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Research Paper

Optimization of vehicle routing problems for cold chain logistics mixed fleet under low-carbon constraints

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ABSTRACT: *In the field of urban distribution, time-varying road network conditions are complex, customers' requirements for delivery time and freshness of goods are stringent, and the current situation of the coexistence of electric vehicles and fuel vehicles has brought new challenges and opportunities to logistics enterprises' distribution path optimization. Logistics enterprises need to optimize the distribution plan. This paper constructs a mixed fleet vehicle routing optimization model with multi factor considerations. Considering the key factors such as electric vehicle charging strategy, carbon emission cost and customer satisfaction, the minimum total distribution cost and the maximum customer satisfaction are the two objectives. In order to improve the efficiency and quality of the solution, this study designs and improves the NSGA-II algorithm, which integrates clustering, path rearrangement greedy strategy based on time window and cost optimization, and verifies the effectiveness of the improved NSGA-II algorithm through the numerical experiment of Solomon standard example, and makes a comparative analysis of the distribution schemes using mixed fleet and charging strategy, so as to help logistics enterprises determine the optimal charging strategy and distribution scheme.*

KEYWORDS: *Mixed Fleet, Cold chain Logistics, Improved NSGA-II algorithm*

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I. INTRODUCTION

Against the backdrop of global climate change mitigation efforts, the low-carbon economy has emerged as a core strategy for sustainable development worldwide. The transportation sector, accounting for 24% of global energy-related carbon emissions, represents one of the primary sources of emissions. Within this sector, freight logistics—particularly cold chain logistics—exhibits 30% to 50% higher carbon emission intensity per unit of cargo compared to conventional freight due to the high energy consumption of refrigeration equipment. Consequently, reducing carbon emissions in logistics has become a critical challenge in achieving the "dual carbon" goals.

In recent years, the rapid development of new energy vehicles has provided a viable pathway toward low-carbon transportation. However, due to constraints such as battery technology, charging infrastructure, and acquisition costs, mixed fleets comprising both conventional fuel-powered vehicles and NEVs will remain the predominant choice for logistics enterprises in the short to medium term. This is particularly evident in cold chain logistics, where the range of NEVs is significantly impacted by temperature control systems, further complicating operational scheduling. The optimization of mixed-fleet routing to minimize both carbon emissions and operational costs while maintaining transport efficiency has thus become a key research focus for both academia and industry.

II. ROUTING OPTIMIZATION MODEL OF MIXED FLEETS

2.1 Problem description

The mixed-fleet cold-chain distribution model constructed in this study operates as follows: Within specified time constraints, the distribution center dispatches a mixed fleet of refrigerated vehicles (including both conventional fuel-powered and new energy vehicles) to deliver goods to multiple customers with known demand before returning to the depot. Customers impose strict requirements on delivery time windows. Each vehicle may serve multiple customer nodes, but its load cannot exceed rated capacity. When an electric vehicle's remaining battery falls below a threshold, it must visit a nearby charging station to recharge fully before continuing its route, with charging stations allowing multiple visits. Given the perishable nature of fresh products, the customer satisfaction evaluation system prioritizes delivery timeliness and product quality. Under cargo capacity and time window constraints, the model optimizes vehicle scheduling to achieve dual objectives: maximizing customer satisfaction while minimizing total system costs.

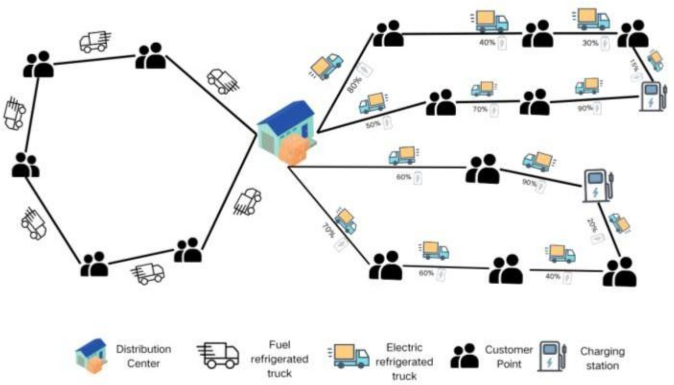


Figure 1: distribution diagram of mixed fleets

2.2 Model assumptions

This study focuses on the distribution problem of a single distribution center, multiple demand points, and a mixed fleet. The goal is to optimize vehicle routes, transport cold chain products from distribution centers to demand points, minimize total costs, and improve customer satisfaction. To simplify the study, we adopt the following assumptions:

(1) The research scope is limited to the cold chain distribution process of specific fresh food categories in a single distribution center.

(2) The vehicle departs from the distribution center, completes all customer point delivery tasks, and returns to the distribution center.

(3) The spatial distribution, demand, expected service time window, and tolerable time range of the distribution center and customer nodes are all included in the model as known conditions.

(4) The vehicle load is a known fixed value, and the total demand of each vehicle on a single path is less than the rated load capacity of the vehicle.

(5) Customer needs must be fully met and cannot be separated, but the same delivery vehicle can provide services for multiple customer nodes.

(6) Customer satisfaction depends on the comprehensive performance of delivery timeliness and product freshness.

(7) The external environment temperature remains constant and does not change over time, and agricultural products are always in a constant temperature state during refrigerated truck transportation.

These assumptions provide the basis for constructing models that balance simplicity and accuracy in routing optimization.

2.3 Notation description

Based on the aforementioned assumptions, the parameters and descriptions are shown in Tables 1.

Table 1: Parameters and meanings

Parameters	Descriptions	Parameters	Descriptions
D	Collection of all nodes， D=IUSU0， 0 is the distribution center	c_{ijk}	Carbon emission rate of vehicle K driving on road section (I, J)
I	Collection of all customer demand points	e	Electric vehicle power consumption rate per unit distance
A	Fuel truck assembly	r	One hour charging capacity of electric vehicle
B	Electric vehicle assembly	d_{ij}	Distance from node i to node j
K	Collection of all refrigerated trucks,K=A∪B={1,2,3,....,A,...,A+B}	t_{ijk}	Travel time of fuel vehicle K on road section (I, J)
S	Collection of charging stations	u_{ijk}	Driving time of electric vehicle K on road section (I, J)
F_{is}^{k}	The collection of customers that vehicle K drives from customer I to charging station s	w_{ijk}	Load capacity of vehicle K from node i to node j
F_{s}^{k}	After the vehicle K drives to the charging station s, the subsequent customer collection	W_{ik}	Load capacity of vehicle K when it reaches node i
P^k	Collection of all customers served by vehicle K， $P^k = F_{is}^k \cup F_s^k$， And $F_{is}^k \cap F_s^k$ is empty set	G_{ijk}	Power consumption of electric vehicle K from node i to node j， Gijk=dij×e
h_i	Demand of customer point I	q_{ik}	Remaining power of electric vehicle K reaching node i
g_i	Service time of customer point I	T_{sk}	Charging time of electric vehicle K at charging station s
$[B_i,E_i]$	Delivery time required by customer point I	α_{isk}	Electric vehicle K is recharged from node i to charging station s
$[MB_i,ME_i]$	Maximum tolerance time window of customer point I	A_{ik}	Time when vehicle K arrives at node i
Q_1	Rated load of fuel oil refrigerator truck	L_{ik}	Time when vehicle K leaves node i
Q_2	Load capacity of electric refrigerator truck	Z_k	0-1 variable. If the refrigerator truck K is selected, then Z_k=1; Otherwise Z_k=0
D_1	Running speed of fuel refrigerator truck	x_{ijk}	0-1 variable, if the refrigerator truck K runs from point I to point J, then X_{ijk}=1; Otherwise X_{ijk}=0
D_2	Running speed of electric refrigerator truck	y_{ik}	0-1 variable. If the refrigerator truck K accesses the I node, then y_{ik}=1; Otherwise, y_{ik}=0
E	Maximum battery capacity of electric vehicles	Y_{isk}	0-1 variable. If the refrigerator truck K is charged from point I to charging station s, Y_{isk}=1; Otherwise, Y_{isk}=0
f_{ijk}	Fuel consumption rate of vehicle K on road section (I, J)	Z_{ijk}	0-1 variable, if the refrigerator truck K runs from point I to point J, then Z_{ijkR}=1; Otherwise, Z_{ijkR}=0

2.4 model design

The objective function constructed by this model consists of a minimum cost function and a maximum customer satisfaction function.The total delivery cost includes fixed vehicle operating costs, transportation energy consumption costs, product quality loss costs, refrigeration energy consumption costs, time window deviation penalty costs, carbon emission costs, and charging costs, which can be calculated as follows:

C1 (fixed operating cost of vehicles): including fixed expenses such as driver compensation, vehicle depreciation and insurance, which are directly related to the number of vehicles used. Let $p1^{c}$ be the unit fixed cost of new energy refrigerated vehicles (yuan/vehicle) and p^{e}_{1} be the unit fixed cost of traditional fuel refrigerated vehicles (yuan/vehicle), then the fixed operating cost of vehicles can be expressed as:

$$C_1 = \sum_{k \in A} p_1^c Z_k + \sum_{k \in B} p_1^e Z_k \tag{1}$$

C2 (transportation energy consumption cost): refers to the fuel consumption cost, and its cost is positively correlated with the vehicle mileage. Let p3 be the unit price of fuel oil (yuan/L).

$$C_2 = p_3 \sum_{i \in I \cup 0} \sum_{j \in I \cup 0} \sum_{k \in A} Z_{ijk} d_{ij} f_{ijk} \tag{2}$$

C3 (product quality loss cost): assuming that the environmental conditions are relatively constant and the product loss is only related to time, it can be divided into two stages for calculation: transportation and loading and unloading. Let p4 be the cost of quality loss per unit time (yuan/h). a1 and a2 respectively represent the quality attenuation coefficient in the transportation stage and the loading and unloading stage. (a1=0.002, a2=0.003)

$$C_3 = p_4 \sum_{i\in I\cup 0} \sum_{j\in I\cup 0} \sum_{k\in K} x_{ijk}\left[W_i\left(1-e^{-a_1(t_{ik}-t_{0k})}\right) + w_{ijk}\left(1-e^{-a_2 g_i}\right)\right] \tag{3}$$

C4 (refrigeration energy consumption cost): energy consumption cost generated by the operation of refrigeration equipment. Assuming that the specifications of refrigeration equipment are uniform and the temperature difference inside and outside the compartment is constant, the energy consumption is only related to time and can be divided into two stages for calculation: transportation and loading and unloading. Let p5 be the refrigeration cost per unit time (yuan/h).

$$C_4 = p_5\left[\sum_{i\in I\cup 0} \sum_{j\in I\cup 0} \sum_{k\in K} x_{ijk}\, t_{ijk} + \sum_{i\in I\cup 0} \sum_{k\in K} Z_k\, max[(B_i - t_{ik}), 0] + \sum_{i\in I} g_i\right] \tag{4}$$

C5 (time window deviation penalty cost): the penalty cost incurred when the delivery time exceeds the service time range required by the customer. Let p6 be the penalty cost per unit time (yuan/min).

$$C_5 = \sum_{i\in I\cup 0} \sum_{k\in K} p_6\, [\max[(t_{ik} - E_i), 0] + \max[(B_i - t_{ik}), 0]] \tag{5}$$

C6 (carbon emission cost): carbon tax mechanism is adopted. Carbon emission cost=carbon emission × carbon tax unit price. The sources of carbon emissions include two parts: one is the carbon emissions generated by the fuel consumption of the power system of transport vehicles; The second is the carbon emission generated by the power consumption of refrigeration equipment. θ is the CO_2 emission coefficient of the refrigeration process, and p7 is the carbon emission cost coefficient.

$$C_6 = p_7\left[\sum_{i\in I\cup 0} \sum_{j\in I\cup 0} \sum_{k\in K} Z_{ijk} d_{ij} c_{ijk} + \sum_{i\in I\cup 0} \sum_{j\in I\cup 0} \sum_{k\in K} \theta d_{ij} w_{ijk}\right] \tag{6}$$

C7 (charging cost):

$$C_7 = p_2 \sum_{k\in B} \sum_{i\in I} \sum_{s\in S} Y_{isk} a_{isk} \tag{7}$$

Linear piecewise function is used to characterize customer satisfaction based on delivery time. When the vehicle arrives within [Bi,Ei] time, the customer is most satisfied; Within the time of [MBi,Bi] or [Ei,MEi], customer satisfaction decreases linearly with the degree of deviation; If the maximum tolerance time window [MBi,MEi] is exceeded, customer satisfaction will be reduced to 0.

$$ST_i = \begin{cases} 0 & A_{ik} < MB_i, A_{ik} > ME_i \\ \dfrac{A_{ik} - MB_i}{B_i - MB_i} \times 100 & MB_i \le A_{ik} < B_i \\ 100 & B_i \le A_{ik} \le E_i \\ \dfrac{ME_i - A_{ik}}{ME_i - E_i} \times 100 & E_i \le A_{ik} < ME_i \end{cases} \tag{8}$$

Assuming that customer satisfaction and product quality maintain a positive correlation, that is, the higher the quality of products received by customers, the higher the level of customer satisfaction. d_c is the initial quality level of the product, d_t is the quality degradation caused by time factors during transportation, where $t_{ia} - T_s$ is the product in transit time. d_o represents the quality loss caused by a single unloading, and NO_i represents the cumulative loading and unloading times of the distribution vehicle when serving the customer point i.

$$SF_i = d_c - d_t(t_{ia} - T_s) - d_o \times NO_i \tag{9}$$

The minimum cost function and the maximum customer satisfaction function are shown as follows:

$$min\, Z_1 = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \tag{10}$$

$$maxZ_2 = \frac{1}{n}\left(\lambda \times \sum_{i=1}^{n} ST_i + \mu \times \sum_{i=1}^{n} SF_i\right) \tag{11}$$

s.t.

$$\sum_{k \in K} y_{ik} = 1, \forall i \in I \tag{12}$$

$$\sum_{j \in I} x_{0jk} \leq 1, \forall k \in K \tag{13}$$

$$\sum_{i \in D} \sum_{j \in I} h_j x_{ijk} \leq Q, \forall k \in K \tag{14}$$

$$\sum_{j \in D, j \neq i} x_{ijk} - \sum_{j \in D, j \neq i} x_{jik} = 0, \forall i \in D, k \in K \tag{15}$$

$$\sum_{i=1}^{n} x_{0ik} = \sum_{i=1}^{n} x_{i0k}, \forall k \in K \tag{16}$$

$$L_{ik} = A_{ik} + g_i \tag{17}$$

$$A_{jk} = L_{ik} + t_{ijk}, \forall i, j \in I, k \in A \tag{18}$$

$$A_{jk} = L_{ik} + u_{ijk}, \forall i, j \in I, k \in B \tag{19}$$

$$L_{sk} = L_{ik} + u_{isk}, \forall i \in I, s \in S, k \in B \tag{20}$$

$$q_{0k} = E, \forall k \in B \tag{21}$$

$$G_{ijk} = d_{ij} \times e, \forall i, j \in D, k \in B \tag{22}$$

$$q_{jk} = q_{ik} - G_{ijk}, \forall i \in D, j \in I, k \in B \tag{23}$$

$$q_{sk} = q_{ik} - G_{isk}, \forall i \in I, s \in S, k \in B \tag{24}$$

$$E - \sum_{i \in P_{is}^{k} \cup 0} \sum_{j \in P_{is}^{k} \cup 0} G_{ijk} x_{ijk} - G_{jsk} Y_{jsk} \geq 0, \forall s \in S, k \in B \tag{25}$$

$$a_{isk} = G_{slk} x_{slk} + \sum_{l \in F_s^k} \sum_{j \in F_s^k \cup 0} G_{ljk} x_{ljk}, \forall i \in P_{is}^{k}, s \in S, k \in B \tag{26}$$

$$a_{isk} = T_{sk} r, \forall i \in I, s \in S, k \in B \tag{27}$$

$$q_{sk} + a_{isk} \leq E, \forall i \in I, s \in S, k \in B \tag{28}$$

$$L_{sk} = A_{sk} + T_{sk}, \forall s \in S, k \in B \tag{29}$$

$$x_{ijk}, y_{ik}, Z_k, Y_{isk}, Z_{ijk} \in 0,1 \tag{30}$$

Constraint Explanation:

Equation 12 indicates arranging only one vehicle service for each demand point, Equation 13 limits vehicles to depart from the distribution center at most once, Equation 14 ensures that the vehicle's loading capacity cannot exceed its rated load capacity, Equation 15 ensures balanced access to each node to ensure path continuity, Equation 16 ensures that the starting and ending points of each vehicle are at the distribution center to ensure path closure, Equation 17 indicates the calculation method for the time it takes for vehicles to arrive at and leave the customer point, Equation 18 indicates the calculation method for the time it takes for fuel vehicles to leave the customer point and travel to the next customer point, Equation 19 indicates the calculation method for the time it takes for electric vehicles to leave the customer point and travel to the next customer point, and Equation 20 indicates the calculation method for the time it takes for electric vehicles to travel from the previous customer point to the charging station. For electric vehicles, the model further considers power management, including Equation 21 to ensure that the initial power of the electric vehicle is full when it departs, Equation 22 to calculate the power consumption of the electric vehicle, Equation 23 to calculate the remaining power of the electric vehicle from the previous customer point to the next customer point, Equation 24 to calculate the remaining power of the electric vehicle when it arrives at the charging station from the customer point, Equation 25 to ensure that the electric vehicle's power can travel from the current node to the next node and charging station, Equations 26-28 to calculate the charging amount of the electric vehicle, the charging time, the relationship between charging rate and charging amount, and to ensure that the charging amount of the electric vehicle does not exceed the battery capacity, and Equation 29 to calculate the time for the electric vehicle to arrive at and leave the charging station. Finally, the model restricts the values of variables, and Equation 30 ensures that the decision variables are binary, ensuring the feasibility of the decision variables. The model comprehensively considers path planning, time windows, power constraints, and charging strategies, and is suitable for cold chain distribution problems with charging stations.

III. ALGORITHM DESIGN

3.1 Algorithm description

This study used NSGA-II to solve the model. Unlike single objective optimization, in multi-objective optimization, the optimization objectives are often contradictory and it is often difficult to achieve simultaneous optimization of multiple objectives. In real-world delivery tasks, logistics companies can select solutions from the Pareto optimal solution set that are suitable for the current scenario, align with the company's business capabilities, and fit the company's preferences as the solution. This article uses K-means clustering method to optimize the initial population based on NSGA-II, and combines time window constraints and cost optimization to design a dynamic sorting algorithm improvement. The algorithm process is as follows.

3.2 Algorithm steps

The flow chart is shown in Figure 2, and the algorithm's steps are given below. Step 1: Population initialization
Configure algorithm parameters, including population size N, current iteration count gen (initialized to 1), and maximum iteration count gen_max. Using K-means clustering of customer nodes based on vehicle load limitations to group delivery plans and ensure the quality of initial chromosomes. Randomly generate delivery sequences within each cluster and construct an initial population P.

Step 2: Genetic Operation
Perform non dominated sorting and crowding calculation on chromosomes to obtain individual fitness. Use the binary tournament selection mechanism to screen high-quality individuals. Perform partial matching crossover

(PMX) and sequential crossover (OX) operators on the selected parent individuals to generate a new offspring population. Perform mutation operations on individuals in the offspring population, introducing a certain degree of randomness to maintain population diversity.

Step 3: Subpopulation Construction and Disturbance Mechanism
Randomly select R chromosomes from the new population P to form subpopulation P1, while the remaining chromosomes form subpopulation P2. Introduce a random perturbation strategy to P1, optimize the path, and prevent the algorithm from getting stuck in local optima.
Step 4: greedy strategy for path rearrangement based on time window and cost optimization
For the chromosomes in population P1, time window constraint optimization and cost optimization strategies are adopted for path rearrangement to improve the quality of solutions and increase the diversity of the population. Calculate the dual objective fitness values Z1 (Li) (total cost) and Z2 (Li) (customer satisfaction) for each path Li. Adopting a dynamic insertion strategy, optimizing the path sequence to ensure that the vehicle's arrival time at the customer meets the time window as much as possible, while reducing refrigeration and cargo damage costs.
Step 5: Non dominated Sorting and Population Update
Use fast non dominated sorting to divide the hierarchy of frontier solutions and calculate crowding to ensure population diversity and distribution uniformity. Combining populations P1 and P2, compare crowding levels and prioritize selecting the first N chromosomes to form the next generation population P.
Step 6: Iteration and Termination
Repeat steps 2 to 5 until the maximum number of iterations is reached. If the frontier solution set is stationary for several consecutive generations, terminate the iteration in advance to improve computational efficiency.

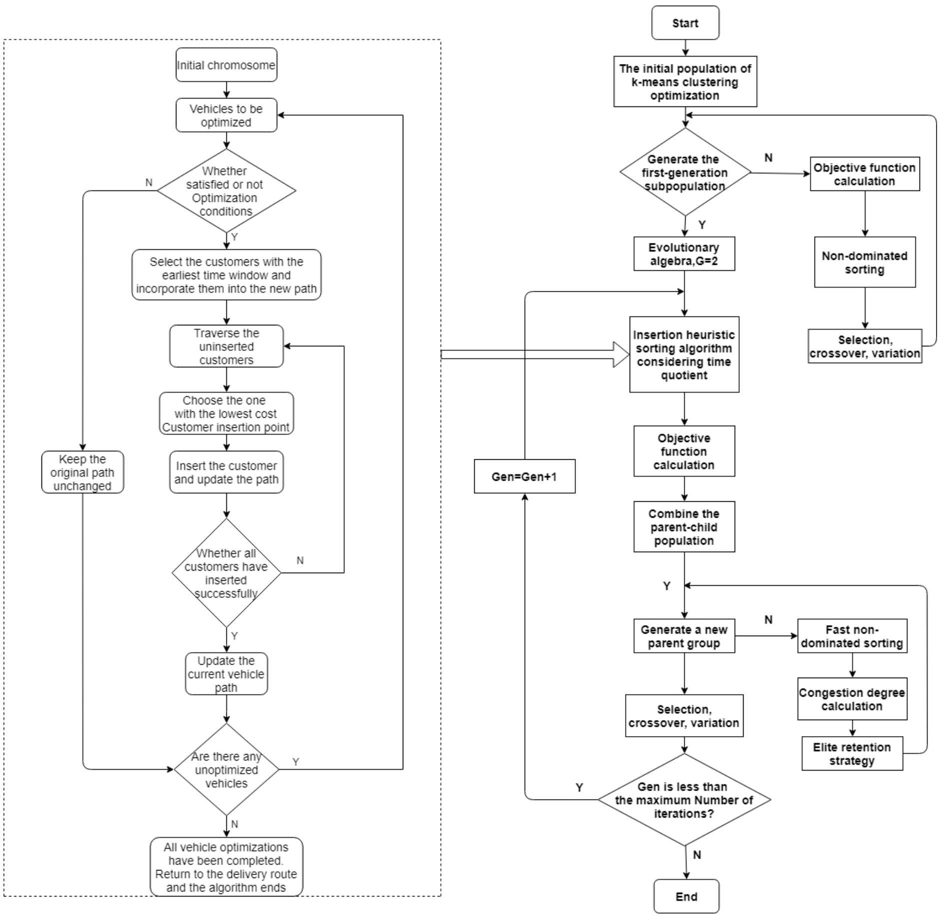


Figure 2: process of improved NSGA-II

IV. NUMERICAL EXPERIMENTS

4.1 Example description

Given the current lack of benchmark test datasets specifically for vehicle path planning problems with charging facilities, this study used RC208 from the VRPTW standard test library developed by international authoritative scholar Solomon as experimental data. Some datasets are shown in Table 2. The geographic coordinates of the distribution center in this case are (40,50), with an operating time of 960 minutes (16 hours), serving 100 demand nodes. On this basis, this study scientifically added location information for 20 charging facilities. The locations of the distribution center and demand points are shown in Figure 3.

Table 2: RC208 Partial Data Table

CUST NO.	XCOORD.	YCOORD.	DEMAND	READY TIME	DUE DATE	SERVICE TIME
0	40	50	0	0	960	0
1	25	85	20	388	911	10
2	22	75	30	30	546	10
3	22	85	10	353	708	10
4	20	80	40	425	913	10
5	20	85	20	40	630	10
6	18	75	20	228	667	10
7	15	75	20	161	558	10
8	15	80	10	229	624	10

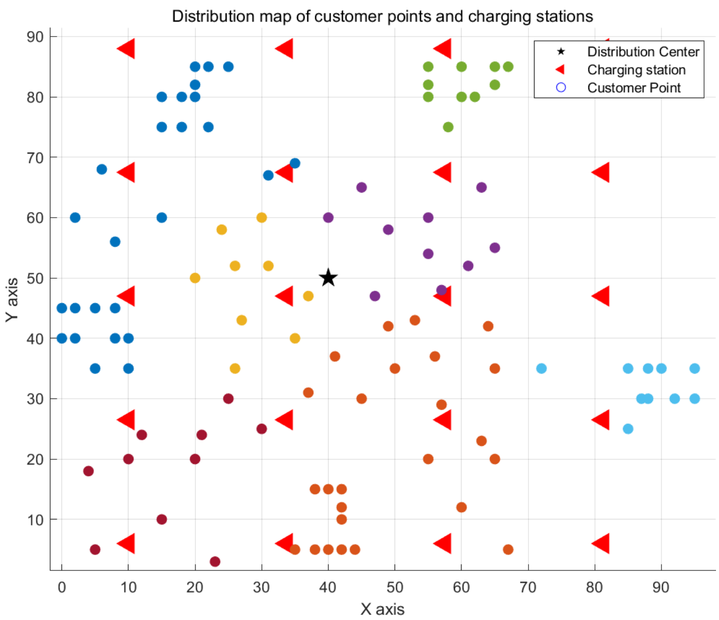


Figure 3: Location map of all nodes

4.2 Parameter setup

To validate the algorithm's performance for the routing optimization model, NSGA-II and improved NSGA-II were used to solve these models.

Choosing appropriate parameters for the algorithm is crucial. In this work, the population size is set to 150, the P_c and P_m are set to 0.9 and 0.1, respectively, the genetic generation gap is set to 0.1, and the number of iterations is set to 100. The other parameters used in the experiment are shown in Table 3.

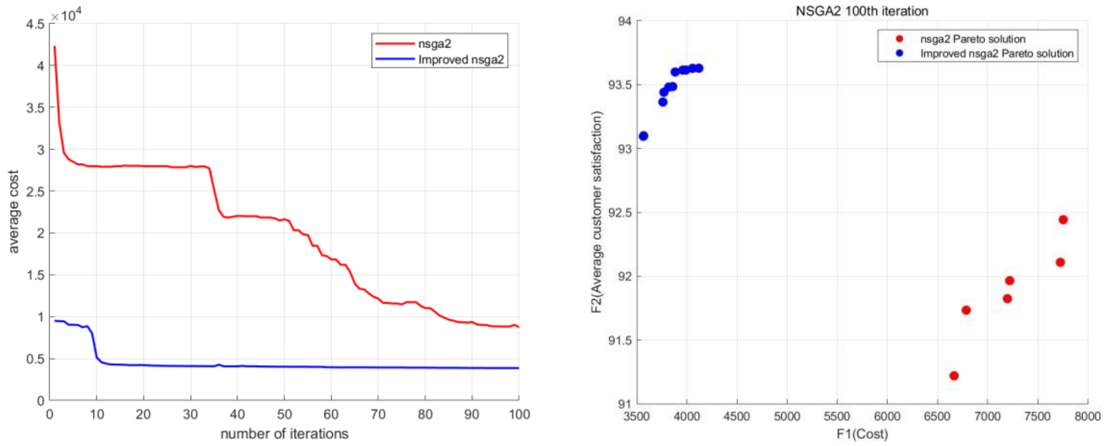
Table 3: Parameter settings

Parameter	Value	Parameter	Value
Q1	250 kg	p_1^e	300 (yuan/ vehicle)
Q2	200kg	P2	1 (yuan/kwh)
E	80kwh	p3	8 (yuan/L)
fijk	0.15(L/km)	p4	1 (yuan/h)
cijk	0.5(kg/km)	p5	0.35 (yuan/h)
e	0.3(kwh/km)	p6	1 (yuan/min)
r	80(kwh/h)	p7	0.05 (yuan/kg)
p_1^c	250 (yuan /vehicle)		

4.3 Result analysis

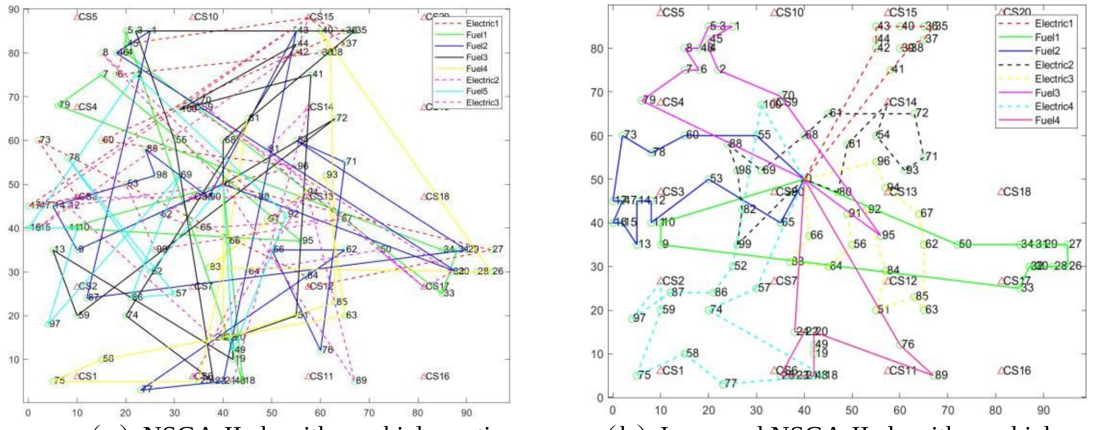
4.3.1 Comparisons of different algorithms

We obtained optimal vehicle routing results via MATLAB 2023a. Following the algorithm design in Section 3, input information of each node, demand , and other data into MATLAB. To verify the effectiveness of the improved NSGA-II in this study, it was compared with traditional NSGA-II. Explored its convergence, the Pareto solution set after 100 iterations and the average total delivery cost and delivery route of each generation population are shown in Figure 4, Figure 5, and Table 4.



（a） Iterative diagram （b）Frontier solution distribution map

Figure 4: RC208 Algorithm effectiveness analysis



（a）NSGA-II algorithm vehicle routing （b）Improved NSGA-II algorithm vehicle routing

Figure 5: RC208 Comparison of vehicle routes

Table 4: The results of the two algorithms are analyzed

algorithm	C1	C2	C3	C4	C5	C6	C7	Total cost	Customer satisfaction	Number of Pareto solutions
NSGA-II	2150	2890.27	289.57	431.90	7.00	140.25	876.52	6664.75	91.22	6
Improved NSGA-II	2200	628.52	220.71	333.09	0	31.21	153.01	3566.53	93.09	12

Through multiple tests, the horizontal axis in Figure 4 (a) represents the number of iterations, while the vertical axis represents the average delivery cost of the Pareto solution set corresponding to each iteration. From the iteration curve, although traditional NSGA-II has a fast decline rate in the early stage, due to the poor quality of the initial solution generated, it begins to converge at the 40th iteration, which can easily lead to local optima and lose the possibility of finding other solutions. The improved NSGA-II algorithm uses clustering methods to generate initial solutions with higher quality, shorter convergence time, and can locate the optimal solution more quickly.

The total delivery cost has been reduced by 47%, with significant savings, indicating that the improved algorithm performs better in cost optimization. Customer satisfaction has increased by 1.29%, although the increase is not significant, it can still maintain or even slightly improve satisfaction while significantly reducing costs, indicating that the improved algorithm still maintains good performance in meeting customer needs. The doubling of the number of Pareto solutions means that the improved algorithm provides more non dominated solutions, which can provide decision-makers with richer options and demonstrate stronger multi-objective optimization capabilities. From the above results, it can be seen that the improved NSGA-II algorithm has shown significant optimization effects in multiple cost dimensions, reducing transportation costs by 78.24%, carbon emission costs by 77.73%, charging costs by 82.48%, and cargo damage costs by 22.42%, achieving significant reductions and effectively improving customer satisfaction. This indicates that the improved algorithm not only enhances the performance of multi-objective optimization, but also effectively reduces various costs, especially in terms of environmental protection and energy utilization, demonstrating stronger sustainability.

4.3.2 Comparisons of different scenarios

In modern logistics transportation, how to reduce operating costs and environmental impact while ensuring delivery efficiency is an important challenge faced by enterprises. Although gasoline vehicles have advantages in range and charging speed, they have higher operating costs and higher carbon emissions. In contrast, electric vehicles have become an important choice for green logistics due to their lower energy consumption and lower carbon emissions. Therefore, adopting a mixed fleet strategy, which involves the coordinated operation of fuel vehicles and electric vehicles, can fully leverage the advantages of both to optimize overall route planning. Below, we will compare the performance of pure fuel fleet and mixed fleet in terms of distribution routes and various costs, and analyze the rationality and necessity of adopting mixed fleet. The costs of these two strategies are shown in Table 5, the results of the vehicle path are shown in Table 6.

The total cost of the pure fuel fleet is 4677.50 yuan, an increase of about 30.8% compared to the mixed fleet's 3577.68 yuan. Among them, transportation costs are the main source of costs. Due to high oil prices, the transportation costs of pure fuel fleets are much higher than those of mixed fleets, indicating that partial substitution of electric vehicles for fuel vehicles can effectively reduce transportation costs. The carbon emission cost of the mixed fleet decreased by 70.8%, indicating that the use of electric vehicles can significantly reduce carbon emission costs. Under carbon taxes or environmental policies, high carbon emissions may bring additional economic burdens. The fixed cost of a mixed fleet is 220 yuan, slightly higher than that of a pure fuel fleet by 200 yuan. This is due to the high fixed operating cost of electric vehicles, which is why companies are unable to fully transition from pure fuel vehicles to pure electric vehicles in the current context. However, due to the total cost savings of 1099.82 yuan, this additional fixed cost can be fully offset by the savings in operating costs. Charging costs increase but do not affect the overall performance. The charging cost of the mixed fleet is 153.01 yuan, but compared to the overall savings of 1099.82 yuan for the pure fuel fleet, this part of the cost can be ignored. The mixed fleet has a shorter driving distance. The total driving distance of the mixed fleet is 1062.14km, while the pure fuel fleet is 1415.19km, a reduction of 353.05km or 25%. In the absence of trams, vehicles require longer distances to cover all customers, which increases time and cost. Under the mixed fleet strategy, the use of trams optimized routes, resulting in a significant reduction in total travel distance. The mixed fleet only needs to be charged twice, which means that the range of the tram can basically meet the delivery needs without significantly increasing operational complexity.

Table 5: The cost of the two strategies are analyzed

Fleet strategy	C1	C2	C3	C4	C5	C6	C7
Fuel fleet	2000	1938.22	286.87	345.43	0	106.97	0
Mixed fleet	2200	628.52	220.71	333.09	0	31.21	153.01

Table 6: The results of the two strategies are analyzed

Fleet strategy	vehicle number	Customer Path	Number of customers	Distance	Charging cycles	Total cost	Satisfaction
	Fuel 1	50-34-31-29-27-26-28-30-32-33-9-10	12	157.39	/		
	Fuel 2	55-60-78-73-17-47-16-15-13-14-12-11-53-65	14	126.41	/		
	Fuel 3	79-7-6-8-46-5-3-1-45-4-2-70-95	13	137.9	/		
	Fuel 4	24-22-25-23-21-48-19-49-20-89-76	11	102.06	/		
Mixed fleet	Electric 1	41-38-39-37-35-36-40-43-44-42	10	65.2	0	3566.53	93.09
	Electric 2	90-99-82-98-88-69-68-61-72-71-93-54-124-81-80	14	147.32	1		
	Electric 3	66-83-64-56-91-92-84-51-85-63-62-67-94-96	14	120.12	0		
	Electric 4	57-74-18-77-58-75-59-112-97-87-86-52-100	12	205.72	1		
	Fuel 1	26-70-2-4-45-3-5-46-8-6-7	11	174.61	/		
	Fuel 2	90-35-79-53-82-99-59-75-86-57-19-65	12	278.40	/		

	Fuel 3	54-72-68-88-10-24-48-76-22-98-69	11	222.33	/		
	Fuel 4	55-100-60-73-17-15-13-11-80-94-71-36-81	13	205.55	/		
Fuel fleet	Fuel 5	61-96-93-31-29-27-28-30-20-18-21-74-58-16-47-14	16	226.43	/	4677.50	93.06
	Fuel 6	34-32-33-89-49-23-25-77-97-87-12-78	12	200.89	/		
	Fuel 7	9-52-51-50-41-38-39-37-40-43-44-42-1	13	206.06	/		
	Fuel 8	66-83-64-56-84-85-63-62-67-95-91-92	12	100.92	/		

V. CONCLUSION

The experimental results show that the improved NSGA-II algorithm exhibits superior optimization ability in multiple cases, reducing the total delivery cost by 47%, significantly increasing the number of Pareto solutions, and maintaining stable customer satisfaction while ensuring cost optimization. Further cost breakdown analysis shows that the improved algorithm has achieved significant optimization in transportation costs, carbon emissions, cargo damage, charging costs, etc., especially in reducing transportation costs and carbon emissions by 78.24% and 77.73% respectively, demonstrating excellent economic value and environmental friendliness. In addition, through the analysis of the mixed fleet strategy, it was found that the collaborative use of electric vehicles and fuel vehicles can effectively reduce operating costs, optimize distribution efficiency, and conform to the development trend of green logistics.

Based on the clustering results, initialize the vehicle path, prioritize expanding outward from the center point, reduce invalid travel, make the initial solution closer to the optimal solution, and improve the convergence speed of the algorithm. The experimental results show that this strategy effectively reduces the instability of the initial solution while ensuring reasonable allocation of vehicles, enabling the improved NSGA-II algorithm to search for high-quality solutions in the early stages and improving optimization efficiency. It provides powerful decision support for logistics enterprises in selecting the optimal distribution scheme and the optimal charging station access strategy, and has certain theoretical significance and practical application value. By optimizing distribution routes and vehicle configuration, enterprises can not only reduce operating costs and improve customer satisfaction, but also improve their market competitiveness in the context of a low-carbon economy.

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