared several common chaotic mapping functions, demonstrating the superiority of Chebyshev chaotic mapping over other mapping functions. Additionally, references [33,34] applied Chebyshev mapping to improve other intelligent optimization algorithms, also achieving better results. Therefore, this paper utilizes Chebyshev chaotic mapping to optimize the initial population of the DBO algorithm, with its iteration process as follows:

$$x_{n+1} = \cos(k \operatorname{arccos} x_n),\ x_n \in [-1, 1] \tag{18}$$

where $k$ denotes the order, with a value of 4 chosen in this study to achieve better performance.

(2) Adaptive Gaussian–Cauchy Hybrid Mutation Disturbance Strategy

To enhance the diversity of the population and facilitate the algorithm escape local optima, mutation disturbance operations are commonly applied to explore the solution space more effectively. In intelligent optimization algorithms, Gaussian mutation and Cauchy mutation are frequently utilized mutation operators, each possessing distinct characteristics. Gaussian mutation exhibits good search capability within a small range [35] and offers a relatively controllable mutation degree. Conversely, the Cauchy distribution, characterized by a heavy-tailed distribution, yields larger mutations compared to the Gaussian distribution, resulting in overly dispersed searches. Drawing insights from the literature [36], this study adopts an adaptive Gaussian–Cauchy hybrid mutation disturbance strategy that integrates the advantages of Cauchy mutation and Gaussian mutation to mutate the optimal individuals. Fitness values before and after the disturbance are compared to select the better solutions for the next iteration.

The specific formula is as follows:

$$M^b(t) = X^b(t) * (1 + \delta_1 * Gauss(\sigma) + \delta_2 * Cauchy(\sigma)) \tag{19}$$

where $X^b(t)$ denotes the optimal position of the individual $X$ at the $t$-th iteration, $M^b(t)$ denotes the position of $X^b(t)$ disturbed by Gaussian–Cauchy hybrid mutation at the $t$-th iteration, $\delta_1 = t/T_{\max}$, $\delta_2 = 1 - t/T_{\max}$, $Gauss(\sigma)$ denotes the Gaussian mutation operator, and $Cauchy(\sigma)$ denotes the Cauchy mutation operator. The coefficients of the mutation operators $\delta_1$ and $\delta_2$ are gradually adjusted in a one-dimensional linear manner to ensure smooth and balanced disturbance in each iteration. After many tests, a value of 1 is chosen for the parameter $\sigma$ to achieve better results in this study.

Following the application of this strategy to mutate the solutions, it is necessary to reevaluate the fitness of the mutated solutions compared to the current optimal solution. Therefore, a greedy rule is introduced to determine whether the optimal solution should be updated.

$$X^b = \begin{cases} M^b(t), f\left[M^b(t)\right] < f\left[X^b(t)\right] \\ X^b(t), f\left[M^b(t)\right] \geq f\left[X^b(t)\right] \end{cases} \tag{20}$$

The improved algorithm flowchart is shown in Figure 3, with the shaded zone denoting the strategies added to the improved DBO algorithm.

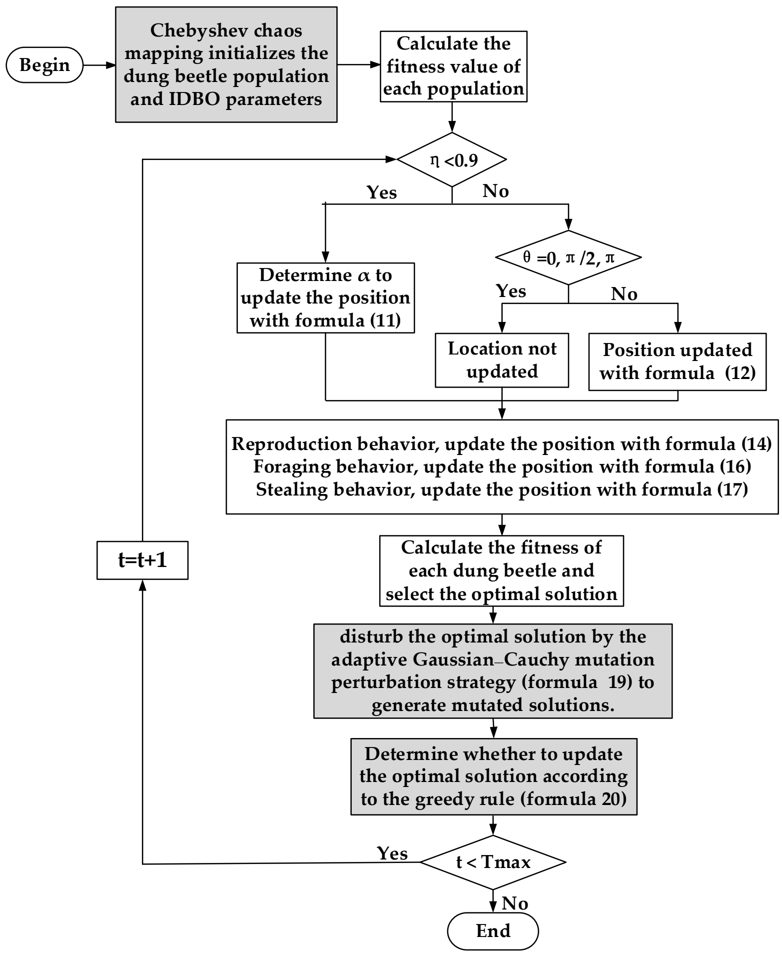



**Figure 3.** IDBO algorithm flow diagram.

## 5. Case Applications

### *5.1. Case Overview*

A certain cold chain logistics center primarily serves as a regional hub for transshipment and warehousing, undertaking the distribution task of cold chain products within the region while also providing initial processing services for these products. Due to the rapid growth in demand for cold chain products in recent years and the upgrading of consumer structures, the center has faced challenges in promptly responding to changes in order demands, resulting in redundant goods flow routes and reduced operational efficiency. Therefore, the next step will focus on addressing the existing issues.

The center is about 460 m long and 280 m wide. According to the functional attributes, there are 10 functional zones: the intelligent control center, refrigerated storage, fresh-keeping storage, ambient temperature storage, circulation packaging zone, multi-temperature shared distribution zone, business office zone, comprehensive service zone, central kitchen, and the exhibition trading zone. The current layout of the center is shown in Figure 4.

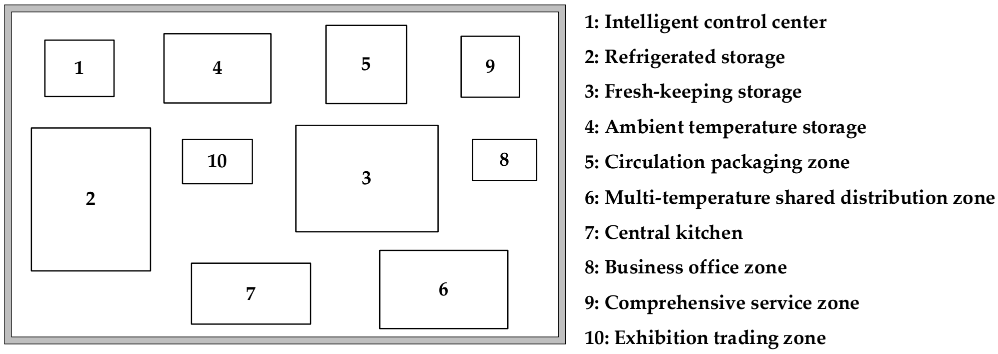



**Figure 4.** Initial layout diagram.

In Figure 4, the initial layout of each functional zone exhibits an upper and lower symmetry, with goods flow paths and channels also being relatively symmetrical. However, during practical operations, adhering to symmetrical paths and channels for transporting goods between two functional zones may lead to redundant logistics routes, thereby reducing the system's operational efficiency. Therefore, considering the internal logistics flow and transportation demands within the cold chain logistics center, an asymmetric layout was employed in this case study to reduce the time and energy consumption during transportation and storage processes. The information for each functional zone is provided in Table 2.

**Table 2.** Information of functional zones.

| Number | Name | Length × Width/(m) | Storage Capacity/t |
|---|---|---|---|
| 1 | Intelligent control center | 70 × 60 | — |
| 2 | Refrigerated storage | 100 × 100 | 2676 |
| 3 | Fresh-keeping storage | 140 × 100 | 3009 |
| 4 | Ambient temperature storage | 100 × 70 | 1455 |
| 5 | Circulation packaging zone | 70 × 80 | 1101 |
| 6 | Multi-temperature shared distribution zone | 120 × 80 | 1926 |
| 7 | Central kitchen | 100 × 70 | — |
| 8 | Business office zone | 64 × 40 | — |
| 9 | Comprehensive service zone | 50 × 56 | — |
| 10 | Exhibition trading zone | 60 × 50 | — |

## *5.2. Optimization Solution*

### 5.2.1. Parameter Determination

According to the research report on the average carbon emission factor of China's regional power grids in 2023, the average carbon emission factor for each province in China is approximately $E_c = 0.608$ kg/kWh. The carbon emissions attributable to the functional zones providing refrigeration services are shown in Table 3. In this case, electric forklifts are used to facilitate the movement of goods between various functional zones, with energy consumption rates of $U^* = 0.876$ kWh/km and $U^0 = 0.732$ kWh/km for full load and empty load, respectively.

**Table 3.** Power consumption and carbon emissions of functional zones.

| Number | Name | Average Daily Electricity Consumption/kWh | Carbon Emissions/kg |
|---|---|---|---|
| 2 | Refrigerated storage | 2493 | 1515.744 |
| 3 | Fresh-keeping storage | 2946 | 1791.168 |
| 4 | Ambient temperature storage | 1389 | 844.512 |
| 5 | Circulation packaging zone | 978 | 594.624 |
| 6 | Multi-temperature shared distribution zone | 1851 | 1125.408 |

The system layout planning method is used to analyze both the non-logistics and logistics relationships. While ensuring the minimization of total logistics costs, it is essential to consider the continuity and connectivity of workflow processes. Therefore, assigning equal importance to both non-logistics and logistics relationships, with a weight ratio of 1:1, and quantifying the grades of logistics and non-logistics, obtains the comprehensive mutual relationship value and its corresponding grades, as illustrated in Table 4.

**Table 4.** Comprehensive mutual relationship.

| Logistics Flow Path | $R_{ij}$ | Cumulative Proportion/% | Grade |
|---|---|---|---|
| 7—6 | 7 | 14.89 | A |
| 3—6 | 7 | 29.78 | A |
| 3—7 | 7 | 44.67 | E |
| 5—6 | 6 | 57.44 | E |
| 2—6 | 5 | 68.08 | E |
| 3—5 | 4 | 76.59 | I |
| 4—6 | 3 | 82.97 | I |
| 2—7 | 2 | 87.23 | I |
| 4—7 | 2 | 91.49 | O |
| 1—6 | 2 | 95.75 | O |
| 4—5 | 1 | 97.88 | O |
| 1—8 | 1 | 100.00 | O |

#### 5.2.2. Comparison of Results

The DBO and IDBO algorithms were applied to solve the problem, respectively, with the number of iterations set to 300, and the initial population size of 30, in which the number of ball-rolling dung beetles, reproducing dung beetles, foraging dung beetles, and stealing dung beetles were 6, 6, 7, and 11, respectively. Since the algorithms yielded different results each time, to avoid differences due to random factors, each algorithm was simulated 30 times. The optimal solutions obtained from both algorithms were compared, and the corresponding iteration curves are shown in Figure 5.

Figure 5 illustrates that the DBO algorithm reached the optimum at the 50th iteration, after which it entered a stagnation phase. Conversely, the IDBO algorithm exhibited relatively rapid convergence in the initial stages, indicating that the introduction of Chebyshev mapping facilitated the generation of a diverse initial population. By the 120th iteration, its fitness value has been better than the optimal fitness value of the DBO algorithm, indicating a significant improvement in the convergence speed. Although stagnation occurred around the 180th iteration, it consistently escapes local optima after brief stagnations. Moreover, even after 300 iterations, there was still a possibility for improvement, indicating the effectiveness of the adaptive Gaussian–Cauchy mixed mutation disturbance strategy in enhancing the algorithm's global exploration capability.

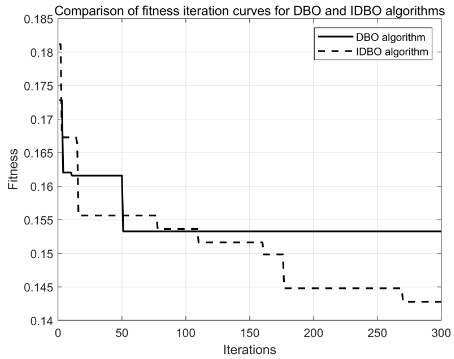


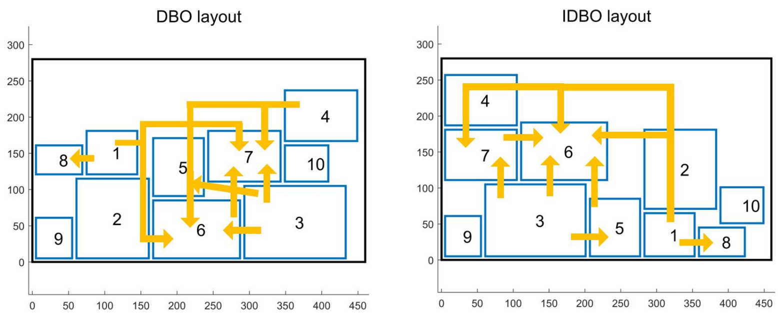

**Figure 5.** Iteration curve plot.

The coordinates of the functional zones obtained by the two algorithms are shown in Table 5. Comparing Figure 5 and Table 5, it can be seen how the algorithm progressively optimizes the layout during iterations and ultimately reaches a stable state. The combination of the convergence of the iterative curve and the final position in the table verifies the effectiveness of the algorithm.

**Table 5.** Position coordinate table.

| Solution / Functional Zone | DBO Optimization | IDBO Optimization |
|---|---|---|
| 1 | (110, 151) | (318, 35) |
| 2 | (111, 60) | (333, 126) |
| 3 | (363, 55) | (131, 55) |
| 4 | (399, 202) | (55, 222) |
| 5 | (202, 131) | (242, 45) |
| 6 | (227, 45) | (171, 151) |
| 7 | (293, 146) | (55, 146) |
| 8 | (37, 141) | (391, 25) |
| 9 | (30, 33) | (30, 33) |
| 10 | (379, 136) | (419, 76) |

Figure 6 depicts the optimal layouts derived from the two algorithms, with yellow arrows representing the flow of goods between functional zones. The numbers indicate the codes for each functional zone (detailed in Figure 4). The coordinates for each functional zone are listed in Table 5. An analysis of Figure 6 reveals that the DBO layout exhibits intersecting logistics routes, which are detrimental to efficient system operation. In contrast, after the IDBO optimized layout, there were no detours or intersections, resulting in more reasonable logistics flow paths between functional zones, thus ensuring continuity in system operations.




(**a**) (**b**)

**Figure 6.** Layout diagram. (**a**) Layout diagram optimized by DBO; (**b**) Layout diagram optimized by IDBO.

To further compare the optimization effects of each layout scheme and ensure the generality of the simulation, the average values of the random simulation results are presented in Table 6. By comparing Figure 6 and Table 6, the improvements in different layout schemes during the optimization process can be observed. The intuitive display in the figure, combined with the specific values in the table, provides a more comprehensive evaluation of the optimization effects. Table 6 demonstrates that after optimization, the DBO algorithm reduces the total logistics cost by 14.47% and the IDBO algorithm by 25.54% compared to the original layout. The adjacency correlation increased by 14.96% and 29.93%, respectively, while carbon emissions decreased by 3.54% and 6.75%, respectively. This indicates that the IDBO algorithm can further reduce total logistics costs, enhance adjacency correlation, and decrease carbon emissions based on the DBO algorithm.

**Table 6.** Comparison of layout optimization effects.

| Layout Plan | Total Logistics Cost/Yuan | Adjacent Correlation | Carbon Emissions/kg |
|---|---|---|---|
| Original layout | 189,021.79 | 27.4 | 6312.96 |
| DBO optimized layout | 161,669.75 | 31.5 | 6089.17 |
| IDBO optimized layout | 140,740.09 | 35.6 | 5886.57 |

## 6. Discussion and Conclusions

The optimization of the cold chain logistics center layout is crucial, as it directly affects the operational efficiency, environmental, and economic benefits of the entire cold chain logistics system. It also significantly influences supply chain stability, food safety, and national and regional public health. However, existing studies have paid little attention to the optimization of cold chain logistics center layouts, and the optimization of the layout of cold chain logistics centers considering carbon emission factors, especially, is scarce. A reasonable cold chain logistics center layout can not only effectively reduce logistics costs but also improve operational efficiency and profitability for businesses [37]. For example, some studies have shown that optimizing the logistics network layout can reduce overall operating costs and improve the service level of cold chain logistics [38]. Additionally, layout optimization can enhance inventory management and distribution efficiency, thereby increasing customer satisfaction [39]. Therefore, studying the optimization of cold chain logistics center layouts, particularly in terms of environmental sustainability, is crucial for promoting green development in the logistics industry and achieving economic benefits for enterprises [40].

Many studies in the existing literature have explored the optimization of logistics center layouts. Compared with the existing studies, this study has the following innovations and advantages:

First, in terms of model establishment, attention is paid to the particularity of cold chain logistics centers. Previous studies have primarily focused on optimizing costs and efficiency, with less attention to environmental influence. By incorporating carbon emission factors, this study not only optimizes the layout of cold chain logistics centers but also reduces carbon emissions, providing a new approach to achieving a low-carbon economy. This is consistent with the current global trends of environmental protection and sustainable development.

Secondly, in terms of algorithm solving, although existing research has employed genetic algorithms and particle swarm optimization algorithms to solve logistics layout problems, these algorithms have certain limitations in convergence speed and solution accuracy. The improved dung beetle algorithm enhances the quality of the initial population by introducing Chebyshev chaotic mapping in the early stages, and introduces the adaptive Gaussian–Cauchy hybrid mutation disturbance strategy in the later iteration to prevent the population from falling into local optima and enhance the algorithm's global exploration capability. This approach can better solve the layout model, demonstrating the algorithm's potential application in optimization problems.

Moreover, the existing literature generally believes that reasonable layout optimization can enhance the overall efficiency of logistics system [41,42], and this study further confirms this point. Meanwhile, consistent with many multi-objective optimization studies, this study adopts a method that comprehensively considers multiple factors and emphasizes the importance of balancing different objectives in the optimization process [43].

However, this study also has some limitations. Firstly, the model simplifies certain real-world issues, such as neglecting complex factors like weather conditions and personnel movements, which may influence the results. Secondly, although the improved dung beetle algorithm has enhanced solving efficiency, its adaptability and stability in various application scenarios need to be further validated, especially in handling problems of different scales and complexities. Lastly, the practical operability and implementation effects of the research results also require validation to further assess the practical effectiveness of deploying optimization models and algorithms in real-world environments.

In the future, the research could further expand to comprehensively consider more environmental factors and societal benefits, for example: ① The real-time optimization of cold chain logistics center layout in dynamic environments, like demand changes and traffic conditions; ② Incorporating more environmental factors into optimization models, such as energy consumption, water resource utilization, and waste management; ③ A comprehensive consideration of the contribution of the cold chain logistics center layout to local economic development, employment opportunities, and social welfare benefits, etc.

Overall, this study provides new methods and perspectives for optimizing the layout of cold chain logistics centers, demonstrating both theoretical significance and practical application value.

**Author Contributions:** Conceptualization, J.L. and Q.Z.; Formal analysis, J.L.; Methodology, J.L.; Software, Q.Z.; Validation, Q.Z.; Visualization, Q.Z.; Writing—original draft, Q.Z.; Writing—review and editing, J.L. All authors will be informed about each step of manuscript processing, including submission, revision, revision reminder, etc., via emails from our system or assigned Assistant Editor. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no funding.

**Data Availability Statement:** The data are part of an ongoing study, so it is not convenient to publish the code and data currently. However, we welcome other researchers to discuss this with us.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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