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Research on the two-stage model of container matching based on vehicle path combination optimization and cargo owner demand

Yan Hu[1], Gefei Shi[1,✉]

[1] *Hunan Modern Logistics College, Changsha, Hunan, 410131, China*

ABSTRACT

Container and cargo matching is a key issue to realize the construction of container and cargo supply and demand matching platform, through the intelligent matching of cargo and container information, improve the efficiency of container and cargo matching, which is conducive to the integration of resources, and improve the platform professional services. In this paper, we analyze the process of container cargo matching and transportation distribution center operation, put forward the two-stage container cargo model assumption in accordance with the basic principle of distribution optimization, and complete the establishment of container cargo matching model under the demand of cargo owners. Optimize the container and cargo matching and vehicle path model respectively, derive the optimized combination mathematical model, and solve the combination optimization model through genetic algorithm. Simulation experiments are designed to analyze the effectiveness of the model. The results of the analyses of the algorithms show that when the crossover probability is increased from 0.6 to 0.8, the average value of the RV value decreases from 1078.76 to 915.76, and the recommended value of the crossover probability is obtained as 0.8. After optimization, the average vehicle load and average loading volume of the recommended scheme of the combined model reach 98.436% and 87.963%, respectively, with a total mileage of 23.456km for distribution, and the total cost of distribution in the region is 1246.489 yuan, which achieves the optimal container-cargo matching and path scheduling scheme.

Keywords: Shipper demand, Container-cargo matching, Two-stage model, Optimal combination, Cross probability

1. Introduction

There are two main forms of transportation of consolidated cargo in crates: straight consolidation transportation and mixed consolidation transportation [1-3]. Pooled transportation refers to the mode

✉ Corresponding author.
E-mail address: 16fg6@163.com (G. Shi).
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of transportation in which several shipments of the same nature, the same flow and the port of destination are assembled in the same container at the port of loading and transported to the port of destination for unpacking, while mixed transportation refers to the mode of transportation in which several shipments of the same nature but different ports of destination are combined in the same container at the port of loading, transported to the established transshipment port and handed over to the transshipment agent to receive and unpack, and then directly transported to the port of destination for unpacking according to the conditions and requirements of direct consolidation [4-7]. Mixed transportation should pay attention to the selection of shipping ports and freight forwarders, as well as the safety of goods [8-10].

In the past, most of the container transportation is full container business, at this stage of the international financial crisis, the traditional European and American market demand is small, so the small volume of goods increased, which makes the market potential of containerized LCL freight expanding [11-12]. At present, many logistics or freight forwarding enterprises have also begun to pay attention to the development of the LCL business. As an enterprise, there are many issues that need attention when choosing this business [13-15].

In containerized cargo transportation, in order to ship, cargo and container safety, must be based on the nature of the goods, type, volume, weight and form to choose the appropriate container [16-17]. In order to save sea freight, more cargo, both shippers and carriers try to make the container "full container full load" [18-19]. The so-called "full container full load", refers to the full use of container volume and rated load. For consolidated cargo, if you can make the average density of the goods and the container unit weight close to, can do "full container full load", which requires a certain proportion of goods in accordance with the container [20-22]. However, in reality, the owner of the consignment of goods is determined by the actual needs of trade, it is difficult to pre-determined by the optimal ratio of packing and transportation. How to choose the container type and how to consolidate the containers according to the actual situation so as to minimize the total freight cost are the problems often encountered by the sea freight business personnel [23-24].

In this paper, combined with the container and cargo matching process and the basic principles of load distribution optimization, the two-stage cargo container matching model assumption under the demand of the cargo owner is proposed, and the functions of the two stages are constrained by the constraints respectively. The model of cargo matching and vehicle path selection problem is deduced respectively, and the mathematical model of optimization of cargo matching and vehicle path combination is established. The method of integer coding is adopted to design the corresponding coding scheme for the established combination optimization model. During the initialization of the population, the designed number of populations is used to generate the initial solution, shorten the solution time and accelerate the convergence of the algorithm. According to the weights of the actual problem, an adaptation function is established for evaluating the advantages and disadvantages indicators of each chromosome scheme. Operate the selection operator, crossover operator and mutation operator respectively to complete the parameter setting of the genetic algorithm solution process, and carry out simulation analysis to evaluate the effectiveness of the algorithm. The model is applied to the actual container and cargo matching and transportation process, and the optimization effect of the path, the container and cargo matching effect, and the combination optimization scheme are examined empirically, respectively.

2. Two-stage model construction for container-cargo matching

2.1. Logistics and distribution optimization study

2.1.1. Transportation and Distribution Center (TDC) operational processes. Figure 1 for the distribution center of the logistics delivery process, logistics distribution is to send goods from the distribution center to the owner of the process, it is directly connected to consumers, in the logistics system occupies an important position. Distribution center in the logistics distribution to meet the needs of the owner, while seeking to reduce logistics costs. Logistics costs occur in all aspects of the distribution process, therefore, how to optimize the distribution process, reduce the distribution process in all aspects of the irrational phenomenon, is to reduce the logistics cost of distribution centers must solve the key problem. The logistics distribution process generally includes the collection of goods, storage, sorting and distribution, loading and distribution, distribution and transportation, delivery to the owner as well as the return of vehicles and other links.

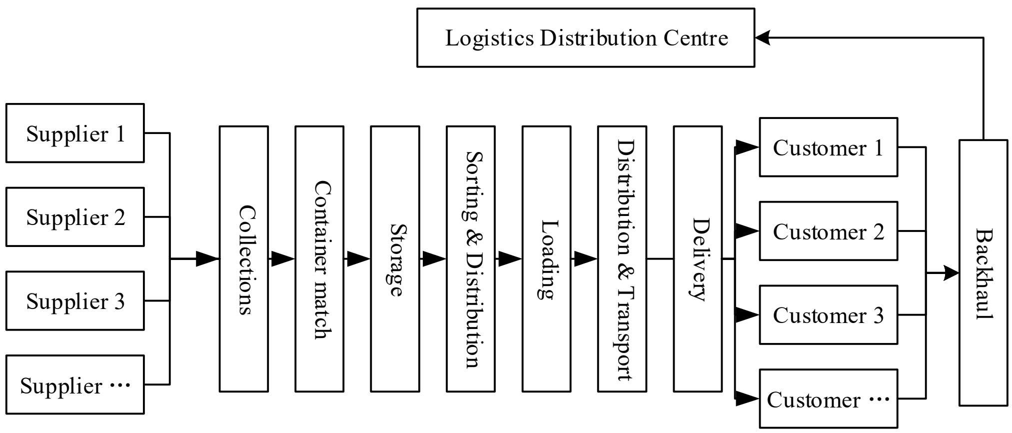

Fig. 1. Logistics distribution process of distribution center

2.1.2. Basic principles of distribution optimization. Logistics distribution optimization is to optimize the above unreasonable logistics distribution phenomenon, which is mainly from the vehicle distribution line to determine the vehicle cargo loading program development and other relevant aspects of the start, through the optimization method to improve the efficiency of the implementation of the distribution process, the basic principles of the following points.

1) The principle of the shortest circuit. In the distribution line planning can be in accordance with the shortest path principle, to ensure that the distribution center to the main point of the goods is the shortest distance.

2) Full load principle. Comprehensive consideration of the needs of all shippers, consolidated transportation, that is, a vehicle loaded with multiple shipper points of goods, rational use of existing vehicles to ensure that the vehicle loading utilization rate is high.

3) Priority principle. For the following cargo owners, the distribution center can choose to give priority to delivery:

(1) Cargo owners with priority.

(2) According to the classification of the owner of the goods, the importance of the owner of a higher degree.

(3) Shippers whose orders contribute significantly to the company, according to the order volume or transaction amount.

(4) According to the credit status of the shipper, the shipper with better credit.

(5) Cargo owners with urgent time requirements.

4) On-time principle. The principle of punctuality means that the distribution center should try to meet the time requirements of the owner of the goods and deliver them to the owner's point within the time required by the owner.

5) The principle of easy loading and unloading. Loading and unloading is to prepare for transportation or transportation of terminal operations, distribution process of loading and unloading of goods is an indispensable work, loading and unloading is not only to consume manpower and material resources, but also may result in the destruction of goods, so in the development of goods distribution program

must be taken into account in the process of loading and unloading of goods to facilitate the implementation of the process.

2.1.3. Container matching process. In the process of container cargo supply and demand, two stages of evaluation indicators are set up, the first stage evaluation indicators are attribute indicators, which are the indicators that must be satisfied when matching container cargo. The second stage indicator is the expectation indicator, which is the indicator that users value more from their own standpoint, and the larger its value is, the higher the user satisfaction is.

Firstly, we screen the published container source information and cargo source information according to the attribute index, eliminate the information that does not meet the requirements of the attribute index, and then calculate the matching degree of container source and cargo source according to the expectation index. Finally, the program with higher matching degree will be actively pushed to container owners and cargo owners for their business matching negotiation.

2.2. A two-stage model for matching containers and cargoes under shippers' demand

2.2.1. Model assumptions. Since the container-cargo matching problem is very complex, the following assumptions are made about the problem in order to simplify the model and abstract the general case of the problem:

1) Each port generates independent demand and supply.
2) Only sea transportation of empty containers is considered, not land transportation after the arrival of empty containers.
3) Only consider the case of a single container type, in this paper the liner company only shipped 20ft standard containers of this type of container.
4) The liner arrives at the port at the same time and leaves the port at the same time.
5) The liner company can directly rent the required empty containers in the port, and there is no limitation on the number of rented containers, and the rented containers are returned once at the end of the decision-making period.
6) Empty containers from port i to port j will be unloaded on the first call to port j and there will be no empty containers from port i to port j on the second call to port j.
7) All cargo requirements must be met.

2.2.2. Mathematical expression of container-cargo matching model under shipper's demand:

1) First stage. In this stage, the decisions faced by the container-cargo matching are decisions made under the certainty of meeting the shippers' needs for containers, so this stage precedes the actual occurrence of empty container transfer. The decisions liner companies have to make at this stage include: the decision to transfer empty containers, the decision to rent empty containers, and the decision to store containers in the first stage.

There are two types of costs involved in the movement of empty containers faced by the liner companies in the first stage, namely the cost of empty container movement and the cost of renting containers. Although empty container storage also incurs costs, the specific empty container storage costs are not considered in the first stage for the time being because the empty container storage will also be used in the second stage.

(1) Empty container mobilization cost:

$$CT=\sum_{k=1}^{K}\sum_{r=1}^{T}\sum_{i=1}\sum_{j=1}\theta(i,j,k,t)X(i,j,k,t)(\cot(i,j,k,t)+cl(i)+cu(j)) \tag{1}$$

Where $\cot(i,j,k,t)$ denotes the transportation cost per unit of empty containers t moment transported via ship k from port i to port j, $cl(i)$ denotes the cost of loading containers at port i, $cu(j)$ denotes the cost of unloading containers at port j, K denotes the number of seagoing vessels, T denotes the number of decision periods, and I denotes the set of all ports of call.

(2) Cost of chartering containers in the first stage:

$$CR1=\sum_{t=1}^{T}\sum_{i\in t}R_1(i,t)(T-t+1)cr(i,t) \tag{2}$$

Where $cr(i,t)$ denotes the per-period rental rate for empty containers in i ports, $(T-t+1)$ denotes the number of rental periods remaining, and $R_1(i,t)$ denotes the number of containers to be rented in the first phase.

(3) The total cost function of the first stage

$$\begin{aligned}Cl=&\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{i\in I}\sum_{j\in I}\theta(i,j,k,t)X(i,j,k,t)(\cot(i,j,k,t)+cl(i)+cu(j))\\&+\sum_{t=1}^{T}\sum_{i\in I}R_1(i,t)(T-t+1)cr(i,t)\end{aligned} \tag{3}$$

2) First stage constraints:

(1) Liner capacity constraint. Vessel k's empty container space in port i + Vessel k's heavy container space in port i ⩽ Vessel k's total container space in port i:

$$\begin{aligned}&\sum_{r\in\{r|t_r,\le t_i\}|}\sum_{q\in\{q|t_q>t_i\}}X(r,q,k,t)\theta(r,q,k,t)\\&+\sum_{r\in\{r|t_r,\le t_i\}|}\sum_{q\in\{q|t_q>t_i\}}F(r,q,k,t)\theta(r,q,k,t)\le U(i,k)\end{aligned} \tag{4}$$

Where t_i is the time when ship k arrives at port i, t_r is the time when ship k arrives at port r, t_q is the time when ship k arrives at port q, and $F(r,q,k,t)$ denotes the number of heavy containers transported from port r to port q at the t th moment.

(2) Iterative relationship of empty container stock. The following mathematical relationship exists for deterministic empty container stock:

Current period i port storage volume = previous period i port storage volume + current period i port supply volume - current period i port demand volume + current period i port rental volume - current period i port empty container output volume + current period i port empty container input volume.

$$\begin{aligned}H_1(i,t)=&H_1(i,t-1)+S(i,t)-D(i,t)+R_1(i,t)\\&-\sum_{k=1}^{K}\sum_{j\in I}X(i,j,k,t)\theta(i,j,k,t)\\&+\sum_{k=1}^{K}\sum_{r\in I}X\left(r,i,k,t-\tau_n\right)\theta\left(r,i,k,t-\tau_{rn}\right)\end{aligned} \tag{5}$$

where $H_1(i,t)$ is the stock of empty containers at port i in the first stage, $S(i,t)$ denotes the deterministic supply at port i, $D(i,t)$ denotes the deterministic demand at port i, and τ_{ri} denotes the shipping time from port r to port i.

(3) Non-negative integer constraints. $X(i,j,k,t)\ge 0$ and is an integer, $R_1(i,t)\ge 0$ and is an integer, $H_1(i,t)\ge 0$ and is an integer.

3) Second stage. In the second stage of decision making, i.e. the current period of empty container transfer. In this stage, the liner company also needs to consider the random supply and demand of empty containers that occur during the current period. Because the liner company has already made plans for empty container movement before the empty container movement actually occurs, in the second stage, it no longer considers the empty container movement problem. Instead, it considers how to solve the stochastic empty container supply and demand problem by storing excess empty

containers or renting empty containers in that period.

(1) Cost of storing containers

$$CH = \sum_{t=1}^{T} \sum_{i \in I} H_2(i,t) ch(i,t) \tag{6}$$

The cost is the actual storage cost incurred by the liner company during the period of transferring empty containers in the port, where $ch(i,t)$ indicates the single-phase storage rate in Phase t Port i, and $H_2(i,t)$ is the second-phase empty container inventory

(2) The second phase of the cost of renting containers

$$CR2 = \sum_{t=1}^{T} \sum_{i \in I} R_2(i,t)(T-t+1) cr(i,t) \tag{7}$$

where $R_2(i,t)$ denotes the amount of empty containers leased by the liner company in the second stage.

(3) The total cost function for the second stage is:

$$C2 = \sum_{t=1}^{T} \sum_{i \in I} H_2(i,t) ch(i,t) + \sum_{t=1}^{T} \sum_{i \in I} R_2(i,t)(T-t+1) cr(i,t) \tag{8}$$

Empty container stock iterative relationship:

$$H_2(i,t) = H_1(i,t) + R_2(i,t) + s(i,t) - d(i,t) \tag{9}$$

where $s(i,t)$ denotes stochastic supply, $d(i,t)$ denotes stochastic demand, and non-negative integer constraint relations: $H_2(i,t) \geq 0$ and an integer, $R_2(i,t) \geq 0$ and an integer.

4) The entire decision-making period. Combining the first stage and the second stage, the decision made by the liner company should be to ensure that under the premise of satisfying the constraints, the total cost of the entire transfer process is minimized, so the objective function for the entire decision-making period is as follows:

$$Min\left(TC\right) = Min\left(C1 + C2\right) \tag{10}$$

$$\begin{aligned} C1 = &\sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{i \in I} \sum_{j \in I} \theta(i,j,k,t) X(i,j,k,t)(ct(i,j,k,t) + cl(i) + cu(j)) \\ &+ \sum_{t=1}^{T} \sum_{i \in I} R_1(i,t)(T-t+1) cr(i,t) \end{aligned} \tag{11}$$

$$C2 = \sum_{t=1}^{T} \sum_{i=1} H_2(i,t) ch(i,t) + \sum_{t=1}^{T} \sum_{i \in I} R_2(i,t)(T-t+1) cr(i,t) \tag{12}$$

(1) Liner capacity constraints1) Liner capacity constraints

$$\begin{aligned} &\sum_{r \in \{r | t_r \leq t_i\}} \sum_{q \in \{q | t_q > t_i\}} X(r,q,k,t) \theta(r,q,k,t) \\ &+ \sum_{r \in \{r | t_r \leq t_i\}} \sum_{q \in \{q | t_q > t_i\}} F(r,q,k,t) \theta(r,q,k,t) \leq U(i,k) \end{aligned} \tag{13}$$

(2) Iterative Relationship for Empty Container Inventory

$$\begin{aligned} H_1(i,t) &= H_1(i,t-1)+S(i,t)-D(i,t)+R_1(i,t) \\ &-\sum_{k=1}^{K}\sum_{j\in 1}X(i,j,k,t)\theta(i,j,k,t) \\ &+\sum_{k=1}^{K}\sum_{r=1}X\left(r,i,k,t-\tau_{rt}\right)\theta\left(r,i,k,t-\tau_{ri}\right) \end{aligned} \tag{14}$$

The above equation shows the relationship between containers in the first stage, and since the second stage also produces a change in the stock of empty containers, the equation has to be corrected appropriately in order to reflect the real scenario:

$$\begin{aligned} H_1(i,t) &= H_2(i,t-1)+S(i,t)-D(i,t)+R_1(i,t) \\ &-\sum_{k=1}^{K}\sum_{j\in 1}X(i,j,k,t)\theta(i,j,k,t) \\ &+\sum_{k=1}^{K}\sum_{r\in I}X\left(r,i,k,t-\tau_{ri}\right)\theta\left(r,i,k,t-\tau_{ri}\right) \end{aligned} \tag{15}$$

$$H_2(i,t)=H_1(i,t)+R_2(i,t)+s(i,t)-d(i,t) \tag{16}$$

Combining (15) and (16), one obtains:

$$\begin{aligned} H_2(i,t) &= H_2(i,t-1)+S(i,t)-D(i,t)+R_1(i,t)+R_2(i,t) \\ &-\sum_{k=1}^{K}\sum_{j\in l}X(i,j,k,t)\theta(i,j,k,t) \\ &+\sum_{k=1}^{K}\sum_{rot}X\left(r,i,k,t-\tau_{n}\right)\theta\left(r,i,k,t-\tau_{n}\right)+s(i,t)-d(i,t) \end{aligned} \tag{17}$$

where $H_2(i,0)$ is a known quantity.

(3) Non-negative restrictions. $X(i,j,k,t)\geq 0$ and an integer, $R_1(i,t)\geq 0$ and an integer, $H_2(i,t)\geq 0$ and an integer, $R_2(i,t)\geq 0$ and an integer.

3. Optimization modeling of container cargo distribution and vehicle path combination

3.1. Mathematical modeling

3.1.1. Container and cargo matching model selection. The parameters are defined as follows: m is the number of vehicles, j is the vehicle number, $j=1,2,\cdots,m$, G_j is the maximum load capacity of the vehicle j, V_j is the maximum volume of the vehicle j, n is the number of cargoes; i is the number of the cargoes, $i=1,2,\cdots,n$, g_i is the weight of the cargoes i, V_i is the volume of the cargoes i.

The variables are defined as follows:

$$\begin{aligned} x_{ij} &= \begin{cases} 1 & Goods\ i\ loaded\ \text{int}\,o\ vehicle\ j \\ 0 & Otherwise \end{cases} \\ y_j &= \begin{cases} 1 & Vehicle\ j\ is\ used \\ 0 & Otherwise \end{cases} \end{aligned} \tag{18}$$

The mathematical model of the cargo distribution problem is as follows:

$$\max Z_e=\sum_{i=1}^{n}\sum_{j=1}^{n}x_i g_j \Bigg/ \sum_{j=1}^{n}y_j G_j \tag{19}$$

$$\max Z_r = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i v_j \Big/ \sum_{j=1}^{n} y_j V_j \tag{20}$$

$$s.t. \sum_{j=1}^{m} x_{ij} \le 1 \tag{21}$$

$$\sum_{i=1}^{n} x_{ij} g_i \le G_j \tag{22}$$

$$\sum_{i=1}^{n} x_{ij} v_i \le V_j \tag{23}$$

$$x_{ij} = 0 \ Or \ 1 \tag{24}$$

$$y_j = 0 \ Or \ 1 \tag{25}$$

The description of each equation in the model is as follows: (19) is the objective function, which indicates that the load utilization of all vehicles is maximized, (20) is the objective function, which indicates that the volume utilization of all vehicles is maximized, (21) is the loading constraint, which indicates that the goods are not divisible and a piece of goods can only be loaded in one vehicle, and (22) indicates that the total weight of the goods loaded into each vehicle must not exceed the maximum load capacity of the vehicle.

3.1.2. Vehicle path model selection. The type of vehicle path problem is also very much, choose the non-full loaded vehicle path problem as the object of combinatorial optimization, firstly, because logistics distribution applies to the transportation of multi-species, small batch of goods, most of the cases of distribution is to concentrate the goods of multiple shippers together for common transportation, so the non-full loaded vehicle path problem is most in line with the actual situation of logistics distribution [25]. Secondly, because the theoretical research on vehicle path problem is summarized, the vast majority of them are for the research on the vehicle path problem of non-full load, and the research on the vehicle path problem of non-full load is more classical and the application of the research results is more extensive.

Vehicle path problem can be described as follows: a distribution center, with K vehicles, vehicle rated capacity of q_k, to deliver to L shippers, shippers i freight volume of g_i, the weight of the goods is less than the rated capacity of the vehicle, to determine the shortest vehicle path to meet the needs of shippers.

Parameters are defined as follows: d_{ij} represents the traveling route from shipper point i^2 to shipper point j.

The variables are defined as follows:

$$x_i = \begin{cases} 1 & \textit{Vehicle x travelling from customer i to j} \\ 0 & \textit{Otherwise} \end{cases}$$
$$y_t = \begin{cases} 1 & \textit{Customer i's task is completed by vehicle k} \\ 0 & \textit{Otherwise} \end{cases} \tag{26}$$

The mathematical model of the vehicle path problem is as follows:

$$\min Z = \sum_{i=0}^{L}\sum_{j=0}^{L}\sum_{k=1}^{K} d_{ij} x_{ijk} \tag{27}$$

$$S.t. \sum_{i=0}^{N} g_i y_{ki} \le q_k \forall k \tag{28}$$

$$\sum_{k=1}^{K} y_{ki} = 1 i = 1,2,\cdots N; \forall k \tag{29}$$

$$\sum_{j=0}^{N} X_{ijk} = y_{ki} i = 1,2,\cdots N; \forall k \tag{30}$$

$$\sum_{i=0}^{N} X_{ijk} = y_{kj} j = 1,2,\cdots N; \forall k \tag{31}$$

$$\sum_{j=0}^{N} X_{0jk} = \sum_{j=0}^{N} X_{j0k} \leq 1 \forall k \tag{32}$$

$$y_{ki} = 0 \ Or \ 1 i = 1,2,\cdots L; \forall k \tag{33}$$

$$X_{ijk} = 0 \ Or \ 1 i, j = 0,1,\cdots L; \forall k \tag{34}$$

The description of each equation in the model is as follows: (27) the objective function, which indicates that the total distance traveled by the vehicle is the shortest, (28) which indicates that the total weight of the goods of all the shippers' points serviced by the vehicle on each route does not exceed the rated capacity of the vehicle, (29) which indicates that each shippers' point can only be serviced by a single vehicle, (30), (31) which indicates the uniqueness of the vehicle arriving at each shippers' point, (32) which indicates that the vehicle starts from the distribution center and returns to the distribution center after completing the distribution task, (33), (34) decision variables 0 and 1 constraints.

3.2. Combinatorial optimization model

Through the above analysis, the optimization mathematical model of cargo distribution and vehicle path combination is established as follows:

$$\min Z_1 = \sum_{i=0}^{L} \sum_{j=0}^{L} \sum_{k=1}^{K} d_v X_{ijk} \tag{35}$$

$$\max Z_2 = \sum_{k=1}^{K} \left(\sum_{i=1}^{t} \sum_{k=1}^{t} a_{ib} g_k y_k \Big/ \sum_{j=1}^{L} X_{ojk} G_k \right) \tag{36}$$

$$\max Z_3 = \sum_{k=1}^{K} \left(\sum_{j=1}^{L} \sum_{h=1}^{H} a_{ik} v_h y_z \Big/ \sum_{j=1}^{L} X_{okk} V_k \right) \tag{37}$$

$$S.t. \sum_{k=1}^{K} y_{ki} = 1 i = 1,2,\cdots L; \forall k \tag{38}$$

$$\sum_{j=0}^{L} X_{jjk} = y_{ki} i = 1,2,\cdots L; \forall k \tag{39}$$

$$\sum_{i=0}^{L} X_{ijk} = y_{kj} j = 1,2,\cdots L; \forall k \tag{40}$$

$$\sum_{j=0}^{L} X_{0jk} = \sum_{j=0}^{L} X_{j0k} \leq 1 \forall k \tag{41}$$

$$\sum_{j=0}^{L} X_{ijk} = \sum_{j=0}^{L} X_{jk} i = 1,2,\cdots L; \forall k \tag{42}$$

$$\sum_{i=1}^{L}\sum_{h=1}^{H} a_{ik} g_h y_{ki} \leq G_k \forall k \tag{43}$$

$$\sum_{i=1}^{L}\sum_{h=1}^{H} a_{ik} v_k y_{ki} \leq V_k \forall k \tag{44}$$

$$y_{ii} = 0 \; Or \; 1 i = 1, 2, \cdots L; \forall k \tag{45}$$

$$X_{iik} = 0 \; Or \; 1 i, j = 0, 1, \cdots L; \forall k \tag{46}$$

The description of each of the above model formulas is as follows: (35) is an objective function indicating that the total distance run by the vehicle is the shortest, (36) is an objective function indicating that the load utilization of the vehicle is maximized, (37) is an objective function indicating that the volume utilization of the vehicle is maximized, and (38) indicates that only one vehicle can come out of the distribution center for each shipper to be serviced and that each shipper can be serviced. (39) (40) denotes the uniqueness of vehicles arriving at each shipper's point, and (41) denotes that each vehicle returns to the distribution center after leaving the distribution center to perform its task. (42) ensures the symmetry of the routes, (43) loaded weight constraints, which indicate that the total mass of the loaded goods of each vehicle does not exceed the rated load of the vehicle, (44) loaded volume constraints, which indicate that the total volume of the loaded goods of each vehicle does not exceed the rated volume of the vehicle, and (45) and (46) decision scalar 0 and 1 constraints.

3.3. Combinatorial optimization model solution

3.3.1. Design of genetic algorithm elements. In this paper, according to the solution of the combined optimization model of cargo distribution and vehicle path problem needs to design the corresponding coding scheme, which consists of five parts, namely, vehicle allocation, distribution order, placement direction, placement level and evaluation parameters. Assuming that there are N shippers and a total of M pieces of goods, the 1st-Nth position in the coding scheme is the allocation of the vehicle path, the N+1-N+M position is the allocation of the loading order, the N+M+1-N+2M is the direction of the goods, the N+2M+1-N+3M is the placement of the goods in the tier, and the N+ 3M+1-N+3M+5 are the evaluation parameters, and all codes except the evaluation parameters are coded in integers.

3.3.2. Population initialization. Population initialization in the number of populations through the design, the initial solution is generated, the initial solution constitutes the initial population as the first generation of chromosomes, the initial population can usually be generated by random or some algorithms, a good initial population can effectively shorten the solution time and accelerate the convergence of the algorithm [26]. In principle, the larger the population size, the larger the number of search points of the parent, reducing the probability of falling into a local solution, but at the same time will increase the search time, the size of the population size is not currently an optimal conclusion, this paper takes the experimental method to take the value of the size of the population experiments to determine a more reasonable population size.

In order to ensure that each individual chromosome is to meet the constraints, this paper designs the initialization algorithm for generating the initial population of each chromosome, the population initialization algorithm is mainly used to allocate vehicles for each shipper to confirm the order of distribution, while meeting the various types of constraints in the model.

3.3.3. Adaptation function. The fitness value of the fitness function is the index used to evaluate the advantages and disadvantages of each chromosome scheme, this paper is a multi-objective mathematical model, the evaluation of the advantages and disadvantages of each chromosome scheme needs to be comprehensively weighed against the weights of the indicators, according to the needs of the actual problem to determine the value of each weight, to determine the fitness of each chromosome scheme by using the normalized objective function as the fitness function, to determine the fitness of each chromosome scheme, to evaluate the advantages and disadvantages of each chromosome scheme.

3.3.4. Genetic operators:

1) Selection operator. In this paper, we take the roulette selection method to select chromosomes into the next generation, the probability that a chromosome individual is selected into the next generation is:

$$P_i = F(x_i) \Big/ \sum_{i=1}^{u} F(x_i) \tag{47}$$

Where $F(x_i)$ is the fitness of chromosome individual i. It is seen that the higher the fitness, the higher the probability that the chromosome will enter the next generation. By means of roulette, it is possible to make the probability of the chromosome with excellent performance to enter the next generation higher, but it is not guaranteed that the chromosome with the best performance will be selected to enter the next generation, therefore, in this paper, at the end of each selection operation, the chromosome individual with the best performance is replaced by the chromosome individual with the worst performance, to make sure that the chromosome individual with the best performance in each generation can be retained to enter the next generation.

2) Crossover operator. The crossover methods commonly used in genetic algorithms include single-point crossover, multipoint crossover, uniform crossover, etc., in this paper, we use multipoint crossover, and at the same time, we determine the appropriate crossover probability through the experimental method to determine whether the chromosome crossover occurs or not according to the crossover probability [27].

3) Mutation operator. Mutation operation is carried out after the selection and crossover operation, which belongs to the operation of searching locally, this paper adopts the method of single-point mutation, and according to the set probability of mutation, the individual chromosomes are subjected to mutation operation.

3.3.5. Parameterization. Genetic algorithms need to set the population size, iteration number, crossover probability, mutation probability in the solution process, different parameters will have different effects on the solution of the model, this paper analyzes the parameters that are more effective for the model and algorithm solution of this paper by setting different algorithm parameters.

Some scholars believe that in this problem, it does not involve the cost problem, but the shortest distance traveled as the optimization objective (48), in this paper, the constraints remain unchanged, the optimization objective is changed to the shortest distance traveled [28].

$$M \inf = \sum_{k=1}^{K} \sum_{j=0}^{N} \sum_{i=0}^{N} x_{ijk} d_{ij} y_{ki} \tag{48}$$

In this paper, we choose the population size from 150 to 300, the number of iterations from 300 to 1,000, the crossover probability from 0.6 to 0.9, and the variance probability from 0.005 to 0.02 to vary, and solve the model's results through different combinations of parameters, and take the average of each set of parameter operations five times as the final results.

3.4. Analysis of model and algorithm effectiveness

Figure 2 shows the trend of the influence of each parameter on the results of the algorithm, and the conclusions of the analysis are as follows:

1) The number of iterations is the most influential on the solution among the four parameters, usually,

too small will lead to convergence too early and end without finding a more optimal solution, and too large will cause a waste of computing time. The number of iterations increases from 300 to 800 with a large change, and the average value of RV decreases from 1138.45 to 985.54. The number of iterations increases from 800 to 1000, and the decrease in the average value of RV slows down and reaches the optimal state, decreasing from 985.54 to 973.46, with a very small decrease.

2) The initial population size and mutation probability have the second highest degree of influence on the solution, and the trend of the influence of these two parameters on the solution is similar, respectively, when the initial population size is 250 and the mutation probability is 0.015, the average value of the RV undergoes a trend turn, and the mechanism of its influence is as follows: too large an initial population size causes the computation time to increase, and also affects the crossover operation, and too small an initial population size causes precocious maturity. Too large mutation probability will change the meaning of genetic algorithm into random search algorithm, too small mutation probability is not easy to produce new individuals.

3) The crossover probability has the smallest degree of influence on the solution, when the crossover probability increases from 0.6 to 0.8, the average value of RV decreases from 1078.76 to 915.76, and when the crossover probability continues to increase then the average value of RV rebounds, and no longer maintains the trend of searching for the best. It should be noted that too large crossover probability will bring the possibility of destruction of high fitness individual structure, and too small crossover probability will make the search process slower or even stagnant. In conclusion, the recommended values of optimization parameters are: initial population size = 200, number of iterations = 800, variation probability = 0.02, crossover probability = 0.8.

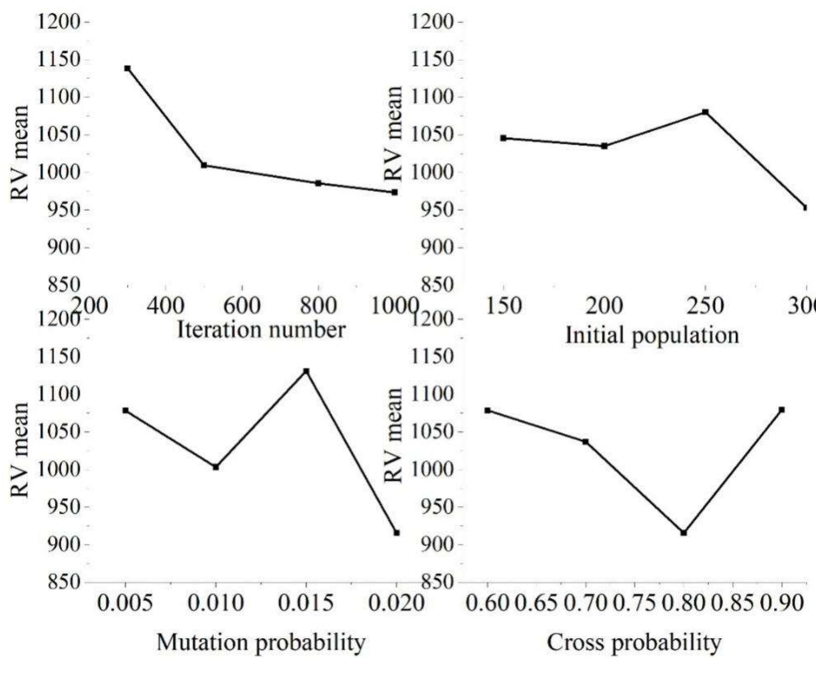

Fig. 2. The parameters are influenced by the algorithm

4. Experimentation and analysis

4.1. Analysis of path optimization effect

4.1.1. Cargo transportation time test. In order to verify the overall effectiveness of the two-stage distribution path optimization model method for regional logistics, it is necessary to conduct experimental comparative testing of the method.

The method proposed in this paper (Method 1), the distribution path optimization model and algorithm considering dynamic demand (Method 2), and the secondary distribution path optimization model and hybrid solution algorithm (Method 3) are used for the experimental test.

Firstly, the distance between vehicle distribution and distribution center is given according to the owner's demand, method 1, method 2 and method 3 are used to distribute the owner's goods respectively, and the effect of the path optimization model is verified according to the owner's satisfaction after the distribution is completed, and the specific test results are shown as follows.

Set the distribution center for 1, the number of owners for 10, distribution vehicles for 3, in the 10 owners, each owner's demand for g_i, the unit of logistics goods for T. Through the given distribution distance, the use of method 1, method 2 and method 3, respectively, the distribution of the vehicle distribution path for a reasonable arrangement, according to the distribution of the distribution of time to reflect the effect of the distribution, in order to show that the user on the distribution of different methods of distribution path arrangement of satisfaction, Figure 3 shows the degree of satisfaction, the distribution path of the user. This shows the degree of user satisfaction with the different methods of delivery path arrangement, as shown in Figure 3.

Analyzing the data in Fig. 3, it is found that the transportation distance set in this experiment is 9000km. during the test period of the three methods, the transportation time of method 1 (92.478h) is lower than that of the remaining two methods, while the transportation time of method 3 is the highest (95.136h). This shows that method 1 is more effective than method 2 and method 3 in planning transportation paths.

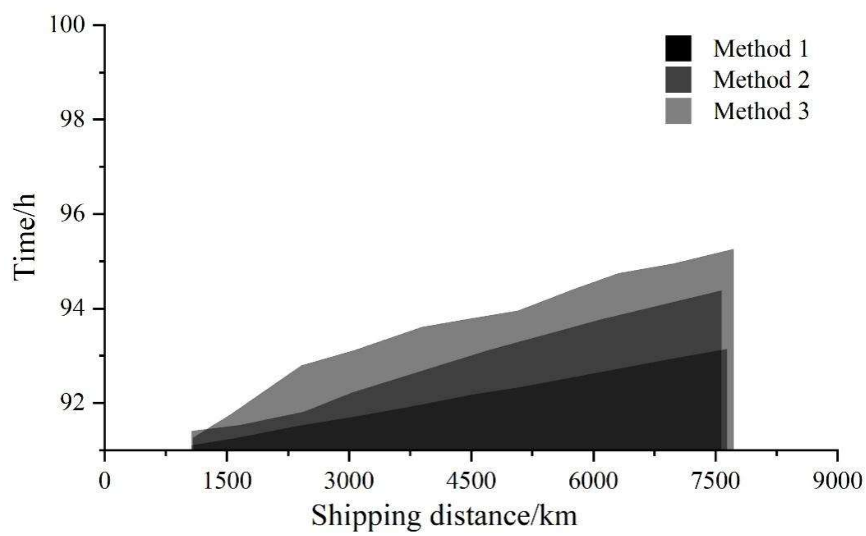

Fig. 3. Vehicle transit time test

4.1.2. User satisfaction tests. Fig. 4 shows the user satisfaction test, according to the data in Fig. 4, it is found that, because the delivery time of method 1 is the shortest, the user is most satisfied with the delivery of method 1, and with the rise of the movement trajectory of method 1, the satisfaction increases from 80.055% to 90.564%, which is higher than that of method 2 and method 3. On the contrary to method 1, the delivery time of method 3 is the longest, and so the user is least satisfied with the delivery of method 3, resulting in a downward trend of the movement trajectory of method 3. Satisfaction level is the lowest, resulting in a downward trend in the trajectory of method 3. The satisfaction is only about 40% when the transportation distance is 9000km. In summary, method 1 has the shortest delivery time and the highest user satisfaction, which is because method 1 effectively analyzes the influencing factors of the delivery transportation cost, so as to improve the delivery effect and reduce the vehicle delivery time.

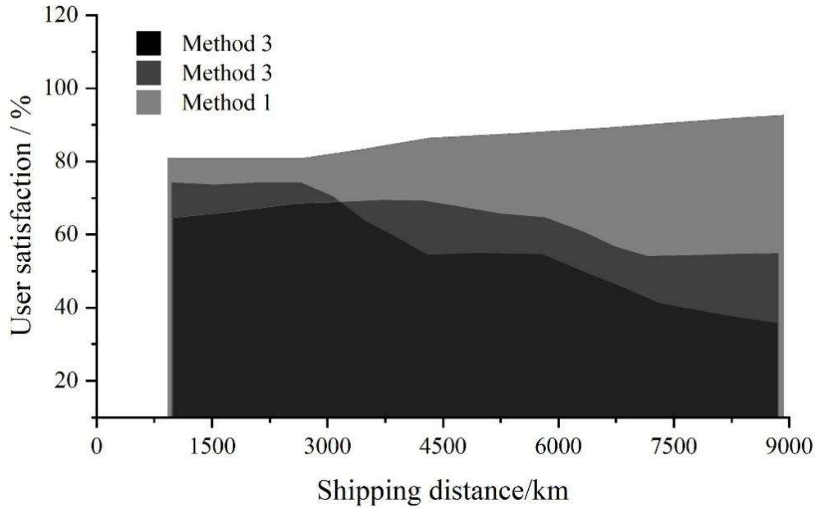

Fig. 4. User satisfaction test

4.1.3. Comparison test of the number of deliveries before and after path optimization. In order to clarify the comparison effect of the number of goods distribution before and after the optimization of the path by the method proposed in this paper, it is necessary to use the method proposed in this paper to test the number of distribution before and after the optimization of the path, and the test results are shown in Figure 5. Through the test results in Figure 5, it can be seen that before optimization, the average distribution of 5.2 times to complete the distribution of the specified goods, while the method proposed in this paper is optimized, the average only need to distribute 2.8 times to complete the distribution. It can be seen that after the optimization of the method proposed in this paper, the number of distribution is reduced, which effectively improves the efficiency of cargo transportation.

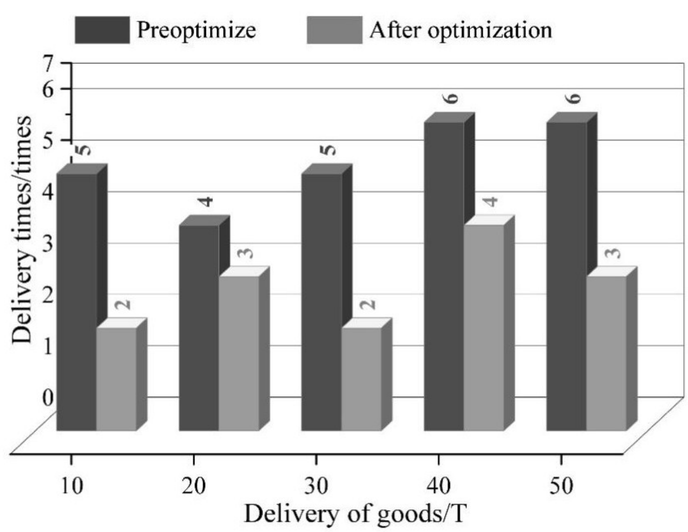

Fig. 5. The path optimization is compared with the number of distribution

4.2. Analysis of the effect of matching containers and cargoes

4.2.1. Comparison of container matching effects. In the case of locking the number of goods, charging a unit price of unchanged, the system output of the 2 car loading results, the surface of the total income or 68,985 yuan, there is no change, in fact, the effect of the optimization is still very obvious, Table 1 for the optimization of the effect of cargo before and after the loading comparison.

1) The volume full load rate of the first container is higher, the loading volume to weight ratio is closer

to the target value of 5, and the freight income of the bicycle reaches 36,485 yuan, exceeding the target value of 36,000 yuan, which is an increase of 2,987 yuan compared with before optimization.
2) The remaining available resources of the second car is more, there is still 23.489m^3 space available, it can be loaded with other goods. According to the minimum price of 168 yuan / party accounting, as long as the control in the range of 1.75T, but also can increase 23.489 * 168 $\approx$ 3946 yuan of logistics revenue, so the second car logistics income of 32500 + 3946 = 36446 yuan, also exceeded the target value of 36000 yuan.

In summary, the original actual occurrence of the 2 car revenue are not up to the standard business, due to the allocation of unreasonable, basically each car can not add new goods. After the optimization model is optimized, the load capacity ratio of the first car is more reasonable and the revenue of each car is higher. The remaining available resources of the second truck are increased so that more goods can be loaded and the revenue per truck is higher.

Table 1. Difference between before-optimization and after-optimization

Container	Preoptimize			
	Weight T	Volume m^3	Capacity ratio	Freight aggregate
Container 1	29.465	132.956	4.512	33498
Container 2	26.048	148.257	5.692	35487
Total				68985
Container	After optimization			
	Weight T	Volume m^3	Capacity ratio	Freight aggregate
Container 1	27.954	148.496	5.312	36485
Container 2	28.495	128.765	5.343	32500
Total		Increase 23.489		Increase 3946 =72931

4.2.2. Container matching response time distribution. In practical applications, a second response is required for the solution of the case matching problem. The method is applied in a real business scenario, and the response time of the experimentally selected test dataset in this distributed system is shown in Figure 6. The horizontal axis is the response time in milliseconds and the vertical axis is the number of containers. The response time scenario is plotted in the figure, where the fastest response time is only 218 milliseconds and the slowest response time is 451 milliseconds. From the figure, it can be seen that in this test dataset, the response time of the method proposed in this paper is basically within 500 milliseconds, and the number of vehicles with response time around 305 milliseconds is the highest, with 15 containers.

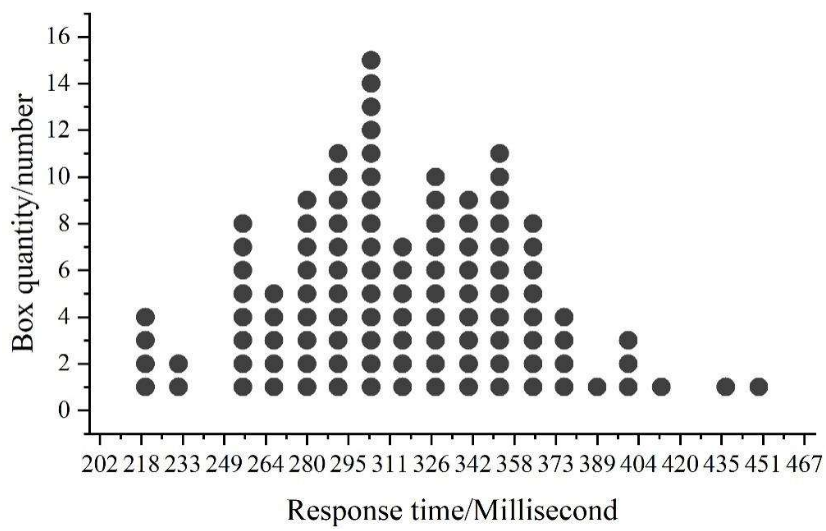

Fig. 6. Container cargo matching response time distribution

4.3. Optimal container and cargo matching and routing scheme

According to the combination of optimization model solving, get the line arrangement program as shown in Table 2, from the line arrangement program at the same time can get the corresponding cargo loading program, according to the principle of “first up and then down”, according to the various routes to visit the customer point of the reverse order of the order of the loading of goods.

Through Table 2 can get its cargo distribution and vehicle path arrangement program, distribution needs to arrange logistics vehicles 5, the average vehicle weight and average loading volume were 98.436% and 87.963%, distribution of the total mileage of 23.456km, the total cost of the regional distribution of 1246.489 yuan. If it can be expanded to optimize the distribution routes of 20 regions, then it can make the space of distribution cost reduction is very large.

From the results of the example verification, this paper establishes the optimization model and the genetic algorithm designed for the model can well solve the problem of co-optimization of the actual distribution activities of cargo loading and vehicle paths, due to the model of the vehicle mileage has a clear limit, and thus more practical for the logistics vehicle used in the example of this paper, and by converting a number of objectives with different scales into the cost of distribution, so that the cost consumption in the distribution of the true reflection of the cost of consumption. By converting multiple objectives with different scales into distribution costs, the model can truly reflect the cost consumption in distribution, which can be represented more intuitively.

Table 2. Optimal assembly and vehicle path arrangement

Cargo loading and route arrangement	Route 1	Route 2	Route 3	Route 4	Route 5
Real load(kg)	1948.596	1869.456	1926.853	1865.151	1897.156
Loading capacity(m^3)	13.078	13.298	11.269	13.156	14.165
Load utilization(%)	98.245	93.216	96.213	95.896	94.652
Capacity utilization(%)	85.265	86.752	82.278	87.952	98.264
Mileage(km)	40.854	51.889	48.269	45.986	49.563
Total mileage(km)			23.456		
Vehicle number(quantity)			5		
Average load utilization(%)			98.436		
Average capacity utilization(%)			87.963		
Assembly book(yuan)			1246.489		

5. Conclusion

In this paper, we sort out the logistics and distribution process, put forward relevant model assumptions based on the demand of shippers, and construct a two-stage container and cargo matching model. Aiming at the needs of container and cargo matching and vehicle path model, a combination optimization model is established, and a genetic algorithm is designed to solve the combination optimization model and optimize the relevant parameters. The effectiveness of the model and algorithm is analyzed through simulation experiments. At the same time, the optimization effect of the path and the matching effect of the container and cargo are analyzed respectively. In the process of increasing the iteration number of the genetic algorithm from 300 to 800, the average value of RV decreases from 1138.45 to 985.54, and reaches the optimal state when the number of times is 800, and the value of RV is 985.54.The experimental transportation distance is set to be 9000km, and the transportation time of the method in this paper is 92.478h, which is lower than that of the remaining two methods, so it can be seen that the method in this paper has a very good effect on the transportation path planning. It can be seen that the method proposed in this paper is very effective for transportation path planning. In user satisfaction, the user satisfaction of the method proposed in this paper increases with the transportation distance, from 80.055% to 90.564%, which is a high level of user satisfaction. Comparative analysis of the effect of matching containers and cargoes before and after optimization, the freight revenue of a single vehicle after optimization gets 36,485 yuan, which is 2,987 yuan more than that before optimization, and the optimization effectively improves the transportation revenue. At the same time, the response time of the container matching is basically within 500 milliseconds, which can be seen that the container matching scheme in this paper is very good effect.

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