The finished vehicle routing problem with a heterogeneous transport fleet

Jiansheng Liu
Nanchang University
Bin Yuan
Nanchang University
Yang Zan (yangzan@ncu.edu.cn)
Nanchang University

Article

Keywords:

Posted Date: June 21st, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2942819/v1

Additional Declarations: No competing interests reported.

The finished vehicle routing problem with a heterogeneous transport fleet

Jiansheng Liu[a], *Bin Yuan*[a], *Yang Zan*[a*]

[a] *School of Mechanical and Electrical Engineering, Nanchang University, Nanchang, China*

Abstract: This paper presents a new variant of the vehicle routing problem, known as the heterogeneous multi-type fleet vehicle routing problem in finished vehicle logistics (HVRP–FVL), which is modeled and solved. The HVRP–FVL considers various transportation costs, such as highway tolls, labor costs, power costs, time penalty costs, and carbon emissions costs. Moreover, the highway toll is charged based on the transport vehicle model, loading weight, and traveled distance, which adds to the complexity of the problem. The objective of the problem is to minimize the total cost of the vehicle fleet. To solve the HVRP–FVL, a metaheuristic is proposed using a genetic algorithm (GA) metaheuristic. The GA incorporates a dual-chromosome encoding method with adaptive crossover, mutation, and climbing operators to improve computational performance. A case study from a logistics company is used to evaluate the effectiveness of the proposed algorithm, and a series of experiments are conducted. The results demonstrate that the proposed approach performs well and satisfies users in practice. The contributions of the paper are the effective modeling and solution of a natural and complex vehicle routing problem in finished vehicle logistics.

1 Introduction

With the rapid expansion of the automotive industry, third-party logistics providers have become more popular for finished vehicle transportation. Finished vehicle logistics can be broadly defined as a series of associated processes from automotive factories to final destinations. Among these processes, the transport cost is a very important economic factor. Third-party logistics companies try to minimize their total transportation cost, which consists of highway toll, labor cost, power cost, time penalty cost, carbon emissions cost, and others. In practice, this is normally done in an ad hoc manner using (and depending on) a manager's experience. With the number of cost factors and a heterogeneous fleet, an ad hoc approach dependent on human expertise needs to be improved upon.

In the classic vehicle routing problem (VRP), it is typically assumed that transport cost is based only on distance traveled. However, in practice, there are different highway toll rates for different loading conditions and geographical areas, which make the problem more challenging. By providing an effective and practical solution approach to this complex finished vehicle routing problem, this paper contributes to the automotive logistics field, both to scholars and to practitioners.

The paper is organized as follows. The next section describes the problem. Section 3 carries out a review of the literature. Section 4 devises a math optimization model for the HVRP-FVL. Section 5 presents a customized GA algorithm. Real test instances and algorithm comparisons are presented in Section 6. Finally, conclusions are drawn in Section 7.

2 Problem overview

Automotive factories produce various types of finished vehicles, such as sedan, pickup truck, and SUV. The set of finished vehicles is initially located at a main depot. A third-party logistics company receives orders from the automotive factories and transports different types of finished vehicles to dealers. The logistics company has its own vehicle fleet consisting of different types of transport vehicles such as 4-axis truck, 5-axis truck, and 6-axis truck. In a typical situation, there are about 100 types of transport vehicles and 600 types of finished vehicles. The dealers can be in different cities and might be far away from each other. Different vehicle transport solutions result in different costs because of the models and numbers of the transport vehicles used. The problem aims to determine a heterogeneous vehicle fleet routing solution to minimize the total cost, which includes toll charge, fuel cost, time penalty cost, and others.

The problem considers a set of ordered items (finished vehicles) characterized by length, width, height, weight, and a set of transport vehicle fleet types characterized by length, width, height, allowable loading weight, and transport cost. The objective is to select the transport vehicles to transport the finished vehicles minimizing the total cost of the transport. We term this problem the Heterogeneous Multi-type Fleet Vehicle Routing Problem in Finished Vehicle Logistics (HVRP-FVL). The HVRP-FVL has its own character different from the classic VRP, which are listed next. (1) Both the shape of the finished vehicles and loading space of the transport vehicles in HVRP-FVL are irregular, which leads to more complex multi-dimensional geometry constraints. The classic VRP mostly consider one-dimensional constraints. (2) Actual highway toll rates are not only based on travel distance, unlike in the classic VRP. (3) Most VRP models simplify the factors that affect vehicle fuel consumption and carbon emissions. Although the HVRP-FVL is found widely in the real automotive supply chain, there are limited related studied in the literature.

According to the description above, the assumptions and constraints are as follows：

(1) Any type of the finished vehicle can be loaded in any kind of transport vehicle.

(2) The finished vehicles to be transported must not exceed the loading limit and geometry constraints of the transport vehicle fleet.

(3) Each transport vehicle is only allowed to visit each customer once.

(4) Each transport vehicle needs return to the distribution center (depot) after completing the delivery task.

(5) Loading and unloading costs are not considered (but could easily be added).

3 Literature review

3.1 Relevant variants of the VRP

Many variants of the VRP have been modeled and applied, such as the capacitated VRP (CVRP) [29], the heterogeneous fleet VRP (HVRP) [26], the VRP with time windows (VRPTW) [8], the Capacitated VRP with Time Windows (CVRPTW) [16], the low-carbon VRP (LCVRP) [22], and the time-dependent VRP (TDVRP) [19]. Among them, the VRPTW is focused on order delivery date. Ghoseiri and Ghannadpour [11] used goal programming and a GA to solve the multi-objective vehicle routing problem with time windows, which aimed to reduce the number of transport vehicles and shorten the total transport distance. Xu et al. [32] studied the VRP with soft time windows considering fuzzy requirements, aiming at reducing costs and improving customer satisfaction.

As for the HVRP, it was proposed by Golden et al. [6]. Later, it was considered by Baldacci et al. [1] and Koç et al. [17], in which one must make additional decisions on fleet composition and customer selection. Kwon et al. [20] considered heterogeneous fixed fleet vehicle routing with carbon emissions to minimizing the sum of variable operation costs and established a mixed integer programming model to assess the value-benefits of purchasing or selling of carbon emissions rights for heterogeneous fleets. Ge et al. [10] designed a quantum GA to solve the HVRP problem, where the optimization goal was to minimize total cost of distribution. Coelho et al. [5] studied a VRP variant inspired by a real case of a large distribution company that could perform multiple trips.

As more attention was paid to environmental protection, fuel consumption became an important economic and environmental factor in the VRP. A model was proposed for calculating total fuel consumption for the time-dependent vehicle routing problem (TDVRP) and solved by an ant colony system (ACS) algorithm hybridized with insertion heuristics [2]. Li and Zhang [21] studied a series of low-carbon VRP problems, which were mainly to study the relationship between carbon emissions and transport costs. Xiao and Konak [31] defined a new mixed integer liner programming model which considered heterogeneous vehicles, time-varying traffic congestion, vehicle time window constraints, the impact of vehicle loads on emissions, and vehicle capacity constraints in the green vehicle routing and scheduling problem.

An exact algorithm was often used to solve the small-scale optimization problems [9], but this approach is not good enough to solve large-scale problems. Heuristic algorithms have commonly been used to solve large-scale problems. Jiang et al. [14] proposed a method that extended an existing tabu search procedure to solve a problem variant of the VRP with time windows. Wei et al. [30] developed an adaptive variable neighborhood search (AVNS) for the heterogeneous fleet routing problem with three-dimensional loading constraints, and numerical experiments showed that the proposed AVNS outperforms other algorithms for HVRP. Mouthuy et al. [27] solved the VRP with soft time windows (VRPSTW) with a multi-stage large neighborhood search algorithm.

Sbai et al. [28] used an adaptive GA to solve the capacitated vehicle routing problem where customer demand is composed of two-dimensional weighted items with a time window (2L-CVRPTW), and the proposed algorithm performed well. Xu et al. [33] incorporated Simulated Annealing (SA) into GA to solve the VRP, since SA could avoid the drawback of premature convergence compared with GA. Ho et al. [12] developed two hybrid genetic algorithms for the multi-depot VRP, the major difference between two algorithms is whether the initial solutions are generated randomly or not. Computational results showed that a selected, rather than random, initial population could enhance the performance of the GA.

3.2 Finished vehicle logistics (FVL)

Fischer and Gehring [7] and Kim et al. [15] applied information technology to Finished Vehicle Logistics (FVL) operations management. Hu et al. [13] proposed a mixed-integer linear programming model for the finished-vehicle transporter routing problem and designed an evolutionary algorithm to solve the model. Liu et al. [25] defined a simplified geometry model of the finished vehicle and transport vehicle, then introduced a greedy search into a traditional branch and bound algorithm to improve the computational performance for solving heterogeneous multi-type fleet vehicle loading problem in FVL. However, these articles ignored the multi-dimensional geometry constraints on both finished vehicles and transport vehicles.

Based on the intrinsic nature of the HVRP-FVL, there are no existing methodologies that can be directly used to solve the HVRP-FVL without substantial modification. To the best of our knowledge, this paper is one of the earliest exploratory research works considering various factors such as multiple types of finished vehicles, multiple types of transport vehicles, dynamical routing cost weight, and so on. Furthermore, the HVRP-FVL is NP-hard as it can be reduced to the general VRP, which is a well-known NP-hard problem [34]. Based on earlier heuristic ideas, we developed a dual-chromosome encoding method that combines adaptive crossover, mutation probability, and a climbing operator to achieve a feasible solution that minimizes the total cost.

4 Optimization model

4.1 Optimization objective

4.1.1 Transport cost f_1 : In the classic VRP model, transport cost optimization is often synonymous with minimizing the travelled distance, ignoring different highway toll rates. Here, a more realistic and comprehensive approach will be presented to calculate total transport cost, which consists of a Fixed cost (C_F) and a Variable cost (C_V).

C_F includes drivers' salaries, depreciation cost, and management expenses, etc.

C_V: toll charge and fuel cost of the transport vehicle.

① In China (and many other countries), the toll charge is a significant part of the transport cost, and depends on some parameters such as unit rate (c), weight (w), and distance (d).

$$C_{toll-charge} = c \times w \times d \quad (1)$$

② The calculation of transport vehicle fuel consumption utilizes the integrated mode approach proposed by Bektas and Laporte [3]. Speed (v), distance (d), weight (w), road condition (α), type of transport (β), and oil prices (c_f) were all considered in this method. The model was simplified to the following.

$$C_{fuel-consumption} = c_f \times \varphi \times (\alpha \times w + \beta \times v^2) \times d \quad (2)$$

4.1.2 Time penalty cost f_2: It is assumed that the i^{th} transport vehicle is required to service the j^{th} customer in the time window $[e_j, l_j]$. If the time t_i when the transport vehicle arrives at customer j is earlier than the prescribed earliest time e_i, an early penalty is invoked (λ_1). Conversely, if the time t_i is later than l_j, a late penalty is incurred (λ_2).

$$f_2 = \lambda_1 \times \max\left(e_j - t_i, 0\right) + \lambda_2 \times \max\left(t_i - l_j, 0\right) \quad (3)$$

4.1.3 Carbon emissions cost f_3: Related work on CO_2 emissions reduction can be found in Koc et al. [18]. According to the relationship between carbon emissions I and fuel consumption (F) [4], carbon emissions can be obtained. We monetize the environmental cost in the form of carbon taxes T_c. The δ is the fuel carbon emission conversion factor related to the transport vehicle type used, different horsepower, air resistance caused by windward areas, etc..

$$f_3 = T_c \times F \times \delta \quad (4)$$

4.2 The math model

Notation

$G = (N, E)$: Delivery network

N: node set, $N = \{0,1,\dots,n\}$, 0 indicates the distribution center or depot, others stand for customer points

E: arc set, $E = \{(i,j) | i,j \in N, i \neq j\}$

K: the type of transport vehicles, $K = \{1,2,\dots,k\}$

P: the type of finished vehicles, $P = \{1,2,\dots,p\}$

U_k: The number of transport vehicles of type k

g_p, l_p, w_p, h_p,: The weight, length, width, and height of finished vehicle type p

G_k, L_k, W_k, H_k,: The limitation loading weight, length, width, and height of transport vehicle type k

D_{ip}: The demand of customer i for finished vehicle type p

Q_k: The self-weight (that is, empty weight) of transport vehicle type k

w_{iju}^k: The total weight of finished vehicles loaded in the uth transport vehicle of type k on arc (i,j)

t_j: The time when arriving at j, and $t_j = \sum_{k=1}^{K}\sum_{u=1}^{U_k}\sum_{i=0}^{N}\left(t_i + t_{ij} + ct_i\right)x_{iju}^k$. ct_i is the service time of customer i, t_{ij} is travel time on arc (i,j)

S_p^k : The available status of transport vehicle k for finished vehicle p

$$S_p^k = \begin{cases} 1, w_p < W_k \; and \; h_p < H_k \\ 0, \quad else \end{cases} \quad \forall p, \forall k \quad (5)$$

Math model

The optimization model below is applied:

$$F = \min(\omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3) \quad (6)$$

$$\begin{aligned} f_1 = &\sum_{u=1}^{U_k}\sum_{k=1}^{K}\sum_{j=1}^{N} C_{FK} x_{0ju}^k \\ &+ \sum_{u=1}^{U_k}\sum_{k=1}^{K}\sum_{j=0}^{N}\sum_{i=0}^{N} x_{ijk}^k c_{ij}\left(Q_k + w_{iju}^k\right) d_{ij} \\ &+ c_f \sum_{u=1}^{U_k}\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} x_{iju}^k \varphi[\alpha_{ij}\left(Q_k + w_{iju}^k\right) \\ &+ \beta_k v_{ij}^2] d_{ij} \end{aligned} \quad (7)$$

$$\begin{aligned} f_2 = &\lambda_1 \sum_{i=1}^{N} max\ (e_i - t_i, 0) \\ &+ \lambda_2 \sum_{i=1}^{N} max\ (t_i - l_i, 0) \end{aligned} \quad (8)$$

$$\begin{aligned} f_3 = T_c \times \{&\delta \times \sum_{u=1}^{U_k}\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} x_{iju}^k \varphi[\alpha_{ij}(Q_k \\ &+ w_{iju}^k) + \beta_k v_{ij}^2] d_{ij}\} \end{aligned} \quad (9)$$

Decision variables

$$x_{iju}^k = \begin{cases} 1, if\ the\ u^{th}\ transport\ vehicle\ of\ type\ k\ are\ on\ arc\ (i,j) \\ 0, \quad else \end{cases} \quad (10)$$

$$y_{iu}^k = \begin{cases} 1, if\ the\ u^{th}\ transport\ vehicle\ of\ type\ k\ serve\ customer\ i \\ 0, \quad else \end{cases} \quad (11)$$

St.

$$x_{iju}^k\left(x_{iju}^k - 1\right) = 0, \forall i,j \in N; \forall k \in K; \forall u \in U_K \quad (12)$$

$$y_{iu}^k\left(y_{iu}^k - 1\right) = 0, \forall i,j \in N; \forall k \in K; \forall u \in U_K \quad (13)$$

$$x_{iiu}^k = 0, \forall i \in N; \forall k \in K; \forall u \in U_K \quad (14)$$

$$\sum_{i=0}^{N} x_{iju}^k = \sum_{i=0}^{N} x_{jiu}^k, \forall j \in N, \forall k \in K; \forall u \in U_K \quad (15)$$

$$\sum_{u=1}^{U_k}\sum_{k=1}^{K} y_{iu}^{k} = 1, \forall i \in N \tag{16}$$

$$y_{iu}^{k}(\mathrm{S}-1) = 0, \forall i \in N; \forall k \in K; \forall u \in U_K \tag{17}$$

$$\sum_{p=1}^{P}\sum_{i=1}^{N} D_{ip} w_p y_{iu}^{k} \leq G_k, \forall k \in K; \forall u \in U_K \tag{18}$$

$$\sum_{p=1}^{P}\sum_{i=1}^{N} D_{ip} l_p y_{iu}^{k} \leq L_k, \forall k \in K; \forall u \in U_K \tag{19}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{N} w_{jiu}^{k} - \sum_{k=1}^{K}\sum_{j=0}^{N} w_{iju}^{k} = \sum_{p=1}^{P} D_{ip} w_p, \forall i \in N; \forall u \in U_K \tag{20}$$

$$\sum_{i,j \in s \times s} x_{iju}^{k} \leq |S-1|, S \subset N \backslash \{0\}; S \neq \emptyset; \forall, k \tag{21}$$

Objective Eq. (6) minimizes the total cost. Eq. (7), Eq. (8), and Eq. (9) are the three sub-objective functions that comprise Eq. (6); Eq. (12), Eq. (13), and Eq. (14) limit the decision value range. The conservation of flow during transport is defined by Eq. (15). Any order must not be split and are only be serviced by one transport vehicle as defined by Eq. (16). And Eq. (17) is the width and height limitation of the transport vehicle. The loading weight limitation of transport vehicle is defined by Eq. (18). Similarly, Eq. (19) is the loading length limitation of the transport vehicle. The loading weight on arc (*i, j*) is defined by Eq. (20). Eq. (21) is the sub-tour constraint.

5 Solution approach

A large amount of literature has shown that the GA is a metaheuristic algorithm with excellent robustness, and it is often combined with other algorithms to solve complicated engineering optimization problems [24]. In this work, a customized GA algorithm is devised for this complex problem.

5.1 Encoding

We used a dual-chromosome encoding method. Firstly, the integer code of the customers in N1 = (1,2,…,*n*) is used as the first chromosome in which each gene represents a customer and its sequence represents the vehicle routing. The second chromosome also uses an integer code such as N2 = (1, 2,…,*m*), which represents the selected transport vehicles and their used sequence.

5.2 Initialization

The initial population can have an important effect on the GA search process. A high-quality initial population can improve the efficiency of the search for the global optimal solution. Commonly, transportation cost $(\boldsymbol{f_1})$ has a large proportion of the total cost ($\boldsymbol{F}$) and the transport distance ($\boldsymbol{d}$) is a key factor in determining the cost of transportation. From the cluster analysis point of view, two close customer points are likely to be serviced by the same transport vehicle. Thus, a sweep strategy is applied to generate a better initial population. The implementation procedures for the sweep strategy are as detailed below.

Step 1. Mark all customer points and the distribution center (depot), 0.

Step 2. Generate a ray by connecting the distribution center (depot) to any customer point *i*, and then begin to sweep all other customer points in a clockwise direction. The swept customer points are recorded one by one in order as an improved initial individual. As shown in Fig.1, there are six customer points, beginning the sweep from 2, and the initial improvement individual obtained is (2 1 5 4 6 3).

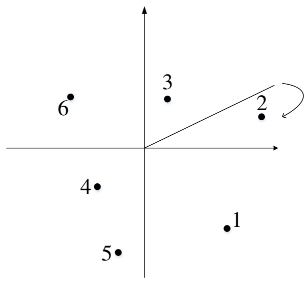

Fig.1 Sweeping Schematic

Step 3. Select different starting points in turn to generate new initial individuals to form the *pop1* number of initial population. As in Fig.1, this results in six improved individuals.

Step 4. if $pop_1 \geq pop$, then terminate; Otherwise, continue to Step 5.

Step 5. Randomly generate the remaining $pop - pop_1$ number of initial individuals. As in Fig.1, if the size of pop is 10, so the remaining four individuals are randomly generated.

Using the above five steps, the first chromosome (N1) is obtained. The second chromosome (N2) is generated uniform randomly to add needed diversity to the population of candidate solutions.

5.3 Fitness function

Calculating fitness is the process of decoding and calculating the final total cost. There exist some constraints of the transport vehicle, such as total loading weight limit and size limit, therefore the transport vehicles must return back to the main depot. Therefore, we need insert '0' into the customer's sequence when the vehicle returns to the main depot.

For example, the customer code is N1 = (1 2 3 4 5 6), and the vehicle code is N2 = (2 1). A corresponding decoding is (0 1 2 3 0 4 5 6 0), which means that No. 2 vehicle starts from the depot, visits customer 1, customer 2, and customer 3 in turn, and then returns to the depot; the No. 1 vehicle transport starts from the depot, serves customer 4, customer

5, customer 6, and then returns to the depot. How many customers to serve and when to return is judged based on the total loading weight limit and the size limit of the vehicles. If the total weight and total length of the cars of the first *i* customers do not exceed the limit, and the first *i*+1 customers exceed one (or both) of the limits, the decoding process inserts "0" after the i^{th} position indicating that the vehicle must return to the depot at this juncture.

Then, we calculate the total cost of the route with the objective of minimizing the total cost. So, the total cost is directly taken as the fitness function.

The dual chromosome encoding method accommodates both of situations of insufficient capacity and excess capacity. The only difference is that some chromosomes do not play a role when decoding. For example, when the capacity is insufficient, the last few customer points cannot be served, and when the capacity is excessive, the last vehicles will have no car to transport. When numbering the vehicles, including the depot's information to which it belongs, the problem involving multiple depots can be solved.

5.4 Selection operator

To ensure that superior individuals are selected for crossover, an elitism strategy is adopted. Individuals whose fitness value is top 5% among population are directly selected and the common Roulette method is used to select the remaining individuals.

5.5 Crossover operator

The crossover operation is performed on the two chromosomes separately. The crossover operations are provided as follows:
Randomly select two inspection positions, swap the codes within the two positions, and then delete any duplicate codes. This is a two point crossover.
For example:

Individual1: 1 2 |3 4 5 6 7 8 |9
Individual2: 9 8 |7 6 5 4 3 2 |1

After cross

New individual1: 1 8 9 7 6 5 4 3 2
New individual2: 9 2 1 3 4 5 6 7 8

During the execution of the algorithm, the average fitness value is treated as a threshold. For individuals below the threshold, the crossover probability (Pc) is increased so that they can have the opportunity to change their fitness; for individuals above the threshold, the crossover probability is reduced to prevent the destruction of outstanding individuals. Therefore, an adaptive crossover probability is used as follows:

$$P_c = \begin{cases} \dfrac{P_c(f_{max} - f_i)}{f_{max} - f_{avg}}, & f_i > f_{avg} \\ P_c, \quad f_i \le f_{avg} \end{cases} \tag{22}$$

5.6 Mutation operator

The mutation operation is designed to enhance the local search ability of the algorithm. The mutation operation is different from the crossover operation. The difference is that the mutation operation only selects one chromosome, while the crossover operation is the crossover of two different chromosomes, and the mutation probability (Pm) is adjusted as the population fitness value changes. Here, the mutation operation is to select randomly two positions on one chromosome, and reverse the order of the middle nodes, an inversion of a randomly selected component of the solution. For example:

Individual: 1 2 |3 4 5 6 7 8 |9
After mutation
Individual: 1 2 |8 7 6 5 4 3 |9

$$P_m = \begin{cases} \dfrac{P_m(f_{max} - f_i)}{f_{max} - f_{avg}}, & f_i > f_{avg} \\ P_m, \quad f_i \le f_{avg} \end{cases} \tag{23}$$

5.7 Local search operator

To increase the local search capability of the algorithm, a local search operator (climbing) is added. It is realized by the transposition of adjacent nodes. The specific operation is: randomly select a position of a chromosome, exchange it with the subsequent nodes, and judge whether the fitness value after the exchange is better. If so, replace the original individual with the exchanged individual, otherwise, keep the original individual. This is performed once on each child. For example:

Individual: 1 2 | 3 4 5 6 7 8 9
Exchange 2 and 3: 1 3 | 2 4 5 6 7 8 9

5.8 Termination condition

Set the maximum evolutional generation ($\boldsymbol{gen_{max}}$) as the termination condition of the algorithm. This is dynamic with the scale of the problem.

6 Computational experience

To verify the validity of the improved GA (IGA), it is tested on a PC with an AMD 2.9 GHz processor, 32.00 GB RAM, and the Microsoft Windows 10 operating system. There are no instances publicly available for the FVRP-FVL, so an actual situation from a logistics company is referred to illustrate the approach.

6.1 A case study

Using the data of a logistics company, the proposed algorithm is run. This case considers the situation where the capacity is sufficient and there is one depot. The information of the available transport vehicles and the finished vehicles are listed in Table 1 and 2, respectively. The information related to the distribution center and customer orders is listed in Table 3. Each order includes the finished vehicles, the customer coordinates, and time windows. Some parameters of model are shown in Table 4. In addition, these parameters are determined by preliminary experimentation:

$popsize = 200,\ P_c = 0.5,\ P_m = 0.1, gen_{max} = 1000$

Table 1 Information of the transport vehicles

Transport vehicle type	Number of such vehicles	Loading length (m)	Loading width (m)	Loading height (m)	Loading weight (T)	Fixed cost (RMB)	Self-weight (T)
1	5	38	1.90	2.10	20	2000	22
2	5	52	1.95	2.10	30	2400	25
3	5	67	2.20	2.15	40	3000	29

Table 2 Finished vehicle information

Parameter	Type A	Type B	Type C	Type D	Type E
Length (mm)	3.460E+3	4.135E+3	4.350E+3	4.515E+3	4.865E+3
Width (mm)	1.690E+3	1.828E+3	1.855E+3	1.880E+3	1.895E+3
Height (mm)	1.450E+3	1.485E+3	1.550E+3	1.550E+3	1.730E+3
Weight (kg)	8.700E+2	1.225E+3	1.270E+3	1.320E+3	1.645E+3

Table 3 21 Customer orders information with time windows

Node set	Latitude	Longitude	Earliest time Et(h)	Latest time Lt(h)	Orders
0 (depot)	28.68	115.68	-	-	-
D1	29.27	117.17	2	9	2A+B+2C
D2	28.26	117.07	1	9	1A+3C
D3	28.46	117.95	3	9	3B+2D
D4	27.95	116.36	3	10	4D
D5	30.12	118.16	1	10	3A+B+2D
D6	28.94	118.88	2	8	4E
D7	30.67	117.49	3	5	2A+2D+2E
D8	30.20	115.05	1	5	3A+E
D9	29.08	119.65	1	6	2A+4C
D10	30.39	114.90	3	8	2A+3B+2C
D11	30.60	114.30	2	9	D+4E
D12	30.93	113.90	3	5	A+3D
D13	29.85	114.30	1	6	2A+2C+2D
D14	29.36	113.10	2	10	2B+C+3D
D15	28.56	112.30	1	7	2A+2C+3E
D16	29.70	116.00	2	10	3A+3B+2D
D17	28.23	112.90	3	6	2C+2E
D18	27.83	113.10	3	10	2D+3E
D19	27.63	113.80	2	5	2A+B
D20	27.82	114.90	2	6	4E
D21	27.12	115.00	2	5	3A+B

Table 4 The model parameters

Parameter	Define	Value	Reference
c_{ij} (rmb/t/km)	Cost per kilometer per ton	[0.03,0.07]	http://www.chinahighway.com

v_{ij} (km/h)	Speed	[40,80]	Enterprise data
c_f (rmb/L)	Oil price	5.8	http://www.sinopecgroup.com
ϕ	Emission index parameter	0.086	[7]
α_{ij}	Road condition factor	[0.09,0.15]	[3]
δ (L/kg)	Fuel carbon emission conversion factor	2.7	[22]
T_c(rmb/L)	Carbon tax	80	[23]
ct(h)	Service time	1	Enterprise data
λ_1/λ_2 (rmb/h)	Early/Late penalty factor	10/30	Enterprise data
$w_1/w_2/w_3$	Weight factor	1/1/1	Enterprise data

For instance, with the 21 customer orders information in the table 3, the program runs 100 times independently (that is, different random number seeds), and the best result is obtained. The optimized solution obtained is in table 5. The optimized route is demonstrated in Fig.2. The calculation results are: F=67564, f_1=35078, f_2=95, and f_3=32391.

Table 5 The optimized solutions

Route No	Transport vehicle type	Route details	Length loading rate(%)	Weight loading rate(%)
1	1	0→D20→D21→0	89.41	72.42
2	3	0→D19→D18→D15→0	96.86	80.60
3	2	0→D14→D17→0	85.76	79.11
4	3	0→D13→D12→D11→0	97.96	86.45
5	2	0→D8→D10→0	83.21	76.75
6	2	0→D16→D1→0	99.17	80.76
7	1	0→D4→D2→0	90.97	71.33
8	3	0→D3→D6→D9→0	97.34	86.54
9	2	0→D7→D5→0	94.66	80.26

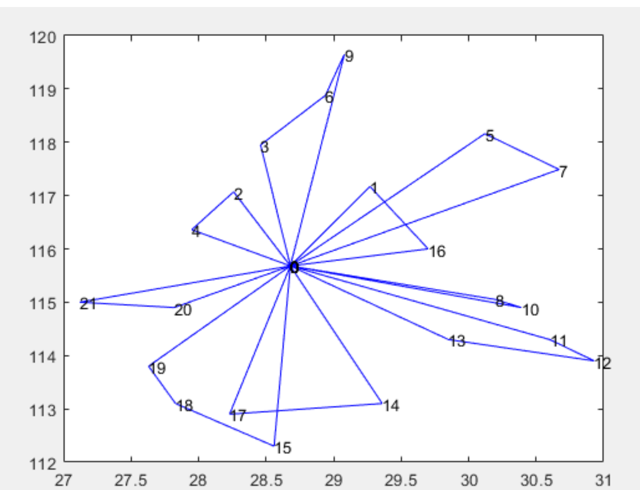

Fig.2 The optimized routes returned by the improved GA

From the analysis of the results, the vehicles are basically fully loaded, especially from the analysis of the length loading rate. Therefore, there is almost no waste of the carrier capacity.

6.2 *Improvement analysis*

To verify whether the improvement of the GA is effective, a general GA was programmed. In the general GA, the input data was the same, and a single chromosome was used. The initial population was randomly generated, the crossover probability and mutation probability were fixed, and there was no local search operator. To ensure the fairness of the comparison, the general GA also runs 100 times independently, and the best results from these runs are presented below, as shown in Fig.3. A comparison of these results is displayed inf Fig.4.

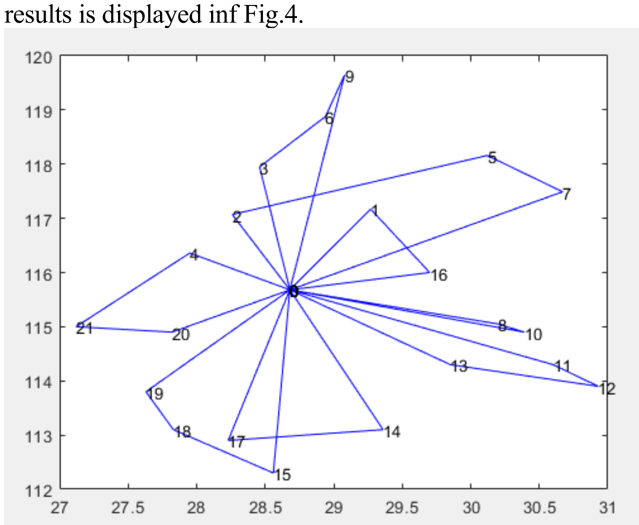

Fig.3 The optimized route returned by the general GA

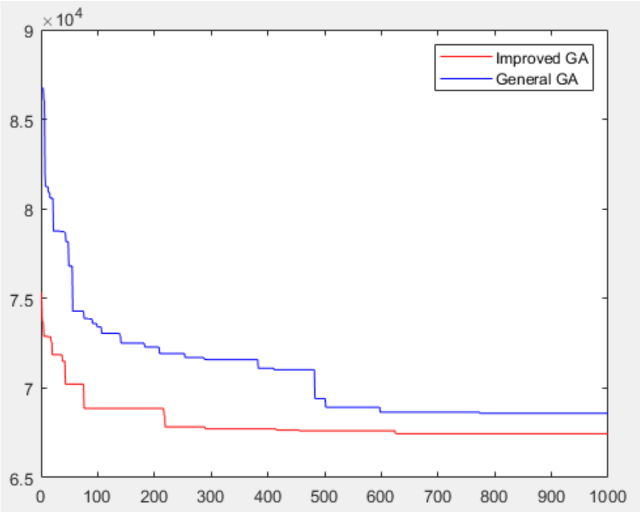

Fig.4 The evolution curve comparison

The experimental results show that the calculation result of the improved algorithm is better than the general algorithm. Taking an average of 100 runs of the algorithm for comparison, the average total cost of the improved algorithm is about 1500 yuan less. The experimental results are shown in Table 6. In table 6, '+' indicates that the improved GA is statistically significantly better than the general GA according to a Wilcoxon rank sum test in all situations. Furthermore, in all the tables below, "Best", "Mean" and "Std", respectively, represent the best found, the mean, and the standard deviation of the experimental results. From analysis of the experimental results, the general GA prefers a large transport vehicle, which can result in a waste of capacity, while the use of the dual chromosome encoding facilitates the selection of an appropriate transport vehicle, improving utilization and decreasing cost.

Table 6 Comparison of the two algorithms

Method	Best	Mean	Std	Wilcoxon rank sum test
General GA	6.859E+4	6.982E+4	1.013E+3	
Improved GA	6.745E+4	6.833E+4	5.310E+2	+

6.3 Extensive computational experience

To further verify the effectiveness of the proposed model and solution approach a series of experiments are conducted. The available transport vehicles and finished vehicles used are as listed in Table 1 and 2, respectively. Population size, crossover probability, and mutation probability are the same as before. Complete customer order information is in Appendix Table 1. The two algorithms are independently run 100 times for each instance. The comparisons of results by the general GA and the improved GA, respectively, are shown in Table 7. The results of the improved GA for the last instance are listed here, that is, the best solution and its path graph for 100 customer orders, which are shown in Appendix Table 2 and in Figure 5. The results show that the improved GA is not only suitable for small cases with 10 customer points, but also effective for large cases such as 100 customer orders, and with the increase of the number of order customers, the improvement effect is more obvious.

Table 7 Comparison of different instances of the two algorithms

Instance No	Number of customer orders	Method	Best	Best improvement ratio	Mean	Mean improvement ratio	Std	Wilcoxon rank sum test
1	10	General GA	3.325E+4		3.325E+4		7.631E-12	
		Improved GA	3.221E+4	3.13%	3.221E+4	3.13%	9.669E-12	+
2	21	General GA	6.859E+4		6.982E+4		1.013E+3	
		Improved GA	6.745E+4	1.66%	6.833E+4	2.13%	5.310E+2	+
3	30	General GA	9.685E+4		9.914E+4		1.929E+3	
		Improved GA	9.582E+4	1.06%	9.689E+4	2.27%	5.891E+2	+
4	40	General GA	1.295E+5		1.335E+5		2.065E+3	
		Improved GA	1.283E+5	0.93%	1.291E+5	3.30%	6.997E+2	+
5	50	General GA	1.601E+5		1.652E+5		2.628E+3	
		Improved GA	1.530E+5	4.43%	1.546E+5	6.42%	8.424E+2	+
6	60	General GA	1.970E+5		2.032E+5		3.769E+3	
		Improved GA	1.854E+5	5.89%	1.870E+5	7.97%	1.187E+3	+
7	70	General GA	2.296E+5		2.354E+5		3.186E+3	
		Improved GA	2.130E+5	7.23%	2.142E+5	9.01%	8.629E+2	+
8	80	General GA	2.760E+5		2.802E+5		2.532E+3	
		Improved GA	2.506E+5	9.20%	2.523E+5	9.96%	1.412E+3	+
9	90	General GA	3.023E+5		3.128E+5		4.857E+3	
		Improved GA	2.725E+5	9.86%	2.750E+5	12.08%	1.733E+3	+
10	100	General GA	3.436E+5		3.522E+5		4.365E+3	
		Improved GA	3.077E+5	10.45%	3.104E+5	11.87%	1.777E+3	+

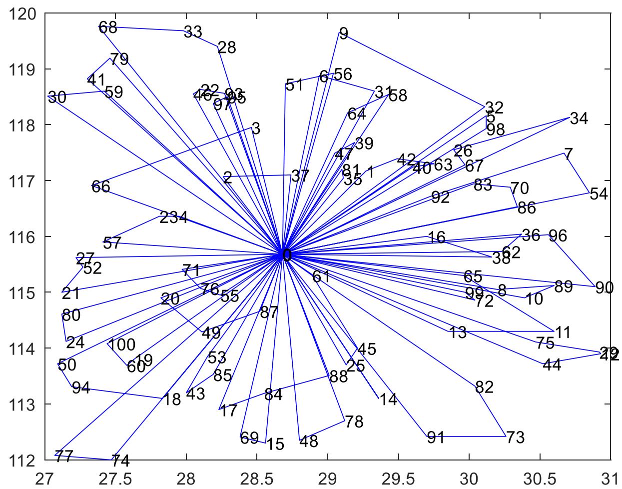

Fig.5 The optimized routes for 100 customer orders returned by the improved GA

7 Conclusion

In this paper, a realistic and complicated vehicle routing optimization problem in finished vehicle logistics is studied. This combines the classic VRP with the characteristics of the finished vehicle logistics. Based on the optimization objectives, the HVRP-FVL model has been established and solved using an improved GA. Real instances provided by a finished vehicle logistics company have been used to conduct a series of experiments to fully evaluate the proposed algorithm. As the problem size increases, the improved matheuristic performs better than a standard GA.

There are several possible enhancements to this work. First, the model depends on multiple factors, and there may be relative relationships among these factors, such as multiple depots and weather factors, which are worth exploring in the future. Secondly, other strategies or methods could be adopted for encoding, decoding, and operations of the GA algorithm. Finally, other hybrid optimization algorithms could be explored to solve the HVRP-FVL.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

References

[1] Baldacci, R., Battarra, M., Vigo, D. Routing a heterogeneous fleet of vehicles. *The Vehicle Routing Problem: Latest Advances and New Challenges.*, Springer, Boston, 2008, pp. 3-27

[2] Balseiro, S.R., Loiseau, I., Ramonet, J. An ant colony algorithm hybridized with insertion heuristics for the time dependent vehicle routing problem with time windows. *Computers & Operations Research.*, 2011, 38, (6), pp. 954-966

[3] Bektas, T., Laporte, G. The pollution-routing problem. *Transportation Research Part B: Methodological.*, 2011, 45, (8), pp. 1232-1250

[4] Brandão, J. A tabu search algorithm for the heterogeneous fixed fleet vehicle routing problem. *Computers & Operations Research.*, 2011, 38, (1), pp. 140-151

[5] Coelho, V.N., Grasas, A., Ramalhinho, H., *et al.*An ILS-based algorithm to solve a large-scale real heterogeneous fleet VRP with multi-trips and docking constraints. *European Journal of Operational Research.*, 2016, 250, (2), pp. 367-376

[6] Chris G, Bruce G, Edward W. A library of local search heuristics for the vehicle routing problem. *Mathematical Programming Computation,* 2010, 2(2), pp.79–101

[7] Demir, E., Bektaş, T., Laporte, G. A comparative analysis of several vehicle emission models for road freight transportation. *Transportation Research Part D: Transport & Environment.*, 2011, 16, (5), pp. 347-357

[8] Fischer, T., Gehring, H. Planning vehicle transshipment in a seaport automobile terminal using a multi-agent system. *European Journal of Operational Research.*, 2005, 166, (3), pp. 726-740

[9] Frifita, M., Masmoudi..VNS methods for home care routing and scheduling problem with temporal dependencies, and multiple structures and specialties. *International Transactions in Operational Research.*, 2020, 27, (1), pp. 291-313

[10] Ge, B.F., Zhang, X.T., Chen, Y.W. Planning model and algorithm for finished vehicle logistic. *Chinese Journal of Management Science.*, 2015, 23, (1), pp. 624-629

[11] Ge, X.L., Xu, M.Z., Wang, W.X. Study on multi-types vehicle routing problem and its quantum genetic algorithm. *Chinese Journal of Management Science.*, 2013, 21, (1), pp. 125-133

[12] Ghoseiri, K., Ghannadpour, S.F. Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. *Applied Soft Computing.*, 2010, 10, (4), pp. 1096-1107

[13] Ho, W., Ho, G.T., Ji, P., Lau, H.C. A hybrid genetic algorithm for the multi-depot vehicle routing problem. *Engineering Applications of Artificial Intelligence.*, 2008, 21, (4), pp. 548-557

[14] Hu, Z., Zhao, Y., Tao, S., Sheng, Z. Finished-vehicle transporter routing problem solved by loading pattern discovery. *Annals of Operations Research.*, 2015, 234, (1), pp. 37-56

[15] Jiang, J., Ng, K.M., Poh, K.L., Teo, K.M. Vehicle routing problem with a heterogeneous fleet and time windows. *Expert Systems with Applications.*, 2014, v41, (8), pp. 3748-3760

[16] Khachay, M. and Y. Ogorodnikov, PTAS for the Euclidean capacitated vehicle routing problem with time windows. *Learning and Intelligent Optimization, LION.,* 2020.p. 224-230.

[17] Kim, J., Ok, C.S., Kumara, S., Yee, S.T. A market-based approach for dynamic vehicle deployment planning using radio frequency identification (RFID) information. *International Journal of Production Economics.*, 2010, 128, (1), pp. 235-247

[18] Koç, Ç, Bektaş, T, Jabali, O, Laporte, G. Thirty years of heterogeneous vehicle routing. *European Journal of Operational Research.*, 2016, 249, (1), pp. 1-21

[19] Koç, Ç., Bektaş, T., Jabali, O., Laporte, G. The fleet size and mix pollution routing problem. *Transportation Research Part B: Methodological.*, 2014, 70, pp. 239-254

[20] Kuo,Y. Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem. *Computers & Industrial Engineering.*, 2010, 59, (1), pp. 157-165

[21] Kwon, Y., Choi, Y., Lee, D. Heterogeneous fixed fleet vehicle routing considering carbon emission. *Transportation Research Part D: Transport and Environment.*, 2013, 23, (8), pp. 81-89

[22] Li, J., Zhang, J.H. Study on the effect of carbon emission trading mechanism on logistics distribution routing decisions. *System Engineering-Theory & Practice.*, 2014, 34, (7), pp. 1779-1787

[23] Li, J., Zhang, J.H. Vehicle routing problem with time windows based on carbon emissions and speed optimization. *System Engineering Theory & Practice.*, 2014, 34, (12), pp. 3063-3072

[24] Li, X., Gao, L., Wang, W., *et al* Particle swarm optimization hybridized with genetic algorithm for uncertain integrated process planning and scheduling with interval processing time. *Computers & Industrial Engineering*., 2019, 135, (9), pp: 1036-1046

[25] Liu, J., Smith, A.E., Qian, D. The vehicle loading problem with a heterogeneous transport fleet. *Computers & Industrial Engineering.*, 2016, 97, pp. 137-145

[26] Meliani, Y., Hani, Y., Elhaq, S.L., *et al.*.A developed Tabu Search algorithm for heterogeneous fleet vehicle routing problem. *IFAC Papers OnLine*., 2019, 52, (13), pp. 1051-1056,

[27] Mouthuy, S., Massen, F., Deville, Y., Van, H.P. A multistage very large-scale neighborhood search for the vehicle routing problem with soft time windows. *Transportation Science.*, 2015, 49, (2), pp. 223-238

[28] Sbai, I., Limem, O., Krichen, S. An adaptive genetic algorithm for the capacitated vehicle routing problem with time windows and two-dimensional loading constraints. *IEEE/ACS 14th International Conference on Computer Systems & Applications, Hammamet, Tunisia*, 2018, pp. 88-95

[29] Tao, Y., Wang, F. An effective tabu search approach with improved loading algorithms for the 3L-CVRP. *Computers and Operations Research*., 2015, 55, pp. 127-140

[30] Wei, L., Zhang, Z., Lim, A. An adaptive variable neighborhood search for a heterogeneous fleet vehicle routing problem with three-dimensional loading constraints. *IEEE Computational Intelligence Magazine.*, 2014, 9, (4), pp. 18-30

[31] Xiao, Y., Konak, A. The heterogeneous green vehicle routing and scheduling problem with time-varying traffic congestion. *Transportation Research Part E: Logistics and Transportation Review.*, 2016, 88, pp. 146-166

[32] Xu, J., Yan, F., Li, S. Vehicle routing optimization with soft time windows in a fuzzy random environment. *Transportation Research Part E: Logistics and Transportation Review.*, 2011, 47, (6), pp. 1075-1091

[33] Xu, Z., Li, H., Wang, Y. An improved genetic algorithm for vehicle routing problem. *IEEE 2011 International Conference on Computational and Information Sciences, Chengdu, China*, 2011, pp.1132-1135

[34] Yüceer, Ü., Özakça, A. A truck loading problem. *Computers & Industrial Engineering.*, 2010, 58, (4), pp. 766-773

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Supplementarymeterial.docx