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Article

Research on Optimization Application of Integer Planning Algorithm in Logistics Economic Network Layout Management

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Abstract: For the various types of costs involved in the logistics economic network, quantitative and qualitative cost models are developed as one of the final solution objectives. In order to improve the distribution rate, it is proposed to use the distribution time satisfaction function and the site selection optimization objective function to achieve the estimation of the positioning range of site selection. The integer planning algorithm using genetic algorithm + branch definition method is used to find the optimal solution of logistics economic network layout branch by branch. The integer planning algorithm iterates about 30 times to obtain the smooth optimal fitness value. The algorithm solves the optimized distribution centers are reduced from 8 to 7, while the distribution routes of each demand point are reasonably adjusted.

Keywords: cost modeling; distribution time satisfaction; site selection optimization objective; integer programming algorithm; logistics economic network

1. Introduction

Logistics economic network refers to a kind of complex system composed of logistics nodes, transportation routes, information networks and other components [1]. It realizes efficient logistics operation by optimizing resource allocation and organically combining various logistics elements [2]. It can improve the efficiency of logistics, through fine planning and coordination, reduce the waste and delay in the logistics link, so as to improve the overall transportation efficiency. In addition, the logistics economic network can also reduce transaction costs, achieve economies of scale and optimize the supply chain by integrating the resources and information of all parties, reduce the cost of intermediate links in the logistics chain, and enhance market competitiveness. This way can not only promote trade between countries and regions, but also promote economic development, industrial upgrading and innovation. It can be seen that the logistics economic network plays an important role in the modern economy, and the optimized management of logistics economic network layout is of great significance for promoting the trade and economic development of countries and regions.

Integer planning is a linear planning problem that requires a part or all of the decision variables must take integer values, it is an important branch of operations research that has been studied earlier, developed faster, applied widely and matured in method, it is a mathematical method that assists people in scientific management [3-4]. In communication network planning, economic management, transportation, industrial and agricultural production and other economic activities, cost reduction is an indispensable requirement for people, and cost reduction is generally through two ways: one is the improvement of technology, such as improving the production process, the use of new equipment and new raw materials [5]. The second is the improvement of production organization and planning, i.e. rational allocation of resources [6]. Integer planning is studied to rationalize the limited resources under certain conditions so that the cost of resources can be reduced [7]. In general, the problem of finding the maximization or minimization of an objective function subject to constraints, the maximization problem is to maximize a function on a set and the minimization problem is to minimize a function on a set [8]. Among them, the solutions that satisfy the constraints are called feasible solutions, and the set consisting

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of all feasible solutions is called the feasible domain, and the decision variables, constraints, and objective function are the three elements of integer programming [9]. With the development and popularization of computer technology, the application of integer programming is becoming more and more widespread, and has become a powerful tool for people to make the best decisions for the rational use of limited resources.

The planning of routing and allocation of network resources for the whole network is a network global optimization design problem [10]. It is common practice to use integer programming algorithms to further approximate the optimal solution, but this algorithm consumes more time, so this approach is generally used for small-scale networks [11]. However, the integer programming algorithm plays a crucial role in finding the global optimal solution, so it is widely used in solving various routing problems. Literature [12] decomposes the logistics network routing problem into several sub-problems, and then converts it into an integer programming model problem, through a series of validation, it can be concluded that the smaller scale optical network using this approach is able to solve its corresponding problems well, and has a very good performance. Literature [13] uses a mixed integer linear programming model to efficiently generate a network layout that ensures that the network elements are arranged, aligned, grouped, and prioritized, and this method can replace the traditional time-consuming network layout approach. Literature [14] optimizes some network scenarios with uniform service requests and selects a number of integer planning models for them, and finally achieves the final optimization by reducing some unnecessary variables in the models and some constraints that are not very critical. Literature [15] proposed an integer planning algorithm for solving the minimum congestion indivisible shortest path routing problem, the algorithm calculates the shortest path from the source to the destination based on the length of the administrative routes of each link in the network, and the experimental results also confirm the efficiency of the algorithm.

Since the end of the last century, as logistics has gradually become a focus of attention, research on the optimal design of logistics networks based on integer planning has emerged widely [16]. Literature [17] investigated a strategic supply chain management problem, specifically, reliable logistics network design considering facility failure scenarios using a mixed integer planning model to reduce the risk of disturbances and to achieve minimum cost without disturbances. Literature [18] developed a bi-objective mixed integer planning model that minimizes the logistics network cost while maximizing the responsiveness of the logistics network, which is combined with a dynamic search strategy of a multi-objective swarm intelligence algorithm to find an optimal non-dominated solution for the design of an integrated logistics network. Literature [19] established a nonlinear mixed-integer planning model with multi-cycle, multi-product, and capacity constraint limitations by integrating forward and reverse logistics networks, and proactively solved the model with a heuristic algorithm based on genetic algorithm. Literature [20] describes the logistics network structure with three levels in the forward direction and two levels in the backward direction as a stochastic mixed-integer linear programming decision form, which maximizes the profitability of the logistics network through the stochastic integer programming model. Literature [21] applied the mixed integer linear programming method to the reverse logistics network design problem, this method fully considered most of the possible network structures in practice, and it has a big advantage in the reverse logistics network design of washing machines and dryers in Germany, which changed the network structure and facility capacity and maximized the profit. Literature [22] investigated a medical waste-based logistics network system during an epidemic and proposed a novel multi-objective multi-period mixed integer planning model for reverse logistics network design during an epidemic to determine the optimal strategy for medical waste transportation. Literature [23] developed a deterministic mixed-integer linear programming model as a solution to the problem of uncertainty in customer demand and transportation cost in logistics supply chain networks, and the deterministic mixed-integer linear programming model is able to generate the optimal strategy in the face of different test problems, with strong robustness.

With the in-depth implementation of the green concept, environmental protection has become an important global issue, and environmental research in logistics networks has also achieved certain academic results [24-25]. Literature [26] designed a multi-product closed-loop green supply chain logistics network with a mixed integer linear programming model as the technical core, which can fully consider the environmental objectives such as carbon dioxide emission reduction in the logistics network, and at the same time ensure that the total cost of logistics network design is minimized. Literature [27] developed a multi-objective optimization model that comprehensively considered economic cost, carbon emission and social service level, and designed a hybrid solution model integrating integer programming and simulated annealing algorithms based on multi-objective optimization, and demonstrated superior performance in case studies. Literature [28] designed a dual-objective mixed integer linear programming model with the objective of minimizing the total cost and minimizing the carbon emission, with a view to designing a sustainable reverse logistics network for power batteries. Literature [29] constructed a multi-objective optimization model for the carbon dioxide emission problem in the design of a sustainable urban logistics network, and made decisions through a genetic algorithm embedded in the stepwise averaging method, and the method used had significant effects on the joint decision-making for the objectives of carbon dioxide emission reduction and the reduction of the investment cost of logistics infrastructure. Literature [30], in order to minimize the total cost involved in the logistics network model as well as the carbon emissions generated by logistics facilities, utilizes a mixed integer linear model for the design of logistics networks based on carbon footprints, and confirms the effectiveness of the mixed integer linear model by examining a case study in the plastics industry. Comprehensively comparing the existing research on logistics network, it can be found that foreign scholars have already had a certain degree of research on logistics network planning and achieved many results [31]. However, the research is still mostly based on a single administrative division to consider the logistics network construction problems, and the results of the research can hardly be extended to the region or the whole country, which lacks practical significance [32].

The arrival of the Internet of Things era makes it more and more important to optimize the layout of enterprise logistics economic network in advance. Under the superposition of the demand for reducing logistics and transportation costs and improving logistics and transportation efficiency, this paper introduces the integer programming algorithm to optimize the optimal logistics economic network. Firstly, quantitative model and qualitative model are constructed to realize the comprehensive coverage and estimation of logistics cost indexes and clarify the economic cost value. Secondly, for the logistics distribution time, the distribution time satisfaction model is established by using the distribution time satisfaction function and customer satisfaction data. Combined with the site selection optimization objective function, under the premise of quantifying the customer's psychological expectations, the alternative objectives that both satisfy the customer's requirements and save costs are determined through site selection. Finally, the genetic algorithm is integrated into the branch definition method to optimize the existing logistics economic network by continuously approaching the optimal solution through the three steps of branching, delimiting and branch cutting.

2. Modeling and solving logistics economic network under integer programming algorithm

2.1. Cost modeling

2.1.1. Parameter selection for quantitative modeling

The optimization goal of the logistics economic network layout is to minimize logistics costs as a means of determining the optimal siting plan.

1) Labor costs. In the process of regional logistics integration, management personnel are mainly adjusted by transferring posts, so their costs will not change significantly. Therefore, the model excludes the cost of management personnel and only considers the cost of logistics operators (CH) that changes in the process of regional logistics integration.

2) Depreciation expense. Depreciation expense mainly includes depreciation expense of equipment and workshop. Workshop construction cost (CJ) and equipment casting cost (CF) are selected as the constituent items of the optimization objective in the model.

3) Transportation cost and fuel cost. This part of the cost is mainly composed of two parts: highway cost and fuel consumption, including the transportation cost from the company to the logistics center and from the logistics center to the transfer station, and this part of the cost varies the most in different regional logistics center siting schemes.

4) Repair costs. Different numbers of regional logistics centers will produce different agglomeration effects, and their scales are also different, so they will produce different equipment needs, and thus produce different equipment repair and maintenance costs.

2.1.2. Indicator measurement for qualitative models

Unlike logistics costs in logistics financial accounting, the cost items in this model refer to the concept in economics, i.e. opportunity costs. The calculation of cost items and the setting of related parameters are mainly based on the following aspects:

1) Operational labor costs. This model in the labor cost accounting only consider the labor cost of warehousing and sorting operations personnel, that is, the actual operation of the logistics center of the labor cost of inputs, does not take into account the management personnel labor costs.

2) Workshop construction cost. Mainly consider the construction input cost of storage area (SSr), conventional sorting area (SBr), shaped sorting area (SYr), production auxiliary and utility

engineering room area (SGr) and recycling area (SHr). The specific accounting formula is as follows:

$$CJ_r = SS_r \times PA_r + \left(SB_r + SY_r + SG_r + SH_r\right) \times PB_r \tag{1}$$

where PA_r denotes the joint workshop storage cost indicator; PB_r denotes the rest of the joint workshop cost indicator.

3) Equipment input cost. Mainly consider the cost of warehousing equipment costs Li sorting equipment costs, are used a few days ago, the highest degree of white dynamic equipment to carry out costing. The established inventory demand is calculated as:

$$Q_r = \left(\Lambda_r \times 7.0 + B_r \times 12.0 + C_r \times 20.0\right) \times K_r / 10000 \tag{2}$$

where, Q , represents the inventory demand of the logistics center $RDC(r)$; Λ_r represents the average daily sales volume in the province; B_r represents the average daily sales volume in neighboring provinces; C , represents the average daily sales volume in the rest of the provinces; and K , represents the peaking factor,. On the basis of establishing the storage demand, in order to measure the cost of storage equipment input, so the storage input accounting formula provided by the professional storage equipment suppliers is used:

$$CS_r = P_s \times Q_r + \frac{MS_r \times (1-\delta)}{10} \times D_m \tag{3}$$

4) Sorting equipment costs. Calculated by the size of the sorting line, the size of the sorting line is calculated by the demand for goods. The specific formula for calculating the number of conventional commodity sorting lines is as follows:

$$N_r = (1-\varepsilon) \times MS_r \times 10^4 \times \rho / \left(T_y \times C \times \eta \times T\right) \tag{4}$$

where ε denotes the proportion of shaped goods; ρ denotes the sales volume fluctuation coefficient; T_y denotes the design annual working days of the logistics center; C denotes the daily sorting capacity of a single set of equipments; η denotes the comprehensive utilization coefficient of the sorting equipments; and T denotes the daily operation time. After obtaining the number of sorting lines, the cost of sorting equipment is calculated:

$$CB_r = P_p \times (1-\varepsilon) \times MS_r + 3 \times N_r \times D_k + \frac{MS_r \times 10^4}{T_y \times T \times E_c} \times D_c \tag{5}$$

where P_p denotes the sorting equipment cost index; D_k denotes the opener price; D_c denotes the depalletizer price; and E_c denotes the depalletizer efficiency. There is no uniform accounting for shaped goods sorting equipment due to its special characteristics.

5) Transportation cost. Considering from the perspective of minimizing the total cost of the supply chain, the transportation cost includes the transportation cost of the upstream section of the logistics center and the transit transportation cost of the downstream section. Calculating the transportation cost between different nodes is accounted for using the unit transportation rate. The calculation formula is as follows:

$$CT = \sum_{f=1}^{F}\sum_{r=1}^{R} x_r D_r w_{f,r} + \sum_{r=1}^{R}\sum_{\varepsilon=1}^{c} x_r y_{r,c} D_c w_{r,c} \tag{6}$$

of which is the unit transportation rate:

$$W = \frac{\begin{array}{c}\text{Single highway round trip mileage} \times \text{highway rate+total round trip mileage} \\ \times \text{fuel consumption per kilometer} \times \text{unit price of diesel fuel}\end{array}}{\text{Bicycle full capacity}} \times 2.0 \tag{7}$$

where D_r denotes the total demand for $RDC(r)$. x_r and y_r are decision variables, where x_r denotes whether 0-1 RDC (r) is selected as a regional logistics center, and $y_{r,c}$ denotes whether $0-1RDC(r)$ has correspondence with $CD(c)$.

6) Equipment maintenance cost. The equipment maintenance cost is mainly obtained by multiplying

the equipment input cost by a fixed rate factor as follows:

$$CW_r = \partial_s \times CS_r + \partial_f \times \left(CB_r + CY_r\right) \tag{8}$$

where ∂_s denotes the warehousing equipment maintenance ratio; and ∂_f denotes the sorting equipment maintenance ratio.

2.2. Logistics and economic network optimization

2.2.1. Distribution Time Satisfaction Function Analysis

In the current fierce competition in the logistics market, delivery time has become the key competitiveness of enterprise development. Relevant studies show that users tend to choose enterprises that can provide faster delivery and better service quality. Since there are subjective differences in customers' evaluation of delivery time, this study will construct a delivery time satisfaction model to quantify customers' psychological expectations into mathematical evaluation indexes.

The first is the time penalty function. Figure 1 shows the time window penalty function expression and function. In the vehicle path optimization model, the time window constraint is defined as the customer's rigid requirement on the cargo delivery timeliness, i.e., $\left[ET_i, LT_i\right]$. According to the difference in constraint strength, time windows can be categorized into three types:

1) Hard time windows

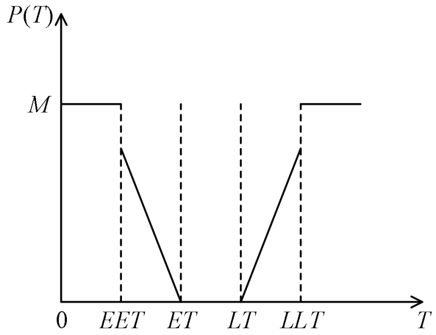
The distribution operation must be completed strictly within the preset time interval, and the service beyond this time period will be regarded as default;

2) Soft Time Window

Distribution is allowed to be completed outside the preset time, but a penalty cost proportional to the amount of time deviation is required, which is reflected as a flexible time window constraint;

3) Fuzzy time window

The use of two-layer time constraint system: the inner layer of the customer's expectations of the time window, the outer layer of the logistics provider can be adjusted time window. The service time is in the inner layer interval without additional cost; between the inner and outer layers triggers the incremental penalty function; beyond the outer layer interval produces unacceptable default cost. In this paper, the composite time window is used to construct the service evaluation system by combining the characteristics of merchandise store operations. Its penalty function $P(t)$ satisfies the staged regulation mechanism, and M denotes a sufficiently large positive number:



$$P(t) = \begin{cases} M & t \in [0, EET) \\ P_E(ET - t) & t \in [EET, ET) \\ 0 & t \in [ET, LT) \\ P_L(t - LT) & t \in [LT, LLT) \\ M & t \in [LLT, +\infty) \end{cases}$$

Figure 1. Expression and Function of Time Window Penalty Function.

The second is distribution time satisfaction processing. In the actual logistics scenario, customer satisfaction is subject to the common effect of various factors such as distribution time, service quality and goods integrity, etc. In this paper, in order to improve the enterprise distribution efficiency, based on the simplified processing, focus on the core element of distribution time, and construct a quantitative model of customer satisfaction based on the fuzzy time window. Specifically, the time window is divided into a fully satisfied interval and a partially satisfied interval: when the distribution time falls completely within the customer's expected time window $\left[ET_i, LT_i\right]$, the customer satisfaction reaches the maximum value; when it is in the middle of the customer's expected time window and the acceptable time window, the satisfaction will change with the size of the time gap. Referring to the principle of service compensation in the instant delivery industry, its payout mechanism has significant segmentation characteristics, which fully reflects the law that customer satisfaction shows an accelerated decline with the increase of overtime, therefore, this paper sets that in the case of overtime delivery, the more overtime there is, the faster the rate of decline of satisfaction. For the early delivery scenario, in view of the lower sensitivity of customers to delivery time advancement, a smoother decay rate is adopted. Figure 2 shows the customer satisfaction function used in this paper.

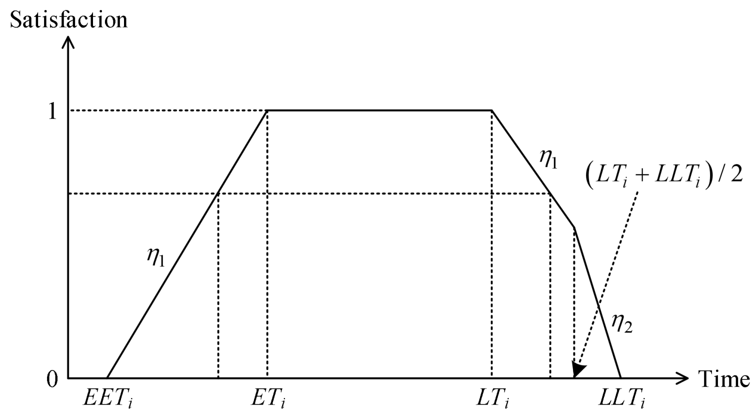


Figure 2. Customer Satisfaction Function.

Therefore, this study establishes a correspondence function between the actual service start time t_{ik} and the customer's desired time period to quantify satisfaction Sat_i as a continuous process over time:

$$Sat_i = \begin{cases} 0.00 & t_{ik} \in [0, EET_i] \\ f\left(\dfrac{ET_i - t_{ik}}{ET_i - EET_i}\right) & t_{ik} \in [EET_i, ET_i] \\ 1.00 & t_{ik} \in [ET_i, LT_i] \\ f\left(2\dfrac{t_{ik} - LT_i}{LLT_i - LT_i}\right) & t_{ik} \in \left[LT_i, \dfrac{LT_i + LLT_i}{2}\right] \\ g\left(2\dfrac{LLT_i - t_{ik}}{LLT_i - LT_i}\right) & t_{ik} \in \left[\dfrac{LT_i + LLT_i}{2}, LLT_i\right] \\ 0.00 & t_{ik} \in [LLT_i, +\infty) \end{cases} \tag{9}$$

The above equation shows that if the service start time is in $[0, EET_i], [LLT_i, +\infty]$, the customer's satisfaction is 0.00; if the service is provided in the customer's core expectation time window $[ET_i, LT_i]$, the Satisfaction is 100.00%; in $[EET_i, ET_i]$, $\left[LT_i, \frac{LT_i + LLT_i}{2}\right], \left[\frac{LT_i + LLT_i}{2}, LLT_i\right]$ during the period, when the actual delivery time whether too early or too late, as long as the gap with the customer's expected time is bigger, the customer's satisfaction will be lower. Empirical analysis based on the operation data of instant delivery platforms finds that there is significant spatio-temporal heterogeneity in the sensitivity of customers to time deviation. For this reason, this model sets the key cut-off point $[LT_i, LLT_i]$ within the elastic tolerance interval $\frac{LT_i + LLT_i}{2}$, and establishes a differentiated attenuation mechanism: in the case of $\left[LT_i, \frac{LT_i + LLT_i}{2}\right]$ time period its satisfaction decreases at a rate of η_1 ; at $\left[\frac{2T_i + LLT_i}{2}, LLT_i\right]$ time period the corresponding rate is η_2 . With the constraint $\eta_1 < \eta_2$, the system portrays the asymmetric loss aversion effect in behavioral economics - the customer's marginal utility loss for delivery delays is significantly higher than that for early delivery scenarios. This asymmetric design reflects the consumer psychology of "on time is better than ahead of time, and delay is intolerable" in delivery scenarios.

2.2.2. Site selection optimization objective function analysis

This study takes reducing the comprehensive cost of enterprise logistics network as the optimization goal, and systematically integrates various costs and expenditures, including the costs of transportation links from factories to distribution centers and from distribution centers to retail stores, the costs of warehousing in distribution centers, the costs of facilities, and the costs of transportation equipment, and at the same time, transforms the carbon emissions generated by the daily operation of the distribution centers and the transportation of vehicles into an economic indicator to be included in the accounting system. The objective function of the upper-level site selection model of the various costs are calculated as follows:

1) Distribution center fixed costs

The fixed expenditure of the distribution center contains the capital investment in the initial stage of construction, and this type of expenditure can be used in the long term. This study uses the average sharing method for annual cost accounting, and divides the annual fixed expenditures of storage facilities into two major parts: depreciation of building facilities and depreciation of transportation equipment. Assets in the building facilities category are depreciated over a 35-year life cycle, with an ending salvage value retention rate of 5% of the original value, while transportation equipment is calculated over a 20-year life cycle, with the salvage value rate set at 2.5%. Based on this, the average daily fixed cost can be broken down into the sum of the daily depreciation charges for construction facilities and transportation equipment.

Depreciation of construction facilities:

$$S_{m1} = \frac{C_m^1(1-10\%)}{10951} \tag{10}$$

Depreciation of transportation equipment:

$$S_{m2} = \frac{C_m^2(1-5\%)}{5476} \tag{11}$$

Then the fixed cost of the distribution center is expressed as:

$$W_1 = \sum_{m=1}^{M} Y_m \left(S_{m1} + S_{m2}\right) = \sum_{m=1}^{M} Y_m \left[\frac{C_m^1(1-10\%)}{10951} + \frac{C_m^2(1-5\%)}{5476}\right] \tag{12}$$

(2) Distribution center operating costs

Distribution center operation process includes the front-end goods receiving link and the back-end order processing link, each operating unit needs to be configured with professional equipment and operators, the resulting variable operating costs follow the principles of operation cost accounting, and the total amount of goods processed shows significant linear correlation. Therefore, the operation cost is expressed as follows:

$$W_2 = \sum_{l=1}^{L}\sum_{m=1}^{M} Y_m q_{lm} C_m^3 \tag{13}$$

3) Transportation Costs

Transportation costs in logistics and distribution are mainly composed of costs incurred in two transportation phases, the first phase is from the factory to the distribution center, and the second phase is from the distribution center to the retail stores. Transportation costs can be expressed as the product of freight unit price per unit mile, actual distance and freight volume, the specific formula is as follows:

Transportation cost from the logistics center to the distribution center (the first stage of transportation):

$$W_3^1 = \sum_{l=1}^{L}\sum_{m=1}^{M} X_{1m} Y_m q_{1m} G_1 d_{1m} \tag{14}$$

Transportation costs from the distribution center to the freight yard (second leg of transportation):

$$W_3^2 = \sum_{m=1}^{M}\sum_{i=1}^{F} Y_m Z_{mi} q_{mi} G_1 d_{mi}^h \tag{15}$$

Transportation costs in logistics and distribution are:

$$W_3 = W_3^1 + W_3^2 = G_1\left(\sum_{l=1}^{L}\sum_{m=1}^{M} X_{lm} Y_m q_{lm} G_1 d_{1m} + \sum_{m=1}^{M}\sum_{i=1}^{F} Y_m Z_{mi} q_{mi} G_1 d_{mi}^h\right) \tag{16}$$

4) Inventory costs

As a key node in the logistics system, the distribution center ensures that the enterprise can continuously deliver goods to retail stores by providing warehousing services for the goods. Inventory costs are affected by multiple factors such as the replenishment frequency of stores, the size of each replenishment and the replenishment cycle. In this paper, we uniformly set the replenishment cycle of each store to be the same, and the replenishment size of each time is consistent with the actual demand, and this simplified treatment helps to exclude the influence of other factors and facilitates the expression of the subsequent mathematical formulas.

In order to simplify the analysis, this study assumes that the ordering cycle of all stores is the same, and ignores the difference in the transportation time of goods from the factory to the distribution center, and defines that the distribution center is in the state of complete inventory at the beginning of distribution. According to the relevant knowledge of calculus, the total inventory cost is equal to the sum of the inventory cost corresponding to each order quantity of the store, which is calculated by the formula:

$$W_4 = \int_0^R \left(T_{r+1} - T_r\right)\left(\sum_{i=1}^{F} q_i - \sum_{i=1}^{F}\sum_{r=1}^{R} q_i^r\right) \tag{17}$$

2.3. Integer Programming Algorithm Solution

According to the planning business process requirements of merchandising companies, the planned volume of merchandise transportation is generally integer. Therefore, the merchandise warehouse layout evaluation problem is constructed as an integer planning problem.

The branch-and-bound method is a computational method that systematically searches all feasible solution spaces of an optimization problem with constraints according to certain rules, so as to find the optimal solution. The branch-and-bound method mainly consists of three steps: branching, delimiting and branch-cutting, i.e., searching all feasible solution spaces, continuously dividing the feasible solution domain into different subregions, and calculating the optimal solution of each subregion, and obtaining the optimal solution of the problem through continuous iterative calculations.

Genetic algorithms are derived from the theory of evolution and the doctrine of heredity. According to the principle of survival of the fittest, the solutions adapted to the environment are selected for replication, crossover and mutation to produce a new generation of solutions with better performance. Through iterative evolution, the optimal solution of the problem is found.

The genetic algorithm-assisted branch delimitation method is to integrate the genetic algorithm into the optimization process of the branch delimitation method, and to explore the optimal solution of a certain branch preferentially with the largest possible probability. The branch delimitation method assisted by genetic algorithm is used to solve the problem of merchandise warehouse layout evaluation, which mainly contains six steps:

Step1: Initialization. Let $i = 0.0, l = 0.0$ and $L(X) = \{OBJ(X)\}, x_{ijmn} \in R$, use genetic algorithm to find an initial arbitrary feasible solution X_0^* of $L(X)$.

Step2: Branching. Let $l = l + 1.0$, and introduce both $X_l \bullet \left[X_0^*\right]$ and $X_l > \left[X_0^*\right] + 1.0$, to construct a new collection of sub-problems, namely, $L^l(X) = \left\{OBJ\left(X_1\right), \cdots, OBJ\left(X_l\right)\right\}$.

Step3: Bounding. Determine whether $OBJ\left(X_i\right)(i = 1, \cdots, l)$ is feasible, if it is feasible, skip to Step 4 (prediction). Conversely, skip to step 6 (cut branch).

Step4: Prediction. Calculate the weight coefficients $P_{OBJ(X_i)}$ of $OBJ\left(X_i\right)(i = 1, \cdots, l)$ using genetic algorithms (where the weight coefficients already existed will not be repeated) to obtain $X_i^* = \{X \mid P_{OBJ(X)} = MinP_{L(X)}\}$.

Step5: Judgment. If $OBJ\left(X_i^*\right)OBJ_{\min}$, then skip to Step 6 (cut branch). Instead, determine whether X_i^* is an integer solution. If X_i^* is an integer solution, then X_i^* is the optimal solution to the problem; otherwise, update $X_{\min}$ and $OBJ_{\min}$ and skip to Step 2 (branching).

Step6: Cut branch. Eliminate $OBJ\left(X_i\right)$ from $L^l(X)$ to form a new set of subproblems, namely $L^l(X)=\left\{OBJ\left(X_1\right),\cdots,OBJ\left(X_{i-1}\right),OBJ\left(X_{i+1}\right),\cdots,OBJ\left(X_l\right)\right\}$.

Figure 3 shows the solution flow of the branch definition method assisted by the genetic algorithm.

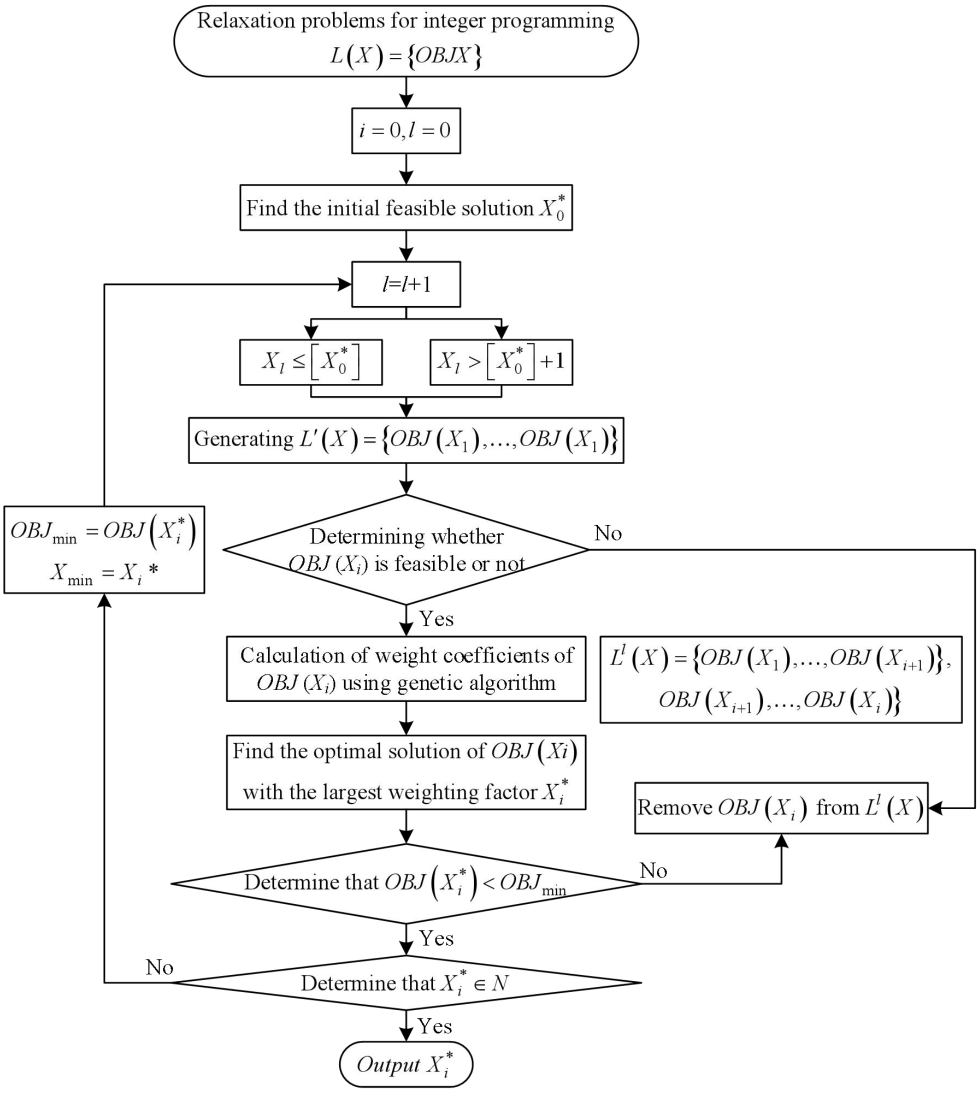


Figure 3. Genetic Algorithm-Assisted Branch and Bound Method.

3. Example analysis of logistics economic network optimization based on integer planning algorithm

3.1. Data collection and analysis

3.1.1. Store coordinates and requirements

In order to prove that the integer programming algorithm can effectively solve the optimal location of the logistics economic network and reduce the logistics cost, this paper chooses the location and path problem of A online shopping supermarket as the research object. In this paper, we choose the location and path problem of the logistics economic network of A online shopping supermarket as the research object.The service mode of A online shopping supermarket is that the factory produces commodities, and the commodities are transported to the distribution centers for storage through the logistics chain, and then distributed to the demand points of each store through the distribution centers. The location of the distribution center's storage area determines the cost of logistics vehicle transportation and the responsiveness of the stores' demand points. According to the development status quo of A online shopping supermarket, take 2 days/time as the distribution frequency of the distribution center to each store's demand point. Table 1 shows the coordinates and demand volume of the demand points of the stores of A online shopping supermarket in G. The latitude and longitude of the demand points of the 15 stores are relatively close to each other, and the demand volume is around 12-22 boxes, and the demand volume of the demand points of each store has a certain gap, which is a high requirement for the location of the distribution center.

Table 1. Store demand point coordinates and demand quantities.

Serial Number	Longitude	Latitude	Demand quantity (boxes)
1	105.97114	28.49396	18
2	104.82414	28.37623	20
3	104.82982	28.39742	16
4	104.81155	28.38679	14
5	104.81784	27.39028	17
6	105.82486	28.38742	15
7	104.81601	28.37395	20
8	104.81079	28.38262	13
9	105.96728	28.48279	12
10	104.80794	29.37273	14
11	104.80293	28.37911	18
12	106.80276	28.36912	19
13	104.82841	29.39772	21
14	104.83782	28.39305	22
15	104.82269	28.37851	18

3.1.2. Alternative Distribution Center Details

The current A Online Shopping Supermarket is preparing for expansion and Table 2 shows the details of the alternative distribution center storage areas. There are 8 alternative distribution center warehousing areas, with longitude locations ranging from 101.69421°-105.00583°E and latitude from 22.24581°-26.58396°N. There are large differences in the area, annual rent, and equipment acquisition costs of the 8 alternative locations, and it is necessary to solve the optimal siting location among them to reduce the operating costs by using integer programming algorithms.

Table 2. Detailed information about storage area of alternative distribution center.

Serial Number	Longitude	Latitude	Area (m^2)	Annual rent (yuan)	Equipment purchase cost (yuan)
1	103.75569	26.19249	764	129609	13090
2	101.69421	22.24581	727	159246	12541
3	104.88358	25.17614	814	150041	13674
4	103.99154	26.16567	772	145642	12392
5	105.00583	24.68764	786	128783	12018
6	103.84649	24.57758	801	162246	12096
7	102.84148	26.58396	845	174617	14293
8	104.84131	26.57397	774	122422	12599

3.2. Integer Planning Modeling

Figure 4 further measures the distance from the 8 alternative distribution center storage areas to the 15 store demand points on the map. By using the delivery time satisfaction function and the site selection optimization objective function, the reachability matrix from the 8 alternative distribution center storage areas to the 15 store demand points in Figure 5 is calculated. Based on the results of the reachability matrix, an integer planning model is constructed, and then the optimization of site selection is performed.The distances from the 8 alternative distribution center warehousing areas to the 15 store demand points vary from 1.6km to 16.8km, with a large difference in the distance between them. In the reachable matrix, “0” represents the unreachable solution and “1” represents the reachable solution.

From the number of 0 and 1 in Fig. 5, it can be judged that the reachable solution and the unreachable solution each account for half of the proportion, and it is necessary to continue to screen the optimal solution.

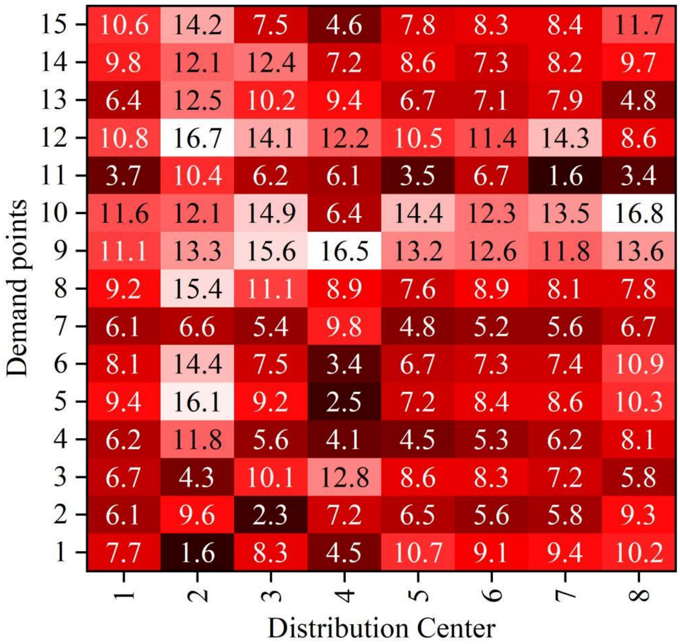


Figure 4. Distance between alternative distribution centers and demand points.

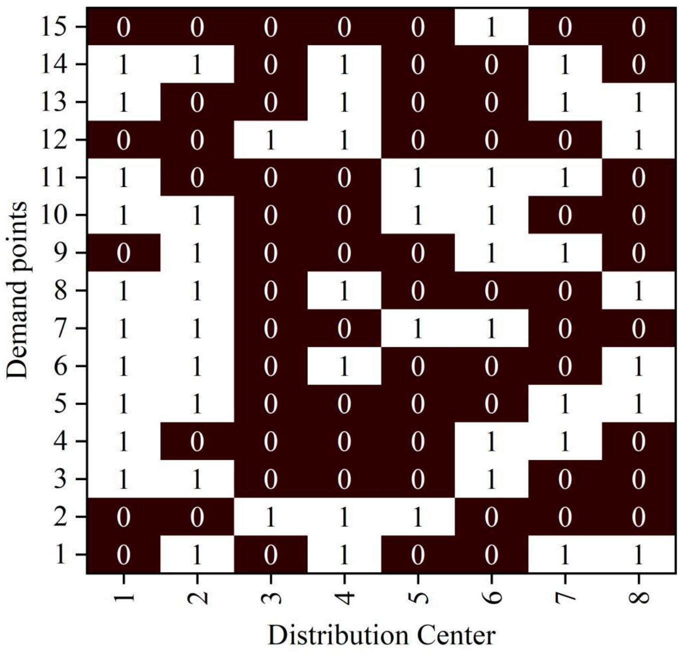


Figure 5. Reachability matrix between distribution center and demand points.

3.3. Distribution Center Warehouse Layout Planning Solution

3.3.1. Region 1 storage area selection and algorithm convergence results

The branch definition method (i.e., integer planning algorithm) integrated with genetic algorithm is utilized for optimal distribution center storage area solving planning by region. Figure 6 shows the convergence curve of the integer planning algorithm. Figure 7 is the selection result of the optimal distribution center storage area in region 1. Algorithm in about 30 iterations, the optimal fitness value is stabilized at 1.27981, branch solving speed is faster. The algorithm solves that when alternative distribution center 1 is selected as the optimal distribution center storage area for region 1, it can be distributed for 5 store demand points. And alternative distribution center 2 can only distribute for 1 store demand point. Therefore, the distribution center of region 1 should be chosen to be established at alternative distribution center 1.

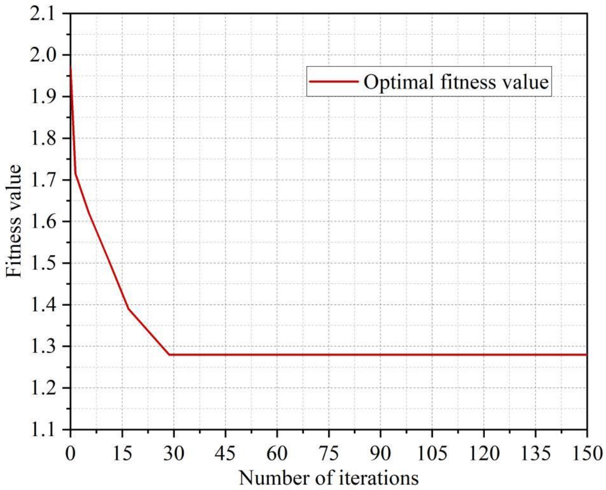


Figure 6. Convergence curve of integer programming algorithm.

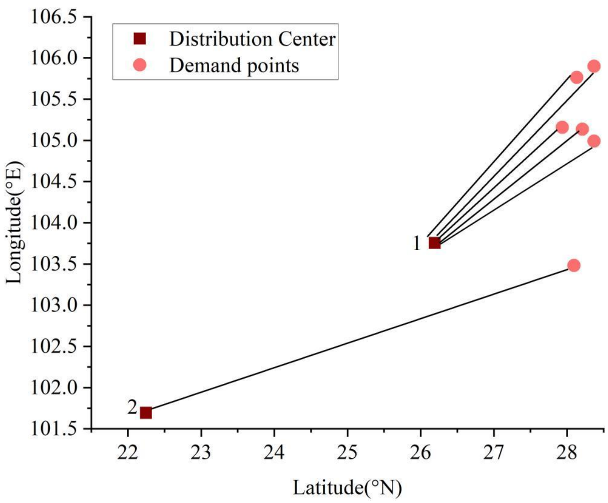


Figure 7. Selection result of optimal distribution center storage area in Region 1.

3.3.2. Planning for storage areas in other regions

Figure 8 shows the optimal distribution center warehousing area planning results for region 2. Figure 9 is the optimal distribution center warehousing area planning results for region 3. According to the integer programming algorithm, the alternative distribution center 3 is selected as the optimal distribution center warehousing area in region 2, which can simultaneously meet the distribution needs of two demand points. In region 3, alternative distribution center 8 as the optimal distribution center storage area, can simultaneously meet the distribution needs of 4 demand points. The alternative distribution center 6 is screened out of consideration in the algorithm solution because it cannot satisfy the distribution demand of any one demand point.

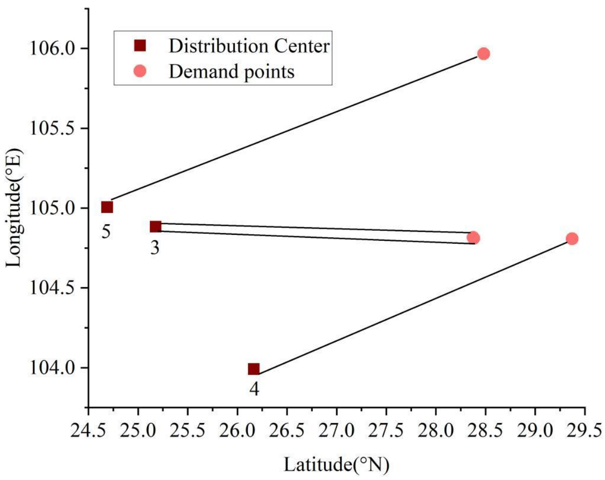


Figure 8. Selection result of optimal distribution center storage area in Region 2.

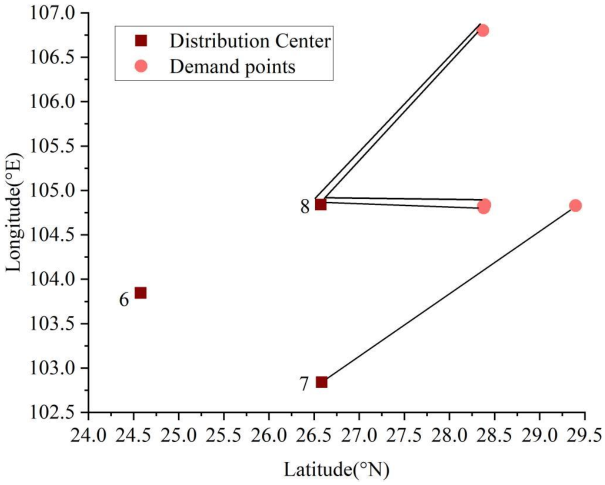


Figure 9. Selection result of optimal distribution center storage area in Region 3.

3.4. Before and after optimization of logistics economic network under integer programming

Figure 10 shows the initial path of the logistics economic network before the integer programming algorithm is solved. Figure 11 is the final path of the logistics economic network after the integer programming algorithm is solved. The initial path of the logistics economic network before the solution, distribution centers 2 and 6 are idle, and the distribution of demand points is concentrated in distribution centers 5, 7 and 8, which is prone to the limitation of difficulty in responding to the demand in time. After integer planning solution, alternative distribution center 6 can be removed, while increasing the distribution routes of distribution centers 1, 2 and 8, which makes the optimized overall logistics economic network more balanced development and reduces the cost of idle areas and distribution routes.

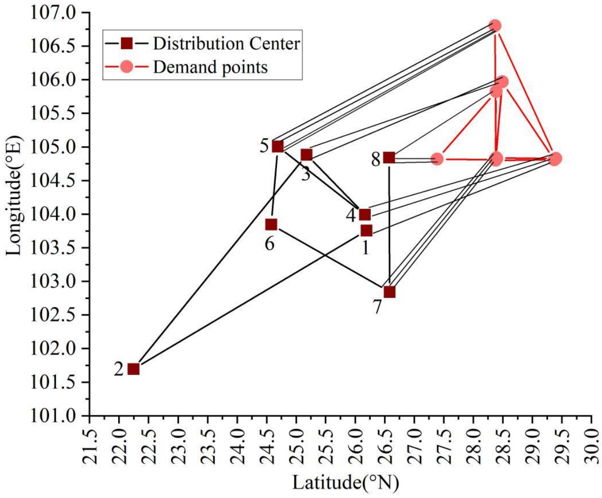


Figure 10. The initial path of the logistics economic network before solution.

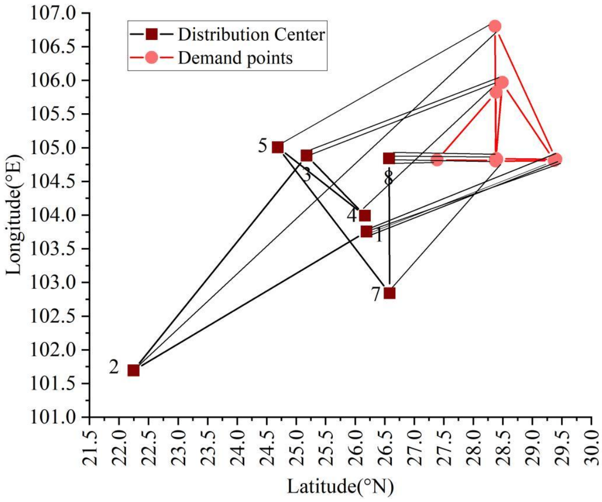


Figure 11. The final path of the logistics economic network after solution.

4. Conclusion

This paper solves the optimal logistics distribution center site by integer planning algorithm to improve the original logistics economic network layout. After solving the integer planning for 8 alternative distribution center storage areas, the idle alternative distribution center storage area 6 is removed, and the distribution routes between each distribution center and store demand points are adjusted to ultimately achieve the optimization of the enterprise's logistics economic network layout. The integer planning algorithm quickly completes the layout adjustment of the logistics economic network with fewer iterations (<30 times), which on the whole helps the enterprise to reduce the logistics cost and seize the service market in advance, and has high application value.

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