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RESEARCH ARTICLE

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Warehouse location optimization in fresh cold chain logistics based on PSO-GA

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Abstract. This study focuses on the site selection problem of fresh cold chain logistics warehouses, using a site selection model to minimize operating costs, improve distribution efficiency, and meet customer needs. The model covers warehouse location selection, special requirements for the fresh and cold chain, and organization of delivery routes. At the same time, a solution algorithm combining genetic algorithm and particle swarm optimization algorithm is proposed to solve the problem of location selection model. This hybrid algorithm encodes the layout problem of logistics points into a chromosome problem in genetic algorithms and utilizes particle swarm optimization to improve the efficiency of the search process and avoid early convergence difficulties. The results indicated that the improved algorithm was more effective than the ordinary genetic algorithm. After only 100 iterations, the objective function value of the algorithm decreased to approximately 31,500. The average total delivery cost of the model was reduced to 75.8369 million yuan, and the calculation was completed within 75 s, with significant efficiency. Therefore, this model can effectively assist logistics enterprises in accurately formulating economically effective distribution plans, achieving the optimal balance between cost and efficiency.

Keywords: PSO / GA / Cold chain logistics / Warehouse location

1 Introduction

Fresh cold chain logistics (FCCL) is a crucial part of modern supply chain management (SCM). It involves the process of transporting agricultural products, seafood, meat, dairy products, and other foods that require refrigeration from producers to consumers. An effective fresh and cold chain ensures the quality and safety of food while reducing losses during transportation and storage. As an important component of the cold chain logistics system, the reasonable location of cold storage has a significant impact on the economy and service efficiency of the system [1]. Cold storage is the core link for storing and transporting fresh products, and it is also a key facility to ensure that food maintains a suitable temperature and environment throughout the entire logistics process. By effectively controlling temperature and humidity, cold storage can significantly slow down the biochemical reaction and microbial growth of food, thereby extending the shelf life of food and maintaining its freshness and nutrients. In addition, the reasonable layout and operation of cold storage can effectively reduce temperature fluctuations during transportation, ensuring that food is always in a safe temperature controlled environment throughout the entire chain from the manufacturer to the consumer. In this way, it can maximize the prevention of food spoilage or contamination due to improper temperature, ensuring the food safety of end consumers [2]. By maintaining a constant low temperature environment, cold storage ensures that the growth rate of bacteria and micro-organisms in food is slowed down, thus effectively reducing the risk of food spoilage. In addition, the cold storage can be adjusted according to the storage requirements of different types of food, preventing too high or too low humidity from negatively affecting the quality of food, and thus maintaining its taste, nutritional value, and appearance. At the same time, the temperature control equipment monitoring system of the cold storage can detect and record temperature changes in real-time to ensure that the appropriate cold chain temperature is not disrupted. This tight control of the environment and a high degree of traceability guarantee the safety of food circulation and enable consumers to have access to fresh, safe food [3]. However, the problem of cold storage site selection is a complex multi-objective decision-making problem. It needs to consider factors such as geographical location, transportation costs, construction costs, and storage

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capacity, as well as environmental sustainability, energy efficiency, and socio-economic impact. Given this, researchers and industry experts are constantly seeking more effective methods to solve the site selection problem in FCCL, thereby optimizing the entire SCM [4–6]. In terms of search strategies, particle swarm optimization (PSO) and genetic algorithm (GA) are two widely studied and applied meta-heuristic algorithms for optimization problems. PSO simulates the collective behavior of birds to search for optimal solutions, characterized by strong global search ability. GA is a search strategy that mimics the process of biological evolution, continuously evolving better solutions through selection, crossover, and mutation operations [7–9]. Therefore, aiming at the location and distribution route optimization of FCCL warehouses, this paper combines the hybrid methods of PSO and GA to reduce operating costs, improve distribution efficiency, and meet customers' demand for freshness and timeliness. Through case analysis and model construction, a more scientific, economical, and practical decision support method has been provided for FCCL. The study aims to provide a scientific decision-making tool that enables logistics companies to allocate resources more effectively, covering as many end-retailers as possible with minimal Distribution Centers (DCs), thereby optimizing cargo transportation routes, reducing transportation time, and losses.

The main contributions of this study are as follows: First, a comprehensive optimization model is constructed that takes into account transportation costs, storage costs, quality loss costs, and time penalty costs. Temperature sensitivity and quality decay mechanisms are introduced to better meet the actual needs of cold chain operations. Second, a hybrid solution strategy integrating PSO and GA is proposed. This strategy effectively combines the global search capabilities of PSO with the diverse solution space exploration capabilities of GA, overcoming the shortcomings of a single algorithm prone to premature convergence and improving solution accuracy and efficiency. In addition, this study also provides optimization solutions for warehouse node layout and transportation routes, providing actionable references for fresh cold chain enterprises to make low-cost and high-efficiency distribution decisions while ensuring food quality and timeliness.

Section 1 proposes the research objectives, while Section 2 designs a site selection model and solution algorithm. Section 3 verifies the effectiveness of the model, while Section 4 obtains research results.

2 Literature review

In recent years, research on the location selection of intelligent logistics warehouses has gradually been enriched. In response to the problems of surging demand, insufficient efficiency and accuracy, and data security risks in the logistics industry, Boujarra M et al. proposed an intelligent solution integrating a deep learning model. This solution achieved a comprehensive improvement in inventory optimization, route planning, and process automation and strengthening data security [10]. Thuengnaitham A et al. applied the Analytic Hierarchy Process to determine the optimal location for the fulfillment warehouse of 4PL Company. Through questionnaire collection, the company's management team was compared and judged, and five candidate locations in the Bangkok metropolitan area and surrounding areas were analyzed. This study analyzed three main standards and nine sub-standards related to facilities, transportation, market, and labor, and found that transportation is the highest priority standard, followed by facilities, market, and labor. Finally, the model successfully determined the importance weight of the location of the fulfillment warehouse [11]. To solve the problem of difficult location selection for logistics DCs under the rapid development of e-commerce, Zhang P proposed a systematic analysis of influencing factors and a step-by-step location selection method. This method optimized logistics efficiency, reduced operating costs, and enhanced enterprise competitiveness [12]. Dagıstanlı HA and Kurtay KG proposed a site selection model that integrates geographic information systems and the Pythagorean fuzzy weighted comprehensive quadrature evaluation method. They tried to address the high risk of storage and transportation of expired ammunition and the need to consider both environmental and personnel safety in site selection. The candidate ammunition depot locations were ranked using the weighted comprehensive quadrature evaluation method, thereby achieving safe storage of high-risk ammunition and scientific decision-making optimization [13].

In addition, the application of PSO and GA is gradually deepening. Sohail A et al. discussed the application of GA in optimization problems. In the fields of engineering and data science, with the advancement of scientific computing and research, optimization strategies are no longer a challenge for small-scale datasets and low-dimensional problems. However, for large-scale, stochastic, and high-dimensional data problems, basic optimization tools are often difficult to apply due to complexity. GA, based on natural selection theory, has played an important role in dealing with such complex problems. In addition, hybrid GA has attracted the interest of researchers from almost all fields, including computer science, applied mathematics, engineering, and computational biology [14]. Muneer S M et al. proposed a GA-based feature selection model to improve prediction accuracy. In their research, GA was used to select the best features and make better predictions through classifiers [15]. Tian J et al. proposed a variable replacement model-based PSO to address the issue of intensive energy consumption assessment schemes in industrial applications over a limited period. The results showed that the method designed by the researchers was effective [16]. Yu Z et al. proposed a new hybrid PSO algorithm. This algorithm improved optimization capability and avoided getting stuck in local convergence by combining the simulated annealing algorithm with PSO. It had a significant effect on drone path planning in complex 3D environments [17].

In the above studies, although many studies have discussed the location and distribution route optimization of cold chain logistics warehouses, there are some limitations. For example, the existing research usually

Table 1. Comparative analysis of different studies.

References	Method/Model	Advantages	Limitations
Boujarra M et al. [10]	Deep learning integrated model (intelligent logistics optimization)	Improves inventory optimization and route planning, enhances data security	High complexity
Thuengnaitham A et al. [11]	Analytic hierarchy process	Systematically determines warehouse location criteria weights	Relies heavily on expert subjective judgment
Zhang P [12]	Stepwise site selection method (e-commerce logistics)	Improves efficiency, reduces costs, enhances competitiveness	Narrow application scenarios
Dagıstanlı H A et al. [13]	GIS + fuzzy comprehensive evaluation method (ammunition depot selection)	Emphasizes safety, considers environmental and personnel factors	Overly case-specific, poor generalizability; lacks distribution route optimization
Sohail A et al. [14]	Single GA algorithm	Suitable for complex large-scale problems	Prone to premature convergence, slow convergence speed
Muneer S M et al. [15]	GA-based feature selection model	Improves prediction accuracy	Application limited to classification and prediction
Tian J et al. [16]	Surrogate model-based PSO	Addresses high-dimensional, time-consuming problems	Application limited to classification and prediction
Yu Z et al. [17]	Improved PSO	Enhances global search ability, avoids local convergence	High practical implementation cost
This study	Hybrid PSO-GA optimization model	Combines GA's solution space diversity with PSO's global search capability	–

focuses on the application of a single algorithm, and lacks the effective combination and innovation of multiple optimization algorithms. Although most studies have demonstrated separate applications based on GA or PSO, they have not fully explored the potential of the combination of the two. In addition, most studies focus on the construction of theoretical models, with limited evaluation of the adaptability of actual logistics scenarios and the practical application effects of algorithms. This leads to a certain disconnect between research results and practical operations. In addition, many studies have not systematically considered the special temperature sensitivity requirements of fresh logistics, and have overlooked the comprehensive consideration of food quality assurance in site selection and route optimization processes. The research innovation lies in constructing a hybrid algorithm with high flexibility and adaptability. In addition, considering the special needs of cold chain logistics, a more comprehensive site selection model and distribution route optimization strategy have been designed to ensure the quality and safety of food throughout the entire transportation process. This study combines GA and PSO organically, while maintaining the diversity of GA solution space exploration, using PAO to improve global search and convergence efficiency, avoiding the disadvantage of a single algorithm easily falling into local optima. Furthermore, this study incorporates key factors such as quality loss, time penalty, and cold chain energy consumption into the theoretical model. Through empirical case studies, the operability and adaptability of the algorithm in real logistics environments have been verified, solving the problem of lack of practical verification in existing literature. Table 1 shows the comparative analysis results of the proposed method and existing studies.

3 Design

When constructing the warehouse location model for FCCL in this study, a series of assumptions are set, and fixed costs and variable costs are subdivided in cost analysis. The cooling cost incurred to maintain fresh quality is also calculated. To solve the problem of model solving, an improved combination of GA and PAO is proposed, aiming to select the optimal warehouse location and delivery path from all options.

3.1 Construction of warehouse site selection model for FCCL

When optimizing the overall FCCL network design, considering site elements alone often leads to high cost issues in delivery paths. Therefore, when selecting a site, it is also necessary to plan the path simultaneously.

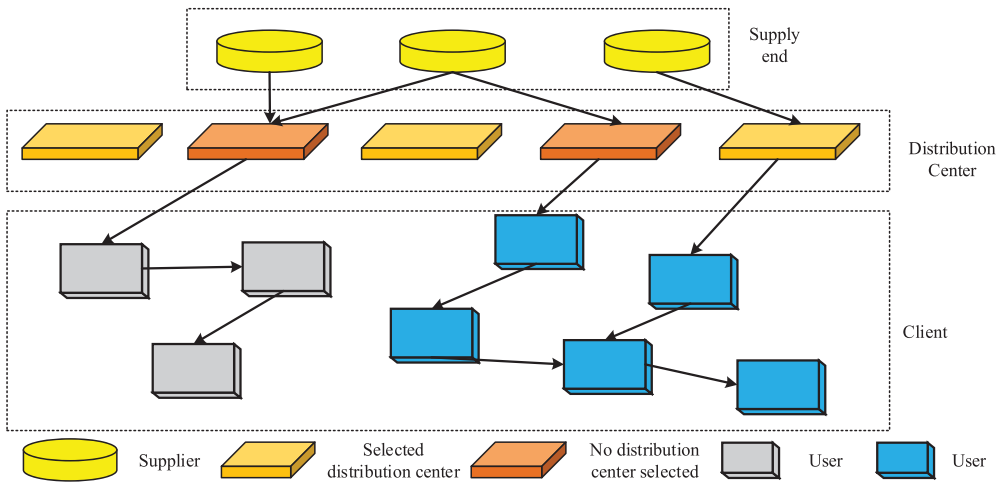

Fig. 1. Site selection service architecture.

Specifically, the integrated planning of stations and routes requires research and consideration of the setting of logistics nodes and the optimal path planning for goods delivery. This strategy helps to propose a balanced solution for cost savings and high-quality service. The optimization research on the logistics system of perishable products must fully incorporate the sensitivity of products to temperature and the rate of decay, ensuring that the entire logistics chain's products are always in a temperature-suitable environment. Ensuring quality and reducing loss are crucial. Considering the strict expectations of customers for the delivery speed of fresh goods, efficiency and timeliness have become the core factors. Figure 1 shows the service framework for site selection.

In the FCCL system, the structure of Figure 1 divides the whole process into three main parts: the supply side, the DC, and the customer. The supply side can ship to selected DCs and unselected DCs, respectively. The reason for this setup is that the supply side needs to be flexible to meet the market demand and the distribution characteristics of customers to optimize transportation efficiency and costs. If the supply side only ships to one DC, it may cause the center to be unable to respond promptly during high demand, increasing the risk of delivery delays and wastage. Therefore, selecting multiple DCs to receive goods from the same supplier at the same time ensures replenishment through multiple channels during peak demand periods or when distribution is tight in a specific region, maximizing the timeliness of service. This study aims to develop a model that minimizes the total cost, which includes the cost of deterioration losses and other economic penalties such as equipment, transportation vehicle usage, and potential delivery delays. In the on-site operation process, the loss of quality is inversely proportional to the passage of time and is affected by temperature. This study can be described using an exponential quality decay model. The decay rate is determined by a constant, and the initial quality and time response coefficient are known variables. In this way of decomposition, the cost of loss consists of two major components: the cost from the supplier to the DC, and then to the end user point. In the process of designing a joint optimization model, this study needs to develop a series of core assumptions. This model is based on the assumption that all delivery and transportation vehicles have consistent performance, and the needs of each customer are predictable and independent of time factors. At the same time, this study rationally simplifies traffic and vehicle operations during modeling. That is, it assumes that delivery vehicles can maintain a stable transportation speed along the planned route. The storage capacity of the DC is a known parameter, and the supplier's inventory can meet customer demand within the constraints of the model. In the process of establishing the model, both fixed costs and variable costs need to be taken into account in delivery. Fixed costs remain consistent with any changes, such as depreciation of vehicles and equipment, as well as labor costs, as shown in formula (1).

$$C_1 = f_v \cdot V. \tag{1}$$

In formula (1), f_v represents the fixed cost of a vehicle, and V represents the number of vehicles. The variable cost depends on the route of the delivery vehicle and the routes it travels, such as fuel consumption and maintenance expenses, as shown in formula (2).

$$\begin{aligned} C_c = &\sum\nolimits_{l\in L}\sum\nolimits_{m\in M}(C_v.d_{lm}.Z_{lm}) \\ &+ \sum\nolimits_{l\in L}\sum\nolimits_{m\in M}(C_v.d_{mn}.Z_{mn}). \end{aligned} \tag{2}$$

In formula (2), C_v represents the distance cost traveled. d_{lm} represents the distance from the supplier to the DC. Z_{lm} represents the judgment of whether the supplier can reach the DC. d_{mn} represents the distance from the DC to the retail point. Z_{mn} represents the judgment of whether the DC can reach the retail point. In terms of cargo damage, the quality of fresh products varies over time, as shown in Figure 2.

This change can be transformed into an exponential function, as shown in formula (3).

$$G(t) = G_0 e^{-\lambda t.} \tag{3}$$

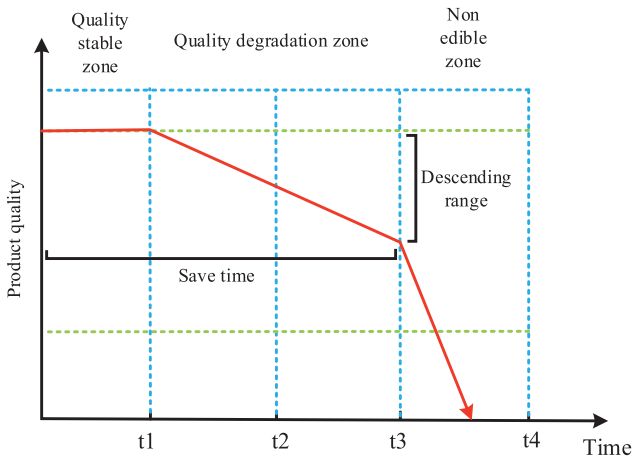

Fig. 2. Product quality change curve.

In formula (3), G_0 represents the initial quality, t represents time, and λ represents the sensitivity of product quality to time. After adding reaction rate g, there is a quality change function as shown in formula (4).

$$G(t) = G_0 \cdot g \cdot e^{-\lambda t}. \tag{4}$$

On this basis, the cost of goods damage can be obtained as formula (5).

$$C_{ab} = C_a + C_b \tag{5}$$

C_a in formula (5) can be calculated by formula (6).

$$C_a = \sum\nolimits_{l \in L} \sum\nolimits_{m \in M} c\left(1 - g e^{-\lambda t_{lm}}\right) \cdot X_{lm}. \tag{6}$$

In formula (6), X_{lm} represents the transportation quality from the supplier to the DC, t_{lm} represents the transportation time during this period. c is a constant that is multiplied by the adjustment factor for the transport mass, which describes the mass loss effect due to the continuation of the transport time. C_b in formula (5) is calculated by formula (7).

$$C_b = \sum\nolimits_{l \in L} \sum\nolimits_{m \in M} c\left(1 - g e^{-\lambda t_{mn}}\right) \cdot X_{mn}. \tag{7}$$

In formula (7), X_{mn} represents the transportation quality from the DC to the retail point, and t_{mn} represents the transportation time during this period. The cost of using the DC is shown in formula (8).

$$C_2 = \sum_{m \in M} (P_m . Z_m). \tag{8}$$

In formula (8), P_m represents the cost of using a single DC, and Z_m represents the judgment of whether a DC exists or not. In addition, to ensure food quality, this study must measure the cooling costs incurred by cold chain equipment in resisting environmental heat during the delivery process. This cost can be understood as the cooling energy required to maintain a suitable storage temperature to resist the loss of environmental heat. That is to say, the cooling cost reflects the amount of coolant used to maintain fresh produce at a safe temperature. This calculation process takes into account the heat transfer rate of the refrigerated truck, as well as factors such as the area and temperature difference inside and outside the vehicle. During the time when the delivery task is completed and returned to the DC, the cooling cost does not need to be further calculated, as there is no need to maintain the quality of any fresh items at this time. The refrigeration cost is as shown in formula (9).

$$C_d = \left\{ \sum_{k \in K} \left(H . \sum_{j \in Y} \sum_{j \in N} (Z_{ijk} t_{mn}) \right) + \sum_{k \in T} \left(H . \sum_{l \in L} \sum_{m \in M} (Z_{lmk} t_{lm}) \right) \right\} \cdot Q. \tag{9}$$

In formula (9), Z_{lmk} and Z_{ijk} represent the judgment of whether the vehicle is passing between two demand points. H represents the heat load. Q represents the unit refrigeration cost. The refrigeration cost parameters are calculated based on the thermal conductivity of the refrigerated truck material, the heat exchange area between the cabin and the external environment, and the temperature difference inside and outside the cabin. The unit refrigeration cost (0.58 yuan/(h · kcal)) is based on industry reports and technical manuals for cold chain transport vehicles [18]. Time is crucial in the delivery process, as customers typically set a delivery window and require timely delivery. If delivery occurs earlier or later than this time period, it may lead to inventory accumulation or loss of sales opportunities, resulting in additional costs, which is known as time penalty costs. The hard time penalty window is shown in Figure 3.

The difference between this cost and delivery time is linear, which means that the longer the time it takes to leave the time window, the greater the penalty cost. Therefore, in the model, this study needs to add a time penalty cost function to ensure timely delivery. The penalty cost parameter is used to reflect the economic losses caused by early or delayed delivery. The soft time penalty window is shown in Figure 4.

The penalty function is shown in formula (10).

$$P(t) = \begin{cases} T_1 \cdot (t_1 - t_{mn}), t_{mn} < t_1 \\ 0, t_1 < t_{mn} < t_2 \\ T_2 \cdot (t_{mn} - t_2), t_{mn} > t_1 \end{cases}. \tag{10}$$

In formula (10), T_1 and T_2 represent the unit opportunity cost of early and delayed delivery. t_1 and t_2 represent the earliest and latest acceptable delivery times. t_{mn} represents the shipping time. The cold chain transportation system for fresh products needs to integrate multiple factors in decision-making, which involves the entire supply chain network, and each node is interrelated and critical. With carefully planned optimization models, this study can effectively address these challenges, ensuring timely product delivery, controlled quality and safety, and achieving maximum cost-effectiveness.

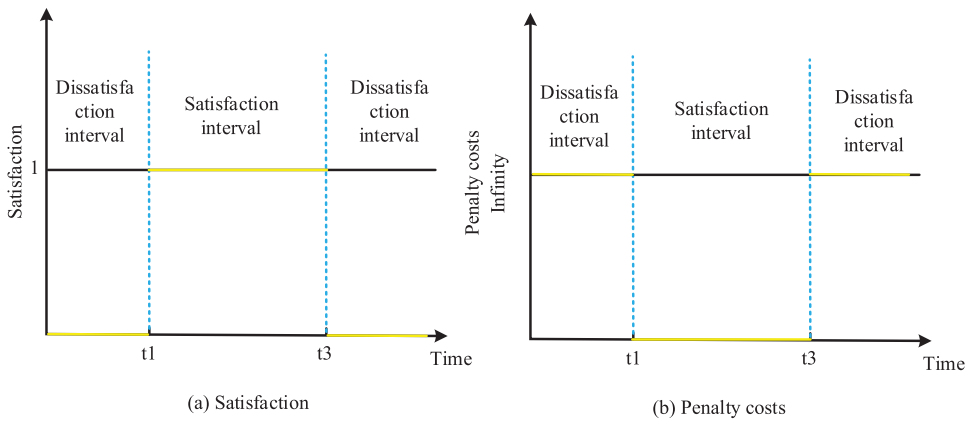

Fig. 3. Hard time penalty window.

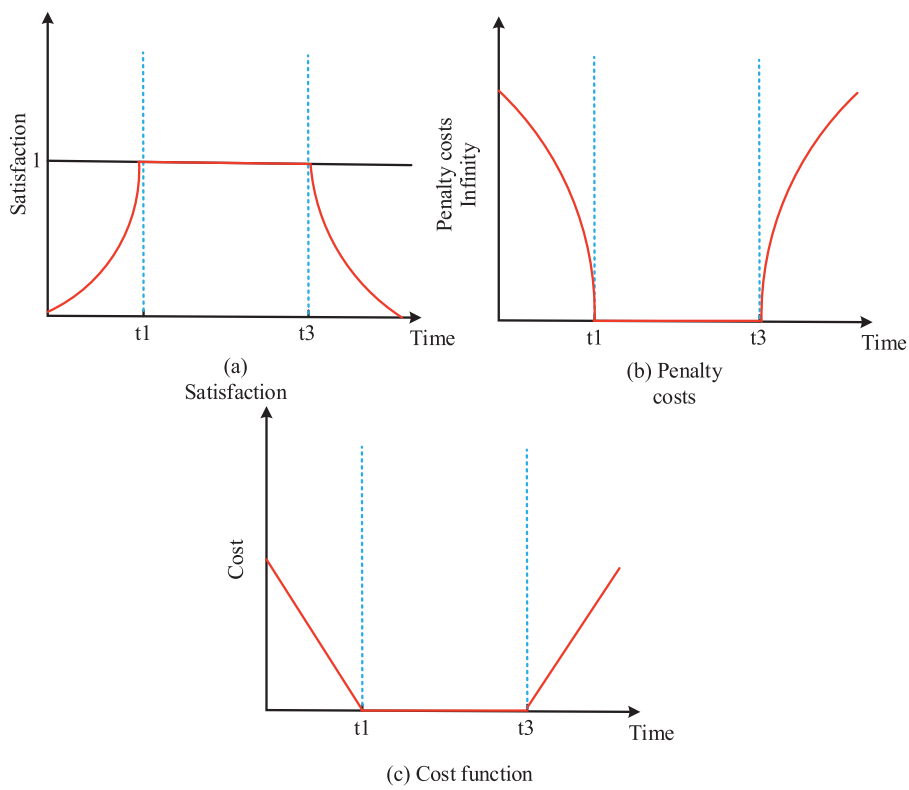

Fig. 4. Soft time penalty window.

3.2 Design of model solving strategy based on improved PSO-GA algorithm

To obtain the optimal solution for the FCCL warehouse location model, this study develops a PSO-GA model. This model incorporates the operational principles of classical GA and PSO, effectively integrating the advantages of both. The proposed method enables efficient search and optimization of solutions in complex nonlinear environments. GA simulates the process of natural selection through selection, crossover, and mutation operations, and is suitable for the exploration of large-scale solution Spaces. PSO draws on swarm intelligence and enhances the global search ability and convergence speed through information sharing among particles. This combination enables the algorithm to better balance exploration and development. PSO-GA can quickly adapt to different optimization requirements and provide more accurate and efficient solution strategies when facing location problems with multiple objectives and constraints.

This study transforms the model solving problem into a series of gene sequences, namely "chromosomes". The length of its sequence corresponds to the total number of candidate DCs, and each gene in the sequence is representative, indicating whether to establish a distribution station in a certain location. The number of sample populations in this genetic process must be set appropriately to avoid being too small to fully display the

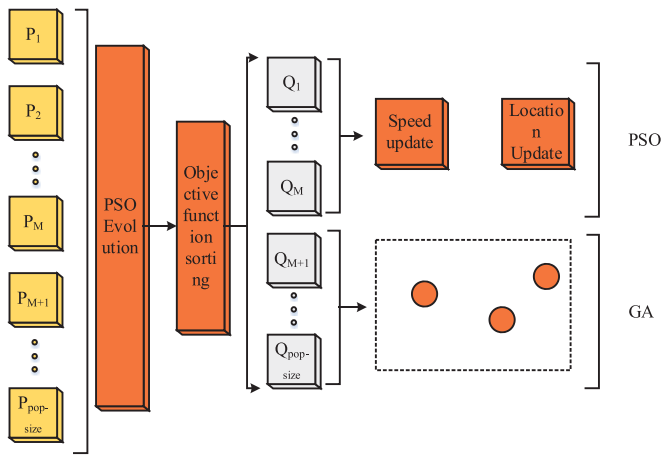

Fig. 5. Optimization of model structure.

advantageous schemes or being too large to overload computational processing. When generating the initial sample population, it is most important to ensure that the number of newly built DCs meets the predetermined standards. Furthermore, based on the principle of maximizing service demand satisfaction, an optimization objective function is constructed. The selection operation adopts a selection mechanism that combines "roulette wheel" and "tournament" methods to prioritize retaining high fitness samples and eliminating low fitness samples. The selection operation is shown in formula (11).

$$p_i = \frac{f_i}{\sum_{i=1}^{M} f_i}. \tag{11}$$

In formula (11), f_i represents the fitness function, which is the objective function of the model. Cross-operation needs to be carried out under the control of the number of DCs to ensure the feasibility of all new solutions. As the process enters the later stage, a more optimized chromosome population is generated. A real-time updated and integrated knowledge base brings the current fresh product cold chain DC data into deeper model analysis. The coding of PSO can be reshaped for each specific service unit with specific needs. The optimized model structure is shown in Figure 5.

When developing PSO technology, this study introduces a transformation strategy when facing solutions that does not meet the standards. Each transfer station in the railway transportation network can allocate goods to dispersed points, which has been correspondingly improved. The iterative process takes into account the suitability score of each particle and combines swarm intelligence to improve search efficiency and ensure that particles evolve in the desired direction. The fitness function is shown in formula (12).

$$f_i{}' = \frac{F_{2\max} - F_2}{F_{2\max} - F_{2min}}. \tag{12}$$

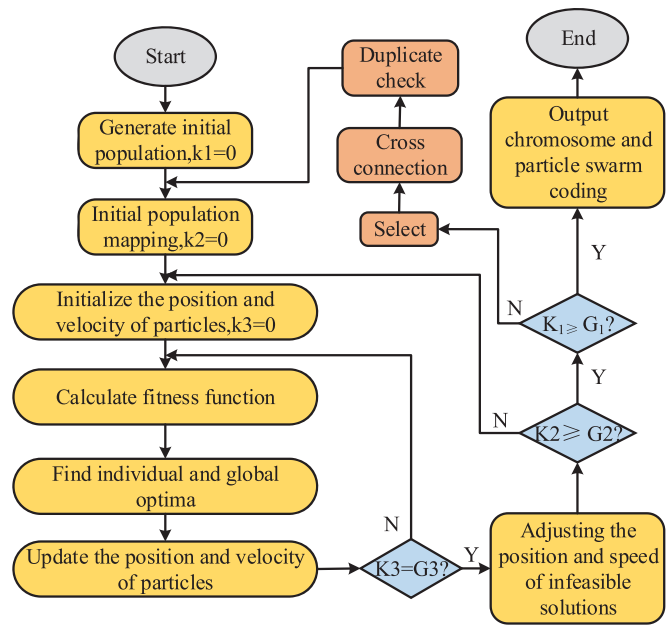

Fig. 6. Algorithm flow.

The particle dimension control formula is shown in formula (13).

$$x_i^k = \begin{cases} 0, x_i^k < 0 \\ 1, x_i^k > 0 \end{cases}. \tag{13}$$

The particle velocity control formula is shown in formula (14).

$$v_i^k = \begin{cases} 0.5, v_i^k > 0.5 \\ -0.5, v_i^k < -0.5 \end{cases}. \tag{14}$$

In addition, the inertia weights assigned to particles can adjust their rates during both comprehensive and local optimization stages, ensuring the execution efficiency of the algorithm. The inertia weight coefficient is shown in formula (15).

$$\omega_k = \omega_{\max} - \frac{\omega_{\max} - \omega_{min}}{N_{\max}} k. \tag{15}$$

In formula (15), $N_{\max}$ represents the maximum number of iterations, and $\omega_{\min}$ and $\omega_{\max}$ represent the lower and upper limits of the weight coefficients, respectively. The algorithm process is shown in Figure 6.

This study integrates the PSO strategy into GA, thereby gaining the benefits of global random search in continuous solution space. In the discrete solution space, the search efficiency of the algorithm is improved, while reducing the early convergence problems that may occur in GA. In the above method, the model clearly divides different cost factors, including transportation cost, storage cost, quality loss cost, and time penalty cost, so that each influence factor can be systematically integrated. The PSO-GA hybrid strategy encodes complex optimization processes into easily operable gene sequences,

Table 2. Algorithm pseudo-code.

Algorithm hybrid PSO-GA for FCCL warehouse location
Input: Candidate distribution centers, supplier and retailer data, cost parameters
Output: Optimal warehouse location and delivery routes
1: Initialize parameters (population size N, crossover probability P_c, mutation probability P_m, inertia weight w, maximum iterations $T_{\max}$)
2: Randomly generate the initial population and encode individuals
3: Evaluate the fitness of each individual (based on total distribution cost objective function)
4: While (iteration $< T_{\max}$) do
5: Apply GA selection operator (roulette wheel + tournament) to retain high-fitness individuals
6: Perform crossover operation to generate offspring
7: Perform mutation operation to maintain diversity
8: Integrate PSO mechanism: update velocity and position
9: $v(t+1) = w^*v(t) + c_1{}^*r_1{}^*(\text{pbest} - x) + c_2{}^*r_2{}^*(\text{gbest} - x)$
10: $x(t+1) = x(t) + v(t+1)$
11: Recalculate the fitness of all individuals
12: Update personal best (pbest) and global best (gbest)
13: Dynamically adjust inertia weight w (decreasing from 0.9 to 0.4)
14: End while
15: Return the global best solution (warehouse location and routing scheme

enhancing the algorithm's adaptability and search ability in nonlinear and multi-objective optimization problems. In the optimization of FCCL warehouse location, this hybrid strategy can find the best balance between efficient handling to meet customer needs and minimizing transportation costs. This algorithm dynamically evaluates the fitness of candidate solutions, optimizes the localization strategy at each iteration, and strengthens the consideration of food quality and time sensitivity. It guarantees to minimize the loss of food during transportation and improve overall distribution efficiency under the requirements of cold chain logistics. Combining the above, the PSO-GA pseudo-code is shown in Table 2.

4 Results

This study first analyzes the efficiency of the algorithm, and then analyzes the impact and results of the model on average total distribution cost, transportation cost, loading efficiency, cargo damage cost, and penalty cost for underloading. Finally, the effectiveness of the model in optimizing site layout, improving transportation loading efficiency, and reducing freight losses is evaluated.

4.1 Model efficiency analysis

To verify the validity of the model, parameters are set according to the previous reference [19]. The population size of the model is set to 100 individuals. The crossover probability is set to 0.8. The probability of variation is set at 0.05. To give the algorithm enough optimization time, the maximum number of iterations is set to 300. In the PSO part, references [16] and [17] set the number of particles to 50, the initial value of the inertia weight to 0.9, and the dynamic attenuation to 0.4. In addition, to prevent particles from moving too fast and missing a potentially good solution, the speed limit is set at ± 0.1.

This experiment sets up a fresh product logistics distribution model with 3 suppliers, 5 alternative DCs, and 15 end retailers. The price of fresh products per ton is 9,800 yuan, and they are loaded onto 12 DC vehicles and 5 supplier vehicles, with a maximum load capacity of 8 tons per vehicle. The driving speed of the delivery vehicle is 47 km/h, and each service time is 10 min. Table 3 shows the specific settings.

In Table 1, the time sensitivity coefficient of fresh products is 0.0011. Due to the aging degree of refrigerated carriages and thermal conductivity factors, the DC faces a usage cost of 650 yuan/day, a fixed cost of 350 yuan/vehicle per day, and a transportation cost of 30 yuan/km. The maximum storage capacity of each DC is 29 tons, and the area where the carriages exchange heat with the outside world is 38.5 m^2. The model also includes an opportunity cost of 1.8 yuan/min.t, a penalty cost of 9.8 yuan/min.t, and a cooling cost of 0.58 yuan/(h · kcal). Table 4 shows the retailer's time window and demand information.

In Table 4, the service time set for retailers in this study is fixed at 10 min. Based on this, the upper and lower limits of the demand time window for different retailers fluctuate. The convergence effect is shown in Figure 7.

In Figure 7, the improved PSO-GA has great advantages over ordinary GA. Under the same number of iterations, the Objective Function Value (OFV) of improved PSO-GA is better than that of ordinary GA. By iterating to 100 generations, the improved PSO-GA has already reduced its OFV to around 31,500, while ordinary GAs need to iterate to 300 generations or more to achieve

Table 3. Experimenter setting.

Parameter category	Numerical value	Unit
Supplier quantity	3	Individual
Number of alternative distribution centers	5	Individual
Number of end retailers	15	Individual
Time sensitivity coefficient of fresh products	0.0011	/\
Product unit price	9800	Yuan/t
Distribution center usage cost	650	Yuan/day
Fixed cost of vehicles	350	Yuan/vehicle. day
Transportation cost of vehicles	30	Yuan/kilometer
Number of vehicles in the distribution center	12	Vehicle
Number of supplier vehicles	5	Vehicle
Vehicle load capacity	8	Ton
Delivery vehicle speed	47	Km/h
Refrigerated truck service time	10	Min
Aging degree of refrigerated carriages	0.07	/
Thermal conductivity of refrigerated truck materials	0.14	Kcal/(h $\cdot^2$•°C)
The area of heat exchange between the carriage and the outside world	38.5	m^2
The maximum storage capacity of the distribution center	29	Ton
Opportunity cost per unit time	1.8	Yuan/min.t
Penalty cost per unit time	9.8	Yuan/min.t
The temperature difference inside and outside the carriage	11.5	°C
Unit refrigeration cost	0.58	Yuan/(h · kcal)

Table 4. Retailer time window and demand information.

Retailer ID	Commodity demand (tons)	Time window ceiling (minutes)	Time window bottom limit (minutes)	Service takes time (minutes)
1	2.4	60	90	10
2	1.6	53	88	10
3	2.5	145	175	10
4	3	85	115	10
5	1.5	110	140	10
6	6.5	45	60	10
7	4	37	52	10
8	3.3	55	75	10
9	3.2	235	270	10
10	2.3	315	345	10
11	3.5	285	315	10
12	1.8	105	130	10
13	5.5	70	95	10
14	1.4	235	260	10
15	2.5	270	305	10

an OFV greater than 32,000. In optimization problems, the size of OFV directly affects the quality of the solution, so reducing the number of iterations of OFV will greatly improve the efficiency of the algorithm. This indicates that

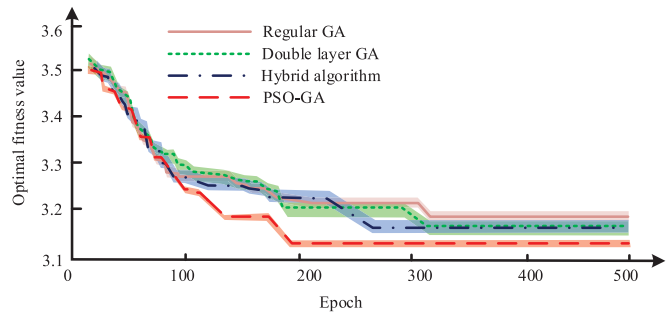

Fig. 7. Convergence effect.

the improved PSO-GA can not only find optimization results faster, but also has higher quality results, which means that the solution effect of the improved PSO-GA is better. In addition, GA sometimes falls into local optima and cannot achieve global optima, and the improved PSO-GA can precisely overcome this disadvantage. During the solving process, the improved PSO-GA can avoid stagnation at local optima and continuously search for global optimal solutions. For this reason, the improved PSO-GA can achieve better solution results with fewer iterations. The model effect is shown in Figure 8.

In Figure 8, comparing the average total delivery cost of the four methods, the improved PSO-GA model calculates the lowest value, reaching 75.8369 million yuan, obtaining the optimal solution. For the computation time, the improved PSO-GA model only takes 75 s, indicating the highest computational efficiency. The sensitivity of model

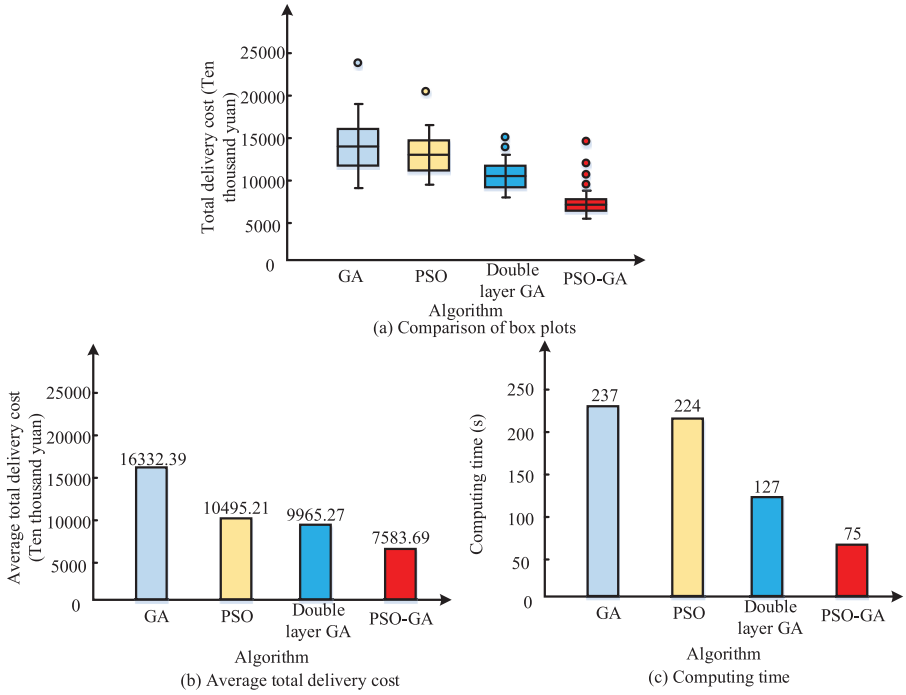

Fig. 8. Model effect.

Table 5. Sensitivity analysis of model cost weight parameters.

Weight coefficient setting	Total delivery cost (ten thousand yuan)	Transportation cost (ten thousand yuan)	Storage cost (ten thousand yuan)	Quality loss cost (ten thousand yuan)	Time penalty cost (ten thousand yuan)	Underloading penalty cost (ten thousand yuan)
Reference model	7583.69 ± 65.42	3200 ± 40.12	2300 ± 35.88	1500 ± 28.91	800 ± 22.47	783.69 ± 18.53
Plan A	7400.8 ± 60.37	3320 ± 38.77	2100 ± 32.10	1300 ± 25.45	680 ± 20.80	780.80 ± 18.95
Plan B	7700.50 ± 68.21	3100 ± 41.25	1800 ± 29.50	1600 ± 27.55	900 ± 23.14	800.50 ± 19.74
Plan C	7450.25 ± 62.89	2900 ± 39.42	2000 ± 31.85	1400 ± 26.12	750 ± 21.37	800.25 ± 19.21
Plan D	7500.10 ± 64.33	3100 ± 40.11	2200 ± 33.60	1200 ± 24.80	750 ± 21.40	850.10 ± 20.33

parameters is further analyzed, and the value of cost weight is verified. The cost factors of the research benchmark model include transportation cost, storage cost, quality loss cost, and time penalty cost, and the corresponding weights are 0.4, 0.3, 0.2, and 0.1, respectively. Firstly, the weight is adjusted. Plan A aims to increase the weight of transportation cost, and the weight coefficients of transportation cost, storage cost, quality loss cost, and time penalty cost are 0.5, 0.25, 0.15, and 0.1, respectively. Plan B is to reduce the weight of storage cost, and the four cost weight coefficients are 0.4, 0.2, 0.25, and 0.15, respectively. Plan C pays attention to the quality loss cost, and the weight coefficients of the four costs are 0.3, 0.3, 0.3, and 0.1 respectively. Plan D is the impact of time cost increase, and the four cost weight coefficients are 0.35, 0.25, 0.2, and 0.2, respectively. Single factor sensitivity analysis can display the independent impact of various cost weights on the total distribution cost and its sub costs, avoiding confusion caused by multiple factors acting simultaneously and facilitating interpretation and comparison. Therefore, this article mainly conducts single factor sensitivity testing, and the specific results are shown in Table 5.

Table 5 shows that different weight configurations have a significant impact on the total distribution cost and various cost factors of the model. The total distribution cost of the benchmark model is 75,836,900 yuan. Plan A (increasing the weight of transportation cost) and Plan D (increasing the impact of time cost) reduce the total cost to 74,008,000 yuan and 75,500,100 yuan, respectively. This indicates that the overall logistics cost can be effectively reduced when paying attention to transportation cost and time cost. However, Plan B (reducing the storage cost weight) results in a rise in the total distribution cost to \$770.50 million, indicating that excessive reduction in the storage cost weight can have a negative impact on overall efficiency. Plan C (emphasis on quality loss costs) shows a

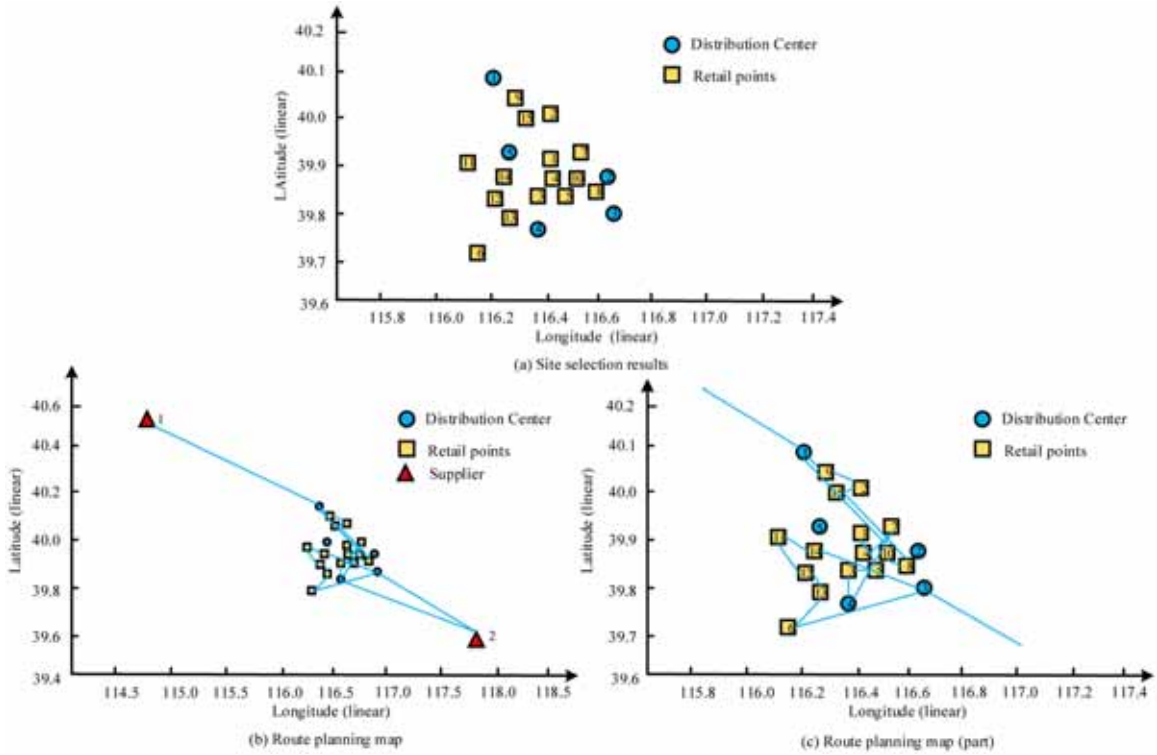

Fig. 9. Site selection effect.

cost of 745.25 million yuan, indicating that after increasing the weight of quality loss, although the overall cost has been reduced, the transportation and storage costs have also been reduced. This result shows that quality control is still extremely important in the overall logistics management strategy. Overall, the sensitivity analysis shows that the small adjustment of weight has a significant impact on the cost structure. Additionally, the reasonable allocation of different cost factors can optimize the economic benefits of FCCL. Therefore, in practical applications, it is necessary to flexibly adjust the weight configuration according to the specific business requirements and cost structure to achieve the optimal balance of costs.

4.2 Analysis of model site selection effect

In considering the location selection of DCs and the design of freight transportation routes, three main logistics nodes have been strategically established: DCs 1, 3, and 4. The node covers the needs of 15 terminal retailers, and the site selection effect is shown in Figure 9.

In Figure 9, the establishment of DC1 successfully links Supplier 1 with five retailers, 9, 2, 15, 8, and 10, constructing an efficient supply network. This network considers the relative positions between retailers to minimize transportation distance, and ensures that goods do not need to pass through any retail points repeatedly from the source to the destination. This ensures the directness and cost-effectiveness of transportation, thereby optimizing the time and economic cost of goods distribution. Secondly, DC3 links Supplier 2 with six other retailers (14, 11, 12, 13, and 6). Through carefully planned routes, a distribution network with wide coverage and concise routes has been formed. This route avoids round-trip transportation and redundant allocation of goods, improving the timeliness and economy of distribution. Finally, by connecting Supplier 2 with five retailers (3, 5, 1, 4, and 7) through DC4, this route also demonstrates the rationality and professionalism of logistics management. This further reduces the complexity of the entire network and ensures the smooth and rapid transportation process. In summary, the overall site selection and transportation route design fully reflect the essence of intelligent logistics planning. It utilizes the minimum number of DCs to cover the largest range of end retailers, accurately formulating the shortest and most economical transportation routes, while balancing cost and efficiency. This design method reduces resource waste and enhances customer satisfaction, ensuring timely and reliable delivery. It is crucial that this logistics design pattern provides a reliable research blueprint for other similar logistics optimization tasks, with practical application value and reference results. In the constantly changing market environment, flexible and economical logistics system design is crucial for enterprises to maintain competitiveness and customer loyalty. Table 6 shows the coverage and cost status of distribution points (DP).

Table 6 shows that, in terms of coverage, DP1 and DP2 each cover 11 demand points, DP3 covers 10, and DP4 covers 7, which are relatively few. Regarding underloaded vehicle fines, the costs for DC01-DC05 are RMB 2,199.5, RMB 2,278.4, RMB 2,237.7, RMB 1,969.8, and RMB 1,803.9, respectively, showing a downward trend, reflecting the gradual improvement in transportation loading

Table 6. Distribution point coverage and cost status.

Project	Delivery point 1	Delivery point 2	Delivery point 3	Delivery point 4	Delivery point 5
Transportation cost (yuan)	18956	20538	20260	17500	15636
Penalty cost for underload (yuan)	2199.5	2278.4	2237.7	1969.8	1803.9
Distribution center cost (yuan)	5020000	5020000	5020000	5020000	5020000
Cost of mainline cargo damage (yuan)	1382	1630	1589	1187	948.2
Storage cost (yuan)	5060	5060	5060	5060	5060
Delivery nodes	Retail demand points				Number
1	1, 5, 6, 7, 8, 9, 10, 12, 13, 14, 15				11
2	2, 3, 4, 7, 8, 9, 10, 11, 12, 13, 14				11
3	1, 3, 5, 6, 9, 10, 12, 13, 14, 15				10
4	2, 4, 5, 7, 8, 11, 15				7
5	1, 2, 3, 4, 6, 7, 8, 11, 13				9

efficiency and optimized management. Fixed costs for DCs remain unchanged at RMB 5.02 million across all scenarios, providing a stable benchmark for comparison. Trunk cargo damage costs fluctuate slightly, indicating that cargo damage is being effectively controlled with enhanced safety measures during operations. Warehousing costs remain unchanged at RMB 5,060 across all scenarios, demonstrating the fixed and stable nature of the warehousing process. Cold chain delivery needs to optimize costs and efficiency while ensuring service quality. The above results show that improved loading efficiency and reduced cargo damage indirectly reflect improved delivery reliability and product freshness, which are important indicators of cold chain service quality. While optimizing routes and costs, the model also potentially promotes improved service levels. This indicates that the hybrid PSO-GA model has value in supporting core cold chain performance goals, while also focusing on cost control and efficiency improvement.

4.3 Model scalability verification

To verify the applicability and scalability of the proposed hybrid PSO-GA model in larger networks, this paper further designs two types of scalability tests based on the original small-scale experiments: a medium-scale network (5 suppliers, 10 candidate DCs, 30 retailers) and a large-scale network (10 suppliers, 20 candidate DCs, 60 retailers). In each scale scenario, the model runs with the same parameter settings, and each experiment runs independently 20 times. The specific results are shown in Table 7.

In Table 7, total distribution costs show a clear increasing trend with increasing network size. The average values for the small, medium, and large-scale scenarios are 75.8369 million yuan, 152.7846 million yuan, and 307.4288 million yuan, respectively. The rate of increase is roughly linear with the expansion of the number of suppliers, DCs, and retailers. This result is consistent with the actual operation of logistics systems and demonstrates that the proposed hybrid PSO-GA model has good adaptability to scale. Regarding runtime, the average computational time for the three scenarios is 42.37 s, 98.64 s, and 192.53 s, respectively. While increasing with network size, the overall rate of increase remains within an acceptable range, indicating that the model can still be solved within a reasonable timeframe despite increasing complexity. Furthermore, the standard deviations for experiments at different scales are all small, demonstrating that the model exhibits strong stability and robustness over multiple independent runs.

Table 7. Scalability test results of the hybrid PSO-GA model under different network sizes.

Network size	Total delivery cost (10000 yuan)	Runtime (s)
Small-scale	7583.69 ± 95.24	42.37 ± 3.18
Medium-scale	15278.46 ± 162.35	98.64 ± 7.29
Large-scale	30742.88 ± 290.64	192.53 ± 12.47

5 Conclusion

In response to the complex challenges faced by FCCL in warehouse location selection and distribution path optimization, the research team adopted a strategy that combines GA and PSO to address these issues. To verify the effectiveness of the method, a simulation network was designed, including 3 suppliers, 6 candidate DCs, and 15 retailers. The results showed that PSO-GA had higher efficiency compared to traditional GA, and its OFV decreased to about 31,500 after 100 iterations. The average total delivery cost of the improved model was 75.8369 million yuan, and the calculation time was significantly reduced to 75 s. This improved algorithm also performed well in optimizing site selection and layout.

The selected DCs 1, 3, and 4 could effectively serve various end retailers, and the penalty cost for non-full load has been reduced from 2,199.5 yuan to 1,803.9 yuan, and the cost of mainline cargo damage has also been reduced from 1,382 yuan to 948.2 yuan. This reflected the improvement of transportation loading efficiency and the reduction of freight losses. In summary, the practical application of the research model in FCCL warehouse location selection and distribution path optimization can significantly improve transportation efficiency and cost control, while also ensure the quality of food and meeting the demand for fast delivery.

Although the proposed model has achieved significant results, it still has certain limitations. First, the research was primarily tested in a simulation environment and has not yet been field-verified in a real-world cold chain distribution scenario. This may lead to certain deviations in the applicability of the results under complex real-world conditions. Second, the data of this model depends on the set simulation parameters and cannot fully capture various scenarios that may occur in actual operations. Third, the sensitivity analysis primarily uses a single-factor experimental approach. Although the independent impact of various cost weights on the results has been clearly revealed, there has been no further research on the interaction effects of multiple factors, which to some extent limits the comprehensive understanding of complex decision trade-offs. Therefore, future research will combine actual operational data of enterprises to conduct field case studies, and introduce multi factor sensitivity analysis at the methodological level. The purpose is to better capture the multidimensional uncertainty and decision complexity in actual cold chain logistics networks, thereby enhancing the dissemination and practical value of research results.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Data availability statement

The data used to support the findings of the research are available from the corresponding author upon reasonable request.

Author contribution statement

Lina Guo: study design, data collection, statistical analysis, visualization, writing, and revision of the original draft. Yi Wei: data collection, statistical analysis, and revised the manuscript.

References

1. X. Mingyue, Research and application progress of cold-chain logistics packaging technology of fresh agricultural products, Food Mach. **39**, 103–109 (2023)
2. S. Wang, Causes and solutions of cold chain logistics chain fracture, Manuf. Serv. Oper. Manag. **4**, 85–90 (2023)
3. B. Han, Z.M. Talib, S. Zhang, Research on the evaluation system of fresh agricultural products cold chain logistics service quality in the context of electronic commerce, Front. Bus. Econ. Manag. **8**, 170–173 (2023)
4. M. Sharma, R. Gupta, S. Premchandani, Warehouse location selection using AHP: a case of third-party logistics provider in India, Int. J. Supply Chain Invent. Manag. **4**, 107–133 (2023)
5. R.E. Gergin, İ. Peker, B. Baki, R.T. Umut, T. Mehmet, Oilseed warehouse location selection with an integrated approach: a case of Turkey, Kybernetes **52**, 3667–3705 (2023)
6. Y. Demirkiran, O. Ozturkoglu, Y. Ozturkoglu, Sustainable frozen food facility location selection under pandemic era, Int. J. Food Syst. Dyn. **13**, 205–224 (2022)
7. Y.S. Yun, M. Gen, T.N. Erdene, Applying PSO-GA-TLBO approach to engineering optimization problems, Math. Biosci. Eng. **20**, 552–571 (2023)
8. Z. Sun, J. Zhang, Research on prediction of housing prices based on PSO-GA-BP neural network model: evidence from Chongqing, China, Int. J. Found. Comput. Sci. **33**, 805–818 (2022)
9. G. Mehdi, H. Hooman, Y. Liu, S. Peyman, R. Arif, Data mining techniques for web mining: a survey, Artifi. Intell. Appl. **1**, 3–10 (2022)
10. M. Boujarra, A. Lechhab, A. Al Karkouri, I. Zrigui, Y. Fakhri, S. Bourekkadi, Revolutionizing logistics through deep learning: innovative solutions to optimize data security, J. Theor. Appl. Inf. Technol. **102**, 1593–1607 (2024)
11. A. Thuengnaitham, Application of analytic hierarchy process for fulfillment warehouse location selection, ISJET **6**, 8–15 (2022)
12. P. Zhang, A study on the location selection of logistics distribution centers based on e-commerce, J. Knowl. Learn. Sci. Technol. **3**, 103–107 (2024)
13. H.A. Dagıstanlı, K.G. Kurtay, Facility location selection for ammunition depots based on GIS and pythagorean fuzzy WASPAS, J. Oper. Intell. **2**, 36–49 (2024)
14. A. Sohail, Genetic algorithms in the fields of artificial intelligence and data sciences, Annal. Data Sci. **10**, 1007–1018 (2023)
15. S.M. Muneer, M.B. Alvi, M.A. Rasool, Genetic algorithm based intelligent system for estate value estimation, Int. J. Comput. Innov. Sci. **1**, 28–38 (2022)
16. J. Tian, M. Hou, H. Bian, L. Junqing, Variable surrogate model-based particle swarm optimization for high-dimensional expensive problems, Complex Intell. Syst. **9**, 3887–3935 (2023)

17. Z. Yu, Z. Si, X. Li, W. Dan, S. Houbing, A novel hybrid particle swarm optimization algorithm for path planning of UAVs, IEEE Internet Things J. **9**, 22547–22558 (2022)
18. L. Zhang, X. Zheng, W. Liu, L. Ma, More habitual deviation alleviates the trade-offs between dietary health, environmental impacts, and economic cost, J. Ind. Ecol. **29**, 503–517 (2025)
19. F. Rahman, M.A.R. Khan, M. Alam, Hybrid PSO-GA Optimization for enhancing decision tree performance in soil classification and crop cultivation prediction, Evol. Intell. **18**, 1–20 (2025)

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