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One-to-many vehicle-cargo matching model considering consignor satisfaction

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Abstract: With the development of the freight platform market, the problem of asymmetric information between vehicles and consignors has been effectively alleviated, and there is still room for improvement in the satisfaction of car owners and consignors, vehicle loading rate, and the cost-borne by consignor. In the context of transportation capacity supply exceeding freight demand, the satisfaction of the consignor becomes the key factor affecting vehicle-cargo matching and platform competitiveness. To make the solution of vehicle-cargo matching more desirable to the requirement of the matching party and attract more customers, a new model is proposed by considering the consignor. The two parties to the vehicle-cargo matching are regarded as the customer side and the service provider involved in logistics services according to the definition of a logistics streamline network. Considering the closeness between the consignor's requirements for cargo integrity, time and cost of transportation, and the motorists' actual service of transportation, the matching degree is defined. Then, a matching satisfaction model is constructed to maximize the matching satisfaction, and an improved genetic algorithm is designed and solved using Python. Three different models of vehicle-cargo matching are compared on the data of the platform. The result shows that the average vehicle loading rate of the proposed model is 31.2% higher than the one of the one-to-one matching model, and the cost of the consignor is 4.3% lower. Compared with the one-to-many vehicle-cargo matching model with transportation cost as the target, the average consignor satisfaction increased by 16.2%, and the cost borne by the consignor decreased by 2.9%. It reduces the total cost borne by the consignor and maintains a high consignor satisfaction and vehicle loading rate while being more in line with the actual scenario.

Keywords: logistics engineering; vehicle-cargo matching; improved genetic algorithm; consignor satisfaction; logistics streamline network

1 Introduction

There are common problems, such as insufficient information exchange and low utilization rate of transportation resources, in China's road freight market. The asymmetry problem of vehicle and cargo information has been effectively alleviated with the development of network freight platforms. However, with the increase in the number of platform sources of goods and vehicles, how to improve satisfaction in vehicle-cargo matching and vehicle full load rate has been crucial to enhancing the competitiveness of the platform. The manual screening and imperfect matching model algorithm have a low success rate, which cannot fully meet the needs of both parties and is not conducive to the low-carbon, green, and high-quality development of road transportation[1]. There is still much room for improvement in terms of the vehicle load rate and the freight cost of the cargo owner. The supply and demand matching satisfied by the owner and the owner, the high-quality service level, and the creation of value for customers is the vitality of the development of the network freight platform.

At present, the research on vehicle-cargo matching in network freight platform mainly focuses on the construction and design of vehicle-cargo matching models and algorithms. According to different matching modes, the

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relevant research on vehicle-cargo matching at home and abroad can be summarized into three categories: “one-to-one matching”, “one-to-many matching” and “many-to-many matching”[2]. For one-to-one matching, the network freight platform schedules the transportation capacity and matches the unique cargo orders and vehicles for vehicle owners and cargo owners, which is the vehicle-cargo matching mode adopted by most platforms at present. As for one-to-many matching, one vehicle matches multiple orders simultaneously, and one order can only be transported by one vehicle. The matching scheme is formed by matching the owner of one party in the matching subject with multiple consignors in the other party. Concerning many-to-many matching, one vehicle can match multiple orders, and the goods of one order can be matched with multiple vehicles. Among the three matching modes, one-to-one matching mode requires that vehicles are paired with goods one-to-one. Even if there is spare space in the vehicle, other goods cannot be loaded, resulting in problems such as low vehicle occupancy rate and poor matching results[3]. The matching result of the many-to-many matching mode includes one vehicle matching multiple vehicles and one cargo matching multiple vehicles. It is relatively simple that one cargo matches multiple vehicles. Typically, when a particular order involves a significant volume of freight, multiple vehicles need to be assigned simultaneously for transportation. By distributing the goods to enough vehicles, a high vehicle occupancy rate can be achieved. The challenge of many-to-many matching mode is essentially a one-to-many matching problem. In one-to-many matching mode, the vehicle occupancy rate can be increased by transporting goods for multiple consignors. For consignors, this mode can also reduce the payment of transportation costs and is an expected win-win matching mode[4]. Therefore, this paper studies the one-to-many matching mode to seek a reasonable matching for vehicles and cargo.

The development of the vehicle-cargo matching model primarily focused on cost in the early stages, constructing the model with minimizing cost. In the transportation of general goods on roads, transportation costs account for a high proportion of total costs. For the convenience of modeling and solving, it is usually directly targeted at minimizing transportation costs as the objective function. Lu et al. developed a vehicle transportation cost model for large-scale freight vehicles in the road network, aiming to maximize transportation cost savings[5]. Zhang Feng proposed a vehicle-cargo matching model to minimize transportation costs from the standpoint of transportation alliance[6]. Mou et al. established the matching mode with the objective function of maximizing matching efficiency while minimizing matching costs[7]. As the demand for vehicle-cargo matching increases, both parties not only consider cost factors but also have increasingly high requirements for product quality and service. Matching satisfaction has become an important factor affecting the survival and development of network freight platforms. The research on the vehicle-cargo matching model has gradually shifted towards constructing models with the objective function of maximizing satisfaction. Yang et al. considered the fairness of the vehicle-cargo matching, proposed three types of indicators, and established an optimization model maximizing the matching satisfaction of both parties[8]. Zhang et al. analyzed the transaction willingness of matching subjects, selected the indicator affecting the common willingness of both vehicle and cargo parties, and constructed a model maximizing willingness to settle[9]. Ni et al. considered the heterogeneous needs of vehicle owners, cargo owners, and platforms, and constructed a multi-objective optimization model including time-sensitive satisfaction[10]. Guo Jingni proposed a fuzzy group decision-making method to maximize the total matching satisfaction between both parties[11]. The satisfaction of both the vehicle and the goods includes cost factors, matching the willingness and needs of the main parties, which is more in line with the current reality of car-goods matching. In summary, it can be found that there are more and more optimization studies considering satisfaction. However, the quantitative factors of satisfaction are relatively single, which cannot well interpret the actual needs of customers. In this paper, the factors of transportation costs, arrival time, and the integrity of goods are comprehensively considered to ensure that the satisfaction indicator is more aligned with actual needs. Under the current situation where the supply of road freight transportation capacity exceeds the demand for freight transportation[12], it can significantly enhance the economic benefits and competitiveness of network freight transportation platforms to improve the satisfaction of shippers[13]. The vehicle-cargo matching model focused on optimizing the satisfaction of shippers is better aligned with the current supply and demand conditions in the actual road freight market.

Based on the above research, this study aims to optimize satisfaction by considering transportation costs, arrival time, and cargo damage. By combining with the streamlined supply and demand network, we build a one-to-many vehicle-cargo matching model and develop an enhanced genetic algorithm to solve it. Compared with the one-to-one matching model and the matching model aiming to minimize transportation costs, the constructed model is analyzed from the perspectives of matching satisfaction, cargo owner's cost, and vehicle load rate, which provides a reference for the research on further improving vehicle-cargo matching.

2 Vehicle-cargo matching model

2.1 Problem description and hypothesis

Assuming that the network freight platform has received n orders from shippers within a certain period, the problem aims to allocate the orders to m truck drivers within the freight platform. Each truck driver is assigned one or more shipper's orders. Each truck driver will pick up the goods and deliver them to their respective destinations.

The definition of a logistics streamline network is introduced[14]. The streamline network is a weakly connected directed graph. V_{ij} is the node at the level i and layer j in the streamline network. The matching process involves one-to-many vehicle-cargo matching, where a vehicle may match with one or more cargo owners' goods. Upon being matched with the corresponding goods, the vehicle will go to the respective goods pick-up points based on the optimal matching solution. Once the goods have been picked up, the vehicle will transport them to the corresponding delivery points. The solid line indicates the flow lines between adjacent nodes, while the dashed line indicates potential flow lines between adjacent nodes. The streamline network of one-to-many vehicle-cargo matching transportation activities is depicted in Figure 1.

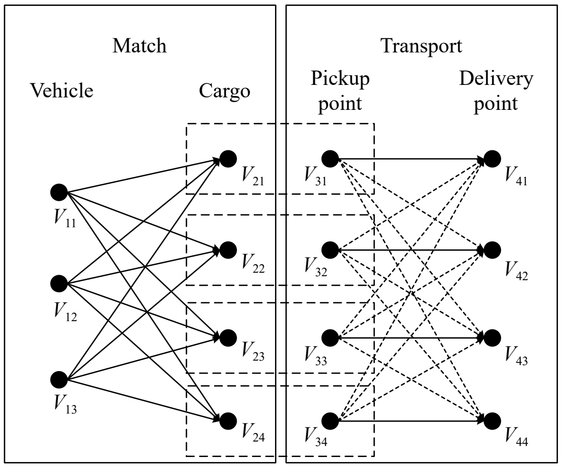

Fig. 1 The streamline network for vehicle cargo matching transportation activities of one to many

When the vehicle is overloaded with goods mid-journey, it can easily cause damage to the cargo and take an excessive amount of time, affecting the subsequent delivery time. The alteration of transportation routes will also increase transportation costs. When matching vehicles with cargo, ensure a vehicle is loaded with goods from no more than three different shippers. Therefore, it is assumed that a vehicle must load goods from no more than three consignors.

The hypotheses of this paper are as follows:

(1) Each vehicle can be matched with goods from up to three orders.

(2) Each order should be matched.

(3) It is assumed that the volume of goods carried by the vehicle does not exceed the maximum capacity.

(4) The loading and unloading time and cost of trucks at each pickup and delivery point are not considered.

(5) The truck maintains a relatively stable average speed during each trip.

(6) The average fuel consumption level of the truck remains consistent during transportation.

2.2 Model parameter description

The descriptions of the symbols required for model construction are shown in Table 1.

2.3 Owner matching satisfaction formula definition

The degree of similarity between the characteristics of logistics organization schemes in terms of item quantity, logistics service time, and logistics costs, and the customer's requirements in terms of item quantity, service time, and logistics costs, between any two adjacent layers of nodes in a streamlined network structure, is referred to as the matching degree[14]. The essence of logistics activities is that logistics services meet logistics needs. In this paper, both parties involved in the vehicle-cargo matching are considered as customers and service

Table 1 Description of model parameters

Symbol	Description	Symbol	Description
t	The actual time spent on transportation services	ρ_j	Expected damage factor of goods j
q	Integrity of goods during the actual transportation	α_j	The maximum damage coefficient of the goods j
e	The cost that the customer needs to pay during the actual transportation process	c_i	Unit freight for the vehicle i
T	Customer's expected shipping service time	Q_i	The rated load of the vehicle i
Q	Customer's expected integrity of goods during transportation	V	The average speed of the vehicle transport process
E	Customer's expected transportation costs	L_j	The distance the goods $j$are transported
$T^\wedge$	The customer can receive the latest time for the delivery to be completed	$\underset{V_{1,j}\to V_{2,j}}{M}(t,q,e)$	The matching degree between the actual freight plan between the point $V_{1,j}$and $V_{2,j}$is the matching satisfaction degree of the cargo owner
$Q^\wedge$	Minimum goods integrity acceptable to the customer during transportation	$F(\cdot)$	Generalized cost function
$E^\wedge$	The maximum shipping cost acceptable to the customer	$f_1(t)$	The owner's actual cost of lost time
m	Total number of vehicles (owners)	$f_1(T)$	Shipper's expected cost of lost time
n	Total number of goods (owners)	$f_1(T^\wedge)$	The maximum time loss cost acceptable to the cargo owner
i	Any vehicle,$i=1,2,3,\cdots,m$	$f_2(q)$	Owner's actual damage cost
j	Any cargo,$j=1,2,3,\cdots,n$	$f_2(Q)$	Owner's expected damage cost
K	The type of goods,$K=1,2,3,4$	$f_2(Q^\wedge)$	The maximum damage cost acceptable to the cargo owner
P	Collection of cargo points (one cargo corresponds to a pick-up point and a delivery point)	$f_3(e)$	The owner's actual transportation cost
d_{ab}	The shortest distance between $a$and b,$a,b\in P$	$f_3(E)$	Shipper's expected transportation cost
$(d_{ab})_1$	The maximum distance between $a$and $b$acceptable to the owner	$f_3(E^\wedge)$	The maximum transportation cost acceptable to the cargo owner
J_1,J_2	Pick-up and delivery points for goods j,$J_1,J_2\in P$	A_K	The moment when Class Kgoods begin to deteriorate
$\left[T_{j1},T_{j2}\right]$	Time window for delivery of goods j	β_j	The latest tolerance factor of the owner for goods j
t_j	Actual delivery time of the goods j	B_K	The moment when Class Kgoods deteriorate to the point where they lose value
β_j	Latest time tolerance factor of goods j	θ_t^K	Rate of deterioration of Class Kgoods at time t,$t\in[A_k,B_K]$
W_j	The penalty cost per unit time of the owner when the goods j arrive late	ρ_j	Owner's expected damage factor for goods j
q_j	The total weight of the goods j	α_j	owner's maximum damage tolerance for the goods j
p_K	Unit price of goods type K	o	The point of departure of any vehicle
θ_t^K	Rate of deterioration of type Kgoods at time t	x_{ij}	A decision variable that means 1 if the vehicle i is matched to the cargo j, 0 if not.

providers participating in logistics services. Since the quantity of goods transported in transportation services is a fixed value, the degree of similarity between supply and demand for item quantity is equivalent to the degree of similarity between supply and demand for goods integrity. The matching satisfaction of the cargo owner[15] can be defined as the degree of closeness between the characteristics of the vehicle transportation plan of the owner's vehicle in terms of cargo integrity, transportation time, and transportation costs, and the owner's requirements for cargo integrity, transportation time, and transportation costs. Its function expression is

$$\underset{V_{1,j}\to V_{2,j}}{M}(t,q,e)=\begin{cases}1, & F(t,q,e)\in(0,F(T,Q,E)]\\ \left[\dfrac{F(t,q,e)-F(T^{\wedge},Q^{\wedge},E^{\wedge})}{F(T,Q,E)-F(T^{\wedge},Q^{\wedge},E^{\wedge})}\right]^2, & F(t,q,e)\in(F(T,Q,E),F(T^{\wedge},Q^{\wedge},E^{\wedge})]\\ 0, & F(t,q,e)\in(F(T^{\wedge},Q^{\wedge},E^{\wedge}),\infty]\end{cases}, \tag{1}$$

where, $F(\cdot)$ is a generalized cost function, aiming is unify the units of time, goods integrity, and cost in different dimensions into cost units. The generalized cost function is calculated according to Equation (2)[16].

$$F(t,q,e)=f_1(t)+f_2(q)+f_3(e) \tag{2}$$

where, $F(t,q,e)$ is the cost to be borne by the cargo owner in the actual freight plan provided according to the needs of the cargo owner; $F(T,Q,E)$ is the shipper's expected cost of transport services in terms of time, goods integrity, and expenses; $F(T^{\wedge},Q^{\wedge},E^{\wedge})$ is the maximum cost of transportation services acceptable to the cargo owner.

(1) To calculate the cost of time loss, the soft time window is used to quantify the time cost [17]. The goods of order j are delivered within the time window $\left[T_{j1},T_{j2}\right]$. If goods are delivered earlier than time T_{j1}, the vehicle owner must wait until time T_{j1}, which has no impact on the cargo owner. If goods are delivered later than time T_{j2}, the time penalty cost to the cargo owner will incur. The time penalty cost is calculated as

$$f_1(t)=\begin{cases}0 & t_j<T_{j2}\\ W_j(t_j-T_{j2}) & t_j>T_{j2}\end{cases}. \tag{3}$$

For the owner, the expected situation is that the goods will arrive on time within a certain time range without incurring time delay costs as shown in Equation (4). The time requirement of the cargo owner is a range, but the actual owner may not be able to deliver to the designated location within the specified time. If the goods are delivered later than time T_{j2}, the cargo owner will pay the time penalty cost. A coefficient β_j called the latest time tolerance is defined and depends on the urgency of the owner's demand. The acceptable time range for the shipper is a range, so the fluctuation range of the value of the latest time tolerance coefficient will not be very large. There are different values for different customer coefficients, so it is necessary to determine the analysis based on analyzing a large amount of data. The maximum time cost acceptable to the owner is calculated as shown in Equation (5).

$$f_1(T^{\wedge})=P_j(T_{j2}\beta_j-T_{j2}), \tag{4}$$

$$f_1(T^{\wedge})=W_j(T_{j2}\beta_j-T_{j2}). \tag{5}$$

(2) Osval et al. pointed out that perishable goods have three stages in their life cycle, and perishable goods will continue to rot over time[18]. The relationship between the rate of goods deterioration and the time of such logistics products is shown in Figure 2, showing a linear distribution. $t\in[0, A]$ is the first stage, the quality of the goods is intact, and the deterioration rate of the goods is 0. $t\in(A,B]$ is the second stage, the quality of goods changes visibly, the deterioration rate of goods develops linearly, and the deterioration rate is $\theta_t=\dfrac{t-A}{B-A}$. $t\in[B, +\infty]$ is the third stage, in which the deterioration of goods is very serious, the deterioration rate of goods is beyond the acceptable range, and the goods lose value.

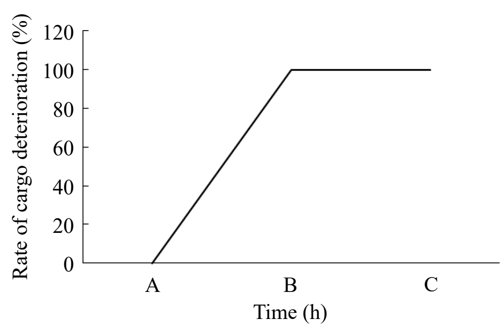

Fig. 2 Change in deterioration rate of cargo over time

The formula for calculating the actual cargo damage cost is:

$$f_2(q)=\begin{cases}0 & t\in[0,A_K]\\ q_j p_k\theta_t^K & t\in[A_K,B_K]\\ +\infty & t\in[B_K,+\infty]\end{cases}. \tag{6}$$

The loss of goods is determined by the nature of the goods themselves, which is unavoidable. However, the owner's expected damage is as little as possible, so a coefficient $\rho_j(0<\rho_j<1)$ is introduced to represent the owner's expected damage, as shown in Equation (7). The cargo owner has a maximum cargo damage tolerance for the goods, which is defined as α_j. The maximum cargo damage cost acceptable to the cargo owner is shown in Equation (8).

(3) For transportation cost calculation, point o is the starting point of any vehicle; $\left(d_{oJ_1}\right)_1$ represents the maximum distance of the truck to the pick-up point J_1 acceptable to the cargo owner, where $d_{oJ_1} < \left(d_{oJ_1}\right)_1$, $\left(d_{oJ_1}\right)_1$ is determined according to the requirements of different cargo owners. When the vehicle owner transports the goods from multiple cargo owners, the cargo owners share the transportation costs. The costs borne by each cargo owner include the costs of the vehicle from the vehicle starting point to the pick-up point and the costs of the vehicle from the transit point to the delivery point of the goods. d_{aJ_2} represents the actual distance between the previous node visited by the vehicle and the current destination of the goods. $d_{J_1J_2}$ represents the shortest distance of the owner's goods from the place of origin to the destination. $\left(d_{J_1J_2}\right)_1$ represents the maximum distance acceptable for cargo transport by the owner, where $d_{J_1J_2} < \left(d_{J_1J_2}\right)_1$.

$$f_2(Q) = \begin{cases} 0 & T \in [0, A_K] \\ \rho_j q_j p_k \theta_T^K & T \in [A_K, B_K] \end{cases}, \tag{7}$$

$$f_2(Q^\wedge) = \begin{cases} 0 & T \in [0, A_K] \\ \alpha_j q_j p_k \theta_T^K & T \in [A_K, B_K] \end{cases}, \tag{8}$$

$$f_3(e) = d_{oJ_1} c_i + d_{aJ_2} c_i, \tag{9}$$

$$f_3(E) = d_{J_1J_2} c_i, \tag{10}$$

$$f_3(E^\wedge) = (d_{oJ_1})_1 c_i + (d_{J_1J_2})_1 c_i. \tag{11}$$

2.4 Model building

Since the cargo owner is concerned about the benefit goal from the individual perspective, the average of the overall matching satisfaction is calculated to reflect the matching effect more intuitively. The objective function is to maximize the average matching satisfaction. A MILP formulation of the proposed problem is presented as follows

$$\max Z = \sum_{i=1}^{m} \sum_{j=1}^{n} M_{V_{1,i} \to V_{2,j}}(t, q, e) x_{ij} \Big/ n, \tag{12}$$

s.t.

$$\sum_{i=1}^{m} x_{ij} = 1, \quad j = 1, 2, \cdots, n, \tag{13}$$

$$\sum_{j=1}^{n} x_{ij} \leqslant 3, \quad i = 1, 2, \cdots, m, \tag{14}$$

$$\sum_{j=1}^{n} x_{ij} q_j \leqslant Q_i, \quad i = 1, 2, \cdots, m, \tag{15}$$

$$t_j \leqslant T_j^\wedge, \quad j = 1, 2, \cdots, n. \tag{16}$$

Equation (13) ensure that each goods must be transported and can only be transported by one vehicle. Equation (14) guarantee that each truck delivers the goods of up to 3 owners. Equation (15) ensure the feasibility of loads. Equation (16) ensure that the vehicle needs to complete the delivery of the goods before the latest delivery time specified.

In the case of one-to-one matching mode, the Equation (14) are $\sum_{j=1}^{n} x_{ij} = 1, i = 1, 2, \cdots, m$.

3 Improved genetic algorithm based on vehicle-cargo matching

3.1 Algorithm selection

At present, there are many intelligent optimization algorithms to solve complex optimization problems, such as particle swarm optimization, ant colony optimization, simulated annealing algorithm, and genetic algorithm. The particle swarm optimization and ant colony optimization are suitable for path optimization[19-20]. The simulated annealing algorithm is more suitable for combining with other algorithms due to its slow convergence [21]. The genetic algorithm with fast convergence rates is relatively successful in solving optimization problems [22]. The proposed vehicle-cargo matching problem aims to find the matching scheme to maximize the average matching degree. An improved genetic algorithm is developed to solve it.

3.2 Algorithmic flow design

In general, the work flow of genetic algorithms is shown in Figure 3.

3.3 Algorithm implementation

3.3.1 Chromosome coding

Generally speaking, the coding method of the algorithm should be determined according to the actual situation of the problem, and the natural number coding

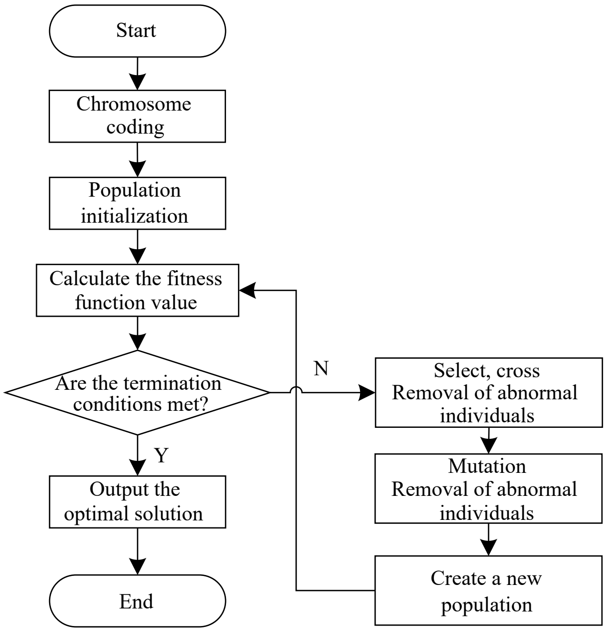

Fig. 3 Genetic algorithm flowchart

method is adopted in this paper. There are n goods and m vehicles participating in the matching. In coding, a natural number string containing n different numbers in the range of $[1,n]$ is randomly generated, and then $m-1$ separators are randomly inserted into the string. The string is divided into m segments, and each vehicle is responsible for the transport of one segment of the goods. There is no cargo in the middle between two adjacent separators, which indicates that the vehicle responsible for this section is idle.

For example, given that there are 10 cargo and 6 vehicles to be matched, an individual can be obtained from the initial population, as shown in Figure 4.

3.3.2 Population initialization

Different from the general situation of population initialization, this paper needs to pay attention to whether

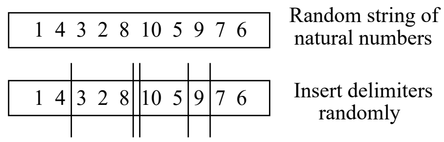

Fig. 4 Encoding renderings

the vehicle can carry the matched total weight of cargo, and whether each truck can match the cargo of three owners at most. Therefore, the above two constraints are taken into account when randomly inserting splitters, which improves the efficiency of the algorithm.

3.3.3 Cross operator improvement

Different from the common cross-operation mode of genetic algorithm, the vehicle-cargo matching problem seeks to find the optimal match between different vehicles and goods. The general cross mode does not include the problem of transport order, so the partial matching cross mode is selected [23]. Partial matching crossover ensures that the genes in each chromosome appear only once, and no duplicate genes appear in each chromosome. Partial matching intersections are described in detail below.

In order to eliminate the duplication, the matching relationship of each chromosome is established in the crossing region, and then the matching relationship is applied to the repeating genes outside the crossing region to eliminate the conflict.

Step 1: As shown in Figure 5(a), several consecutive genes in the same position in the two parent chromosomes were randomly selected.

Step 2: Exchange the selected genes of the two sets of chromosomes, as shown in Figure 5(b).

Step 3: Establish a mapping relationship according to the two groups of genes exchanged, as shown in

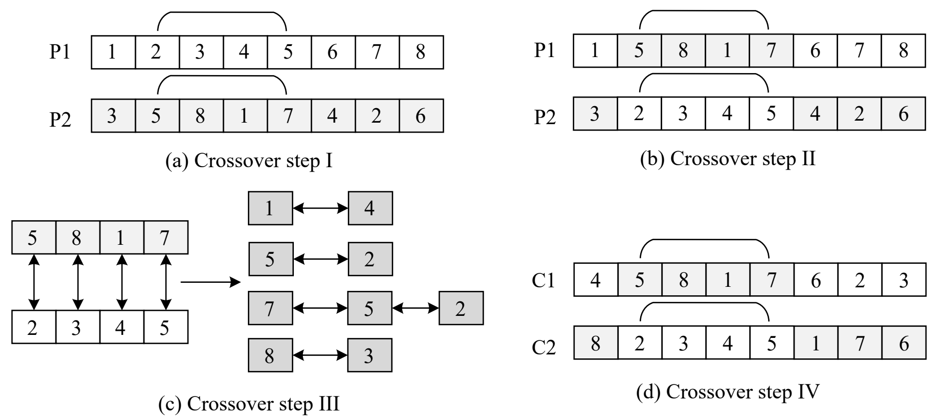

Fig. 5 Cross process

Figure 5(c).

Step 4: Perform conflict detection and repeat mapping until there is no conflict. According to the mapping relationship, the conflicting genes of the two parent chromosomes that are not exchanged are replaced. Finally, all the conflicting genes will be mapped to ensure that the new pair of offspring genes formed are conflict-free. The resulting offspring chromosomes are shown in Figure 5(d).

3.3.4 Mutation operator improvement

Due to the need to consider the order of pick-up and delivery points when matching vehicles and goods, the general variation method can not guarantee the sequence of owners through the cargo node, so the improved variation operation is adopted. A segment of a gene separated by a separator is randomly selected and the sequence of gene segments is mutated. The mutation process is shown in Figure 6.

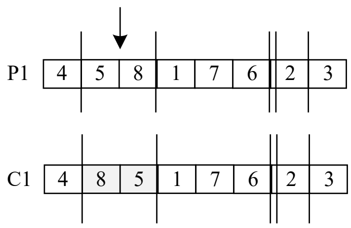

Fig. 6 Mutation process

3.3.5 Selection operator based on elite reservation

In addition to the roulette strategy, the algorithm uses the elite retention strategy. By retaining a certain amount of excellent individuals from the parent group, the algorithm further iteratively optimizes the total population with other newborn offspring individuals.

4 Computational experiments

4.1 Benchmark instances

The data in this paper was obtained from an online freight platform on the domestic Internet, including cargo weight, starting point, destination, route length, cargo type, and so on. The data of long-distance transportation goods originating within Shaanxi Province is selected and preprocessed to obtain the data with high integrity. match the transportation distance with different types of goods to generate the time requirements of the owners. Based on the transportation distance and different types of goods, the time requirements for the owner of the goods are generated. For perishable fruits and vegetables, the time requirements for the owner are more strict, while for other goods that are not easily perishable, the time requirements are relatively less strict. In the test instance, the average speed of the vehicle is taken as 55 km/h. To ensure the randomness of the time requirements, a random number is taken from the interval [0.9−1.1]. The ratio of distance to average speed multiplied by this random number is the time requirement for the owner of the goods. When the goods are fruits or vegetables, the time requirements are strict and calculated according to the above interval; when the goods are livestock products, the interval is multiplied by a factor of 1.05; for other types of goods, the factor is 1.1. The information generated is shown in Table 2.

In this case, the starting point of goods is all around Xi'an, and the study is on long-distance transportation between cities or provinces. In solving the problem, the starting point of goods is simplified to the same point.

4.2 Result analysis

In the calculation example, a truck with a rated load of 28 tons of 9.6 meters and a truck with a rated load of 35 tons of 14−17 meters are used for transportation. The truck uses No. 0 diesel and the price is 7.62 yuan/liter. The fuel consumption of 28 tons of truck No. 0 diesel is 0.2 liters/km, and the fuel consumption of 35 tons of large truck diesel is 0.3 liters/km. The case uses 30 batches of cargo data, and a total of 30 trucks with a load capacity of 28 tons (No. 1-15) and 35 tons (No. 16-30) are analyzed and calculated.

4.2.1 Basic result analysis

Aiming at the vehicle and cargo matching model constructed above, the improved genetic algorithm is applied to solve the problem with the goal of the highest matching satisfaction of the cargo owner. The convergence process of the algorithm is shown in Figure 7.

In this case, 30 vehicles were used to transport 30 batches of goods. In the obtained results, only 23 vehicles were used in the cargo matching process, and 7 vehicles were idle. The transportation cost of the owner was CNY32 835.75, the cargo damage cost was CNY6 808.46, the time cost was CNY2 245.95, and the total cost borne by the owner was CNY41 890.16. The average satisfaction of matching between the shipper's demand and the actual delivery is 0.889, and the total cost is CNY41 890.16.

Table 2 Information about the consignor's order

Consignor	Type of goods	Weight (t)	Terminal position	Distance (km)	Time requirement (h)
1	other	16	(130.372 612, 46.813 512)	2 269.21	41.77
2	vegetable	10	(107.244 575, 34.368 916)	156.41	2.83
3	fruit	15	(104.966 864, 33.376 032)	383.39	6.59
4	vegetable	16	(107.657 391, 35.736 864)	194.24	3.33
5	fruit	17	(108.671 612, 31.953 391)	267.71	4.70
6	vegetable	16	(112.182 456, 37.195 601)	431.16	7.37
7	other	17	(101.809 569, 36.605 708)	693.87	12.15
8	Animal product	10	(110.050 395, 40.582 228)	700.86	11.91
9	fruit	8	(106.681 415, 35.548 815)	246.16	4.40
10	Animal product	15	(113.837 541, 34.053 251)	451.45	8.02
11	vegetable	16	(106.356 518, 38.560 407)	523.13	9.07
12	vegetable	14	(111.480 398, 33.313 316)	261.04	4.60
13	vegetable	14	(114.654 576, 37.905 816)	648.1	11.27
14	other	10	(116.872 433, 38.320 367)	836.64	14.61
15	Animal product	17	(107.776 097, 30.660 553)	424.84	7.34
16	vegetable	12	(106.295 494, 38.479 579)	517.62	9.10
17	fruit	14	(104.119 566, 35.848 851)	470.25	8.45
18	Animal product	13	(111.231 406, 35.622 63)	252.14	4.43
19	vegetable	18	(111.676 607, 35.303 015)	271.2	4.89
20	fruit	12	(101.809 569, 36.605 708)	693.87	12.30
21	fruit	16	(110.688 546, 36.103 999)	251.66	4.43
22	Animal product	15	(123.426 644, 41.795 236)	1 512.58	27.56
23	vegetable	16	(111.773 58, 30.175 342)	535.18	9.54
24	Animal product	11	(115.567 392, 29.850 441)	799.9	13.92
25	Animal product	21	(98.514 322, 39.751 246)	1 103.77	19.87
26	vegetable	15	(105.650 555, 36.570 781)	387.99	6.59
27	Animal product	15	(113.982 485, 34.725 011)	463.66	8.27
28	vegetable	15	(104.626 438, 28.772 052)	743.48	13.13
29	Animal product	16	(120.856 417, 37.341 418)	1 124.25	19.63
30	other	13	(98.226 473, 39.806 466)	1 128.23	20.21

4.2.2 Comparative analysis

(1) Model comparison

Hereby, we studied the computational performance of the proposed vehicle-cargo matching model compared with the current road freight transport model with the minimum transportation cost[24] and the "one-to-one matching" model adopted by most platforms. Matching satisfaction, cost, and load factor are the factors related to the improvement of the competitiveness of the current network freight platform. Various cost data can reflect the impact of each model on the cost, and the number of vehicles required can directly reflect the saving of trans-

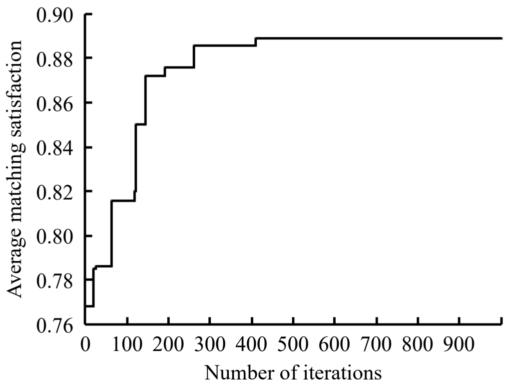

Fig. 7 Improved genetic algorithm convergence process

port capacity. Based on the data in Table 2, the results are respectively shown in Table 3, Figure 8, and Figure 9.

From Table 3, Figure 8, and Figure 9, we can see that compared with the matching model with the minimum transportation cost, the matching satisfaction of the cargo owner is increased by 16.2%. The cargo damage cost and time cost are controlled, and the total cost borne by the cargo owner is reduced by 2.9%. Compared with the matching model with the minimum transportation cost, the matching satisfaction of the "one-to-one" matching model is increased by 21.9% when the vehicle capacity is increased by 36.3%, while the matching satisfaction of the proposed model is increased by 16.2% when the transport capacity is increased by only 4.5%. The performance of improving satisfaction is better than that of one-to-one matching. The total cost borne by shippers is decreased by 4.3% and the average load rate is increased by 31.2%. The one-to-many matching model with the greatest owner matching satisfaction can improve load rate and reduce cost while maintaining high owner satisfaction.

Table 3 Model comparison results

Matching Contrast model index	One to many matching with maximum satisfaction of cargo owner	Minimizing transportation costs is the goal of one-to-many matching	One to one match with maximum satisfaction from cargo owners
Average matching satisfaction	0.889	0.765	0.933
Transportation cost (CNY)	32 835.75	28 721.22	38 812.73
Damage cost (CNY)	6 808.46	7 224.79	4 846.04
Time cost (CNY)	2 245.95	7 213.43	97.57
Total cost (CNY)	41 890.16	43 159.44	43 756.34
Average load factor	0.601	0.612	0.458
Match the desired truck (veh)	23	22	30

Compared with the "one-to-one" matching model, the biggest advantage of this model is that the load rate is increased by 31.2%, the transport capacity is saved by 23.3% and the total cost is 4.3%, which means that the vehicle owners will get more benefits. The benefits are mainly attributed to the 15.4% savings in transportation costs. However, the cargo damage cost and time cost increased by 40.5% and 225.0%, respectively. The "one-to-

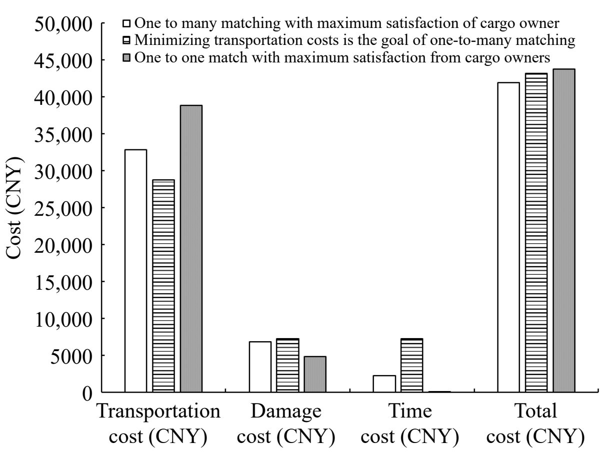

Fig. 8 Cost comparison

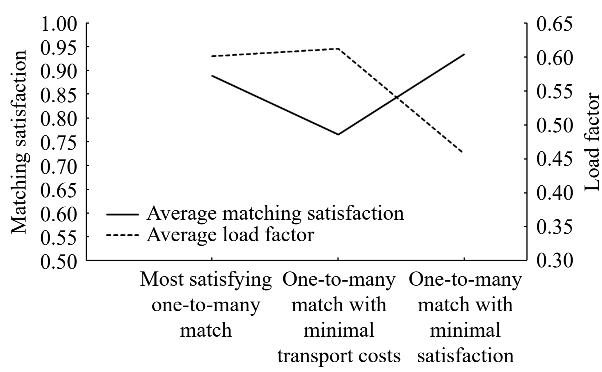

Fig. 9 Comparison of satisfaction and loading rate

many" vehicle and cargo matching model is more suitable for the vehicle owner.

(2) Algorithm comparison

To evaluate the performance of the improved genetic algorithm, the results obtained by this algorithm were compared with those obtained by the standard genetic algorithm[25]. In this comparative experiment, the parameters of the standard genetic algorithm, such as population number, chromosome number, and mutation probability, were the same as those of the improved genetic algorithm. The number of iterations was set to 3 000 times, and the algorithms ran independently 10 times. The comparison results are shown in Figure 10. The average convergence iteration times of the improved genetic algorithm is about 500 times, the average convergence time is 34 s. The optimal matching satisfaction is 0.889, and the accuracy is 90%. The average convergence iteration times of the standard genetic algorithm is about 2 400 times. The average convergence time is 195 s, and the optimal satisfaction is 0.889 and 80%, respectively. Therefore, it can be found that the improved genetic algorithm has better-solving efficiency, and the situation that the standard genetic algorithm easily falls into local optimality has been improved.

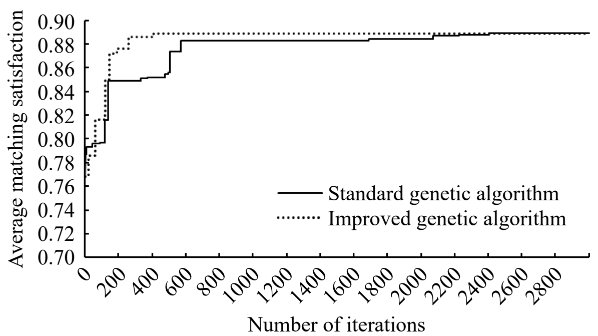

Fig. 10 Comparison of algorithm solutions

(3) Model applicability analysis

The one-to-many truck-cargo matching model considering the satisfaction of cargo owners is proposed based on the background that the supply of freight transportation capacity exceeds the demand for cargo freight. The satisfaction of cargo owners can have a greater impact on the realization of vehicle-cargo matching. The vehicle-cargo matching problem with satisfaction is more in line with the current supply and demand in the road freight market. However, in reality, there will also be a shortage of transport capacity in a specific period where the impact of freight owners' satisfaction degree on the matching of vehicles and cargo will be reduced. To adapt to this special situation, the expected time delay cost, freight damage cost, and transportation cost of freight owners in model (1) should be increased accordingly to ensure the applicability of the model under the situation of insufficient transport capacity.

5 Conclusions

The vehicle-cargo matching problem studied in this paper aims at the long-distance transport scenario of multi-variety goods in road freight transport. The problem is prioritized with the consignor's satisfaction and takes into account the costs associated with the categories of goods. The one-to-many vehicle-cargo matching model is established. The model is in line with the current supply and demand situation of the freight market and improves the load rate of highway freight vehicles.

This research has developed a "one-to-many" vehicle-cargo matching model aimed at maximizing the satisfaction of cargo owners and taking into account factors such as transportation time, cost, and cargo damage. The model is verified through case study analysis based on freight data from a network freight platform. The one-to-one vehicle-cargo matching model achieves high satisfaction for cargo owners and reduces time and damage costs, but suffers from low load rates and a certain degree of waste in transportation capacity, which leads to higher transportation and total costs. In contrast, the proposed one-to-many matching model without significantly compromising the satisfaction level compared to the one-to-one model reduces the number of vehicles required and the total cost borne by the cargo owners, which is more aligned with the actual matching needs.

In the proposed model, the starting point of every vehicle is set to the same starting point, and the time and cost of loading and unloading goods is considered. In future research, dynamic location information of vehicles and cargoes and loading and unloading costs can be considered, which improves the vehicle-cargo matching and is aligned with real-world needs.

Declaration of competing interest

The authors have no competing interests to declare thatare relevant to the content of this article.

References

[1] Jia, Y.L., Yang, X.L., Liu, M. Vehicle-cargo matching of carrier broker based on customer's green preference[J]. Journal of Transportation Engineering and Information, 2019, 17(4): 141–148.

[2] Fu, Y. An improved ant colony algorithm for vehicle and cargo matching of freight logisties platform[D]. Hefei: Hefei University of Technology, 2020.

[3] Huang, Z.B. Research on matching strategy and path optimization ofnetwork freight platform based on spatial feature analysis[D]. Xi'an: Chang'an University, 2022.

[4] Wang, Z.H., Li, Y.Y., Gu, F., et al. Two-sided matching and strategic selection on freight resource sharing platforms[J]. Physica A: Statistical Mechanics and its Applications, 2020, 559.

[5] Lu, Z.B., Tian, K.J., Fang, M.X., et al. Cooperative scheduling and speed planning of vehicles on highways based on transportation cost[J]. Control and Decision, 2023, 38(6): 1637–1645.

[6] Zhang, F. Research on vehicle freight matching and cost allocation based on shipper alliance[D]. Chongqing: Chongqing Jiaotong University, 2021.

[7] Mou, X.W., Chen, Y., Gao, S.J., et al. Vehicleand Cargo Matching Method Based on Improved Quantum Evolutionary Algorithm[J]. Chinese Journal of Management Science, 2016, 24(12): 166–176.

[8] Yang, B.Z., Ye, X.Y., Wang, R., et al. Method of vehicle-cargo matching considering fairness based on intuitionistic fuzzy optimization[J]. Computer Integrated Manufacturing Systems, 2023, 29(5): 1696–1707.

[9] Zhang, H.F. Research on vehicle and cargo matching model based on transaction intention of both parties[D]. Xi'an: Xidian University, 2018.

[10] Ni, S.Q., Luo, X., Xiao, B. Optimization of vehicle-cargo matching regarding interests of three parties[J]. Journal of Southwest Jiaotong University, 2023, 58(1): 48–57.

[11] Guo, J.N. Vehicle-cargo matching using a fuzzy group decision-making approach[J]. Journal of Transportation Engineering and Information, 2017, 15(4): 141–146.

[12] Ye, Z. Research on one to multiple vehicle cargo matching based on credit evaluation system[D]. Chengdu: Southwest Jiaotong University, 2021.

[13] Wang, Y.X. Research on lmproving E-Commerce Customer Satisfaction Based on Logistics Optimization[J]. Logistics Sci-Tech, 2023, 46(18): 76–79.

[14] Zhang, J., Wang, K. Stream line optimization model with matching degree between logistics supply and demand as objective function[J]. Journal of Southwest Jiaotong University, 2010, 45(2): 324–330.

[15] Bai, J.R., So, C.K., Tang, S.C., et al. Coordinating supply and demand on an on-demand service platform with impatient customers.[J]. Manufacturing & Service Operations Management, 2019, 21(3): 556–570.

[16] Wang, J. Research on model and algorithm of highway freight vehicle-cargo matching optimization[D]. Xi'an: Chang'an University, 2020.

[17] Vidal, T., Crainic, G.T., Gendreau, M., et al. A hybrid genetic algorithm with adaptive diversity management for a large class of vehicle routing problems with time-windows[J]. Computers and Operations Research, 2013, 40(1): 475–489.

[18] Osvald, A., Stirn, Z.L. A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food[J]. Journal of Food Engineering, 2007, 85(2): 285–295.

[19] Ling, H.F., Fu, Y., Hua, M., et al. An adaptive parameter controlled ant colony optimization approach for peer-to-peer vehicle and cargo matching[J]. IEEE ACCESS, 2021, 9: 15764–15777.

[20] Chen, Z.X., Yan, H.W., Zhang, X.Y., et al. Vehicle routing optimization under B2B urban distribution mode based on improved ant colony algorithm[J]. Journal of Highway and Transportation Research and Development, 2023, 40(7): 231–238.

[21] Tang, Y., Xu, R., Huang, K.D., et al. Optimization of multi-temperature co-distribution vehicle route based on temperature zone refining[J]. Journal of Highway and Transportation Research and Development, 2021, 38(3): 136–143.

[22] Guan, D.Y., Wu, X.F., Zhao, J., et al. Dispatch and route optimization of demand-responsive bus[J]. Journal of Highway and Transportation Research and Development, 2022, 39(5): 140–148.

[23] Chan, K.C, Tansri, H. A study of genetic crossover operations on the facilities layout problem[J]. Computers & Industrial Engineering, 1994, 26(3): 537–550

[24] Wang, Y., Huang, Q.B., Liu, Y., et al. Study on vehicle routing problem with mixed time windows based on importance of customers[J]. Journal of Highway and Transportation Research and Development, 2019, 36(11): 151–158.

[25] Miao, X.H., Zhou, X.N., Lin, S., et al. Study on routing optimization for cold-chain logistics distribution of 3PL[J]. Operations Research and Management Science, 2011, 20(4): 32–38.