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Big Data Swarm Intelligence Optimization Algorithm Application in the Intelligent Management of an E-Commerce Logistics Warehouse

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ABSTRACT

A dynamic mutation probability formula is utilized to optimize the model. In order to solve the logistics warehouse path problem, the ant colony optimization algorithm, optimized by a genetic algorithm, is employed to construct a logistics warehouse path optimization model. This model effectively optimizes the logistics warehouse paths. Test results comparing the convergence and distribution of non-inferior solutions demonstrated that the proposed model outperforms others in terms of convergence and non-inferior solution distribution. In practical logistics warehouse optimization, applying the proposed model to optimize cargo locations can significantly enhance the effectiveness of the objective function. The optimization resulted in improvements for all four objective functions related to cargo location, with reduction rates of 10.38%, 30.88%, 51.78%, and 88.49%, respectively. For the optimization of logistics warehouse paths, the original distance was 47.6m, which was reduced to 27.8m after optimization. Consequently, the picking distance decreased by 41.60%.

KEYWORDS

E-commerce warehouse, Intelligent management, Path optimization, Particle Swarm Optimization, test

INTRODUCTION

According to available data, the e-commerce logistics industry has experienced significant growth in recent years. As of 2022, the global e-commerce logistics market reached a value of $3.51 trillion and is projected to continue growing steadily in the foreseeable future (Zhao et al., 2020). Traditional logistics systems are no longer capable of meeting the increasing demands of e-commerce logistics, particularly in terms of efficient goods planning and convenient accessibility. Moreover, traditional technologies face numerous challenges in equipment integration and optimizing goods management, resulting in operational issues such as slow delivery and inefficient warehouse paths (Pan et al., 2022). Furthermore, although traditional logistics management has become increasingly intelligent,

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there is still a lack of effective management and scheduling mechanisms, including path selection and space allocation, which significantly impact the management of logistics warehouse goods. To address these issues, a highly efficient logistics warehouse operation and management model based on big data technology is proposed. This model introduces an innovative population-based intelligent optimization model to achieve efficient management of logistics warehouse operations (Pu et al., 2022). Specifically, the proposed model presents a Multi-Objective Particle Swarm Optimization (MOPSO) approach for optimizing warehouse allocation, aiming to tackle the problem of slow cargo allocation within warehouses. Additionally, a dynamic mutation probability formula is introduced to optimize traditional models that frequently converge towards local optima. To enhance the efficiency of logistics warehouse paths, the study employs Ant Colony Optimization algorithms based on genetic algorithms (GA-ACO) to develop a logistics warehouse path optimization model, thereby achieving optimized logistics warehouse paths. The research content includes four parts. The first part introduces the current situation of e-commerce logistics warehouse management and the specific application of related technologies. At the same time, it studies and discusses the multi-objective optimization technology of e-commerce. The second part studies the e-commerce logistics warehouse system and related technologies, analyzes the optimization objectives of e-commerce management, and constructs two optimization models for e-commerce logistics warehouse management. The third part is to apply the mentioned technology to specific scenarios and verify the optimization effect of the proposed logistics warehouse management model in actual scenarios. The fourth part summarizes and analyzes the entire article, and elaborates on the improvement direction of the research.

RELATED WORKS

Warehouse management optimization is a key area of research within the e-commerce logistics industry, with a focus on optimizing picking paths and goods allocation, both of which are important objectives of intelligent warehouse management. Minashkina et al. (2023) researched existing logistics management systems, highlighting the current research focus on their implementation and layout. Intelligent e-commerce management systems play a crucial role in clarifying e-commerce operations and system interaction management, while digital technology provides essential technical support for effective management. By reviewing relevant literature and materials, this research contributes to the digital and intelligent development of logistics warehouses and helps determine their future direction. In their study, Hu et al. (2023) analyzed the growth of domestic e-commerce and its impact on the logistics industry. They recognized the significance of solving sorting efficiency issues in logistics warehouses and proposed a system layout scheme. To achieve this, they developed a nonlinear programming model for logistics warehouses, which was solved through functional objective relationships. Compared to traditional particle swarm optimization models, this scheme demonstrated superior convergence and significantly optimized costs after layout, leading to reduced operating costs and improved efficiency in logistics warehouse management. Sun et al. (2022) investigated order instructions in traditional logistics warehouses. In such settings, there tends to be a focus on the volume occupancy rate of goods, often overlooking human biases, which results in decreased efficiency in warehouse management. To address this issue and reduce warehouse management costs, the researchers introduced two optimization mechanisms. They proposed a human concept packing strategy and estimated human biases to mitigate these deviations in logistics warehouse management. Experimental results showed that this approach significantly enhanced the effectiveness of logistics warehouse management, reduced operating costs, and decreased average packaging time for target packages by 4.5%. Tufano et al. (2022) studied modern e-commerce logistics management systems, which generate substantial amounts of daily goods flow data, thereby imposing a significant burden on system operations. To reduce system energy consumption and enhance the efficiency of logistics warehouse management, the researchers introduced a training classifier to improve system performance. Through data training, this classifier effectively predicts warehouse system behavior and can be applied to specific logistics warehouse environments. The proposed solution optimizes the management effectiveness of logistics warehouses, enables effective data classification and recognition, and improves operational efficiency. Xidias et al. (2023) focused on intelligent logistics warehouse management, utilizing task schedulers, motion planners, and route planners in intelligent logistics warehouses to facilitate the planning and scheduling of warehouse robots. Considering the impact of path planning on execution requirements, they introduced a genetic improvement algorithm in the control layer for particle path optimization, resulting in more efficient logistics management for robots. Simulation testing demonstrated that this solution enhances the operational efficiency of intelligent logistics warehouses and improves robot operating costs.

In the realm of modern e-commerce logistics warehouse management, the complexity and uniqueness of logistics warehouses make them multi-objective optimization problems. Researchers have conducted studies on multi-objective logistics management to address these challenges. Surury et al. (2021) focused on modern logistics transportation and identified it as a cost-effective and energy-efficient aspect of the logistics industry. They introduced multi-objective optimization solutions to optimize warehouse operations, goods allocation, and vehicle transportation, resulting in the development of an advanced logistics management system. Additionally, they researched logistics paths to create an optimization model that aimed to reduce fuel consumption, control costs, and ensure the timely delivery of products. Experimental tests demonstrated the effectiveness of the proposed scheme in optimizing logistics management. However, this study only considers simple path planning within logistics warehouses and does not fully address the optimization problems associated with complex spatial states within warehouses. Gupta et al. (2021) researched the current development of e-commerce and identified the challenges faced by companies in increasing their customer base and gaining a competitive advantage while dealing with industry cost and expense constraints. To tackle these issues, they identified the inefficiency in the e-commerce supply network and introduced a two-level decision-making mechanism to optimize the target problem. Linear and nonlinear membership functions were utilized to solve the multi-objective problems. The proposed solution was implemented in specific environments and effectively optimized logistics objectives, leading to improved costs and efficiency compared to traditional approaches. This study primarily focuses on the optimization of cost and logistics planning without fully considering goods storage optimization for distribution, indicating the need for further optimization. Praneetpholkrang et al. (2021) researched multi-objective problems in logistics operations and introduced multi-objective optimization models to address them. The initial step involved studying the problem model and constructing a goal optimization model by incorporating the Epsilon constraint method and the goal programming method. The model was then applied to specific environments. Through comparison, the proposed solution significantly improved the management cost and transportation efficiency of logistics operations while meeting customer service requirements. In contrast to previous research, which mainly focuses on target optimization in specific scenarios, this study emphasizes the perspective of goods management to enhance the overall effectiveness of logistics warehouse management.

Based on the research discussed above, the development of the e-commerce industry and the effectiveness of logistics warehouse management have a direct impact on the efficiency of supporting services in e-commerce. The application of big data intelligent management technology has greatly enhanced the management of traditional e-commerce logistics warehouses. Additionally, advanced machine learning technology can effectively address the multi-objective optimization problems in e-commerce logistics. While previous research has focused on logistics transportation and management, the implementation of corresponding technologies for optimization has improved the effectiveness of logistics warehouse management. However, a comparison of these studies has revealed that the optimization of logistics warehouses is not entirely comprehensive, focusing only on path and logistics transportation management. Further improvement could be achieved by incorporating big data technology throughout the entire logistics warehouse process, enhancing the overall management effectiveness of logistics warehouses and promoting the development of the e-commerce industry.

E-COMMERCE LOGISTICS WAREHOUSE MANAGEMENT MODEL CONSTRUCTION BASED ON SWARM INTELLIGENCE OPTIMIZATION ALGORITHM

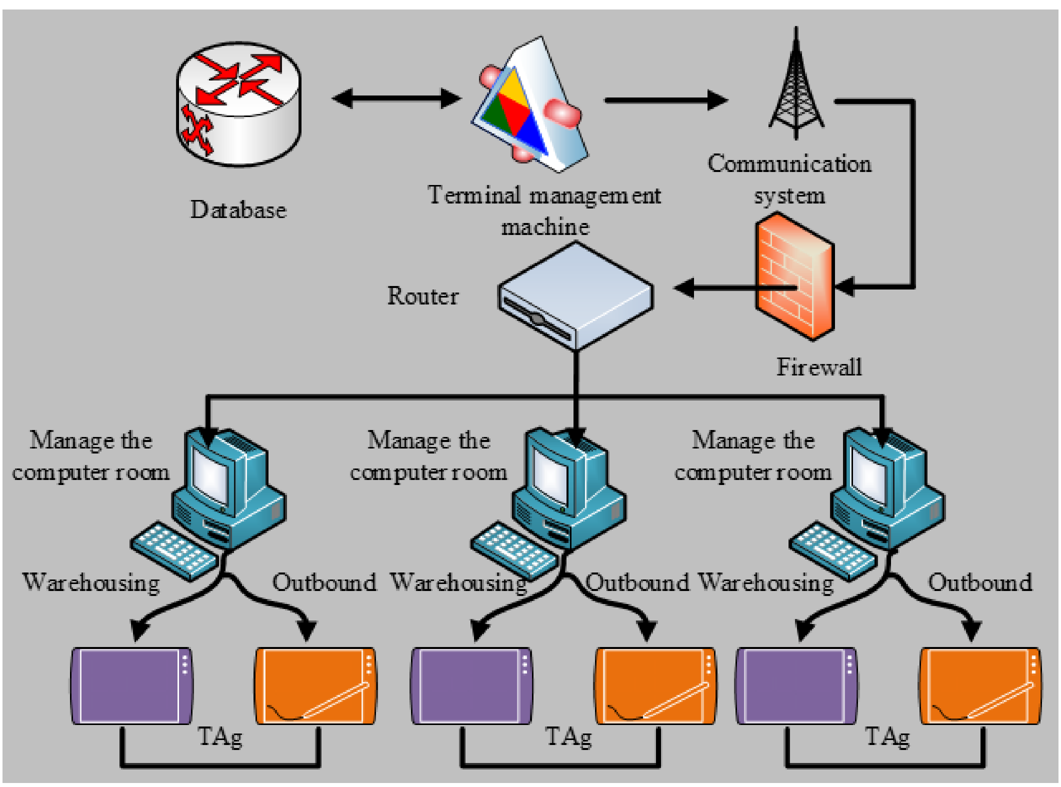
This section focuses on the research of e-commerce logistics warehouse management, which involves the determination of warehouse allocation optimization goals and the development of a multi-objective warehouse allocation optimization model. In addition, the picking process is also studied, leading to the construction of a logistics warehouse path optimization model.

Multi-Objective Warehouse Allocation Optimization Model Construction

Effective management of e-commerce logistics warehouses plays a crucial role in ensuring service quality and operational efficiency within the e-commerce industry. However, the current approach to warehouse management in e-commerce typically relies on distributed systems that lack automation and efficiency, thus failing to meet the evolving demands of the logistics industry (Beiki et al., 2020). Therefore, it is imperative for e-commerce enterprises to proactively establish intelligent and automated distributed management systems, enabling smarter job management within the e-commerce ecosystem. The intelligent e-commerce logistics warehouse management system using IoT big data is shown in Figure 1 (Sun et al., 2022).

In the intelligent logistics warehouse management system, optimization is performed from two perspectives: warehouse goods allocation and warehouse picking paths, aiming to enhance warehouse management efficiency (Ghasemi et al., 2022). Regarding warehouse goods allocation, a MOPSO is utilized to establish a model that optimizes the allocation of goods within the warehouse. Initially,

Figure 1. Intelligent e-commerce logistics warehouse management system



the mathematical model defining the problem of warehouse location-allocation is thoroughly examined. The warehouse has row a, column b, and layer c, with coordinates (x, y, z) indicating that the goods are located in row x, column y, and layer z. Assuming the study has a set of inbound goods S, where each goods $i \in S$ has a weight w_i. The optimization objectives of the study include improving storage efficiency, shelf stability, and cargo correlation. The research defines d_{ij} as the correlation between i and j of goods. If i and j perform inbound and outbound operations at the same time, then the value of d_{ij} is larger. The optimization objectives of the study can be expressed as the following three sub-objectives. Goal 1 is to improve the efficiency of warehousing (Ghasemi et al., 2022). The transportation speed of the equipment is fixed, and research aims to improve the efficiency of warehousing by shortening the distance of warehousing operations. l_{ijk} is set as the distance at which cargo i is stored at position (j, k, l). So, this goal is shown in equation (1).

$$\min f_1(S) = \sum_{i \in S} l_{ijk} \tag{1}$$

Goal 2 is to improve shelf stability. The research aims to minimize the sum of the product of the quality of the goods and the number of layers it belongs to in order to improve shelf stability, as expressed in equation (2).

$$\min f_2(S) = \sum_{i \in S} w_i \cdot z \tag{2}$$

Goal 3 is to improve the relevance of goods. It is hoped that goods that undergo both inbound and outbound operations at the same time can be placed in adjacent locations as much as possible. Where p_{ijkl} is defined as the distance between goods i and j at $\left(k, l, m\right)$ and (n, o, p), respectively, the expression of this objective is shown in equation (3).

$$\min f_3(S) = \sum_{i, j \in S, i \neq j} d_{ij} \cdot p_{ijkl} \tag{3}$$

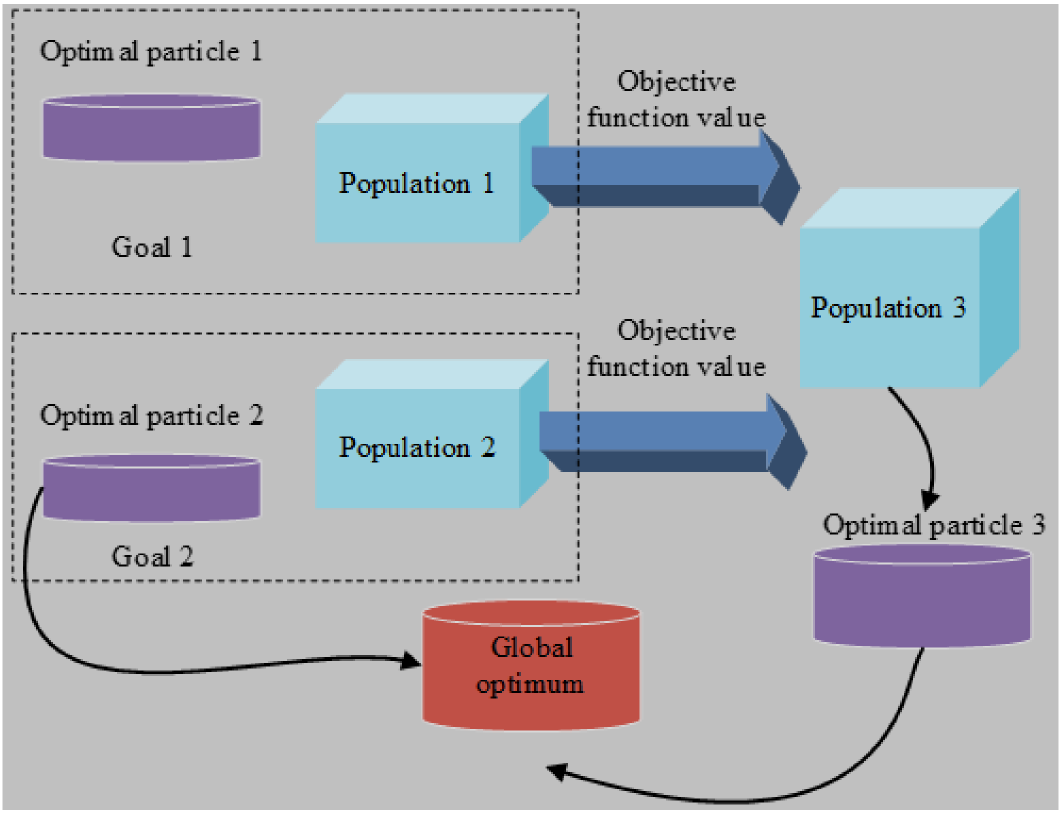
Therefore, the multi-objective optimization model for warehouse location-allocation constructed through research is shown in equation (4).

$$\min F(S) = (f_1(S), f_2(S), f_3(S)) \tag{4}$$

Subsequently, the enhanced algorithm is employed to solve this model, leading to the development of a warehouse allocation optimization algorithm utilizing the improved particle swarm optimization approach. The particle swarm optimization algorithm, being an evolutionary computation technique, leverages swarm intelligence to facilitate information sharing among particles and thereby identify optimal solutions for optimization problems. Figure 2 illustrates the underlying principle of the MOPSO (Boonmee et al., 2020).

To address the challenge of multi-objective optimization problems, traditional particle swarm optimization (PSO) algorithms often encounter the issue of converging to local optima. Therefore, this study proposes an enhanced PSO algorithm (Shadkam et al., 2021). A dynamic mutation probability formula is introduced, which induces particle mutation, thereby mitigating the risk of

Figure 2. Principle of MOPSO



getting trapped in local optima and promoting population diversity. This improvement aims to enhance the algorithm's performance in solving multi-objective optimization problems. r_i denotes the mutation probability of particle i, t denotes the current iteration, T denotes the maximum iteration, and r_{min} and r_{max} denote the lower and upper bounds of the mutation probability. The dynamic variation probability formula studied is shown in equation (5).

$$r_i = r_{min} + (r_{max} - r_{min}) \cdot \frac{T - t}{T} \tag{5}$$

At the same time, using Crowding distance and Pareto dominance relationships to update EA and select learning samples for particles, this method can ensure that non-inferior solutions can be uniformly distributed. In the study, the Pareto dominance relationship C is used to measure the density of solutions around solution i. Specifically, assuming the j-th target value of solution i is f_{ij}, the Crowding distance of solution i is shown in equation (6).

$$C_i = \sum_{j=1}^{m} \frac{f_{i+1,j} - f_{i-1,j}}{f_{max,j} - f_{min,j}} \tag{6}$$

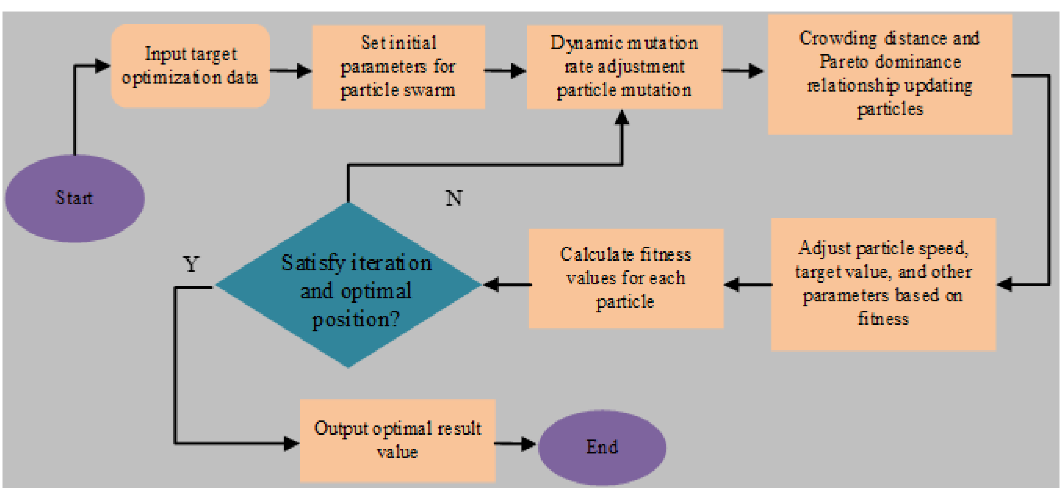
In equation (6), $f_{max,j}$ and $f_{min,j}$ are the maximum and minimum values of the j-th target, respectively, and m is the number of targets. Incorporating parallelization methods enables the reduction of computational costs while achieving high-quality optimization outcomes. The entire model optimization process is shown in Figure 3.

In the optimization of large-scale logistics warehouse problems, efficiency enhancement can be achieved through research on parallel computing techniques. Particularly, by parallelizing the update operation of particles and incorporating Crowding distance and Pareto dominance relationships for each particle update, the algorithm's runtime can be significantly reduced. This parallelization approach not only improves the overall performance of the model in multi-objective processing but also enhances its capability to handle large-scale optimization tasks efficiently.

Logistics Warehouse Path Optimization Model Construction

Logistics warehouse path optimization refers to maximizing the picking efficiency of the warehouse and reducing logistics costs through reasonable path planning and optimization algorithms in the logistics warehouse. The Ant colony optimization algorithms optimized by genetic algorithm will be used for logistics warehouse path optimization. Firstly, the study describes the problem of optimizing the path of logistics warehouses. Assuming there are n shelves in the logistics warehouse, with m storage spaces on each shelf. There are several aisles in the warehouse, each with a width of W and shelves with a width of d. The distance between cargo spaces is s, and the distance between aisles and shelves is c. The research needs to calculate the shortest path between any two pickup points i and j. Distance calculation, based on parameters such as shelves, aisles, and cargo spaces, research can calculate the distance between two pickup points i and j. According to the description of the topic, research needs to consider two situations: equal ordinates and unequal ordinates. The vertical coordinates are equal. When the vertical coordinates of two pickup points i and j are equal, research needs to consider two situations: the opposite side and the same side of the main aisle. The opposite side indicates that two pickup points are on different aisles, while the same side of the main aisle indicates that two pickup points are on the same aisle. In the case of different sides, the difference between the horizontal coordinates of two pickup points is x. Based on the description of the problem, the study can calculate the distance between the two pickup points as shown in equation (7) (Barma et al., 2022).

Figure 3. Multi-Objective optimization process of improved PSO



$$distance = (2 \times d + 2 \times s) \times x + c \tag{7}$$

When the main aisle is on the same side, the distance between two pickup points is shown in equation (8).

$$distance = | i_j - i_i | + | j_j - i_j | \tag{8}$$

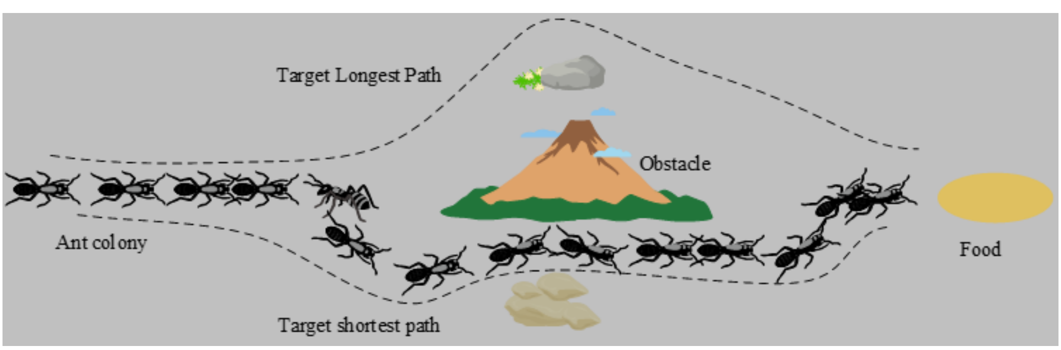
In equation (8), i_i represents the horizontal axis of the aisle where pickup point i is located, j_j represents the horizontal axis of the aisle where pickup point j is located, and i_j represents the vertical axis of the aisle where two pickup points are located. At the same time, in actual logistics warehouse pickup, it is also necessary to consider the issue of unequal vertical coordinates. When the vertical coordinates of two pickup points i and j are not equal, research needs to consider the position of the points on the left and right sides of the aisle. If the point is on the right side of the aisle, the distance is the distance from the point to the aisle plus the difference between the horizontal coordinates of the two points on the aisle. If the point is on the left side of the aisle, the distance is the sum of the distance from the point to the aisle and the horizontal coordinates of the two points on the aisle. At this moment, the distance is expressed as shown in equation (9).

$$distance = | i_i - j_i | + d + 2 \times s \tag{9}$$

In equation (9), i_i represents the horizontal axis of the aisle where pickup point i is located, and j_i represents the horizontal axis of the aisle where pickup point j is located. The Ant colony optimization algorithms optimized by genetic algorithm can solve warehouse path optimization problems. Among them, Ant colony optimization algorithms simulate ants' foraging behavior and can be used to solve combinatorial optimization problems (Ershadi and Shemirani, 2022). Its path optimization principle is shown in Figure 4.

Set ant number N, iteration number T, Pheromone volatilization factor ρ, Pheromone importance factor α, heuristic factor β, and Pheromone initial value τ_0. First, the Pheromone is initialized, and the initial value τ_0 is assigned to the Pheromone on the path between each node on each path. In each iteration, the Pheromone is updated according to the ant's search results. Suppose

Figure 4. Path optimization principle of ant colony optimization algorithms



ant k passes the path between and j on the path, and the Pheromone update formula left by ant L is shown in equation (10).

$$\Delta\tau_{ij}^{k} = \frac{Q}{L_k} \tag{10}$$

In equation (10), $\Delta\tau_{ij}^{k}$ represents the Pheromone increment left by ant k on the path between i and j, Q represents the Pheromone increment coefficient, and L_k represents the path length of ant k. Pheromone concentration is updated. During each iteration, the Pheromone on all paths is updated according to the Pheromone volatilization factor ρ. The update of Pheromone is shown in Formula (11).

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{N} \Delta\tau_{ij}^{k} \tag{11}$$

In equation (11), τ_{ij} represents the Pheromone concentration between i and j on the path. The probability of ants selecting the next node i at node j is calculated. The probability calculation formula for ant k to select the next node i at node j is shown in equation (12).

$$P_{ij}^{k} = \frac{\tau_{ij}^{\alpha} \times (\eta_{ij})^{\beta}}{\sum_{l \in allowed} (\tau_{lj}^{\alpha} \times (\eta_{lj})^{\beta})} \tag{12}$$

In equation (12), P_{ij}^{k} represents the probability of Ant k selecting the next i at j, and η_{ij} represents the heuristic information between j and i. Path selection is based on the probability of ants selecting the next node. According to probability P_{ij}^{k}, according to the wheel. Considering the parameterization problem of Ant colony optimization algorithms, the genetic algorithm is introduced to optimize the ant colony parameters, and the path length can be selected as the fitness function. Assuming the path length is d, the fitness function F can be defined as shown in equation (13).

$$F(d) = \frac{1}{d} \tag{13}$$

The selection operation is the process of selecting the next generation population by the results of the fitness function. In genetic algorithms, the commonly used selection strategy is based on roulette wheel selection strategy (Waziri and Yakasai, 2023). Assuming that the fitness of the i-th individual in the population is F_i, the selection operation is shown in equation (14).

$$P_i = \frac{F_i}{\sum_{j=1}^{P} F_j} \tag{14}$$

In equation (14), P_i represents the probability of selecting the i -th individual. Cross-operation is the process of crossing selected individuals to generate new ones. In ant colony parameter optimization, research can choose a single-point crossover operator (Yousefi et al., 2021). Assuming that the two selected individuals are A and B , the crossover operation can be represented by equation (15).

$$\begin{cases} C_1 = A[:k] + B[k:] \\ C_2 = B[:k] + A[k:] \end{cases} \tag{15}$$

In equation (15), k represents the position of the intersection point, while C_1 and C_2 represent the two individuals generated after the intersection. Mutation operation is the process of mutating individuals obtained through crossover to generate new individuals. In ant colony parameter optimization, research can choose a random mutation operator, assuming that the mutation operation mutates individual C_1 , and the mutation operation can be defined as shown in equation (16).

$$C_1' = C_1 + \Delta C \tag{16}$$

In equation (16), ΔC represents the amount of variation. Finally, research needs to define the operation of updating the population. In genetic algorithms, the operation of updating the population is to add individuals obtained from crossover and mutation to the population for the evolution of the next generation (Qin et al., 2022). A warehouse logistics path optimization model is constructed through research, and the specific process is shown in Figure 5.

ALGORITHM MODEL SIMULATION TESTING

This section primarily focuses on validating the practical applicability of the two proposed models and establishes an experimental environment for testing. The key evaluation metrics encompass Pareto front performance testing, path planning performance testing, and other relevant indicators. These tests aim to assess the effectiveness and performance of the models in real-world scenarios.

Multi-Objective Warehouse Allocation Optimization Testing

To evaluate the performance of the proposed multi-objective warehouse allocation optimization model, experimental testing was conducted on the Windows 10 64-bit platform. The simulation analysis was carried out using the Matlab platform. As the basis for testing, the ZDTI, ZDT2, and ZDT6 functions were selected. These functions belonged to the widely used Zitzler-Deb-Thiele (ZDT) test function set, which was renowned for evaluating multi-objective optimization algorithms. Additionally, six different variations of the test functions, namely DZT1-DZT6, were utilized to effectively assess the model's multi-objective performance. The initialization parameters of the experimental model are provided below.

The Non-Dominant Sorting Genetic Algorithm-II (NSGA-II) and MOPSO were selected as the benchmark models for testing. The Pareto frontier results of the proposed improved MOPSO algorithm under the function are shown in Figure 6.

Figure 6 shows the Pareto frontier results of the improved MOPSO algorithm under three benchmark functions, F1 and f2 are two objective optimization functions. Figure 6 (a), (b), and (c) show the test results of the ZDTI, ZDT2, and ZDT6 functions, respectively. Based on the test results depicted in the figure, the true Pareto front was illustrated by the red dots, while the algorithm's test

Figure 5. Flow chart of warehouse logistics path optimization

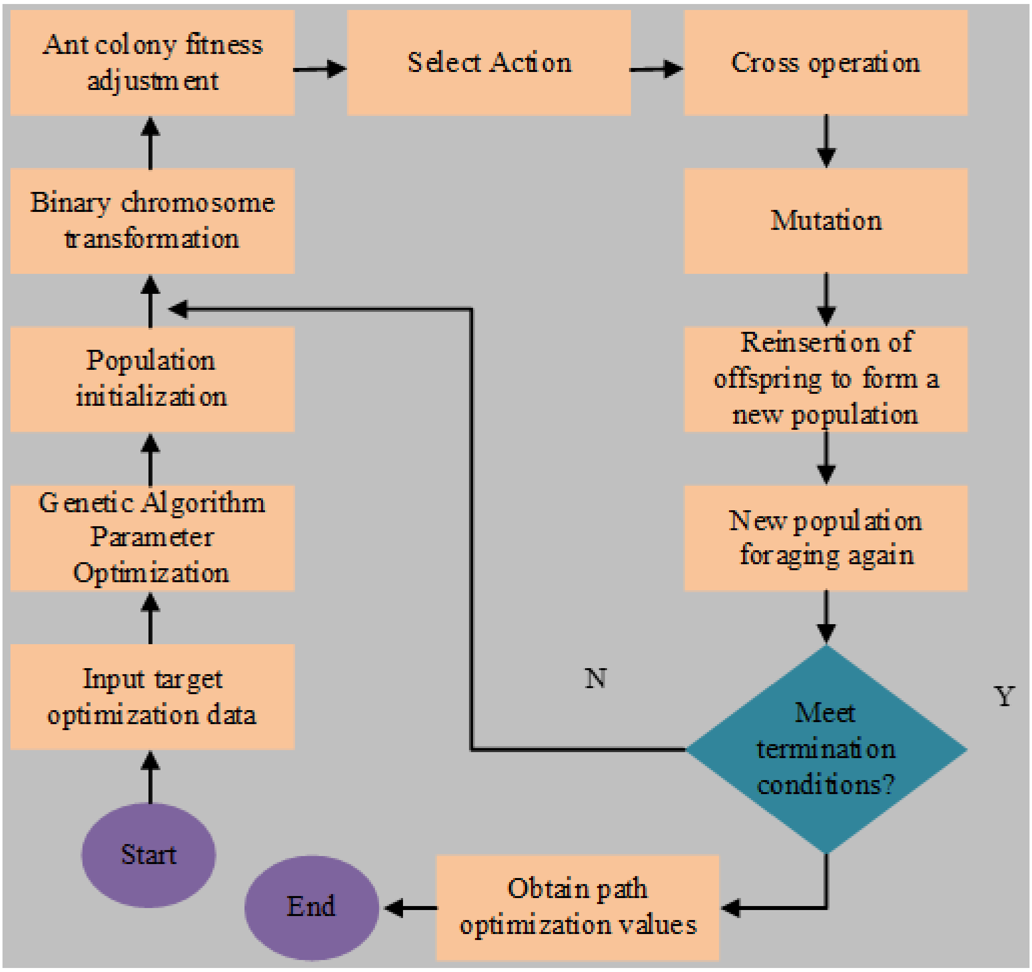


Table 1. Model initial parameters

Parameter indicator type	Numerical value
Number of particle clusters	400
Number of model iterations	1000
External Archive Scale	400
Learning factor	2.0

results were represented by the solid purple lines. Among the three functions analyzed, the enhanced MOPSO model aligned closely with the actual curve results. Furthermore, the model consistently generated uniformly distributed non-dominated solutions in the target space, validating its feasibility in tackling multi-objective problems. Table 2 shows the specific test results.

Table 2 presents a comparison of the test results for three models using the benchmark function. A smaller convergence value indicated better convergence performance, while a smaller non-inferior

Figure 6. Test results under three benchmark functions

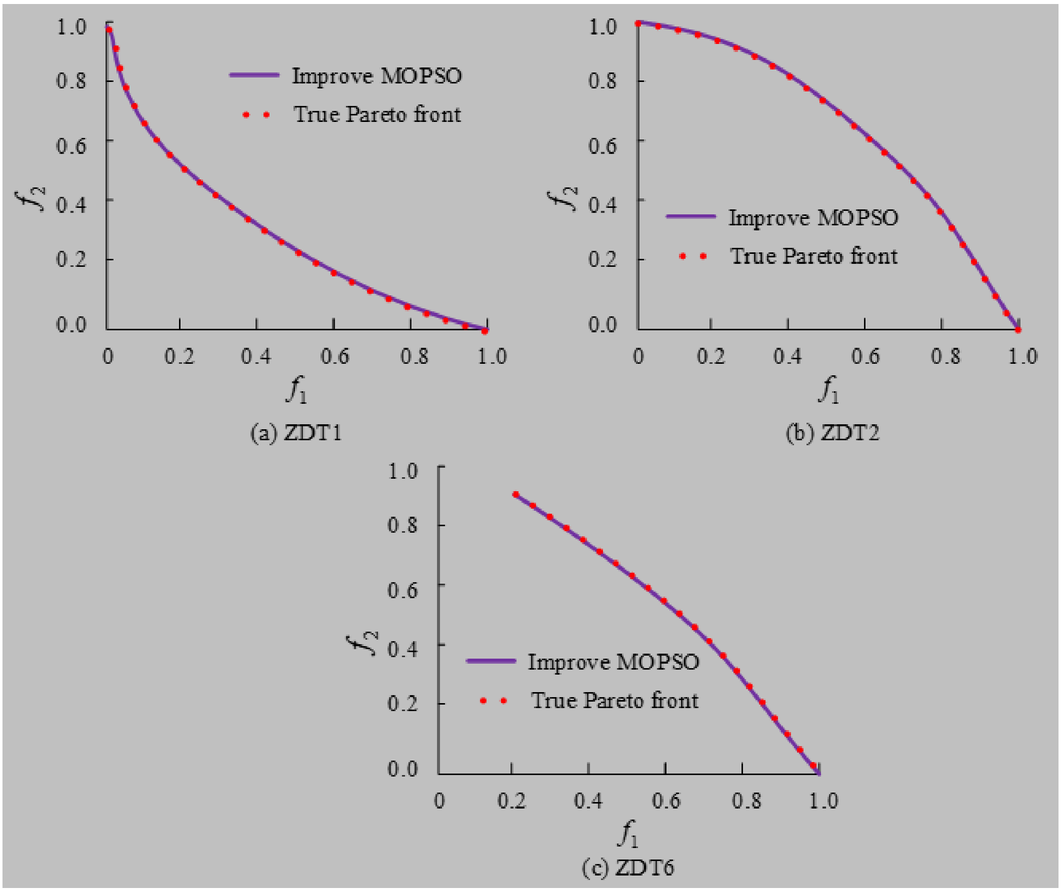


Table 2. Comparison of pareto frontiers among three models

Model		ZDT1		ZDT2		ZDT6	
		Standard deviation	Average value	Standard deviation	Standard deviation	Standard deviation	Standard deviation
Nsga-II	Astringency	0.01697	0.20969	0.02653	0.32497	0.03869	0.63489
	Non-inferior solution division Cloth	0.00066	0.01893	0.00099	0.02502	0.01679	0.14268
MOPSO	Astringency	0.01608	0.20852	0.01837	0.24437	0.01289	0.08477
	Non-inferior solution division Cloth	0.00026	0.01447	0.00035	0.01421	0.00015	0.01069
Improve mopso	Astringency	0.01009	0.16397	0.01153	0.19026	0.01261	0.08272
	Non-inferior solution division Cloth	0.00026	0.01360	0.00030	0.01352	0.00001	0.01043

solution distribution value suggested a superior distribution of non-inferior solutions by the model. Under the ZDT1 function, NSGA-II exhibited a convergence standard deviation of 0.0167 and a non-inferior solution distribution standard deviation of 0.00066. On the other hand, the MOPSO model achieved values of 0.01608 and 0.00026, respectively, for these indicators. Additionally, the proposed improved MOPSO model attained values of 0.2009 and 0.00026 for the respective indicators. The test results indicated that the proposed improved MOPSO model achieved the minimum values. This improvement can be attributed to the utilization of the relationship between crowding distance and Pareto dominance in the EA update process, leading to enhanced optimization performance. These results demonstrate that the model exhibited good convergence and distribution performance compared to the other two models, highlighting its effectiveness during training. In the tests conducted under the ZDT2 and ZDT6 functions, the proposed improved MOPSO model consistently outperformed the others. This finding underscored the excellent performance of the research model in multi-objective optimization. To optimize a randomly selected storage location within the logistics warehouse, the improved MOPSO model was employed. The location accommodated 30 items, while the entire shelf held a total of 826 items belonging to six different types of goods. Figure 7 illustrates the solution for cargo allocation space resulting from the optimization process.

Figure 7 shows the allocation space solution of the target cargo location. Based on the coordinate information of the cargo location, the cargo coordinate position of the cargo location was adjusted to meet the requirements of storage efficiency, stability, and correlation. The final solution is shown in Table 3.

Table 3 shows the optimization results of the objective functions, which were optimized for the four objective functions on the cargo location. The optimization of objective functions was related to

Figure 7. Cargo allocation space solution

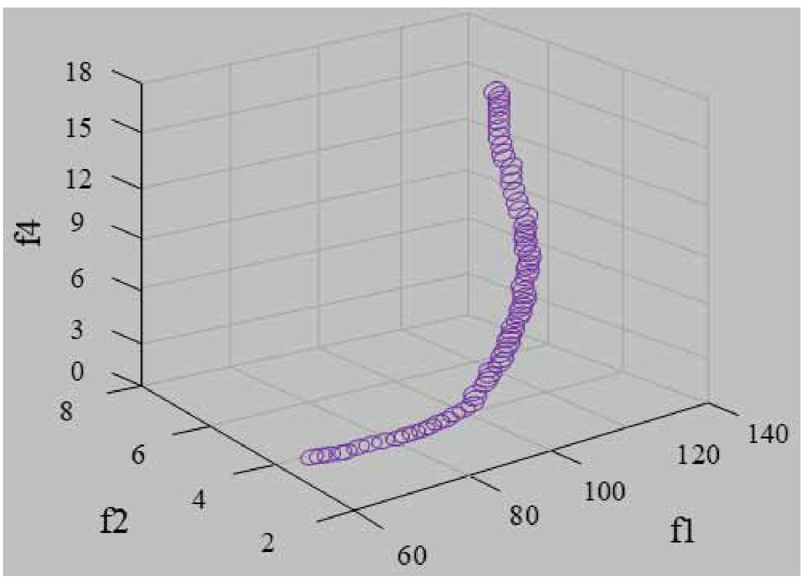


Table 3. Final optimization result of cargo location objective function

Objective function	Initial value	Optimal value	Reduce the amount	Reduction rate (%)
F1	50.57826	45.33468	5.24	10.38
F2	2.225647	1.538365	0.6875	30.88
F3	326316	157658	168781	51.78
F4	3.74358	0.4303	3.31189	88.49

cargo turnover rate, shelf center of gravity, shelf stability, and cargo correlation. After optimization, all four function objectives were improved. The reduction of objective function F1 was 5.24, with a reduction rate of 10.38%. The reduction of objective function F2 was 0.6875, with a reduction rate of 30.88%. The reduction of objective function F3 was 168781, with a reduction rate of 51.78%. The reduction of objective function F4 was 3.31189, with a reduction rate of 88.49%. The distribution of goods before and after optimization is shown in Figure 8.

In Figure 8, Figure 8 (a) shows the spatial distribution of cargo locations before optimization, and Figure 8 (b) shows the spatial distribution of cargo locations after optimization. According to the requirements of goods turnover rate, the position of turnover rate was adjusted in pink, green, blue, red, yellow, and light purple. At the same time, the placement and center of gravity of the goods were optimized and adjusted, ultimately improving the turnover rate and relevance of the goods.

Logistics Warehouse Path Optimization

This section focuses on evaluating the performance of multiple proposed models for optimizing the path in logistics warehouses. Since optimizing the picking path in a logistics warehouse involves a variant of the traveling salesman problem that requires considering data from different regions of the warehouse, it becomes challenging to select a benchmark model for experimental comparisons. To address this, the Oliver30 model, known as a standard performer, was introduced for experimental testing. Moreover, genetic algorithm (GA) and ant colony optimization (ACO) were used as benchmark models for the tests. The results of the performance tests for several models in terms of path planning are depicted in Figure 9.

Figures 9 (a), 9 (b), and 9 (c) show the training optimization results of the ACO model, AG model, and the proposed GA-ACO model, respectively. Among the three models considered, the GA-ACO model demonstrates the best performance in terms of path planning. It achieves a path planning length of 425, resulting in a shorter optimized path distance compared to the other two methods. This superiority can be attributed to the exceptional optimization capability of the GA-ACO model. The introduction of the GA algorithm in optimizing the model's parameterization problem enhances its performance. However, it should be noted that the traditional ACO model and AG model encounter challenges with their parameterization, leading to suboptimal results. Specifically, the optimized path planning lengths achieved by these models are 453 and 433 respectively, indicating significantly poorer optimization effects. In contrast, the proposed GA-ACO model showcases excellent path planning performance. Figure 10 illustrates the optimization of a specific cargo path within a logistics warehouse resulting from the proposed GA-ACO model.

Figure 8. Distribution results of goods before and after optimization

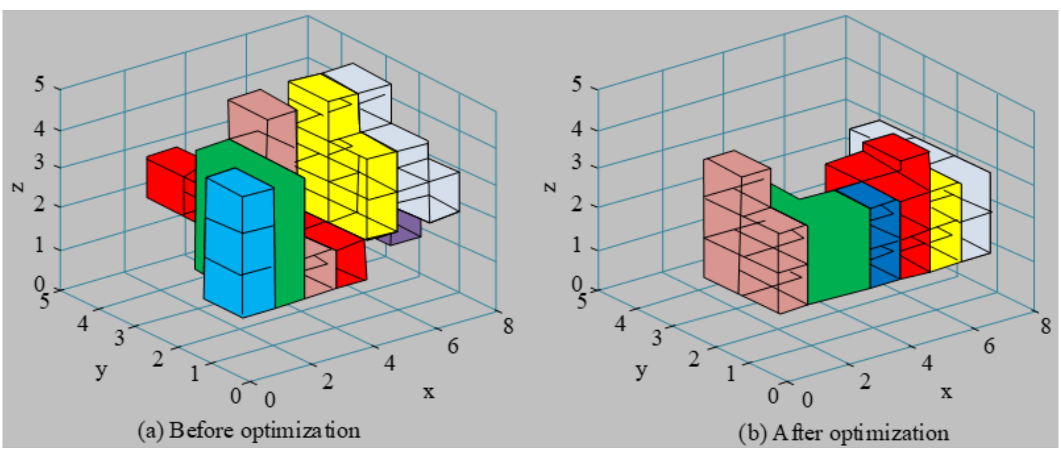


Figure 9. Comparison results of path planning algorithm performance test

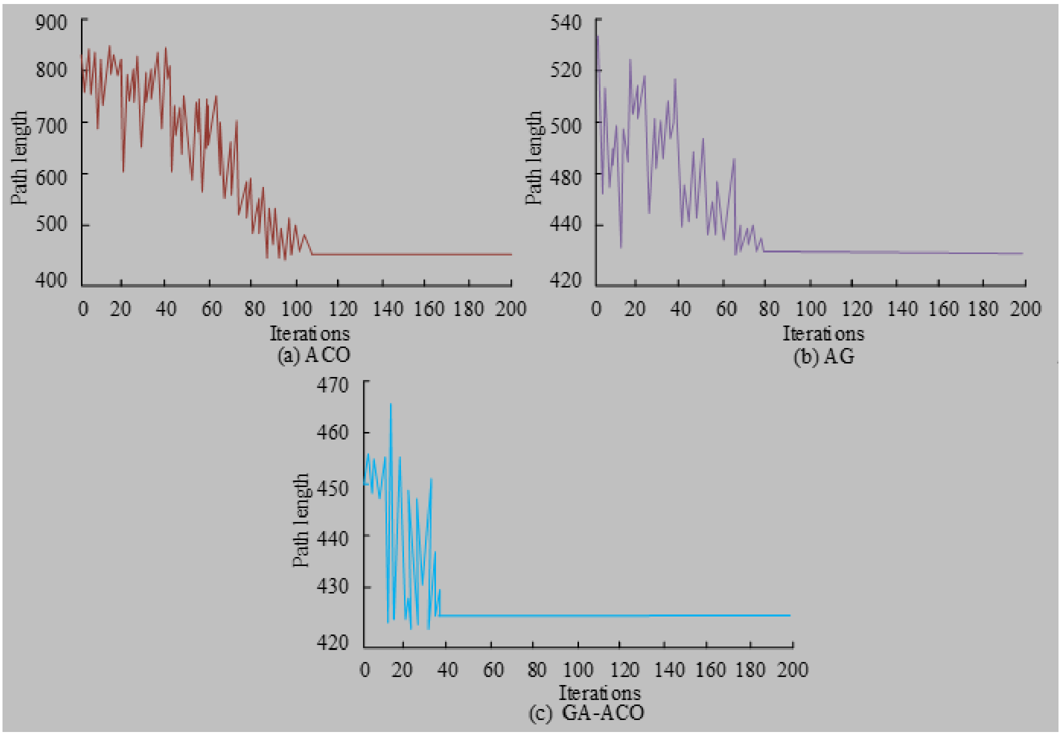
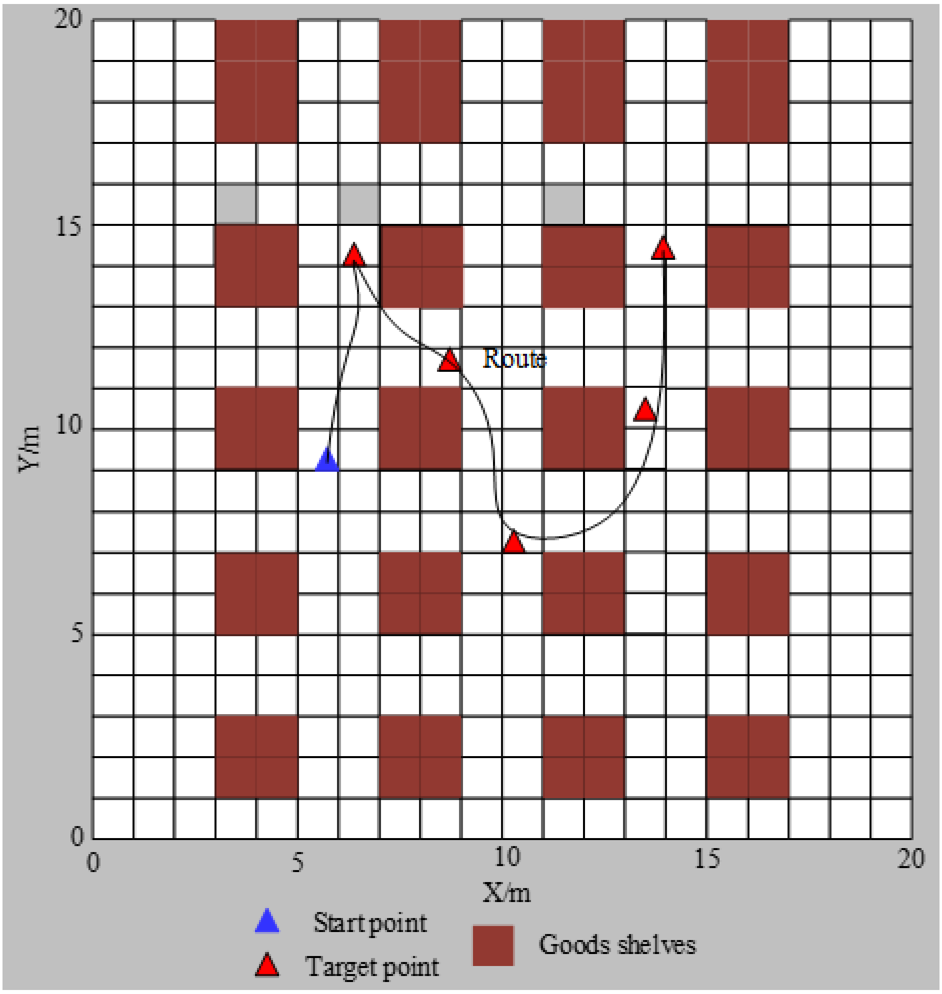


Figure 10 shows the optimization results of the picking path in the cargo warehouse. The picking path for item 1 was renumbered, with an original distance of 47.6m. After optimization, the picking distance was 27.8m, which decreased by 41.60%. This proved that the proposed model had good application results.

CONCLUSION

The rapid growth of the e-commerce logistics industry has raised the bar for efficient logistics warehouse management. The objective is to enhance the operational efficiency of e-commerce logistics warehouses, address issues related to slow goods distribution and logistics warehouse paths, and achieve effective management of logistics operations within warehouses. To tackle these challenges, a swarm intelligence optimization model is employed to construct a target warehouse allocation optimization model. Additionally, a dynamic mutation probability formula and Pareto dominance relationship are introduced to optimize the allocation model. Simultaneously, the Ant Colony Optimization (ACO) algorithm enhanced by Genetic Algorithm (GA) is utilized to develop a logistics warehouse path optimization model, enabling comprehensive optimization of logistics warehouse management. In the multi-objective warehouse allocation optimization test, the ZDT1 function is selected as the benchmark for evaluation. The Pareto frontier results obtained through the improved MOPSO algorithm align closely with the real Pareto frontier. This outcome demonstrates the algorithm's efficacy in solving multi-objective problems and generating uniformly distributed solutions in the target space. The convergence standard deviation of NSGA-II was 0.0167, and the standard deviation of the distribution of non-inferior solutions was 0.00066. For MOPSO, the corresponding values were 0.01608 and 0.00026. Notably, the proposed improved MOPSO model

Figure 10. Optimization results of cargo warehouse path



achieved even better optimization performance, with respective values of 0.2009 and 0.00026 for the two indicators. In terms of goods table optimization, the objective function f1 exhibits a reduction of 5.24, representing a reduction rate of 10.38%. This optimization led to improvements in the turnover rate and correlation of goods. Furthermore, in the optimization of logistics warehouse paths, a specific cargo underwent optimization resulting in a 41.60% reduction in picking distance. The proposed technology demonstrates significant application benefits in multi-objective warehouse configuration and optimization of logistics warehouse paths and surpasses comparable technologies from the same period. Looking ahead, as logistics robots become increasingly prevalent in warehouse scenarios, it will be crucial to consider their interaction and connectivity with different devices. Consequently, future efforts will focus on collaborative management among diverse devices to enhance the effectiveness of logistics warehouse management.

AUTHOR NOTE

The authors of this publication declare there are no competing interests.

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