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Route Optimization for Cold Chain Distribution with Mixed Fleets Considering Charging Station Alliance Strategy

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Abstract. With the strengthening of the country's carbon emission control efforts, cold chain logistics is facing the problem of reconfiguring fleets and optimizing routes to adapt to more stringent environmental standards while improving customer satisfaction. This study investigates the route optimization problem for cold chain logistics with mixed fleets and time windows, with a focus on exploring the application of mixed fleet and charging station alliance strategies in cold chain distribution. A three-objective optimization model is constructed to minimize total distribution cost, waiting time, and carbon emissions, and the IVY-NSGA-III hybrid algorithm is adopted for solving the model. The algorithm combines the efficient optimization ability of the Ivy algorithm and the global search ability of the NSGA-III algorithm, and an evaluation mechanism for solution quality is constructed. Based on the Solomon standard test instances, simulation instances are built to verify the effectiveness and feasibility of the algorithm. The results show that reasonable fleet ratios and charging station alliance strategies can effectively reduce enterprise distribution costs, improve customer satisfaction, and reduce carbon emissions. This study provides route optimization solutions for small and medium-sized cold chain logistics enterprises, thus possessing certain practical application value.

Keywords: Vehicle Routing Problem (VRP), Cold Chain Logistics Distribution, Mixed Fleet, Charging Station Alliance, IVY-NSGA-III Hybrid Algorithm

1. Introduction

In November 2021, the 14th Five-Year Plan for the Development of Cold Chain Logistics issued by the State Council further accelerated the promotion of new energy refrigerated trucks [1], bringing new challenges and opportunities to logistics enterprises.

Over the past few decades, many different VRP variants have been extensively studied, most of which are based on traditional fuel-powered vehicles. However, the cruising range of electric vehicles (EVs) is shorter than that of traditional vehicles. Although the current charging stations in urban areas can barely meet daily travel needs, logistics companies must not only consider the problem of violating time windows due to excessively long charging waiting times during peak hours but also address power supply issues when using EVs to serve customers in suburban areas with insufficient charging facilities.

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According to the definition of the traditional Capacitated Vehicle Routing Problem (CVRP), the objective of the Capacitated Electric Vehicle Routing Problem with Time Windows (CEVRPTW) is to minimize the total travel distance of EVs. If a vehicle cannot complete its journey using only initial power, it can recharge at a charging station. After serving all customers, all EVs should return to the distribution center [2]. Early studies on the Electric Vehicle Routing Problem with Time Windows (EVRPTW) mainly focused on minimizing logistics companies' operating costs or maximizing customer time satisfaction. In practice, large logistics companies can achieve their objectives through strategies such as multiple distribution centers, self-built charging facilities, and customer reallocation. However, multiple distribution centers and self-built charging stations often lead to a significant increase in costs for small and medium-sized logistics companies. Therefore, this study proposes mixed fleet and charging station alliance strategies for such enterprises.

Up to now, existing methods for solving the EVRPTW can be roughly divided into two categories. In the first category, scholars transform the EVRP into a mixed-integer linear programming problem [3] and use commercial software (e.g., CPLEX) to call exact algorithms for solving the problem [4]. Individual-based heuristic algorithms belong to the second category; due to their excellent performance in large-scale EVRPTW, they can usually obtain satisfactory solutions within a reasonable time frame. When dealing with EVRPTW with different charging requirements —such as pickup and delivery requirements [5], time-dependent road travel times [6], and logistics distribution considering customer credit ratings—heuristic algorithms like the Variable Neighborhood Search (VNS) algorithm, Genetic Algorithm (GA), and Tabu Search (TS) are often integrated to improve solution quality.

In the aforementioned studies, objective functions usually focus on minimizing total logistics cost or travel distance. However, considering various environmental issues and sustainable development, multi-objective EVRPTW incorporates factors such as carbon emissions [7] and resource utilization into the research. Converting multi-objectives into a single objective is a common approach, such as the weight coefficient method [8] and the ε-constraint method. Nevertheless, these methods have shortcomings, such as the lack of consideration for interactions between multiple objectives. To overcome these limitations, more studies adopt multi-objective optimization algorithms to solve the EVRPTW problem. It is worth noting that the non-dominated sorting algorithms NSGA-II (Non-dominated Sorting Genetic Algorithm II) and NSGA-III (Non-dominated Sorting Genetic Algorithm III)—based on the concept of the Pareto solution set—have been proven to exhibit excellent search performance in solving EVRPTW problems with pickup and delivery requirements, but they lack an evaluation mechanism for solution quality. Therefore, this study proposes the IVY-NSGA-III hybrid algorithm to solve the VRP problem for mixed fleets under the charging station alliance strategy.

2. Problem description and model construction

2.1. Problem description

This study considers the route optimization of cold chain distribution for small and medium-sized logistics enterprises with a single distribution center and a mixed fleet. All vehicles depart from the distribution center, return to the distribution center after completing the specified distribution tasks, and no overloading or power depletion is allowed during the distribution process. Vehicles that cannot complete the distribution with a single charge can recharge at charging stations, but the charging waiting time and charging time will affect the distribution progress. If a distribution company does not form an alliance with charging stations, the charging stations will not reserve charging piles for the distribution vehicles, and the vehicles will have to wait in line—resulting in

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the company incurring charging fees and queuing time costs. If an alliance is formed, the charging stations will reserve sufficient charging piles, and the distribution vehicles will not have to wait in line, but the company will pay alliance fees.

2.2. Variable definition

The definitions of relevant variables are shown in Table 1.

Table 1. Variable definitions

Variable Name	Definition
(st_i, et_i)	Time window of customer point i, $i \in I$
t_{ser}	Service time of vehicle for serving customer
P_{full}	Rated capacity of electric vehicle
$\overline{p}$	Power consumption per unit distance of electric vehicle
Q_k	Rated load capacity of electric vehicle
Q_v	Rated load capacity of fuel-powered vehicle
T	Number of working periods of the distribution center per year
q_i	Goods demand at customer point i
at_{ik}	Arrival time of electric vehicle at customer point, distribution center, or charging station i, $i \in A$
dt_{ik}	Departure time of electric vehicle from customer point, distribution center, or charging station i, $i \in A$
$at_{iv}^{'}$	Arrival time of fuel-powered vehicle at customer point, distribution center, or charging station i, $i \in A$
$dt_{iv}^{'}$	Departure time of fuel-powered vehicle from customer point i, distribution center, or charging station, $i \in A$
wt_{ik}	Waiting time of electric vehicle when arriving early at customer point for service, $i \in I$
$wt_{iv}^{'}$	Waiting time of fuel-powered vehicle when arriving early at customer point for service, $i \in I$
$wt_{hk}^{''}$	Charging waiting time of electric vehicle at non-alliance charging station. $i \in H$
d_{ij}	Euclidean distance from point i to point j
$\overline{v}$	Average driving speed of vehicle
AEL_{ik}	Power of electric vehicle k upon arrival at a point i, $i \in A$
DEL_{ik}	Power of electric vehicle k upon departure from a point i. $i \in A$
M	A sufficiently large positive number

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Table 1. (continued)

Decision Variables	
x_{ijk}	0-1 variable; 1 indicates that electric vehicle k travels from point i to point j, 0 otherwise. $k \in K, i, j \in A$
y_{ik}	0-1 variable; 1 indicates that the task at customer point i is completed by an electric vehicle k
$x_{ijv}^{'}$	0-1 variable; 1 indicates that fuel-powered vehicle v travels from point i to point j, 0 otherwise, $v \in V, i, j \in O \cup I$
$y_{iv}^{'}$	0-1 variable; 1 indicates that the task at customer point i is completed by a fuel-powered vehicle v
η_h	0-1 variable; 1 indicates that the distribution company forms an alliance with charging station h, 0 otherwise
z_{hk}	0-1 variable; 1 indicates that electric vehicle k recharges at charging station h, 0 otherwise

2.3. Model construction

$$minTE = PEX + TEX + BEX + MEX + AEX \tag{1}$$

$$minWT = \sum_{i\in I}\sum_{k\in K} wt_{ik} + \sum_{i\in I}\sum_{v\in V} wt_{iv}^{'} + \sum_{h\in H}\sum_{k\in K} z_{hk}\cdot\left(1-\eta_h\right)\cdot wt_{hk}^{''} \tag{2}$$

$$minCOE = \sum_{i,j\in A}\sum_{k\in K} x_{ijk}\cdot emc\cdot d_{ij} + \sum_{i,j\in A}\sum_{v\in V} x_{ijv}^{'}\cdot emc^{'}\cdot d_{ij} \tag{3}$$

$$PEX = \sum_{i\in I}\sum_{k\in K} y_{ik}\cdot w_{epu}\cdot green_{index}\cdot max(st_i - at_{ik}, 0) + \sum_{i\in I}\sum_{k\in K} y_{ik}\cdot w_{lpu}\cdot green_{index}\cdot max(at_{ik} - et_i, 0)$$

$$+\sum_{i\in I}\sum_{v\in V} y_{iv}^{'}\cdot w_{epu}\cdot max(st_i - at_{iv}^{'}, 0) + \sum_{i\in I}\sum_{v\in V} y_{iv}^{'}\cdot w_{lpu}\cdot max(at_{iv}^{'} - et_i, 0) \tag{4}$$

PEX represents the penalty cost incurred by vehicles for violating the agreed time windows with customers, which consists of the penalty cost of electric vehicles and fuel-powered vehicles. For electric vehicle distribution, this study introduces a green coefficient g_{index} to appropriately adjust the penalty cost of electric vehicles. Among them, w_{epu} represents the unit time penalty cost when the distribution vehicle arrives at the customer point earlier than the customer's time window, and w_{lpu} represents the unit time penalty cost when the distribution vehicle arrives later than the customer's time window.

$$TEX = \sum_{i,j\in A}\sum_{k\in K} x_{ijk}\cdot d_{ij}\cdot tf_k + \sum_{i,j\in A}\sum_{v\in V} x_{ijv}^{'}\cdot d_{ij}\cdot tf_v^{'} \tag{5}$$

TEX represents the total transportation cost of vehicles, which consists of the transportation cost of electric vehicles and fuel-powered vehicles. Among them, tf_k represents the unit distance

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transportation cost of electric vehicles, and $tf_v^{'}$ represents the unit distance transportation cost of fuel-powered vehicles.

$$BEX = \sum_{i\in I}\sum_{k\in K} y_{ik}\cdot bf_k + \sum_{i\in I}\sum_{v\in V} y_{iv}^{'}\cdot bf_v^{'} \tag{6}$$

BEX represents the total cost of purchasing electric vehicles and fuel-powered vehicles, where bf_k is the cost of purchasing electric vehicles and $bf_v^{'}$ is the cost of purchasing fuel-powered vehicles.

$$MEX = \sum_{i\in I}\sum_{k\in K} y_{ik}\cdot \frac{M_k}{T} + \sum_{i\in I}\sum_{v\in V} y_{iv}^{'}\cdot \frac{M_v^{'}}{T} \tag{7}$$

MEX represents the average maintenance cost of electric vehicles and fuel-powered vehicles, where M_k is the annual maintenance cost of electric vehicles and $M_v^{'}$ is the annual maintenance cost of fuel-powered vehicles.

$$AEX = \sum_{h\in H} \eta_h \cdot \frac{af_h}{T} \tag{8}$$

AEX represents the average alliance cost for the distribution company to form an alliance with charging stations, where af_h is the annual alliance cost for the distribution company to form an alliance with charging stations.

Route Optimization Constraints for Mixed Fleets with Time Windows:

$$\sum_{k\in K} y_{ik} + \sum_{v\in V} y_{iv}^{'} = 1 \ \forall i \in I \tag{9}$$

$$\sum_{i\in I} y_{iu}\cdot q_i \le Q_u \ \forall u \in U \tag{10}$$

$$DEL_{ik} = AEL_{ik} - p_{cl}\cdot t_{ser}\ , \forall i \in I, k \in K \tag{11}$$

$$AEL_{jk} \le DEL_{ik}\cdot(1 - z_{hk}) + P_{full}\cdot z_{hk} - x_{ijk}\cdot d_{ij}\cdot \overline{p}\ , \forall i, j \in I, i \ne j, k \in K, h \in H \tag{12}$$

$$AEL_{ik} \ge 0\ , \forall i \in A, k \in K \tag{13}$$

$$DEL_{ik} = P_{full}\ , i \in O \cup H \tag{14}$$

$$REL_{ik} = P_{full} - AEL_{ik}, i \in A, k \in K \tag{15}$$

$$\sum_{j\in A} x_{jiu} = y_{iu}\ , \forall i \in I, i \ne j, \forall u \in U \tag{16}$$

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$$\sum_{j\in A} x_{iju} = y_{iu}\ , \forall i \in I, i \neq j, \forall u \in U \tag{17}$$

$$at_{ik} + wt_{ik} + set_{ik} - M(1 - y_{ik}) \leq dt_{ik}\ , i \in I, k \in K \tag{18}$$

$$at_{ik} + wt_{ik} + set_{ik} + M(1 - y_{ik}) \geq dt_{ik}\ , i \in I, k \in K \tag{19}$$

$$at_{hk}^{''} + \left(1 - \eta_h\right) \cdot wt_{hk}^{''} + ct_{hk} - M \cdot \left(1 - z_{hk}\right) \leq dt_{hk}^{''} \tag{20}$$

$$at_{hk}^{''} + \left(1 - \eta_h\right) \cdot wt_{hk}^{''} + ct_{hk} + M \cdot \left(1 - z_{hk}\right) \geq dt_{hk}^{''} \tag{21}$$

$$dt_{ik} + t_{ij} - M(1 - y_{ik} - z_{hk}) \leq at_{ik}, (i \in I \cap j \in H) \cup (i \in H \cap j \in I), k \in K, h \in H \tag{22}$$

$$dt_{ik} + t_{ij} + M(1 - y_{ik} - z_{hk}) \geq at_{ik}, (i \in I \cap j \in H) \cup (i \in H \cap j \in I), k \in K, h \in H \tag{23}$$

$$dt_{iv} + t_{ij} - M\left(1 - y_{iv}^{'}\right) \leq at_{jv}\ , i \in O \cup I, j \in I, v \in V \tag{24}$$

$$dt_{iv} + t_{ij} + M\left(1 - y_{iv}^{'}\right) \geq at_{jv}, i \in O \cup I, j \in I, v \in V \tag{25}$$

$$at_{iv} + wt_{iv}^{'} + set_{iv}^{'} + t_{ij} - M\left(1 - y_{iv}^{'}\right) \leq at_{jv}^{'}, i \in I, j \in O \cup I, v \in V \tag{26}$$

$$at_{iv} + wt_{iv}^{'} + set_{iv}^{'} + t_{ij} + M\left(1 - y_{iv}^{'}\right) \geq at_{jv}^{'}, i \in I, j \in O \cup I, v \in V \tag{27}$$

$$\sum_{j\in I} x_{oju} = 1\ , \forall u \in U \tag{28}$$

$$\sum_{j\in I\cup H} x_{oju} - \sum_{i\in I\cup H} x_{iou} = 0, \forall u \in U \tag{29}$$

3. Research on the IVY-NSGA-III hybrid algorithm

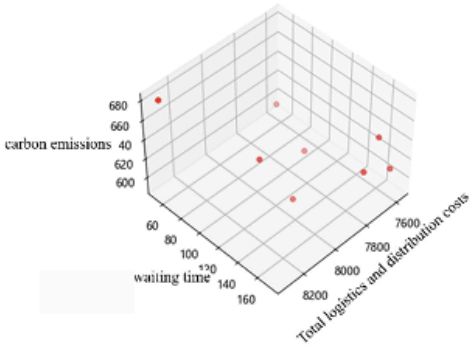
3.1. Algorithm description

Considering that the cold chain distribution with mixed fleets studied in this paper is a multi-objective problem, the IVY-NSGA-III multi-objective hybrid solution algorithm is designed. To optimize the random generation process of the initial population in NSGA-III, the IVY (Ivy) algorithm is integrated, and an elitist retention strategy is adopted to pass the optimized solutions to the genetic algorithm. To improve solution quality, an evaluation mechanism for solution quality is added during the cyclic iteration of NSGA-III. This algorithm improves the quality of the initial population while increasing the convergence speed of NSGA-III and ensuring the diversity of solutions.

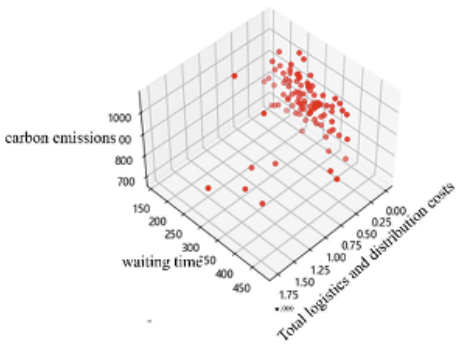
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3.2. Algorithm verification

In this section, the research model is solved and the effectiveness of the algorithm is verified. Based on the Solomon test instances, the instances are localized according to the characteristics of the problem in this study, with specific charging station nodes added. The total node scales are 50 and 100 respectively; the nodes of the distribution center and charging stations remain unchanged, and only the number of customer points is increased. Relevant parameters are obtained by referring to existing literature and conducting multiple experiments. To verify the effectiveness of the algorithm, this paper conducts a comparative analysis between the improved IVY-NSGA-III algorithm and the NSGA-III algorithm, using test instances with a node scale of 50 for verification.



Distribution Diagram of Solutions from the Improved IVY-NSGA-III Hybrid Algorithm



Distribution Diagram of Solutions from the Unimproved NSGA-III Algorithm

Figure 1. Distribution diagrams of solutions from the IVY-NSGA-III hybrid algorithm and the NSGA-III algorithm

Table 2. Comparison of optimization results between the IVY-NSGA-III hybrid algorithm and the NSGA-III algorithm

		IVY-NSGA-III					NSGA-III				
Scale	Instance	Total Logistics Distribution Cost (Yuan)	Waiting Time	Carbon Emissions	Number of Charging Station Alliances	Running Time (s)	Total Logistics Distribution Cost (Yuan))	Waiting Time	Carbon Emissions	Number of Charging Station Alliances	Running Time (s))
	r101	5573	207	513	1	106.52	5662	167	516	4	99.87
	r103	4987	262	480	2	107.27	5282	244	525	2	99.39
	c101	8760	4789	572	2	99.41	9901	2086	438	3	96.70
	rc101	8079	253	779	3	124.81	110011136	270	781	2	93.15
	c201	13313	7441	446	2	111.96	21849	7535	486	3	92.44

It can be seen from Figure 1 that the improved IVY-NSGA-III hybrid algorithm has stronger global search ability compared with the unimproved NSGA-III algorithm, and the finally obtained

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Pareto frontier solutions are more diverse, which can meet the needs of decision-makers with different preferences. As shown in Table 2, the IVY-NSGA-III hybrid algorithm outperforms the NSGA-III algorithm in terms of total distribution cost. Especially when customers are unevenly distributed with high density, the unimproved NSGA-III algorithm struggles to escape local optima, resulting in higher total logistics distribution costs and route optimization schemes that lack practical reference value. In contrast, the IVY-NSGA-III hybrid algorithm exhibits stronger optimization stability and obtains reasonable Pareto frontier solutions both when customer points are evenly distributed and clustered. Additionally, the average running time of the 5 groups of data solved by the IVY-NSGA-III hybrid algorithm is not significantly different from that of the NSGA-III algorithm, but the overall solution quality is superior. Therefore, the IVY-NSGA-III hybrid algorithm proposed in this paper has better stability and reliability than the unimproved NSGA-III algorithm.

4. Conclusions

This study investigates the route optimization problem of whether cold chain logistics companies with mixed fleets should form alliances with charging stations. It designs the IVY-NSGA-III hybrid algorithm and customized encoding/decoding methods to solve the model. The hybrid algorithm leverages the fast convergence ability of the improved IVY algorithm to ensure algorithm efficiency while providing high-quality initial populations for subsequent multi-objective optimization, and the global search ability of NSGA-III ensures the diversity of final solutions.

A comparative analysis of the results between the IVY-NSGA-III hybrid algorithm and the single NSGA-III algorithm shows that the IVY-NSGA-III hybrid algorithm is superior. Sensitivity analysis is also conducted on two factors: charging queuing time and customer distribution density. The results indicate that: 1) The shorter the waiting time, the more inclined cold chain logistics companies are to avoid forming alliances with charging stations; 2) The higher the customer distribution density, the more inclined cold chain logistics companies are to use electric vehicles for distribution services.

This paper provides new insights for the optimization of cold chain logistics distribution routes. With the continuous breakthroughs and advancements in charging technology, future research can explore route optimization incorporating radio wave charging to provide ideas and recommendations for the practical application of vehicle route distribution.

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