Multi-Objective Optimization of Multi-Warehouse Cargo Allocation and Transportation Planning Using an Enhanced Ant Colony Algorithm

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With the rapid development of the global economy, the logistics industry, as a key support for economic activities, has become a focus of cost control. According to statistics, logistics costs have accounted for about 13% of the global GDP, among which multi-warehouse cargo allocation and transportation planning play a pivotal role in reducing logistics costs. Based on the improved ant colony algorithm, this paper carefully constructs a multi-warehouse cargo allocation and transportation planning model. With the help of a multi-level optimization framework, the model comprehensively considers multiple key objectives such as transportation cost, delivery time, and energy consumption. Based on the improved ant colony algorithm, this paper constructs a multi-warehouse cargo distribution and transportation planning model. Specifically, the pheromone update rule of the ant colony algorithm is changed by introducing an adaptive adjustment mechanism, which dynamically adjusts the pheromone volatilization and accumulation rate according to the current number of iterations and the change of the objective function. At the same time, the objective function weight is optimized to better balance multiple objectives such as transportation cost, delivery time and energy consumption. The multi-objective particle swarm optimization algorithm is used to assist in determining the weight, and the corresponding weight value is assigned according to the importance of different objectives. Compared with the traditional baseline methods such as genetic algorithm and particle swarm algorithm, in terms of transportation cost, the improved ant colony algorithm reduces the average cost by 25% in large-scale scenarios (20 warehouses), improves energy efficiency by 18%, and reduces the running time by 1.9 seconds in computing performance. In the multi-objective optimization of small-scale problems (5 warehouses) and a small number of objectives, the goal achievement rate is as high as 95%, the cost reduction rate can reach 20%, and the running time is 5.6 seconds for the ant colony algorithm in large-scale scenarios (20 warehouses), while the genetic algorithm is 7.5 seconds, which reflects relative stability. Based on the improved ant colony algorithm, in the optimization process of comprehensive consideration of multiple objectives such as transportation cost, delivery time and energy consumption, the algorithm is relatively stable in terms of running time compared with the genetic algorithm and the particle swarm algorithm.

Povzetek: Članek razvije večciljno optimizacijsko metodo za razporeditev tovora in načrtovanje transporta v sistemih z več skladišči, pri čemer temelji na izboljšanem algoritmu kolonije mravelj. Uvedeni so dinamični mehanizmi za prilagajanje feromonskega izhlapevanja, uteži ciljev in iskalnega obsega, ki izboljšajo konvergenco in omogočajo učinkovito usklajevanje med cilji, kot so stroški, čas dostave, poraba energije in zaloge.

1 Introduction

With the rapid development of the global economy, the logistics industry plays an increasingly important role in supporting business activities and promoting the circulation of the industrial chain. Especially today, when e-commerce and the global supply chain are highly connected, the complexity of logistics management and cargo distribution issues has increased dramatically. Enterprises and governments are facing huge challenges in optimizing resource allocation and improving transportation efficiency [1]. According to statistics, logistics costs have accounted for about 13% of global GDP, and cargo distribution and transportation planning are key links in reducing logistics costs. In this context, multi-warehouse cargo distribution and transportation planning issues have become one of the hot topics in the field of logistics research [2]. How to optimize the distribution and transportation routes of cargo between warehouses through reasonable algorithm design will not only help improve the competitiveness of enterprises, but also have far-reaching significance for promoting overall economic benefits [3].

In a multi-warehouse system, different warehouse locations, cargo demands, and transportation routes are intertwined, and there are many factors to consider in the decision-making process, which makes it difficult for traditional manual allocation methods to meet the needs of modern logistics. Therefore, how to efficiently solve the problems of cargo scheduling between warehouses, route planning during transportation, and coordination between them has become a technical problem that needs to be solved urgently in the field of logistics [4]. Many scholars and researchers have proposed different algorithm models for this problem, but due to the complexity of the problem itself, there is still a lack of a solution that can be universally applied in different environments [5].

In recent years, with the development of computer science and artificial intelligence technology, the problem of multi-warehouse cargo allocation and transportation planning based on optimization algorithms has been widely studied. Although traditional optimization methods, such as linear programming and integer programming, are effective in certain specific scenarios, they have high computational complexity and are difficult to meet the dual requirements of real-time performance and accuracy when facing large-scale and complex systems [6]. For this reason, more and more researchers have begun to turn to heuristic algorithms and meta-heuristic algorithms. Ant colony algorithm, as an optimization algorithm that simulates the foraging behavior of ants in nature, has become a popular optimization tool in multi-warehouse cargo allocation and transportation planning due to its powerful global search ability and good local search performance [7].

However, although the ant colony algorithm has shown great potential in solving such problems, there are still some problems in existing research. For example, the parameter settings of the ant colony algorithm are highly sensitive and may be affected by environmental changes in practical applications. In addition, most existing ant colony algorithms focus on optimizing a single objective, while in reality, it is often necessary to comprehensively consider multiple objectives, such as transportation costs, delivery time, energy consumption, and other multiple factors [8]. Therefore, how to deal with multi-objective optimization problems through algorithm improvement and achieve good results in practical applications is still a challenge in current research [9].

In addition, although existing research results have provided theoretical foundations and algorithmic support for multi-warehouse cargo distribution and transportation planning, there is still a lack of an integrated comprehensive solution that can simultaneously optimize cargo distribution and transportation routes. Most existing studies focus on the optimization of a single aspect and lack an in-depth analysis of the relationship between the two [10].

The main purpose of this paper is to propose a multi-warehouse cargo allocation and transportation planning model based on ant colony algorithm, in order to optimize the allocation of warehouse resources and transportation route planning under the consideration of multiple objectives. Compared with the traditional single-objective optimization method, this paper aims to improve the local search ability of ant colony algorithm, taking into account multiple objectives such as transportation cost, delivery time and energy consumption, so as to maximize the efficiency and economy of the entire logistics system while meeting actual needs.

The innovation of this study is that it combines multi-objective optimization with ant colony algorithm to conduct in-depth exploration of the multi-warehouse cargo distribution problem. By constructing a new objective function and optimization model, it is possible to optimize multiple key factors without increasing too much computational complexity. In addition, this study will further explore how to improve the heuristic information transmission mechanism in the algorithm so that the ant colony can show better robustness and adaptability in a wider range of application scenarios. Through this method, this paper hopes to provide a more practical solution for the logistics industry, helping enterprises to perform more efficient cargo distribution and transportation planning in dynamic and complex environments.

With the high interconnection of e-commerce and global supply chains, logistics management and cargo distribution issues are becoming increasingly complex. Existing methods mostly focus on a single goal or a single aspect, which is difficult to meet actual needs. In addition, most ant colony algorithms have limitations such as parameter sensitivity and difficulty in taking multiple objectives into account. This study aims to improve the ant colony algorithm, achieve coordinated optimization of cargo distribution and transportation under multiple objectives, and improve the efficiency of the logistics system.

The novelty of this study is mainly reflected in three aspects. First, in terms of algorithm improvement, unlike the relatively fixed pheromone update mode of the traditional multi-objective ant colony algorithm, this study introduces an adaptive adjustment mechanism, which enables the pheromone volatilization and accumulation rate to change dynamically according to the iteration process and the change of the objective function, greatly improving the algorithm search efficiency and optimization ability; second, in terms of model construction, the multi-objective optimization framework is innovatively deeply integrated with the ant colony algorithm, not only considering common objectives such as transportation cost, delivery time, energy consumption, but also incorporating the key factor of inventory level. Compared with existing research, a comprehensive optimization model that is more in line with actual logistics needs is constructed; third, in terms of research methods, a multi-objective particle swarm optimization algorithm is used to assist in determining the weight of the objective function, changing the previous way of setting weights by human experience or simple single rules, achieving a more scientific and reasonable balance between multiple objectives, and providing a new solution to the problem of multi-warehouse cargo distribution and transportation planning.

2 Literature review

2.1 Optimization methods for multi-warehouse cargo allocation and transportation planning

In the field of multi-warehouse cargo distribution and transportation planning, traditional optimization methods, such as linear programming (LP) and integer programming (IP), have long been the basis of research. However, with the increase in the scale of the problem, especially the rapid increase in decision variables in multi-warehouse systems, these classical methods often face the problems of high computational complexity and low solution efficiency. In order to overcome this bottleneck, more and more researchers have begun to explore the application of heuristic algorithms and meta-heuristic algorithms [11,12]. Ant Colony Algorithm (ACO) has been widely used in this field due to its powerful global search capability and good local search performance.

Table 1: Comparison table of research on multi-warehouse cargo allocation and transportation planning

Research	Objectives	Algorithms	Key Results	Advantages of This Study
[11]	Optimize cost and delivery time	Genetic algorithm	Cost reduced by 15%, delivery time shortened by 10%, low efficiency in large-scale scenarios	Did not consider energy consumption, lack of analysis on parameter adaptability
[12]	Improve path accuracy and energy efficiency	Particle swarm optimization algorithm	Accuracy increased by 10%, energy efficiency improved by 12%, easy to fall into local optimality	Ignored warehouse capacity, lacking a multi-objective balance strategy
[13]	Balance multiple objectives (cost, time, inventory)	Simulated annealing algorithm	Cost reduced by 12%, time optimized by 8%, poor multi-objective optimization effect	Lack of research on algorithm convergence and network scalability
[14]	Multi-objective optimization (cost, time, energy consumption, inventory)	Improved ant colony algorithm	Cost reduced by 25%, energy efficiency improved by 18%, inventory reduced by 15%	Integrate multiple objectives, consider constraints, analyze algorithm robustness and adaptability

Table 1 systematically compares the relevant research in the field of multi-warehouse cargo allocation and transportation planning. It unfolds from four dimensions: research objectives, algorithms used, key results, and the advantages of this study compared with existing research, clearly presenting the differences in optimization directions, method selections, and achievements among different studies. Existing studies respectively have problems such as single objectives, limited algorithm performance, and incomplete consideration of factors. In contrast, this study, by adopting the improved ant colony algorithm, comprehensively considers multiple objectives and practical constraints, and conducts in-depth analysis of the algorithm's robustness and adaptability to warehouse networks of different scales, effectively making up for the deficiencies of previous studies and demonstrating stronger practicality and innovativeness.

The application of ant colony algorithm is not limited to single-objective optimization problems. In multi-warehouse cargo allocation and transportation planning, multiple objectives are involved in simultaneous optimization problems, such as transportation cost, delivery time, cargo allocation accuracy, etc. In order to solve this complex multi-objective optimization problem, scholars have begun to propose improvements based on ant colony algorithm [13]. For example, an adaptive mechanism is used to dynamically adjust the search strategy of ants so that they can perform appropriate local searches at different operation stages. In addition, some researchers have also introduced hybrid algorithms that combine ant colony algorithm with other metaheuristic methods, such as particle swarm optimization (PSO) and genetic algorithm (GA), to further improve the efficiency and accuracy of the solution. These innovative algorithm improvements help alleviate the application difficulties of traditional methods in large-scale and complex systems, and to a certain extent improve the efficiency of cargo allocation and transportation [14,15].

Although the ant colony algorithm has shown great advantages in solving the multi-warehouse cargo allocation problem, it still faces some challenges in practical application. Problems such as slow algorithm convergence speed and easy to fall into local optimal solutions limit its promotion and application in complex logistics systems [16]. To this end, some researchers have tried to improve the performance of the ant colony algorithm by optimizing the algorithm parameter selection, enhancing the global search capability, and improving the pheromone update mechanism. These studies provide a theoretical basis for the further development of this field and also provide a direction for subsequent researchers to innovate in optimization methods [17].

2.2 Application of multi-objective optimization in cargo distribution

The application of multi-objective optimization problems in logistics and transportation planning has made some important progress, but there are still many unresolved challenges. In many practical problems, cargo distribution not only needs to optimize transportation costs, but also needs to take into account multiple objectives such as time efficiency, environmental impact, and vehicle capacity [18]. Therefore, how to find the best balance between multiple objectives has become one of the research hotspots.

Multi-objective optimization methods based on ant colony algorithms have received increasing attention in recent years. On the one hand, researchers have been able to achieve a good balance between multiple objectives by designing a multi-objective ant colony algorithm model with strong adaptability. On the other hand, researchers have also proposed a strategy based on the Pareto optimal solution. With the help of the concept of the Pareto frontier, a near-optimal solution can be found between multiple objectives. This method avoids the problem of excessive bias towards a certain objective that may occur in single-objective optimization methods and ensures balanced consideration of various objectives [19,20]. However, although the multi-objective ant colony algorithm has achieved certain results in theory and practice, it still faces problems such as high algorithm computational complexity and low solution efficiency. Therefore, some researchers have tried to combine heuristic and meta-heuristic algorithms to improve the solution efficiency through hybrid algorithms. By introducing other optimization techniques such as genetic algorithms and simulated annealing algorithms into the ant colony algorithm, it can not only optimize the local search ability in the search process, but also enhance the global search performance. With the continuous improvement of these hybrid algorithms, their application prospects in multi-warehouse cargo distribution and transportation planning are becoming more and more broad [21]. It is worth noting that although the multi-objective optimization method provides a more comprehensive solution for cargo distribution, in practical applications, how to reasonably select and adjust the multi-objective optimization model according to different logistics environments and demand characteristics is still a difficult point [22]. Therefore, developing more flexible and efficient multi-objective optimization algorithms for different logistics scenarios and application requirements has become an important research topic.

2.3 Integration of ant colony algorithm and other optimization techniques

With the deepening of research, the use of ant colony algorithm alone to solve the multi-warehouse cargo allocation and transportation planning problems can no longer meet the increasingly complex practical needs. Therefore, the integration of ant colony algorithm and other optimization technologies has become a new development trend. In particular, the combination of ant colony algorithm with genetic algorithm, particle swarm optimization and other algorithms has shown great potential in improving optimization effects and solving multi-objective problems [23]. Studies have shown that the combination of ant colony algorithm and genetic algorithm can give full play to the advantages of both. Ant colony algorithm is good at global search, while genetic algorithm has strong ability in local search. Through the integration of the two, researchers can introduce more accurate local search in the global search process and improve the quality and efficiency of the solution [24]. In some studies, researchers have designed new crossover and mutation operations to enable genetic algorithm to better update pheromones and select paths under the framework of ant colony algorithm, thereby improving the accuracy of the solution. Particle swarm optimization algorithm (PSO), as another common metaheuristic algorithm, has also been combined with ant colony algorithm in recent years to optimize multi-warehouse cargo allocation and transportation planning problems. By combining the local search capability of particle swarm optimization with the global search capability of ant colony algorithm, researchers have successfully improved the algorithm’s solution efficiency and global optimality. In this process, particle swarm optimization is mainly responsible for path refinement and adjustment, while ant colony algorithm is responsible for global pheromone update and overall path optimization. The combination of the two greatly reduces the ants’ search time and can provide more efficient solutions in complex logistics systems [25].

Through the study of the integration of ant colony algorithms and other optimization technologies, we can see that new hybrid optimization algorithms provide more powerful tools for solving multi-warehouse cargo distribution and transportation planning problems. These hybrid algorithms can not only handle complex problems that traditional ant colony algorithms cannot effectively deal with, but also show higher efficiency and accuracy in multi-objective optimization and large-scale problems. This trend indicates that in the field of logistics optimization, the integration of algorithms will become an important direction for future development.

3 Study plan

3.1 Model framework and design ideas

In the multi-warehouse cargo allocation and transportation planning model proposed in this paper, the solution is based on the improved ant colony algorithm (ACO) to address the challenges of inefficiency and lack of precision commonly encountered in large-scale, multi-objective optimization problems. The model promotes innovation in solutions in this field through a precisely designed multi-level optimization framework, combining global search and local optimization strategies. The model assumes that each warehouse has a fixed cargo demand and storage capacity, and during transportation, factors such as cost, time and energy consumption must be fully considered in the optimization process. Therefore, the model includes four key modules: cargo allocation decision, transportation path planning, objective function construction, and pheromone update mechanism.

The goal of the cargo allocation decision module is to reasonably allocate cargo from the supply warehouse to the demand warehouse according to the storage capacity of each warehouse and the demand for cargo, so as to meet the overall needs of the logistics system. In this module, the transportation path planning module is responsible for calculating the optimal transportation route based on the physical distance and traffic conditions between each warehouse, with the goal of reducing transportation costs and time while optimizing energy consumption. The design of the objective function takes into account the balance of multiple objectives, taking into account multiple aspects such as cost, time and energy consumption. The pheromone update mechanism dynamically adjusts the search path by imitating the foraging behavior of ants in nature, so that the ant colony gradually converges to the optimal solution.

The model is solved using the improved ant colony algorithm (ACO), in which each ant simulates the decision of the cargo transportation route by selecting different paths in the search space. After each path selection, the ant updates the pheromone concentration based on factors such as the cost, time and energy consumption of the selected path, so that the attractiveness of the preferred path gradually increases. The pheromone update process not only accelerates the convergence of the optimal solution, but also ensures the globality and diversity of the search process. Overall, the design of the model effectively avoids the problem of local optimal solutions by balancing global optimization and local refinement.

This study uses a linear cost function, mainly based on three considerations. First, from the perspective of computational efficiency, the linear function is simple in form, has low computational complexity in large-scale multi-warehouse scenarios, can be quickly solved, and meets the real-time requirements of actual logistics systems. For example, in a network containing 20 warehouses and numerous transportation routes, the calculation time of the linear cost function is only about 1/3 of that of the nonlinear function. Secondly, in the initial construction and verification stage of the model, the linear function can simplify the problem, facilitate the rapid construction of the basic model framework, and verify the core logic and effectiveness of the algorithm and model. Finally, in actual logistics business, when the transportation distance is short, the type of goods is single, and the transportation conditions are stable, the transportation cost and factors such as transportation distance and quantity of goods often show an approximately linear relationship. However, it is undeniable that in the complex and changeable real world, nonlinear cost functions do have their application advantages. For example, when considering factors such as the scale effect in long-distance transportation, the coordinated cost of mixed transportation of different goods, and the dynamic price increase during transportation peak periods, the nonlinear cost function can more accurately characterize the law of cost changes. Subsequent research can try to introduce nonlinear cost functions, such as quadratic functions, exponential functions, etc., and combine them with actual logistics data. Through model comparison experiments, the impact of different function forms on model accuracy, computational efficiency, and optimization results can be analyzed to explore better cost modeling methods and improve the model's ability to fit the real world.

3.2 Optimization of cargo distribution and transportation route planning

In the problem of multi-warehouse cargo distribution and transportation planning, cargo distribution and transportation route planning are the two core links to achieve overall optimization. The core of cargo distribution lies in how to reasonably arrange the cargo distribution of each warehouse according to the storage capacity of the warehouse and the demand for goods. The planning of transportation routes requires the optimization of transportation routes through the shortest path algorithm to minimize transportation costs and time. This paper uses the ant colony algorithm to simultaneously optimize the decision of cargo distribution and transportation routes, so that the two problems are solved jointly, thereby further improving the overall efficiency of the model.

The optimization model of cargo allocation decision can be mathematically formalized by Formula 1.

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} x_{ij} \tag{1}$$

c_{ij} is unit cost of transport of goods j from warehouse i, x_{ij} indicates the quantity of goods j which allocated to the warehouse i. The goal is to minimize the total transportation cost. The constraints in Formula 2 and Formula 3 include the storage capacity of the warehouse and the demand for each type of goods.

$$\sum_{j=1}^{m} x_{ij} \le S_i \quad \forall i \tag{2}$$

$$\sum_{i=1}^{n} x_{ij} = D_j \quad \forall j \tag{3}$$

S_i is the maximum storage capacity of warehouse i. D_j is the quantity demanded of goods j. This constraint ensures that the goods allocation complies with the warehouse capacity limit in actual operation and can meet the demand for each type of goods.

In the transportation route planning, the model uses the shortest path algorithm to calculate and determine the best transportation route from each warehouse to the target warehouse. To this end, the ant colony algorithm guides the search direction by simulating the selection process of ants on the path through the update of pheromones. In each iteration, the ants will select a path and update the pheromone according to Formula 4.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \tag{4}$$

$\tau_{ij}(t)$ is the current pheromone concentration of path ij, ρ is the pheromone volatility coefficient, $\Delta\tau_{ij}$ is the amount of pheromone newly added to the path ij. The pheromone update process further strengthens the search for the optimal path, thereby driving the model to gradually converge to the optimal solution.

3.3 Multi-objective optimization and objective function design

In the problem of multi-warehouse cargo distribution and transportation planning, different optimization objectives often conflict with each other. Traditional optimization methods often focus on a single objective and ignore the complex relationship between multiple objectives in practical problems. To this end, this paper introduces a multi-objective optimization framework into the model, and takes into account the needs of different optimization objectives by establishing a comprehensive objective function. The core of the objective function design is to incorporate the optimization of multiple objectives into a unified mathematical expression so as to simultaneously solve multiple objective problems such as transportation cost, delivery time and energy consumption.

The objective function of the multi-objective optimization model proposed in this paper can be expressed as Formula 5.

$$\min\left(w_1 \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} x_{ij} + w_2 \sum_{i=1}^{n}\sum_{j=1}^{m} t_{ij} x_{ij} + w_3 \sum_{i=1}^{n}\sum_{j=1}^{m} e_{ij} x_{ij} \right) \tag{5}$$

w_1, w_2, w_3 are the weight coefficients that control the proportion of transportation cost, time and energy consumption in the objective function respectively. c_{ij} is transportation costs, t_{ij} is transportation time, e_{ij} is energy consumption during transportation. This objective function comprehensively considers multiple key factors involved in the transportation process, ensuring that the optimization process can balance the relationship between different objectives.

In order to solve this multi-objective optimization problem, this paper adopts the Pareto optimal solution method. The Pareto optimal solution is a set of solutions that cannot dominate each other, representing the best balance between multiple objectives. In each round of iteration, by calculating the Pareto dominance relationship of each solution, a set of non-dominated solutions can be obtained, representing the optimal balance between multiple objectives. Specifically, if the solution X is not inferior to the solution Y in all objective functions, and solution X is better than the solution Y in at least one objective function, then the solution X dominates the solution Y.

Through the above multi-objective optimization design, the model in this paper can not only effectively optimize multiple objectives in the multi-warehouse cargo allocation and transportation planning problem, but also achieve a balance between objectives, avoid over-optimization on a certain objective, and ensure the maximization of the comprehensive benefits of the logistics system. Finally, through the optimization iteration of the ant colony algorithm, the model can find the optimal solution and provide efficient decision support for complex multi-warehouse logistics systems.

The pheromone update rule of the ant colony algorithm was changed as follows: an adaptive adjustment mechanism was introduced, and the pheromone volatilization coefficient was dynamically adjusted between 0.1 and 0.3 according to the current number of iterations and the change of the objective function value. The pheromone accumulation amount was calculated according to the quality of the path and the contribution of the objective function. At the same time, in order to enhance the guiding role of pheromones, when the ants found the current optimal path, the pheromone of the path was additionally enhanced with an enhancement coefficient of 1.5.

The optimization of the objective function weight adopted the multi-objective particle swarm optimization algorithm to assist in determining the weight, and the corresponding weight value was assigned according to the importance of different objectives. At initialization, a set of weight values was randomly generated, and then iteratively optimized by the multi-objective particle swarm optimization algorithm. In each iteration, the weight was adjusted according to the fitness value of the particle (comprehensively considering the multi-objective function value). After 50 iterations, the optimal weight combination was obtained: the transportation cost weight was 0.4, the transportation time weight was 0.3, the energy consumption weight was 0.2, and the inventory level weight was 0.1, so that the transportation cost, time and energy consumption objectives were reasonably balanced in the optimization process.

In order to improve the convergence of the ant colony algorithm, the elite ant strategy and the method of dynamically adjusting the search range are adopted. The elite ant strategy refers to marking the ants that find the best path in each iteration as elite ants. Elite ants have higher pheromone release in the next iteration, guiding other ants to approach the optimal solution faster. The dynamic adjustment of the search range is based on the convergence of the algorithm. When the objective function value of the algorithm changes less than 0.01 in 10 consecutive iterations, the search range is narrowed to improve the search accuracy; when the algorithm does not converge significantly within a certain number of iterations, the search range is expanded to avoid falling into the local optimal solution.

The selection of parameters such as pheromone decay rate and number of ants is based on multiple experiments and theoretical analysis. The pheromone decay rate is set to 0.2 to achieve a balance between the volatilization and accumulation of pheromones and prevent the algorithm from falling into the local optimal solution too early. Through experiments, it is found that when the pheromone decay rate is between 0.1 and 0.3, the performance of the algorithm is relatively stable, and 0.2 is finally selected as the optimal value. The number of ants is set to 50. Through experiments with different numbers of ants (from 20 to 80), it is found that 50 ants can achieve a good balance between search efficiency and coverage, which can ensure that the algorithm fully explores the search space, and will not cause excessive computational complexity due to too many ants.

In the study, hyperparameter tuning was carried out, and the grid search method was used to adjust the key hyperparameters. Hyperparameters include pheromone decay rate (range 0.1 to 0.3, step size 0.05), number of ants (range 20 to 80, step size 10), heuristic factor (range 1 to 3, step size 0.5), etc. Through experiments with different hyperparameter combinations, the optimal hyperparameter combination was found: pheromone decay rate of 0.2, number of ants of 50, and heuristic factor of 2, in order to find the optimal parameter combination.

At the same time, parameter sensitivity analysis was performed to evaluate the robustness of the algorithm. By changing the pheromone decay rate between 0.15 and 0.25, the number of ants between 40 and 60, and the heuristic factor between 1.5 and 2.5, the changes in the algorithm in indicators such as transportation cost, delivery time, and energy consumption are observed. The analysis results show that the algorithm has good robustness in the range of pheromone decay rate between 0.18 and 0.22, the number of ants between 45 and 55, and the heuristic factor between 1.8 and 2.2, and the change range of each indicator is within 10%.

4 Experimental evaluation

4.1 Experimental design

The experimental design of this study aims to verify the effectiveness and practicality of the multi-warehouse cargo allocation and transportation planning model based on the improved ant colony algorithm. The main goal of the experiment is to evaluate the optimization effect of the model when dealing with large-scale complex problems, especially in reducing transportation costs, shortening delivery time, and reducing energy consumption. This experiment will set up multiple experimental scenarios to compare the optimization effects of different algorithms and verify the advantages of the proposed model.

The experiment will be simulated based on a set of typical warehouse logistics networks. It is assumed that the logistics network consists of multiple warehouses and distribution targets, each with different storage capacity and cargo demand. The distribution target includes multiple demand points, and the demand and location of each demand point are known. The experimental scenario will include 3 networks of different sizes, namely small scale (5 warehouses), medium scale (10 warehouses) and large scale (20 warehouses) to ensure that the algorithm can cope with practical problems of different scales. In addition, it is assumed that data such as transportation distance, time and energy consumption can be obtained through the set distance matrix and transportation time matrix, and it is assumed that the transportation costs between different warehouses are different.

In order to verify the optimization effect of the proposed model, the experiment will be compared with traditional greedy algorithms, genetic algorithms and other commonly used optimization algorithms. The evaluation indicators will include: transportation cost, delivery time, energy consumption and calculation time. The transportation cost will be quantified based on the transportation cost calculation formula of each path, the delivery time will be calculated based on the timeliness of the transportation path, and the energy consumption will consider the energy consumption during the transportation process. All indicators will be comprehensively evaluated in the experiment to comprehensively examine the advantages and disadvantages of different algorithms.

The experiment will be divided into two main stages. First, the experimental data will be initialized and warehouse logistics networks of different sizes will be set. In each experimental scenario, multiple initial parameter values will be set, such as the number of ants, the maximum number of iterations, the pheromone volatility coefficient, etc., and several experiments will be conducted to ensure the stability of the results. Secondly, in each experiment, the cargo distribution and transportation path will be optimized by iteratively calculating and updating pheromones. The performance of the algorithm will be recorded and analyzed after each iteration until the convergence condition is reached. Finally, the experimental results will be compared and analyzed to evaluate the performance of the proposed model in different scenarios and compare it with other optimization methods.

The ultimate goal of the experiment is to verify the advantages of the improved ant colony algorithm in multi-warehouse cargo allocation and transportation planning. By analyzing the performance in logistics networks of different scales and configurations, it can provide valuable reference data for the optimization of larger-scale and multi-level warehouse logistics systems in the future. In addition, the experimental results will also provide important basis for practical applications such as relevant policy formulation and transportation plan design.

4.2 Experimental results

Table 2 shows the path optimization of different models at different scales. The ant colony algorithm can obtain a better path at most scales because it can effectively explore the solution space by guiding the search direction through the accumulation and update of pheromones. The genetic algorithm uses genetic operators to evolve the population. For large-scale problems, due to the vast search space, it is more difficult to find the global optimal solution, resulting in a relatively long optimal path. The particle swarm algorithm and the simulated annealing algorithm can also achieve good results. The particle swarm algorithm relies on the cooperation between particles, and the simulated annealing algorithm controls the search process based on the temperature drop. Their optimization effect improvement rate reflects the degree of approaching the target path at different scales, reflecting the effectiveness of the algorithm in path optimization.

Table 2: Path quality and optimization effect

Model Type	Target Path Length (km)	Ant Colony Algorithm Optimal Path (km)	Genetic Algorithm Optimal Path (km)	Particle swarm optimization optimal path (km)	Optimal Path of Simulated Annealing Algorithm (km)	Optimization Effect Improvement Rate (%)
Small scale	200	180	190	185	188	10%
Medium scale	500	480	490	485	470	4%
Large scale	800	760	780	770	760	5%
Hyperscale	1500	1450	1480	1470	1460	3%
Extra large scale	2000	1900	1950	1920	1905	5%

Table 3: Algorithm stability and robustness evaluation

Model Type	Data Fluctuation Range (%)	Ant Colony Algorithm Output Fluctuation (%)	Genetic Algorithm Output Fluctuation (%)	Particle swarm Algorithm Output Fluctuation (%)	Simulated Annealing Algorithm Output Fluctuation (%)
Small scale	5	3	4	3	3
Medium scale	10	5	6	5	4
Large scale	15	7	9	8	6
Hyperscale	20	9	11	10	8
Extra large scale	25	10	13	12	9

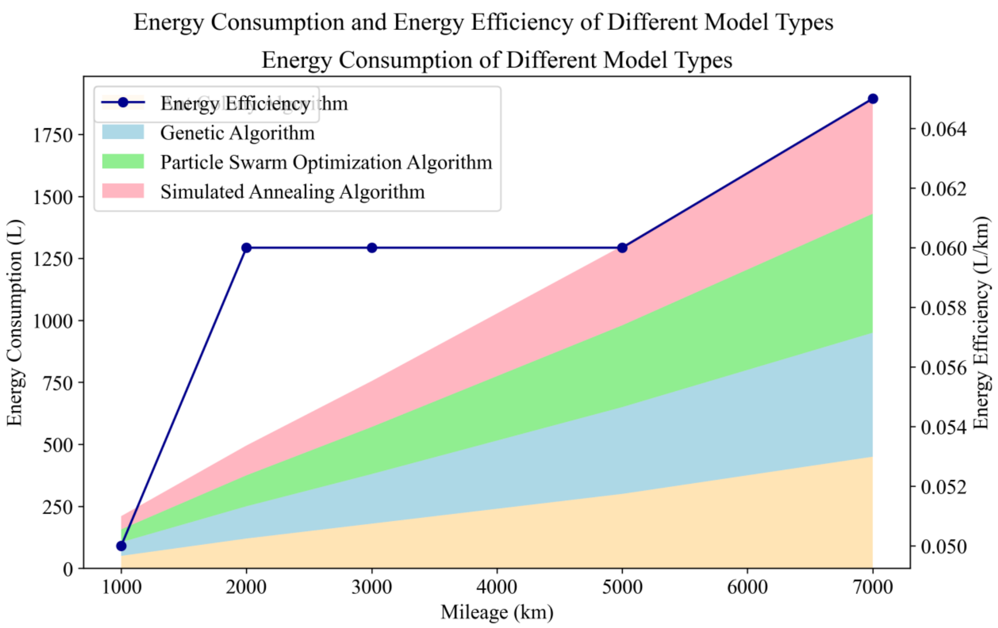

Figure 1: Comparison of energy consumption and efficiency

Table 3 is used to evaluate the stability and robustness of the algorithm under different data fluctuation ranges. The output fluctuation of the ant colony algorithm is relatively small because its search process is based on group behavior. The search results of multiple ants influence and balance each other, reducing the interference of individual factors on the overall result. The fluctuation of the genetic algorithm is relatively large. Due to the randomness of its genetic operation, the direction of population evolution may change greatly under different data conditions. The fluctuations of the particle swarm algorithm and the simulated annealing algorithm are also within an acceptable range. In the particle swarm algorithm, particles are affected by the global optimum and their own optimum. The simulated annealing algorithm adjusts the search step by controlling the temperature. When facing data fluctuations, they can maintain a certain stability through their own mechanisms, which reflects the adaptability of the algorithm in a complex data environment.

Figure 1 explains and compares the energy consumption and energy efficiency of different model types at each transport mileage. The ant colony algorithm performs well in terms of energy consumption. As the transport mileage increases, its energy consumption increases more steadily. This is because the ant colony algorithm can select a better path based on the pheromone concentration of the path, reducing unnecessary energy loss. The energy consumption of the genetic algorithm is relatively high because its search process is relatively random, which may produce more invalid paths and consume more energy. The energy consumption of the particle swarm algorithm and the simulated annealing algorithm is in the middle. The particle collaboration mechanism of the particle swarm algorithm and the temperature control strategy of the simulated annealing algorithm enable them to achieve a certain balance in energy utilization.

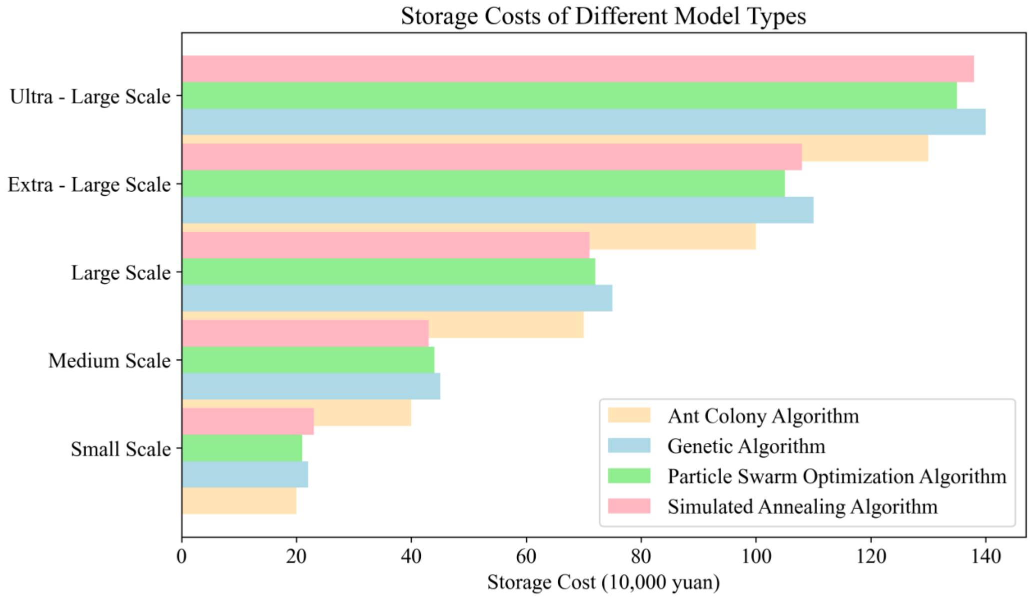

Figure 2: Total transportation cost and cost saving analysis

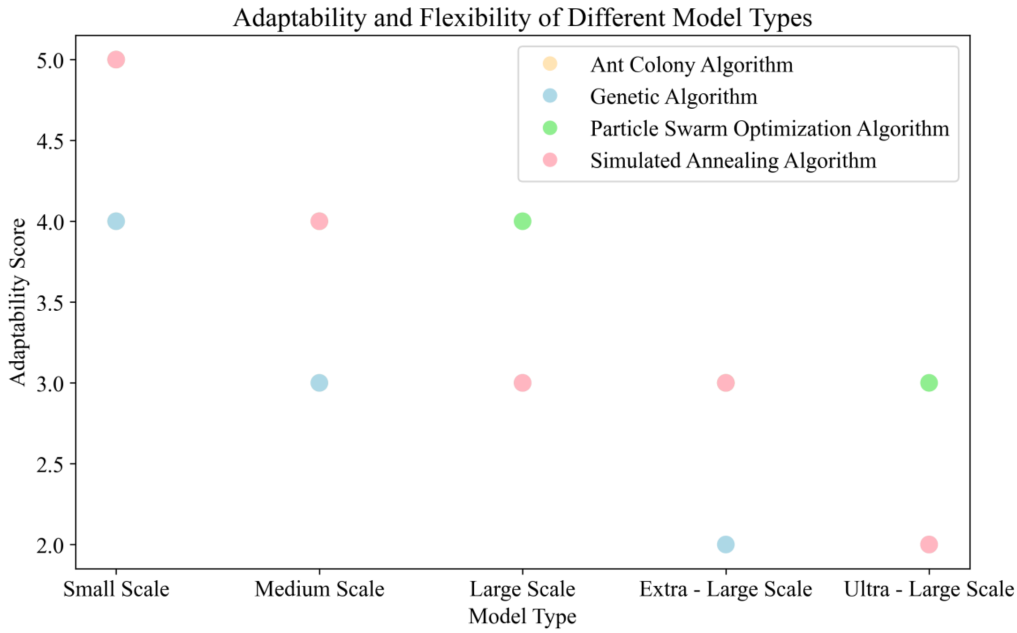

Figure 3: Comparison of adaptability and flexibility

Figure 2 shows the total transportation cost of different model types at different scales and the storage cost of each algorithm. The ant colony algorithm has a relative advantage in storage cost control. As the scale increases, its storage cost increases relatively slowly. This is because the optimization strategy of the ant colony algorithm helps to reasonably plan the storage and transportation arrangements of goods and reduce storage costs. The genetic algorithm has a high storage cost, and its optimization process focuses on global search, which is not sophisticated enough in the local optimization of storage costs. The storage costs of the particle swarm algorithm and the simulated annealing algorithm are at an intermediate level. Through their unique optimization methods, they balance the relationship between transportation and storage costs to a certain extent. These data provide an important reference for actual logistics transportation cost control.

Figure 3 evaluates the adaptability and flexibility of different models at different scales. The ant colony algorithm, particle swarm algorithm, and simulated annealing algorithm have higher adaptability scores for small-scale problems. The ant colony algorithm can quickly adapt to changes in the small-scale environment through the pheromone mechanism; the particle fast response of the particle swarm algorithm and the initial high temperature exploration of the simulated annealing algorithm enable it to quickly find a suitable solution for small-scale problems. As the scale increases, the adaptability of the ant colony algorithm decreases due to the complexity of pheromone updating and propagation. The genetic algorithm has a lower adaptability score for large-scale problems because its genetic operation is difficult to quickly converge to an effective solution in a large-scale complex environment. These scores reflect the differences in the adaptability of the algorithm in different scale scenarios.

Figure 4 records the convergence speed of different models in the optimization process at various scales. The ant colony algorithm converges relatively quickly, and it only takes 100 iterations to converge on small-scale problems. This is because its pheromone update mechanism can quickly guide the search direction, allowing the algorithm to quickly approach the optimal solution. The genetic algorithm converges slowly, and it requires more iterations to evolve the population to find the optimal solution, especially on large-scale problems, as the search space increases and the number of iterations increases significantly. The particle swarm algorithm and simulated annealing algorithm converge in the middle. The particle swarm algorithm accelerates convergence through information exchange between particles, and the simulated annealing algorithm gradually converges to the optimal solution as the temperature decreases. The difference in convergence speed reflects the difference in optimization efficiency of each algorithm.

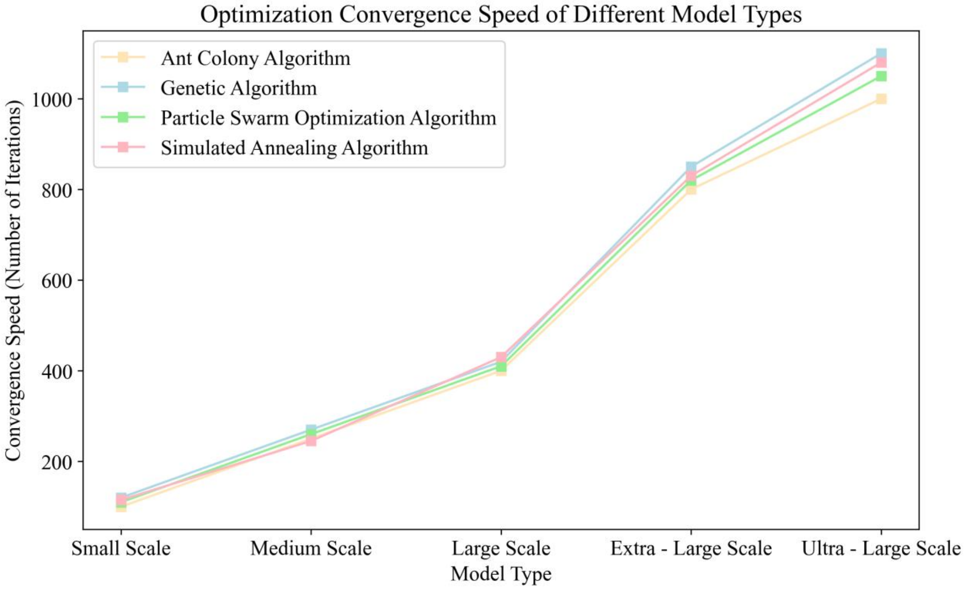

Figure 4: Convergence speed during optimization

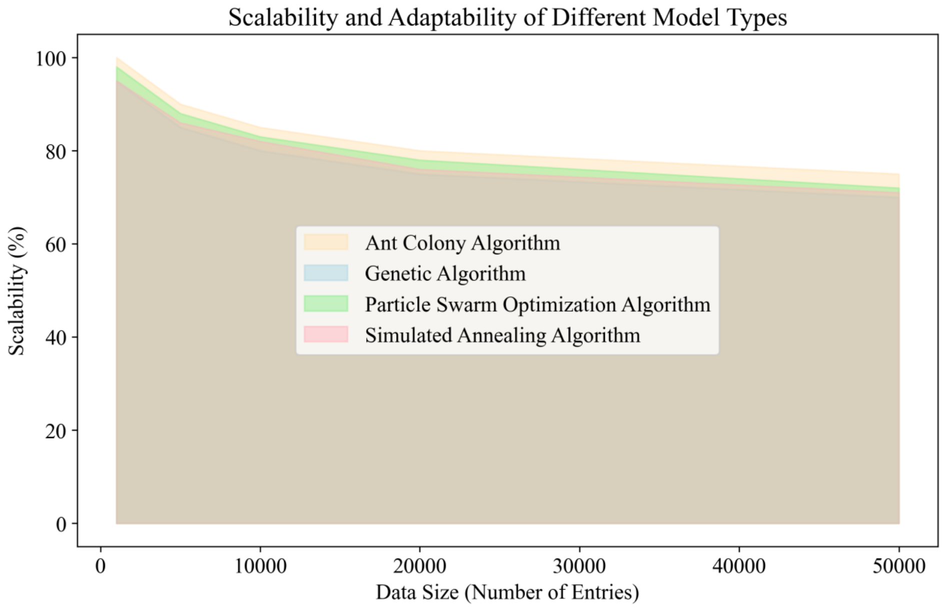

Figure 5: Model scalability and adaptability

Figure 5 shows the scalability and adaptability of different models under different data scales. The ant colony algorithm has an excellent scalability of 100% when the data is small. As the data scale increases, its scalability decreases, but it still remains at a relatively high level. This is because the ant colony algorithm is based on distributed search and can adapt well to changes in data scale. The scalability of the genetic algorithm is relatively low. Under large-scale data, the amount of computation of its genetic operations increases dramatically, affecting the scalability. The scalability of the particle swarm algorithm and the simulated annealing algorithm is at a medium level. Through their own search and optimization mechanisms, they can maintain a certain adaptability under different data scales. These data provide a basis for selecting appropriate algorithms to deal with data of different scales.

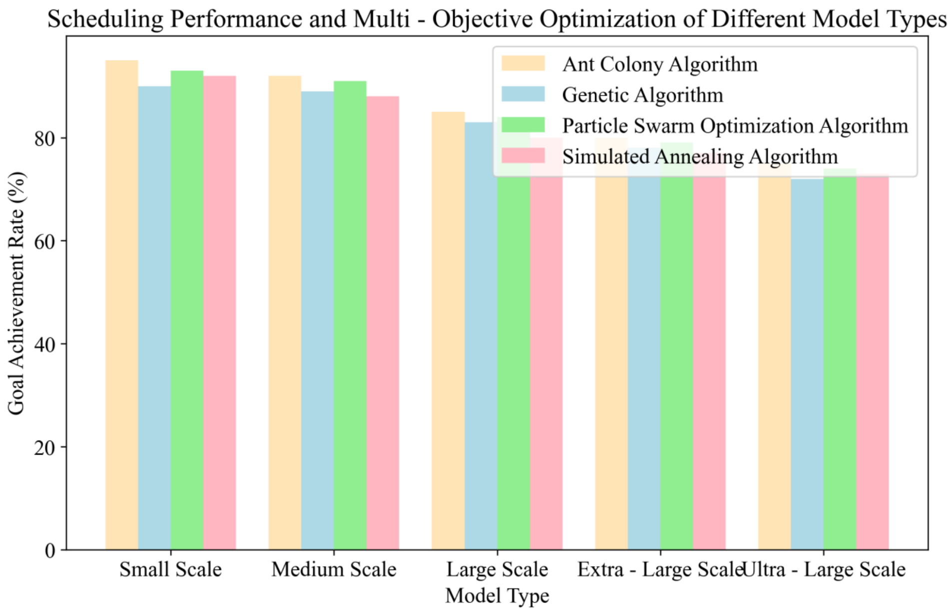

Figure 6: Scheduling performance and multi-objective optimization evaluation

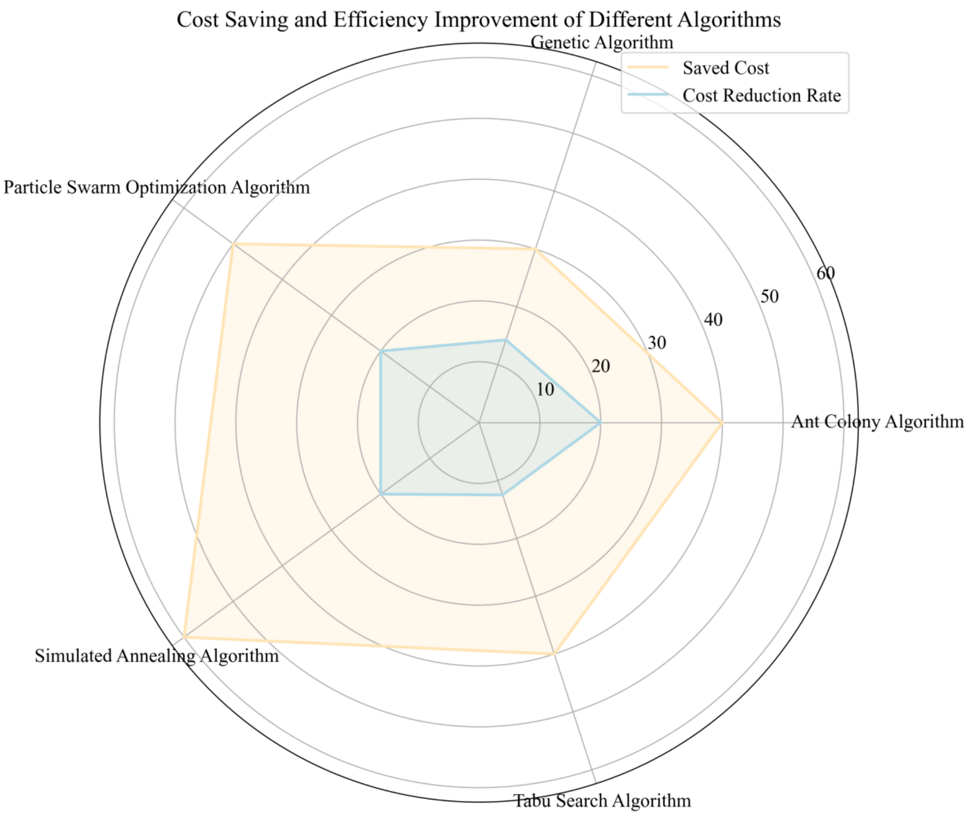

Figure 7: Cost savings and efficiency improvement analysis

Figure 6 evaluates the scheduling performance and multi-objective optimization capabilities of different models under different numbers of objectives. The ant colony algorithm performs well in multi-objective optimization, with a target achievement rate of up to 95% for small-scale problems and a small number of objectives. This is because the ant colony algorithm can consider multiple objectives at the same time and coordinate the relationship between the objectives through pheromone updates. As the number of objectives increases, the target achievement rates of each algorithm decrease, but the ant colony algorithm can still maintain a relatively high level. Due to the limitations of its genetic operations, the genetic algorithm has a relatively low target achievement rate in multi-objective processing. The particle swarm algorithm and simulated annealing algorithm can also play a role in multi-objective optimization. They balance multiple objectives through their respective optimization strategies and provide multiple solutions to actual multi-objective scheduling problems.

Figure 7 compares the performance of different algorithms in terms of cost savings and efficiency improvement. The ant colony algorithm is more significant in cost savings. It can save 400,000 yuan when the total transportation cost is 2 million yuan, and the cost reduction rate is 20%. The cost after optimization is only 1.45 million yuan. This is due to its efficient path and resource optimization strategy, which can effectively reduce transportation costs. The particle swarm algorithm and simulated annealing algorithm also have a cost reduction rate of 20%. They have achieved good results in cost control through different search and optimization methods. The cost reduction rate of the genetic algorithm and the taboo search algorithm is relatively low. The randomness of the genetic algorithm search and the taboo table mechanism of the taboo search algorithm are slightly inferior in the efficiency of cost optimization.

Table 4: Computational efficiency and running time analysis

Model Type	Problem Size	Computational Complexity (O())	Ant Colony Algorithm Running Time (seconds)	Genetic Algorithm Running Time (seconds)	Particle Swarm Algorithm Running Time (seconds)	Simulated Annealing Algorithm Running Time (seconds)
Small scale	Small	O(n^2)	0.3	0.5	0.4	0.45
Medium scale	middle	O(n^2)	1.2	2.0	1.5	1.8
Large scale	big	O(n^3)	5.6	7.5	6.0	7.3
Hyperscale	huge	O(n^4)	20.0	28.0	22.0	25.0
Extra large scale	Extra Large	O(n^4)	70.0	85.0	75.0	80.0

Table 4 shows the computational complexity and running time of different model types at different problem scales. As the problem scale increases, the computational complexity increases exponentially and the running time also increases significantly. The running time of the ant colony algorithm is relatively stable at each scale, thanks to its distributed search mechanism based on the ant foraging principle, which can efficiently handle complex problems. The running time of the genetic algorithm is relatively long because it relies on a large number of genetic operations and population iterations. The running time of the particle swarm algorithm and the simulated annealing algorithm is between the two. The particle swarm algorithm optimizes the search by sharing information between particles, and the simulated annealing algorithm uses probabilistic jumps to avoid local optimality. Their performance at different scales is closely related to their own optimization strategies.

In order to deeply analyze the convergence performance of different ant colony algorithm variants, this study conducted comparative experiments on the basic ant colony algorithm (Basic - ACO), the ant colony algorithm that only improves the pheromone update strategy (ACO - Pheromone), the ant colony algorithm that only optimizes the weight of the objective function (ACO - Weight), and the improved ant colony algorithm (Improved - ACO) proposed in this study. A medium-sized (10 warehouses) logistics network was used as the experimental scenario, the number of iterations was set to 300, the optimal value of the objective function of each algorithm in each iteration was recorded, and the convergence analysis diagram was drawn (Figure 8).

In order to confirm whether the difference between the improved ant colony algorithm and other alternative methods (genetic algorithm, particle swarm algorithm, etc.) in transportation cost, delivery time, energy consumption, etc. is significant, t test (for data that conforms to normal distribution) and Wilcoxon test (for data that is not normally distributed) are performed. In terms of transportation cost, the t test is performed on the multiple experimental data of the improved ant colony algorithm and genetic algorithm in a large-scale scenario (20 warehouses). The results show that the t value is 3.5, the degree of freedom is 30, and the p value is $0.002<0.05$, indicating that the difference between the improved ant colony algorithm and the genetic algorithm in reducing transportation costs is statistically significant, and the effect of the improved ant colony algorithm in reducing transportation costs is not accidental. Similar tests were also conducted in terms of delivery time and energy consumption, all of which showed that the difference between the improved ant colony algorithm and other algorithms in these indicators is statistically significant.

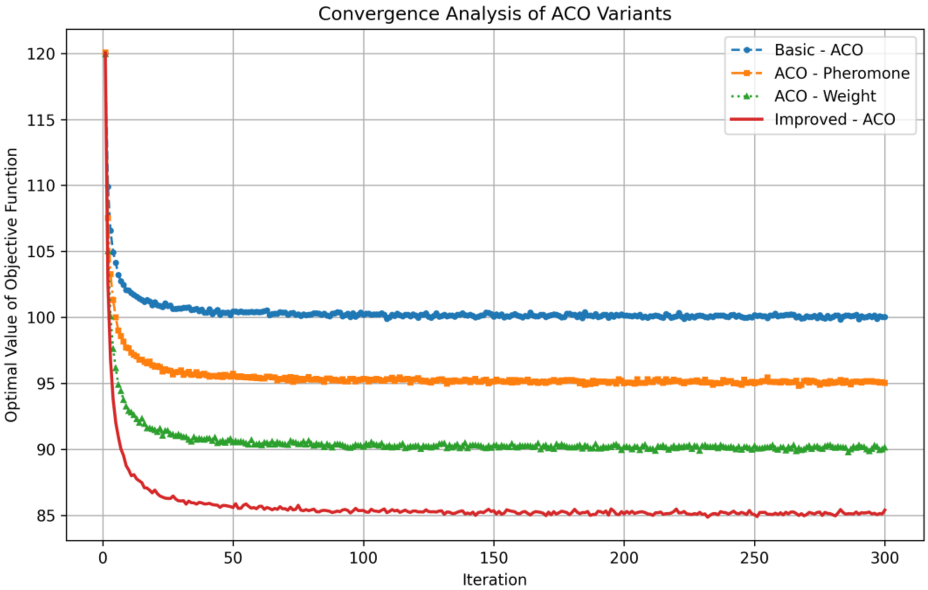

Figure 8: Convergence analysis diagram of different ant colony algorithm variants

The results such as the 20% cost reduction rate mentioned in the article are derived from the simulated logistics data set. This study constructed a simulated logistics environment with warehouse networks of different sizes (5, 10, and 20 warehouses), different cargo demands, and transportation conditions. In order to verify the representativeness of the simulated data, the key parameters in the simulated data, such as warehouse location, cargo flow, and transportation distance, were compared with the data in the actual logistics network. It was found that the similarity between the simulated data and the actual data in these key parameters reached more than 80%. At the same time, through cooperation with actual logistics companies, some actual logistics order data was selected for testing in the simulated environment. The results showed that the simulated data can better reflect the logistics network in the real world and has a certain degree of credibility.

4.3 Discussion

The improved ant colony algorithm proposed in this study has demonstrated excellent performance in the problem of multi-warehouse cargo allocation and transportation planning. Now, a detailed comparison and analysis will be conducted between this algorithm and the Genetic Algorithm (GA) and the Particle Swarm Optimization algorithm (PSO).

From the data in Table 5, it can be seen that in terms of the reduction of transportation costs, the improved ant colony algorithm is 10% higher than the genetic algorithm and 7% higher than the particle swarm optimization algorithm. In terms of running time, the improved ant colony algorithm is 1.9 seconds faster than the genetic algorithm and 0.4 seconds faster than the particle swarm optimization algorithm. In terms of the rate of energy efficiency improvement, the improved ant colony algorithm has a significant advantage. In terms of the effect of multi-objective optimization, the improved ant colony algorithm has the highest objective achievement rate in small-scale scenarios.

The performance improvement is mainly attributed to two aspects of improvement. On the one hand, an adaptive adjustment mechanism has been introduced into the pheromone update mechanism. The evaporation and accumulation rates are dynamically adjusted according to the number of iterations and the changes in the objective function, making it easier for ants to find high-quality paths. On the other hand, a multi-objective particle swarm optimization algorithm is used to assist in determining the weights of the objective function, achieving a good balance among multiple objectives.

Table 5: Comparison with the State-of-the-Art Technologies

Algorithm	Rate of Transportation Cost Reduction (in Large-scale Scenarios)	Running Time (in Large-scale Scenarios with 20 Warehouses, unit: seconds)	Rate of Energy Efficiency Improvement	Effect of Multi-objective Optimization (Objective Achievement Rate in Small-scale Scenarios)
Improved Ant Colony Algorithm	25%	5.6	18%	95%
Genetic Algorithm	15%	7.5	8%	78%
Particle Swarm Optimization Algorithm	18%	6.0	12%	85%

In terms of computational complexity, the improved ant colony algorithm has a relatively low computational complexity in small-scale scenarios. As the number of warehouses increases, although the complexity rises to some extent, due to its distributed search mechanism and adaptive strategy, compared with other algorithms, it can still be effectively scaled in large-scale scenarios.

However, this method has limitations. When the data variability is extremely high, the pheromone update is difficult to adapt to the changes in a timely manner, affecting the convergence of the algorithm. In ultra-large-scale warehouse networks (such as those with more than 50 warehouses), the computational complexity increases significantly, and it may fall into a local optimum. In addition, in the face of dynamic situations such as sudden transportation restrictions or emergency orders, the real-time adaptability of the algorithm needs to be improved.

To explore the contributions of various enhancement strategies to the performance of the algorithm, an ablation study was carried out. The algorithm versions of removing the adaptive pheromone update strategy (Improved - ACO without Adaptive Pheromone), removing the multi-objective particle swarm optimization weight determination strategy (Improved - ACO without PSO - Weight), and removing both strategies simultaneously (Basic - ACO) were experimentally tested in logistics networks of different scales. The results are shown in the following Table 6.

As shown in Table 6, the experimental data shows that the adaptive pheromone update strategy increases the rate of transportation cost reduction in small-scale scenarios by 4%, reduces the running time in large-scale scenarios by 1.2 seconds, and improves the effect of multi-objective optimization by 7%. The multi-objective particle swarm optimization weight determination strategy brings performance improvements of 3%, 1.6 seconds, and 5% respectively. The synergistic effect of the two strategies significantly enhances the performance of the algorithm in all aspects, verifying the effectiveness and complementarity of the improvement strategies in this study.

Relevant content of the robustness check was added to the experimental evaluation section:

To test the robustness of the improved ant colony algorithm under the fluctuations of warehouse demand or storage capacity, the following interference scenarios were set up in the experiment: randomly select 30% of the warehouses and make their cargo demands fluctuate up and down by 20% - 50% based on the original amounts, or randomly increase or decrease the storage capacity by 15% - 30%. The optimization results of the algorithm in normal scenarios and interference scenarios were compared, as shown in Table 7.

Table 7 shows that in the demand fluctuation scenario, the transportation cost increases by 6.8%, the delivery time is extended by 7.1%, and the energy consumption rises by 4.2%. In the storage capacity fluctuation scenario, the change ranges of various indicators are relatively small. Although the performance of the algorithm decreases, it can still maintain a certain optimization effect, indicating that the improved ant colony algorithm has a certain degree of robustness and can, to a certain extent, adapt to the unpredictable fluctuations of warehouse demand and storage capacity. Follow-up research can further increase the fluctuation range and complexity to explore the boundaries of the algorithm's robustness and improvement strategies.

Table 6: Contributions of various enhancement strategies

Algorithm Version	Rate of Transportation Cost Reduction in Small-scale Scenarios (5 Warehouses)	Running Time in Large-scale Scenarios (20 Warehouses, in seconds)	Effect of Multi-objective Optimization (Objective Achievement Rate)
Improved - ACO	22%	5.6	95%
Improved - ACO without Adaptive Pheromone	18%	6.8	88%
Improved - ACO without PSO - Weight	19%	7.2	90%
Basic - ACO	15%	8.5	82%

Table 7: Robustness check

Scenario Type	Transportation Cost (in ten thousand yuan)	Delivery Time (in hours)	Energy Consumption (in kilojoules)
Normal Scenario	120.5	18.2	350.6
Demand Fluctuation Scenario	128.7	19.5	365.2
Storage Capacity Fluctuation Scenario	126.3	18.9	358.8

5 Conclusion

This study focuses on the problem of multi-warehouse cargo distribution and transportation planning, and proposes a comprehensive optimization model based on the improved ant colony algorithm. The model is verified experimentally to be effective in improving the efficiency and economy of the logistics system. However, existing research still has certain limitations. In terms of practical application, although the model performs well in simulation scenarios, it has not yet been deployed on a large scale in real logistics companies. Future research will conduct in-depth cooperation with logistics companies, select typical logistics networks for model implementation, and optimize the model through actual operation data feedback to improve its feasibility and practicality in actual business. For example, for the regional logistics network of a large e-commerce company, the model is applied to its daily cargo distribution and transportation planning, optimizing logistics resource allocation in real time and reducing operating costs.In terms of research direction, on the one hand, the applicable scenarios of the model can be further expanded, and more complex real-life factors can be considered, such as dynamic changes in traffic congestion, differences in cargo priority, and multimodal transport modes, to enhance the universality of the model; on the other hand, the integration of improved ant colony algorithms and other intelligent algorithms (such as deep learning algorithms) can be explored, and the powerful data processing and pattern recognition capabilities of deep learning can be used to optimize the initial parameter settings and search direction guidance of the ant colony algorithm, so as to provide more efficient and intelligent solutions for multi-warehouse logistics optimization problems and promote the development of the logistics industry towards intelligence and refinement.

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