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Multi-Objective Low Carbon Vehicle Routing for Cold Chain Distribution with Customer Time Loss Aversion

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Abstract The elevated refrigeration expenses linked to cold chain distribution contribute to increased overall logistics costs and carbon emissions. Concurrently, the sensitivity of consumers to delivery delays also impacts the design of cold chain distribution operations. This paper considers the logistics costs of cold chain, consumer time loss aversion, and the efficiency of low-carbon distribution to construct a multi-objective cold chain vehicle routing problem. It combines a decomposition-based multi-objective solution algorithm and fruit fly optimization algorithm to solve the proposed model, and validates the algorithm and model through a large number of numerical experiments. Firstly, our computations of the C-metric, IGD value, Hypervolumn, and CPU time demonstrate that the algorithm employed in this study has yielded notable advantages in terms of convergence and the overall performance of the non-dominated solutions. Secondly, we find that increasing logistics satisfaction requires a significant investment in logistics costs, thus requiring a delicate balance between logistics expenditure and service advantages. Finally, we used a typical example to analyze the size of different cost modules in cold chain distribution and find that vehicles can optimize their routes without needing to make extensive diversions to reach distant customers, ultimately leading to reduced fuel consumption and carbon emissions. Besides, the traditional assumption that a higher utilization of logistics vehicles results in increased carbon emissions and fuel usage is not universally valid. Our research contributes to the current balance between cold chain costs and consumer satisfaction in cold chain distribution. Additionally, leveraging multi-objective algorithm design, we provide feasible solutions for current cold chain delivery operations. Further, by incorporating consumer time loss aversion model, we aid in understanding the impact of consumer behavior on the design of cold chain delivery solutions.

Keywords multi-objective; low carbon vehicle routing; cold chain distribution; customer time loss aversion

1 Introduction

E-commerce platforms have enabled online transactions between customers and sellers, promoting the growth of the logistics industry[1]. This mode of transaction entails customers placing orders online and receiving goods offline. Importantly, contactless e-commerce has gained

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significance during the COVID-19 outbreak as it aids in avoiding viral interference. For example, consumers are increasingly using fresh food e-commerce platforms to buy food that is then delivered to their homes. In-process cold chain logistics services are employed to transport temperature-sensitive goods such as fresh agricultural products, seafood, and pharmaceutical drugs, in order to maintain freshness and minimize decay or deterioration[2]. Nevertheless, these services raise logistics costs. Consequently, e-commerce logistics companies encounter the challenge of balancing associated expenses with customer contentment, particularly when limited resources are available. This is especially critical during times like the COVID-19 outbreak, where logistics infrastructure may not suffice[3].

It has been shown that high delivery speed is closely related to both consumer satisfaction and energy consumption[4]. Fast delivery is frequently considered a crucial element in promoting consumer satisfaction, especially in the e-commerce industry where customers demand quick order fulfillment. Delivery speed is strongly associated with customer expectations, and companies that can meet or exceed these expectations are more likely to foster loyalty and repeat business[5]. On the other hand, fast delivery usually necessitates greater resource allocation, resulting in higher energy consumption[6]. When delivering perishable goods like fresh food, refrigeration equipment is often used to maintain product freshness, resulting in increased energy usage. This can have adverse environmental effects, including elevated carbon emissions and waste generation[7]. Furthermore, the IPCC (2021) has released a concerning report emphasizing the irreversible impacts of mounting greenhouse gas emissions and the critical requirement for every country to adopt more assertive mitigation measures. The report stresses the current need for the planet to acclimate to a warmer climate. Various measures have been implemented to address climate change, such as the widespread adoption of new energy vehicles, the use of renewable packaging materials, and the establishment of green storage infrastructure. While these efforts have contributed to reducing carbon emissions to some degree, there remains a significant delivery challenge, particularly in relation to the "range anxiety" phenomenon in the transportation of new energy vehicles. It is essential to find effective solutions to overcome this challenge and ensure the successful transition to more sustainable transportation options. As a result, existing distribution practices heavily rely on traditional fuel-powered vehicles, which necessitates a reconsideration of distribution techniques with an unyielding focus on sustainability.

There is a need for a balance to be struck between delivery speed, consumer satisfaction, and energy consumption. To optimize their operations and reduce their environmental impact, companies need to explore alternative delivery options such as consolidating packages or using electric vehicles that prioritize sustainability. Companies could offer consumers the choice of slower, more sustainable delivery options in exchange for incentives or discounts. Balancing high delivery speed, consumer satisfaction, and energy consumption is critical for e-commerce companies looking to succeed while minimizing their environmental impact[8]. Therefore, a crucial question arises: How can we achieve balance by optimizing delivery routes in the transportation chain to enable cost-effective logistics and enhance customer satisfaction? To tackle the problem of logistics optimization as a dual-objective project, it is necessary to concentrate on decreasing logistics expenditures through optimized distribution routes while catering to varied customer needs, sans additional costs. When establishing multiple warehouses or depots across different regions, it is essential to analyze the balance between logistical expenses and customer satisfaction on a global scale. In addition, the design of distribution routes and optimization of scheduling schemes pose additional challenges[9].

To the best of our knowledge, this study explores the Multi-Depot Vehicle Routing Problem (MDVRP) by accounting for both low carbon and cold chain costs[9,10]. Additionally, this research examines the Multi-Depot Vehicle Routing Problem with Time Window (MDVRPTW)[11], where customers require delivery vehicles to complete services within specific time windows. In strict terms, the earliest receipt time represents the earliest possible moment for the customer to receive the goods, while the latest receipt time represents the latest acceptable moment. The traditional MDVRPTW approach consistently aligns the customer's psychological perception of time with the theoretical time of wait[12]. We discovered that although a customer's time sensitivity is not linearly related, their psychological perception of delivery time is consistent with real-time, which is in line with the loss aversion phenomenon in behavioral economics[13]. Essentially, customers prefer to receive goods earlier and do not anticipate receiving them later. For instance, the customers may experience different levels of anxiety and loss when the goods arrive one hour early or one hour late, respectively, in relation to their psychological reference time.

In this study, we have integrated carbon emissions into logistics costs from a low-carbon perspective to address low-carbon operations concerns. Additionally, we have established a customer satisfaction-based compensation function from the loss aversion perspective of prospect theory. Finally, we designed a multi-objective MDVRPTW model that focuses on minimizing total logistics cost and maximizing customer satisfaction. Given that the model under study embodies a typical NP-Hard problem[9], unable to produce a precise solution within the allotted time, the present study proposes a new algorithm that fuses fruit fly optimization algorithm (FFO)[14] and MOEA/D[15] - Multi-objective Fruit Fly Optimization (MOFFO). To verify the effectiveness of the algorithm and the model, multiple numerical examples are analyzed.

Based on the model and algorithm presented in this paper, we first examine the trade-off relationship between various objectives, such as environmental and social benefits, corporate profits, and logistics cost. It has been noted that, in certain circumstances, customer satisfaction and company expenses may be traded off for logistics cost without necessarily requiring larger capital expenditures. Secondly, our comprehensive analysis of path planning issues demonstrates that companies can attain environmental benefits by revising certain solutions to fulfill their corporate social responsibilities, thereby contributing to society. While this reduction in carbon emissions may not have a significant impact, it is possible to believe that as many companies commit to contributing to corporate social responsibility, carbon emissions will gradually decrease, resulting in a bluer world. Finally, this study asserts that due to the growing significance of e-commerce platforms on consumer satisfaction, amid the constraint of limited logistics resources, it is crucial to invest more in front warehouses and other facilities to alleviate the waiting times for delivery and provide proper compensation for dissatisfied customers affected by such delays. Due to the trade-offs between logistics expenses and customer contentment, e-commerce companies must invest in building more infrastructure, such as expanding warehouse capacity and increasing the number of distribution vehicles, to offer dependable, timely, and effective same-day delivery services.

This paper is organized as follows. In Section 2, we provide an objective and thorough review of the related literature. Section 3 presents our proposed problem and models in clear, concise, and logical manner without any biased language. We then offer an overview of the algorithm employed to handle the problems under study in Section 4. Section 5 contains the computational results on different instances, demonstrating a remarkable cost reduction and significant gains in customer satisfaction level. Finally, we conclude our findings and contributions in Section 6.

2 Literature Review

Our study draws from three areas of research: Low-carbon vehicle routing problem, multi-depot vehicle routing problem, and customer satisfaction in vehicle routing problem. We provide a comprehensive review of each topic in succession.

2.1 Low-carbon Vehicle Routing Problem (LCVRP)

The low-carbon Vehicle Routing Problem (VRP) aims to optimize driving routes and dispatch distribution vehicles to reduce fuel consumption and carbon emissions[12,16]. This approach promotes energy-saving measures and reductions in consumption within logistics and distribution processes. In this aspect, Qian, et al.[17] developed an objective function model aimed at minimizing fuel consumption through the segmentation of delivery time into multiple periods. Their study concluded that targeting carbon emissions could result in a reduction compared to solely focusing on total driving time, highlighting the significant impact of reducing carbon emissions. Turkensteen[18] analyzed the carbon emission in vehicle routing problem based on the Comprehensive Modal Emissions Model and indicates the effect of speed of vehicle on the total carbon emission. Guo, et al.[19] examined the effect of the low-carbon emission consideration on the network and route planning problem of a two-stage forward/reverse logistics. Liu, et al.[20] considered the environmental impact and resource efficiency in green vehicle routing optimization problem and designed a novel algorithm to achieve the optimal allocation of resources and the carbon emission. Xiao, et al.[21] investigated the electric vehicle routing problem with time window (EVRPTW) considering the energy/electricity consumption rate and then use the CPLEX solver to get the solutions of the model.

Recently, Wang, et al.[22] examined the green logistics location-routing problem with eco-packages involves solving a two-echelon location-routing problem and the pickup and delivery problem with time windows. Cai, et al.[23] investigated the low-carbon distribution problem of Connected and Automated Vehicles by considering vehicle speed as a decision variable. Wang, et al.[24] investigated a truck-drone hybrid routing problem with time-dependent road travel time and designed an iterative local search heuristic algorithm to solve this problem. Chen, et al.[25] studied urban cold chain distribution problem utilizing both electric vehicles (EVs) and gasoline and diesel vehicles, and propose an improved Variable Neighborhood Search (VNS) algorithm to enhance computational performance. Zhang, et al.[26] examined the low-carbon vehicle routing problem with environmental regulation to determine the transportation path, driver, and vehicle type in a joint manner. Goli, et al.[27] investigated the energy awareness of non-permutation flow-shop scheduling and lot-sizing using modified novel meta-heuristic algorithms. Lou, et al.[28] studied a problem with high granularity time-dependent speeds and designed a hybrid genetic algorithm with adaptive variable neighborhood search.

2.2 Multi-Depot Vehicle Routing Problem

The Multi-depot Vehicle Routing Problem (MDVRP) is considered more realistic than the Vehicle Routing Problem (VRP) in the logistics industry[10,29]. MDVRP involves high complexity and optimization difficulties[9,30], which has prompted widespread research on solution strategies. Numerous scholars have conducted extensive studies on MDVRP's solution methods. Desfontaines, et al.[31] combined the vehicle schedule to create a model for vehicle scheduling. They developed a two-stage solution strategy and found that the algorithm effectively reduces vehicle usage when there are limited schedule changes. Shen, et al.[32] investigated a low-carbon multi-depot open vehicle routing problem with time windows (MDOVRPTW) and designed a two-phase algorithm to solve the problem model. Zhen, et al.[33] investigated a multi-depot multi-trip vehicle routing problem with time windows and release dates and proposed a combineted algorithm to solve this problem. Sadati, et al.[34] proposed algorithm applies a granular local search mechanism in the intensification phase and a tabu shaking mechanism to solve a class of MDVRPs. Zhang, et al.[35] investigated a heterogeneous multi-depot collaborative vehicle routing problem (HMCVRP) anded proposed a Benders-based branch-and-cut algorithm with the technique of combinatorial Benders' cuts to solve a mixed-integer programming formulation.

However, few studies have analyzed the cost factors and carbon emissions in cold chain distribution, as well as the impact on the design of multi-depot logistics distribution schemes. In this field, Wang, et al.[36] tackled a collaborative multi-center vehicle routing problem with resource sharing and temperature control constraints in the transportation and distribution of fresh and perishable products. Li[3] combined the vehicle routing problem framework for multiple distribution centers, analyzed the impact of considering the huge loss of life caused by delivery delays in the presence of multiple vaccine production centers, and studied the optimal distribution of vaccines. However, none of the above articles considered the impact of low-carbonization on the logistics and distribution links. Liu, et al.[37] investigated the optimization of unmanned electric vehicles delivery routes and charging strategies and develop an efficient double-adaptive variable neighborhood search (DA-GVNS). Goli and Tirkolaee[38] proposed a multi-objective mathematical model to optimize diary supply chain by designing a closed-loop supply chain. Wang, et al.[39] examined the optimization of a bi-objective two-echelon multi-depot multi-period location-routing problem with pickup and delivery by using a hybrid multi-objective particle swarm optimization (HMOPSO) algorithm and introduces a three-dimensional (3D) k-means clustering. Goli, et al.[40] investigated a organ transplantation problem in the organ transplants supply chain considering shipment time uncertainty and proposed a novel simulation-based optimization with the credibility theory to deal with the uncertainty in the model optimization.

2.3 Customer Satisfaction in Vehicle Routing Problem

There exist significant differences between online and offline shopping experiences. In offline shopping, customers pay for and receive goods in person, enabling them to directly evaluate factors like performance, texture, and quality. This hands-on experience integrates control and ownership of the product for the customer. Conversely, in online shopping, there is a clear separation between ownership and control, potentially causing customer insecurity due to the temporal gap between the two realms[41]. The delivery time in online shopping has emerged as a critical factor influencing customer satisfaction[42]. Efficient logistics and distribution services play a vital role in enhancing online shoppers' confidence and managing their expectations regarding delivery times[43]. Research by Funches[44] revealed that delays beyond customers' expectations in online shopping can breed distrust towards the platform. This could result in negative feedback and reviews, significantly impacting the company's market standing. Therefore, it is crucial for e-commerce firms to minimize wait times and prevent delivery delays for online customers. This proactive measure will notably enhance the overall customer experience and foster loyalty to the platform.

As the timeliness of logistics and distribution significantly influences customers' online purchasing decisions, it predominantly revolves around meeting the customer's time constraints. Current research endeavors to delve deeper into the relationship between time constraints and customer satisfaction. For example, Barkaoui, et al.[45] argued that disruptions in the inherent logistics infrastructure can disturb a customer's delivery time window, leading to decreased customer satisfaction. Consequently, logistics providers may need to compensate for these inconveniences by paying fines. McNabb, et al.[42] developed a distribution vehicle scheduling model using the ant colony algorithm to address delivery time window constraints and minimize customer waiting time. Goli, et al.[46] designed a blockchain-enabled closed-loop supply chain (BCSC), considering the role of the product portfolio, then employ an exact solution method using GAMS software to solve the above model. Liang, et al.[47] examined the perishable goods delivery problem while simultaneously considering transportation cost and customer satisfaction by minimizing the loss of perishable freshnes and proposed an combined VNS and SA metaheuristic algorithm.

2.4 Limitations and Our Contributions

Table 1 compares our study with extant studies in several critical model construction aspects (In Table 1, LC, MO, MD, LA, and CC respectively stand for Low-carbon, Multi-objective, Multi-depot, Consumer Time Loss Aversion, and Cold chain distribution.). Firstly, unlike previous studies solely focusing on optimizing low-carbon vehicle distribution, we consider the impact of varying consumer sensitivities to delivery time delays on distribution schemes, which enriches the vehicle routing problem. Secondly, compared to earlier studies that only address logistics costs and low-carbon efficiency as dual objectives, we introduce consumer satisfaction as an additional objective dimension, making the vehicle routing problem more realistic. Lastly, our research extends the optimization problem in cold chain distribution by utilizing a multi-objective solution algorithm to solve a multi-objective cold chain distribution optimization problem that takes into account carbon emissions, consumer satisfaction, and cold chain operational costs.

Table 1 Comparison with existing studies in model construction

Existing studies	LC	MO	MD	LA	CC
Our paper	√	√	√	√	√
Zhen, et al.[33]			√		
Wang, et al.[22]	√				
Cai, et al.[23]	√				
Sadati, et al.[34]			√		
Soriano, et al.[9]			√		
Zhang, et al.[35]			√		
Liang, et al.[47]		√		√	√
Chen, et al.[25]					√
Li[3]	√	√	√	√	
Goli and Tirkolaee[38]		√		√	
Zhang, et al.[26]	√				
Liu, et al.[37]			√		
Goli, et al.[27]	√				
Lou, et al.[28]	√				

Drawing from the model and algorithm outlined in this paper, we conduct an initial examination of the trade-off relationship among various objectives, encompassing environmental and social utility along with corporate benefits. Firstly, our analysis reveals that certain aspects of customer satisfaction and company costs may be compromised to optimize logistics expenses, without necessarily entailing significant capital expenditures. Furthermore, our thorough investigation into path planning challenges demonstrates how companies can achieve environmental advantages by tailoring specific strategies to fulfill their corporate social responsibility obligations and contribute meaningfully to society. While the reduction in carbon emissions may appear modest, it is noteworthy that many firms are actively dedicated to upholding their corporate social responsibility commitments. As more companies take steps to reduce their carbon footprint, the world moves closer towards a cleaner and more sustainable future. Additionally, this study underscores the growing importance of e-commerce platforms in enhancing consumer satisfaction despite facing constraints in logistics resources. Therefore, it becomes imperative to ramp up investments in initiatives such as front warehouse management to alleviate customer apprehension during product receipt. Moreover, enhancing compensation for dissatisfied customers due to delivery delays is crucial. Given the delicate balance between logistics costs and customer satisfaction, e-commerce platforms must prioritize enhancing their infrastructure to deliver top-notch, swift, and efficient same-day delivery services. This may entail expanding the fleet of distribution vehicles, increasing warehouse capacities, and implementing other pertinent strategies.

3 Problems and Model Formulations

3.1 Problem Description

The low-carbon MDVRP of fresh goods (as shown in Figure 1) can be described as follows: A fresh goods e-commerce platform has a series of fresh product depots D_I $(I = 1, 2, \cdots, m)$, where orders are received from n customers. To maintain the freshness level of fresh products and prevent decay, e-commerce companies need to use refrigerator trucks with maximum load capacity Q to perform delivery services. And the maximum travel distance is limited to L. The customer's demand for fresh products is q_i $(i = 1, 2, \cdots, n)$. When the consumer places an order from the platform, the e-commerce platform promises the latest delivery time l_i. If the delivery exceeds the promised latest delivery time l_i, the e-commerce platform needs to pay the consumer a certain fine. Here, fines may be paid to consumers in the form of cash discounts, coupons, or cash back.

Assuming that the e-commerce platform has a limited number of refrigerated trucks due to the scarcity of workers and delivery vehicles caused by the COVID-19 pandemic, a well-thought-out delivery route plan is essential. The conditions for a viable delivery route are as follows: 1) Each refrigerated truck starts from its respective depot, loads fresh products, delivers them along the designated driving route to customers, and then returns to the depot. 2) While a single refrigerated truck can serve multiple customers, each customer should only be served once by a refrigerated truck. All proposed delivery plans must comply with these conditions.

To illustrate this concept, we have provided a distribution route map for the MDVRP based on a specific scenario involving 20 consumers and three e-commerce companies operating distinct fresh food warehouses (depots) with varying numbers of refrigerated vehicles. The feasibility of a delivery plan meeting these criteria is demonstrated in Figure 2.

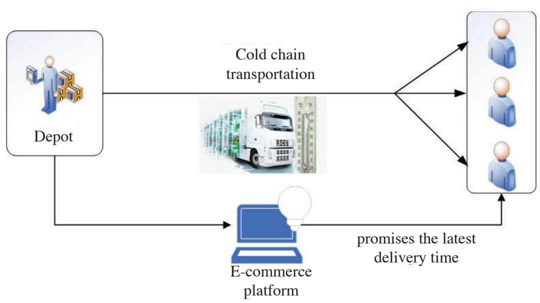

Figure 1 MDVRP of fresh goods

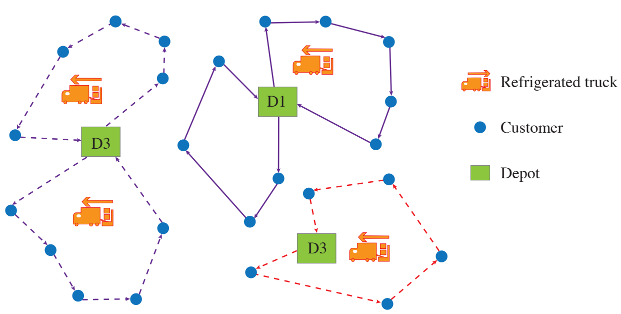

Figure 2 A feasible delivery scheme for the given case

Based on the analysis of the problem, we summarize our notations in Table 2.

Table 2 List of notations

Notation	Definition
C	The set of customers, $C = \{v_1, v_2, \cdots, v_n\}$, with n customers to be served.
D	The set of depots, $D = \{v_{n+1}, v_{n+2}, \cdots, v_{n+m}\}$, with m-depots.
N	The union of customers and depots, $N = C \cup D$.
A	The set of paths between any two points, $A = \{(i, j) \mid i, j \in N, i \neq j\}$.
K	The set of available delivery vehicles, $K = \{k_1, k_2, \cdots, k_j\}$, J indicates the total number of vehicles owned by the e-commerce platform.
K_g	The set of vehicles owned by the depot $g, g \in D, \quad K_g \subset K$, here, $\lvert K_g \rvert$ is the number of vehicles in the specific depot g.
i	The subscript denotes the customer i.
Q_k	The maximum load capacity of the refrigerator car k $(k \in K)$.
L_k	The maximum mileage of refrigerator car k $(k \in K)$.
q_i	The demand from customer $i \cdot (0 < q_i < Q, i \in C)$.
s_i	The service time spent in customers i.
t_i	The promised the latest delivery time to the customer i.
t'_i	lerance time of the customer i.
d_{ij}	The Euclidean distance (km) between any two points i and $j\cdot$ as $d_{ij} = d_{ji}, i, j \in N$, with a symmetrical back-and-forth path.
C_{fc}	The fixed cost of each refrigerator vehicle (including vehicle rental, insurance, maintenance, etc.).
c_{vc}	The variable cost of vehicle unit mileage (mainly including variable costs such as driver's salary cost).
c_{ce}	The fuel consumption cost per unit mileage.
c_{trx}	The cold chain cost per unit mileage during transportation.
c_{urc}	The cold chain cost per unit time during unloading.
C_{cold}	The total cold chain cost during transportation.
c_{cm}	The unit carbon emission cost during transportation.
C_E	The total carbon emission cost.
C_{Pi}	The cost of delay penalties that need to be paid to the consumer i when delivery is delayed.
V	The average speed of the vehicle during driving.
ρ^*	The fuel consumption rate of refrigerated vehicles when fully loaded.
ρ^0	The fuel consumption rate of refrigerated vehicles when traveling with no load.
x_{ijk}	0-1 binomial variable indicates that the refrigerated truck k passes through the path (i, j) when the value is 1, otherwise it is zero.
f_{ijk}	A load of fresh products when the refrigerator car k passes through the route (i, j).
ρ_{ijk}	The fuel consumption rate of the refrigerator car k when driving on the route (i, j).
a_i	The arrival time when the vehicle arrives at the consumer i,$i \in C$.
h_i	The departure time of the vehicle from the customer i to the next customer j, $i, j \in C$.
o_i	The delayed service time of the customer i, $i \in C$.
M	M represents a very large number.

3.2 The Model Setup

3.2.1 Fuel Cost

Several studies have highlighted the substantial role of fuel costs within logistics expenses in the industry[48]. For instance, Sahin, et al.[49] discovered that when a fully loaded truck, with a maximum capacity of 20 tons, travels an average distance of 1000 km, fuel expenses make up 60% of the overall logistics expenditure. Moreover, the rise in fuel usage results in increased emissions of CO2 and other greenhouse gases[50]. Research indicates that fuel consumption is intricately linked to the total mileage covered by the vehicle and the volume of goods transported[51]. To mitigate carbon emissions and fuel usage during transportation, Xiao, et al.[52] devised a fuel consumption model that incorporates driving routes and load capacities, offering a more precise estimation based on empirical data. Suzuki[48] conducted a study encompassing transportation firms of diverse sizes, ranging from large corporations to small businesses. The investigation unveiled that actual load capacities and driving distances significantly influence fuel consumption in delivery vehicles. Therefore, optimizing delivery routes and reorganizing service sequences for each customer can effectively decrease unit fuel consumption and carbon emissions[50].

By the above analysis, in this section, we build a fuel consumption model as shown in Equation (1) based on the studies of Xiao, et al.[52] and Suzuki[6]. Here, $\rho\left(f_{ijk}\right)$ indicates the fuel consumption per unit mileage (km) in the case of vehicle loading f_{ijk} (kg).

$$\rho\left(f_{ijk}\right)=\left(\rho^0+\frac{\rho^*-\rho^0}{Q} f_{ijk}\right). \tag{1}$$

More specifically, if denoting the actual load of the delivery vehicle on the path (i, j) is f_{ijk}. Then we can calculate the fuel consumption per unit mileage on this route as $\rho_{ijk}=\rho\left(f_{ijk}\right)$. As such, the fuel consumption cost can be expressed as Equation (2), where the Euclidean distance of the path (i, j) is d_{ij}.

$$C_{\text{fiel}}^{ij}=C_{ce} \rho_{ijk} d_{ij}. \tag{2}$$

As a result, supposing r is the set of consumers served by the refrigerator car k, then the total fuel cost of the vehicle during the transportation is given in Equation (3):

$$C_{\text{fuel}}=\sum_{i=1}^r \sum_{j=1}^r C_{\text{fuel}}^{ij} x_{ijk}=\sum_{i=1}^r \sum_{j=1}^r C_{ce} \rho_{ijk} d_{ij} x_{ijk}. \tag{3}$$

Since the variable $x_{ijk}=1$ when the specific driving route (i, j) exists, it is zero otherwise and (i, j) is f_{ijk} is affected by the load sequence. Therefore, the delivery route can be designed rationally to reduce fuel consumption, thereby achieving the goal of reducing logistics costs.

3.2.2 Cooling Cost

The cold chain plays a crucial role in transporting fresh food under controlled temperatures[26]. Without properly controlled transportation, fresh food is susceptible to rapid spoilage during transit. To maintain the freshness of perishable goods and prevent product damage, refrigerated trucks are utilized, albeit at an additional cooling cost. This cooling cost encompasses the expenditures linked to sustaining low temperatures in refrigerated trucks and consists of two main components, as depicted in Equation (4): The cooling cost during transportation and the refrigeration cost during unloading of fresh products.

$$C_{\text{cold}} = \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} C_{trc} x_{ijk} d_{ij} + \sum_{i\in C} C_{\text{urc}}\, s_i. \tag{4}$$

3.2.3 Carbon Emission Cost

In addition to the costs mentioned earlier, it is essential to factor in the carbon emission cost during transportation. Each unit of fuel consumption results in a specific quantity of carbon emissions, and the refrigeration process also contributes significantly to carbon emissions[26]. Thus, our model encompasses consideration for two types of carbon emissions:

$$C_E = \sum_{i=1}^{r}\sum_{j=1}^{r} c_{emi}\rho_{ijk} d_{ij} x_{ijk} + \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} c_{emi} x_{ijk} d_{ij} + \sum_{i\in C} c_{ems} s_i. \tag{5}$$

As demonstrated in Equation (5), the first component represents the carbon emissions resulting from fuel consumption. The second and third components signify the costs associated with carbon emissions, primarily attributed to refrigeration during transportation and the loading and unloading processes.

3.2.4 The Penalty Function

Fresh food e-commerce platforms often pledge to deliver products within a specified timeframe upon order placement, thereby boosting customer satisfaction through establishing a benchmark for measuring delivery efficiency. However, constrained by limited logistics resources, ensuring timely delivery to all customers as promised may not always be feasible. E-commerce platforms are faced with the challenge of striking a balance between delivery costs and customer contentment. To control logistics expenses, platforms may need to make compromises that impact customer satisfaction, or alternatively, they can elevate customer satisfaction levels by accepting higher logistics costs. The logistical challenges exacerbated by the COVID-19 pandemic, including resource shortages and labor deficits, have heightened this dilemma. Rapidly augmenting logistics resources to improve customer satisfaction amid widespread staff isolation and incapacity to manage distribution tasks presents a formidable obstacle.

Based on the prospect theory's perspective on loss avoidance[53], we equate the loss of time to the loss of customers. It is crucial to emphasize that the psychological cost associated with late arrivals aligns with loss aversion, as opposed to early product delivery. This preference stems from individuals generally favoring timely delivery and facing challenges when confronted with delays. To address this, e-commerce companies often provide financial compensation to customers for receiving goods after the agreed delivery time. Consequently, this research introduces a penalty function for delayed deliveries, outlined in Equation (6).

$$P_i = \begin{cases} 0, & a_i \le t_i, \\ c_{pi}\left(a_i - t_i\right), & t_i \le a_i \le t'_i, \\ M, & a_i \ge t'_i. \end{cases} \tag{6}$$

In Equation (6), when it is delivered earlier than the time t_i which represents the latest delivery time promised by e-commerce companies, the delay time is zero, and the e-commerce platform does not need to pay a fine to the consumer. When the delivery is later than t_i but not exceeding the latest tolerance time ${t'}_i$ of the customer i, the platform needs to pay a certain fine to the consumer, and the amount of the fine increases with the length of the overtime. However, when the delivery is later than the latest tolerable time t_i (namely, the customer psychological deadline), the penalty M is infinite, which means that the customer's latest tolerable time cannot be exceeded. For instance, when the latest tolerable time is exceeded, the customer may return the goods because the product has deteriorated and cannot be used.

3.3 Multi-Objective Model

By aggregating the aforementioned cost function, the multi-objective model examined in this study is formulated as follows:

$$\mathrm{Min}\, C_{fc} \sum_{k\in K}\sum_{g\in D}\sum_{j\in C} x_{gjk} + C_{vc}\sum_{k\in K}\sum_{i\in N}\sum_{j\in N} d_{ij}x_{ijk} + \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} C_{trc}x_{ijk}d_{ij} + \sum_{i\in C} C_{urc}s_i, \tag{7}$$

$$+C_{ce}\sum_{k\in K}\sum_{i\in N}\sum_{j\in N}\left(\rho^0 + \frac{\rho^* - \rho^0}{Q} f_{ijk}\right) d_{ij}x_{ijk} + C_b, \tag{8}$$

$$\mathrm{Min} \sum_{i\in C} P_i, \tag{9}$$

s.t.

$$\sum_{k\in K}\sum_{j\in C} x_{gik} \le |K_g| \quad \forall g \in D, \tag{10}$$

$$\sum_{k\in K}\sum_{j\in N} x_{ijk} - \sum_{k\in K}\sum_{i\in N} x_{ijk} = 0 \quad \forall i,j \in C, k \in K, \tag{11}$$

$$\sum_{i\in N} q_i \sum_{j\in N} x_{ijk} \le Q_k \quad \forall i \in C, \tag{12}$$

$$\sum_{i\in N}\sum_{j\in N} d_{ij}x_{ijk} \le L_k \quad \forall k \in K, \tag{13}$$

$$\sum_{i\in D}\sum_{j\in C} x_{ijk} \le 1 \quad \forall k \in K, \tag{14}$$

$$\sum_{j\in D}\sum_{i\in C} x_{ijk} \le 1 \quad \forall k \in K, \tag{15}$$

$$\sum_{k\in K}\sum_{u\in N\setminus\{i\}} f_{uik} - \sum_{k\in K}\sum_{j\in N\setminus\{i,u\}} f_{ijk} = q_i \quad \forall i \in C, \tag{16}$$

$$q_j x_{ijk} \le f_{ijk} \le (Q_k - q_i)\, x_{ijk} \quad \forall (i,j) \in A, k \in K, \tag{17}$$

$$a_j \ge h_i + \sum_{k\in K}\sum_{i\in N} x_{ijk} d_{ij}/V \quad \forall j \in C, \tag{18}$$

$$a_i + s_i \le h_i \quad \forall i \in C, \tag{19}$$

$$a_i - t_i \le o_i \le {t'}_i \quad \forall i \in C, \tag{20}$$

$$x_{ijk} \in \{0,1\} \quad \forall i,j \in N, k \in K, \tag{21}$$

$$a_i, h_i, o_i, f_{ijk} \geq 0, \quad \forall i,j \in C; k \in K. \tag{22}$$

The objective function comprises three components denoted as (7), (8) and (9) respectively. Equation (7) encapsulates the fixed and variable logistics costs, including rental and variable expenditures for refrigerator cars, along with refrigeration costs. Fuel consumption and carbon emission expenses are summarized in Equation (8), while Equation (9) represents consumer penalty charges. In terms of constraint conditions, (10) sets the maximum allowable number of refrigerator cars at each depot. Constraint (11) ensures that each customer is served by one car only, ensuring continuous vehicle travel. Constraints (12) and (13) mandate vehicle capacity and travel time limitations, respectively. Additionally, Constraints (14) and (15) determine vehicle availability status — whether in use or not. Constraints (16) and (17) specify individual segments of the vehicle's journey. (18) and (19) define the current delivery time limit, with (20) addressing delayed customer deliveries. Constraint (21) pertains to the 0-1 variable constraint, while Constraint (22) establishes a non-negative variable limit. It is notable that the model under examination comprehensively considers three cost aspects. Firstly, logistics costs encompass expenses related to the refrigerator vehicle, variable costs, and cooling expenses during transportation. Secondly, fuel and carbon emission costs reflect external drawbacks during transit. Finally, minimizing compensation due to delayed deliveries is also an objective, demonstrating a commitment to ensuring consumer satisfaction.

4 The Algorithm

The Fruit Fly Optimization Algorithm (FFO), a novel meta-heuristic approach that emulates the hunting behavior of fruit flies by leveraging their acute senses of smell and vision to conduct iterative group search in the solution space, has garnered significant attention and application since its inception[54,55]. In contrast to various traditional swarm-based methods, FFO offers a straightforward framework for incorporating problem-specific operators and ensures rapid convergence[55]. Owing to its exceptional precision, the algorithm has been widely employed to tackle combinatorial optimization challenges, such as scheduling workflows in cloud environments[55]. Given the distinctive attributes of FFO and its efficacy in addressing combinatorial optimization problems, this paper introduces a multi-objective fruit fly optimization algorithm (MOFFO) to optimize logistics costs and enhance consumer satisfaction in the aforementioned model.

4.1 Fruit Fly Optimization Algorithm

FFO, a direct and effective algorithm, takes inspiration from the foraging behavior of fruit flies, which relies on olfaction and vision. As the flies search for food, they follow the scent with the highest concentration, guided by their sense of smell. As they approach their food source, their keen vision becomes crucial in identifying superior food sources. In the context of FFO, optimal solutions correspond to the food sources with the highest odor concentration, while candidate solutions are represented by the locations of the fruit flies. The entire foraging process is executed iteratively to explore the optimal solution within the problem space. The standard FFO procedure unfolds as follows:

Step 1: Solution Initialization involves generating all fruit fly locations within the swarm in the solution space, followed by calculating the objective function value in the objective space.

Step 2: Smell-Oriented Foraging Process entails each fruit fly randomly exploring a location near its initial position, with subsequent calculation of the smell concentration at the new location.

Step 3: Vision-Oriented Foraging Process identifies locations with the highest odor concentrations through calculations for each food source. Fruit flies then move towards these promising areas and update their positions.

Step 4: Termination Condition triggers a return to Step 2 if the termination condition is not met.

The main reasons for choosing FFO for solving the proposed model in this paper are attributed to its algorithm efficiency and the advantages it offers. Firstly, in terms of algorithm efficiency: FFO is a population-based algorithm that explores the solution space through the interaction of multiple solutions. This parallelism allows FFO to search for optimal or near-optimal solutions more effectively compared to traditional optimization techniques[55]. In the meanwhile, FFO utilizes a randomized search strategy, which enables it to quickly converge towards good solutions without being trapped in local optima. This property is crucial for solving complex optimization problems like VRP[3]. Besides, FFO incorporates a local search mechanism that helps refine the solutions obtained during the exploration phase. This local search process enhances the algorithm's convergence speed and solution quality.

Secondly, as for the advantages of FFO itself, FFO is conceptually simple and easy to implement, making it accessible for researchers and practitioners alike. It doesn't require complex mathematical modeling or problem-specific knowledge[56]. Also, FFO is a versatile algorithm that can be adapted to different problem variations and constraints[57]. It allows for customization by incorporating specific VRP characteristics, such as time windows, capacity constraints, and multiple depots. Furthermore, FFO possesses good scalability, allowing it to handle large-scale instances of VRP efficiently[54,55]. It can effectively deal with the combinatorial explosion of possible solutions and find high-quality solutions within a reasonable time frame. Finally, FFO has demonstrated competitive performance in comparison to other metaheuristic algorithms when applied to VRP. It has shown effectiveness in finding near-optimal solutions and improving the solution quality over iterations[54−56]. As such, based on the advantages of the FFO in solving the vehicle routing problem, and combined with a decomposition-based multi-objective optimization algorithm, a multi-objective Fruit Fly Optimization Algorithm was designed to solve the above model.

4.2 The Multi-Objective FFO

Building upon the foundations of FFO, there is a need to extend a discrete version of MDVRP FFO to tackle the multi-objective MDVRP. In the subsequent section, we will delve into the intricacies of the multi-objective FFO (MOFFO).

4.2.1 Initialization of Solution

In this section, we establish the coding framework and initialize solutions within the swarm for MDVRP. Given that MDVRP is a discrete optimization problem, we adopt a natural number coding approach (as illustrated in Figure 3). Additionally, for clarity, MDVRP can be transformed into multiple VRPs to be concurrently solved.

Figure 3 showcases an instance featuring three depots and 15 customers. Initially, customers are grouped based on their proximity to depots. The e-commerce platform assigns customers to the nearest depot, thereby minimizing transportation expenses. Subsequently, the e-commerce company randomly sequences customer service orders and devises an initial delivery plan for each depot. In the example depicted in Figure 3, Depot I serves Customer 1, Customer 2, and Customer 6 using Vehicle 1, while Customer 3, Customer 8, and Customer 12 are serviced by Vehicle 2. Similarly, Depot II attends to Customer 7 and Customer 4 through Vehicle 3. This approach is consistent across various scenarios.

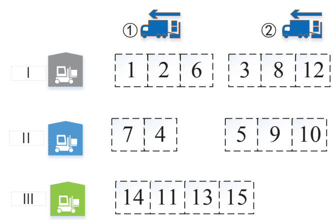

Figure 3 Real number coding structure

4.2.2 Smell-Based Foraging Process

The foraging behavior of the fruit fly population revolves around their search for food, primarily guided by a sharp sense of smell. This behavior can be analogized to the quest for an optimal solution within an optimization-solving process. In pursuit of this goal, we incorporate three distinct operators in this subsection to facilitate the optimization process of individual population members. The single-point exchange operator entails the random selection of two distinct positions within a solution, exchanging information between them, and subsequently updating the individual sequence. This process is illustrated in Figure 4. Through this exchange, a child is derived, involving the swapping of information between the delivery paths ($6 \to 3 \to 12$) and ($8 \to 10 \to 11 \to 13$), thereby resulting in the interchange of customers 13 and 6.

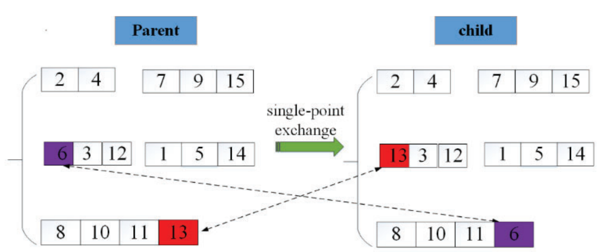

Figure 4 The single-point exchange

The multipoint exchange operator, depicted in Figure 5, enables the exchange of information between two individuals by exchanging multiple positions at different points, thereby extending beyond the limitations of a single-point crossover.

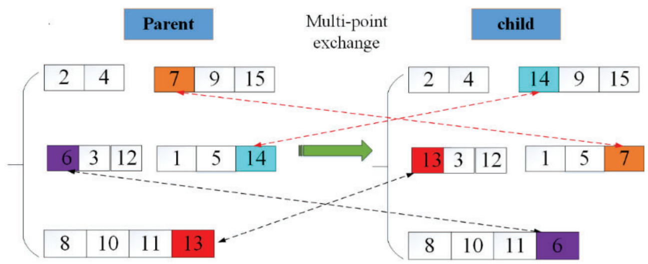

Figure 5 The multi-point exchange

The inversion operator, illustrated in Figure 6, entails the random selection of two points along the path and exchanging all information between them, leading to the interchange of individual gene positions.

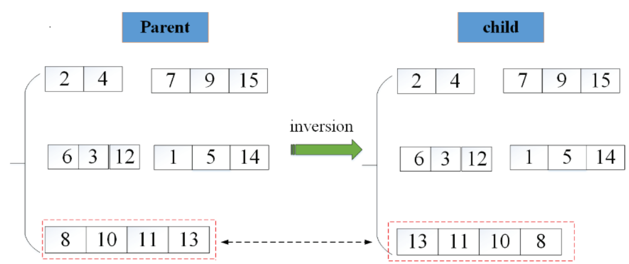

Figure 6 The inversion operator

4.2.3 Vision-Based foraging process

Following the completion of the smell-based foraging process, the algorithm transitions to the vision-based foraging process. In this phase, two operators are employed to further enhance the candidate solution. The first operator is the random insertion operator, as depicted in Figure 7, which involves the random selection of a consumer from one position and its insertion into another random position to improve fitness. After the smell-based foraging process, the algorithm enters into the vision-based foraging process. In this subsection, we apply two operators to furthermore optimize the candidate solution.

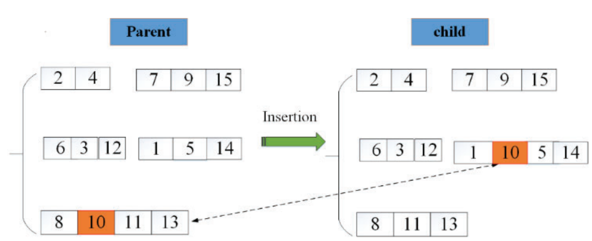

Figure 7 The random insertion

The shift operator selects an entire delivery route at random and replaces all customers on the route (as illustrated in Figure 8).

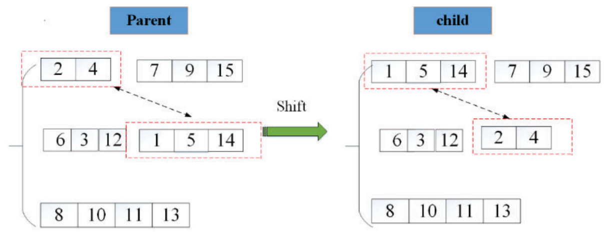

Figure 8 The shift operator

As per the coding method outlined in this article, the random insertion and shift operations are capable of selecting two positions within the same sub-path or across different sub-paths, leading to the generation of distinct paths. By enabling the exchange of information between solutions, these operations effectively broaden the search range within the solution space.

4.3 Multi-Objective Decomposition Mechanism

4.3.1 The Concept of Multi-Objective Problem

Prior to delving into the MOEA/D algorithm framework, it is essential to elucidate the relevant concepts of multi-objective algorithms. We begin by examining a multi-objective optimization problem (MOP) with multiple objectives, which can be formulated as follows:

$$\begin{aligned} &\max F(x) = (f_1(x), \cdots, f_m(x))^{\mathrm{T}}, \\ &\text{subject to } x \in \Omega, \end{aligned} \tag{23}$$

where Ω denotes the decision space (variable), and $F : \Omega \to R^m$ consists of m objective function and R^m is called the objective space. As a feasible result, the attainable objective set is set as the set $\{F(x) \mid x \in \Omega\}$.

Typically, conflicting objectives inherently hinder the attainment of a feasible solution that ensures the maximization of all objectives simultaneously. To tackle this challenge, a natural approach involves devising solutions that strike a balance among the various objectives[3,58]. The most favorable tradeoffs among objectives can be characterized in terms of Pareto optimality.

Supposing two solutions $\mu, v \in R^m$, it can be said that μ dominates v ($\mu \succ v$) if and only if $f_i(\mu) \geq f_i(v)$ for every $i \in \{1, \cdots, m\}$ and $f_j(\mu) \geq f_j(v)$ at least one objective $j \in \{1, \cdots, m\}$. Moreover, we can say that a solution $x^* \in \Omega$ is Pareto optimal to the multiobjective problem if there are no other solutions $x \in \Omega$ to make $F(x)$ dominates $F(x^*)$. Finally, all such Pareto solutions form the Pareto solution set (PS).

4.3.2 MOEA/D Algorithm

Population-based evolutionary algorithms are widely employed for solving multi-objective problems due to their capability of acquiring multiple solutions within a single algorithm iteration. To obtain the aforementioned Pareto solution set, various multi-objective algorithms have been developed. For example, Deb, et al.[59] introduced the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which is a swift and elitist multi-objective genetic algorithm founded on the domination concept. The algorithm incorporates a selection operator that merges the parent and offspring populations to form a mating pool, from which the best solution is selected. However, the domination approach falls short in establishing a comprehensive ordering of solutions in the objective space, thereby hindering the generation of Pareto optimal solutions that represent the entire Pareto Front with maximal diversity. In response to these challenges, Zhang and Li[15] implemented multiple decomposition methods to convert multi-objectives into N scalar optimization sub-problems utilizing clustering functions. They proposed the Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D), where N individuals in the population concurrently optimize N sub-problems, and the scalar function of these sub-problems is refined through neighborhood relationships. Consequently, a set of multi-objective Pareto solutions is derived. The MOEA/D process unfolds as follows: 1) During the initialization stage, the distance between any two weight vectors is computed to establish the neighborhood for each weight vector. Subsequently, population individuals are randomly initialized within the feasible space, and their fitness values are calculated to initialize the extreme point objective function value. 2) In the update solution stage, two individuals are selected within each individual's neighborhood, crossover and mutation operations are performed on them, and the neighborhood solution is updated. As for the termination condition and output, the algorithm concludes and outputs the set of Pareto optimal solutions when it reaches a specific number of iterations or satisfies a predefined termination condition. If not, it returns to the second step to continue the search for a solution. The pseudo code for MOEA/D is illustrated in Figure 9.

Algorithm MOEA/D

Input:

1) The Stop criterion of algorithm;
2) K: The number of the subproblems considered in MOEA/D;
3) Generate a uniform spread of K weight vectors: $\{\lambda^1, \lambda^2, \cdots, \lambda^K\}$;
4) T: The number of the weight vectors in the neighborhood of each weight vector.

Output: EP: A set of nondominated solutions of multi-objective optimization.

Initialization: Set $EP = \emptyset$

Generate an initial population $\{x^1, x^2, \cdots, x^K\}$ randomly. And compare their objectives values $\{F_1, F_2\}$ and use them to set $\{P_1, P_2, \cdots, P_K\}$.

While the stop criterion is not met **do**
  for $k \leftarrow 1$ to K do
    for each $x \in P_k$ **do**
      Randomly choose y from P_k;
      Apply smell-based-foraging operators on x and y
      Apply vision-based-foraging operators on x and y to
      generate a new solution z;
      Compute $F(z)$;
      $R := R \cup \{z\}$;
      end
      $EP := R \cup \{\cup_{k=1}^{K} P_k\}$;
  end
  Find all the nondominated solutions and output EP.
end

Figure 9 The pseudo code of MOEAD

4.4 Calculation of Fitness and Infeasibility

Note that this paper involves two interrelated objectives: Cost reduction and customer satisfaction enhancement. It is crucial to recognize that mitigating the penalty cost associated with delayed deliveries directly correlates with improved customer satisfaction. Consequently, this approach optimizes customer delivery wait times by implementing a systematic delivery sequence.

Let Y^t ($Y^t = \{y_1^t, y_2^t, \cdots, y_n^t\}$) represent the set of solutions of the population in the t^{th} algorithm iteration. Hence, when we get an updated solution y_s^{t+1} ($s = 1, 2, \cdots, n$) each time, we need to determine whether the solution obtained in the previous iteration is Pareto dominated by the updated solution. To be specific, if one new solution y_s^{t+1} dominates any solutions of the set Y^t, for instance, $y_s^{t+1} \prec y_r^t$, $y_r^t \in Y_t$, then we will delete this solution y_r^t from and accept the new solutionY_t as a member of the Pareto solution set.

When assessing the superiority between two solutions, it is crucial to evaluate their objective functions, particularly their fitness. This process entails three steps, starting with determining the total mileage of each vehicle. Following this, the logistics cost and delay penalty function values are computed based on the load assigned to each sub-path.

In the second step, we need to deal with the infeasible situation when the mileage and actual load of the vehicle exceed the maximum limit value. Here, by assuming that the total mileage and actual load of the vehicle k are $\Phi_k = \sum_{i \in N} q_i \sum_{j \in N} x_{ijk}$, $\Upsilon_k = \sum_{i \in N} \sum_{j \in N} d_{ij} x_{ijk}$, respectively, then we can set two infinite numbers G_k, J_k as the penalty when the vehicle disturbs the constraint limit. And the total penalty in the case of a vehicle disturbing the restraint limit is given as:

$$\mathbb{N} = G_k \max\{\Phi_k - Q_k, 0\} + J_k \max\{\Upsilon_k - L_k, 0\}. \tag{24}$$

To uphold the integrity of our solution and prevent the inclusion of infeasible solutions from impacting the overall outcome, it is imperative to adopt a cautious approach. In the subsequent steps, we proceed by calculating the logistics cost and the penalty for delayed distribution for each vehicle. By summing up the costs across all vehicles, we can obtain the total logistics cost of the distribution process. Similarly, we are able to determine the comprehensive penalty for delayed distribution.

As such, our designed algorithm possesses the following innovations. Firstly, we integrated the decomposition-based multi-objective algorithm framework into the Fruit Fly Optimization Algorithm, combining the population evolution mechanism of the Fruit Fly Optimization Algorithm with the decomposition-based approach. Note that, the multi-objective algorithm based on decomposition offers several advantages over other algorithms. By explicitly considering multiple conflicting objectives and optimizing them simultaneously, it provides decision-makers with a diverse set of trade-off solutions along the Pareto front. Secondly, the decomposition-based approach strikes a balance between convergence and diversity, ensuring a wide exploration of the solution space and efficient convergence towards optimal trade-offs. This adaptability to problem-specific characteristics, efficient exploration of the objective space, and robust handling of non-convex Pareto fronts make it a powerful tool for addressing complex real-world optimization problems. And also, its scalability and performance have been demonstrated in handling large-scale and computationally intensive problems, making it a valuable choice for multi-objective optimization tasks. In addition, we have also designed a method to handle infeasible solutions for the vehicle routing problem addressed in this paper. This approach involves incorporating a penalty mechanism to prevent the algorithm from getting trapped in local optima.

5 Computational Experiments and Results

The designed algorithm was developed using Microsoft®Visual Studio 2022 in C++. Computational testing was conducted on a desktop computer featuring an Intel Core i5-8250U processor operating at 1.8 GHz and 8.00 GB of RAM. To mitigate the influence of random variance on the outcomes, each algorithm was iterated 30 times for every example. The final result was derived as the average of 30 iterations.

5.1 Data Sets and Parameter Setting

Our study was conducted using 20 MDVRPTW cases sourced from the literature by Cordeau, et al.[60] As shown in Table 3, these instances were categorized into two distinct sets: Set 1 (p01-p10) consisting of 10 cases with tighter time windows, and Set 2 (p11-p20) comprising 10 cases with relatively lenient time windows. The dispatch of vehicles from each depot is constrained, and customer-specific service times are assigned to all customers.

Table 3 The values of the stopping criterion

Number of Customers	Iteration Times of Algorithm
$n \leq 50$	500
$50 < n \leq 100$	350
$100 < n < 200$	200
$200 \leq n$	100

Some parameter configurations related to the algorithms are based on corresponding original references. Furthermore, the number of fruit flies NP is set at the following five levels $\{20, 50, 100, 150, 200, 250\}$ to calibrate the parameter, and then find the performance of the proposed approach is optimal when $NP = 200$. As such, we set $NP = 200$ through all instances. Besides, the stopping criterion was set according to the number of customers in the problem as given in Table 3[3,34]. Lastly, given the reality of transportation, refrigerated vehicles have many different types[3.61]. Without loss of generality, in our experiments, we set parameters related to refrigerated vehicles as follows, $Q_k = 1300$ kg, $L_k = 800$ km, $C_{fc} = 300, C_{vc} = 120$, $c_{ce} = 5, c_{trc} = 10, c_{\mathrm{urc}} = 2, V = 80$ km/h (All the cost is calculated in U.S. dollar).

5.2 Results on MDVRPTW Instances

In this section, we put our algorithm to the test using 20 instances of the MDVRP and present a summary of the results in Table 4. To ensure an equitable comparison, we employ three multi-objective algorithms (NSGA-II, SPEA2, and MOEAD) in our experiments. Each instance is independently executed 30 times, and the resulting data is juxtaposed with that obtained from NSGA-II, SPEA2, and MOEAD. Subsequently, we calculate the algorithm's effectiveness based on the performance comparison across all 20 examples.

Table 4 C-metric of the MOFFO and other MOEAs

Instance	MOFFO(a) vs NSGA-II(b)		MOFFO(a) vs SPEA2(c)		MOFFO(a) vs MOEA/D(d)		MOFFO(a) vs MOABC(d)	
	$C(a,b)$	$C(b,a)$	$C(a,c)$	$C(c,a)$	$C(a,d)$	$C(d,a)$	$C(a,e)$	$C(e,a)$
P01	0.61/0.25	0.10/0.21	0.87/0.20	0.01/0.02	0.98/0.11	0.25/0.18	0.42/0.13	0.23/0.20
P02	0.75/0.05	0.21/0.01	0.86/0.22	0.03/0.13	1.00/0.00	0.12/0.13	0.75/0.25	0.10/0.29
P03	0.69/0.16	0.25/0.18	0.86/0.30	0.03/0.08	0.86/0.30	0.15/0.25	0.62/0.25	0.28/0.39
P04	0.73/0.26	0.12/0.13	0.93/0.20	0.08/0.17	1.00/0.00	0.22/0.25	0.75/0.05	0.21/0.01
P05	0.76/0.29	0.15/0.25	0.80/0.29	0.05/0.10	0.83/0.01	0.15/0.10	0.69/0.16	0.25/0.18
P06	0.62/0.30	0.22/0.25	0.70/0.39	0.04/0.08	0.72/0.20	0.02/0.09	0.73/0.26	0.12/0.13
P07	0.66/0.20	0.16/0.18	0.62/0.31	0.12/0.17	0.72/0.21	0.22/0.10	0.76/0.29	0.15/0.25
P08	0.64/0.30	0.22/0.25	0.78/0.29	0.00/0.01	0.95/0.17	0.00/0.00	0.62/0.30	0.22/0.25
P09	0.75/0.32	0.14/0.15	0.67/0.31	0.04/0.08	1.00/0.00	0.00/0.00	0.87/0.20	0.01/0.02
P10	0.85/0.21	0.03/0.02	0.76/0.23	0.07/0.17	0.68/0.11	0.00/0.00	0.86/0.22	0.03/0.13
P11	0.90/0.10	0.26/0.12	0.71/0.35	0.07/0.19	0.91/0.28	0.04/0.10	0.86/0.30	0.03/0.08
P12	0.82/0.27	0.25/0.23	0.53/0.34	0.01/0.02	0.77/0.32	0.25/0.08	0.93/0.20	0.08/0.17
P13	0.64/0.31	0.38/0.21	0.86/0.22	0.00/0.00	0.57/0.54	0.01/0.02	0.80/0.29	0.05/0.10
P14	0.87/0.28	0.29/0.25	0.70/0.33	0.03/0.08	0.54/0.41	0.00/0.00	0.70/0.39	0.04/0.08
P15	0.76/0.31	0.38/0.25	0.59/0.35	0.06/0.22	0.83/0.32	0.00/0.00	0.62/0.31	0.12/0.17
P16	0.74/0.28	0.02/0.20	0.82/0.22	0.11/0.26	0.70/0.26	0.14/0.15	0.78/0.29	0.00/0.01
P17	0.79/0.25	0.14/0.15	0.75/0.27	0.01/0.02	0.82/0.22	0.00/0.00	0.66/0.12	0.21/0.35
P18	0.90/0.20	0.25/0.08	0.76/0.29	0.06/0.17	0.59/0.35	0.01/0.02	0.75/0.23	0.43/0.34
P19	0.77/0.17	0.10/0.21	0.61/0.37	0.00/0.00	0.76/0.29	0.05/0.08	0.58/0.21	0.16/0.22
P20	0.82/0.26	0.00/0.00	0.86/0.39	0.04/0.10	0.90/0.28	0.00/0.00	0.69/0.25	0.20/0.33

Our methodology is briefly outlined, and the rationale behind selecting the algorithms is explained. For a more comprehensive understanding, please refer to the original studies[15,59,62]. NSGA-II utilizes a rapid nondominated sorting process, an elitist preservation strategy, and a parameterless niching operator to generate a range of Pareto-optimal solutions. It is evident that both algorithms follow the dominant approach. SPEA2[63] employs density estimation and improved archive truncation methods to address multi-objective problems (MOPs), offering superior performance compared to other multiobjective evolutionary algorithms. However, these algorithms take a holistic approach to address MOPs by attempting to identify as many dominant solutions as possible in one iteration. The authors of this study do not attribute each solution to a specific scalar optimization problem[15]. As a result, traditional selection operators initially developed for scalar optimization cannot be directly employed in other multiobjective evolutionary algorithms (MOEAs). MOEA/D decomposes the MOP into multiple scalar optimization subproblems, providing a simple and effective way to implement decomposition approaches in multiobjective evolutionary computation. Besides, we also compared our computational results with those obtained by the Multi-objective Artificial Bee Colony

(MOABC) algorithm.

As previously mentioned, researchers commonly rely on three algorithms for addressing multi-objective problems[3,16,27,54]. In light of our study's focus on tractability, we have opted to employ these three algorithms in order to derive comparative results on instances of the MD-VRPTW problem. It is imperative to acknowledge that, unlike in single-objective optimization problems, multi-objective optimization entails the consideration of multiple objectives. Consequently, the sole reliance on the objective function value is insufficient to determine the quality of a solution[15]. Hence, evaluating the performance of solutions assumes significant importance. In this regard, two fundamental evaluation criteria must be established, namely the convergence towards the Pareto-optimal set and the preservation of diversity within the solutions comprising the Pareto-optimal set[59]. These aspects cannot be adequately assessed through a single performance metric. Fortunately, various recommended performance metrics have been proposed[15,64]. Within this study, we employ two performance metrics to assess each of the aforementioned objectives within the solution set obtained through the application of a multiobjective optimization algorithm.

1) C metric

Denote A and B as two approximations to the Pareto front of a multi-objective problem, $C(A,B)$ equals the percentage of the solutions in the set that are dominated by at least one solution in the set A, i.e.,

$$C(A,B)=\frac{\mid\{\mu\in B\mid\exists v\in A: v \text{ dominates } \mu\}\mid}{|B|}, \tag{25}$$

where $C(A,B)$ is not necessarily equal to $1-C(B,A)$. In addition, $C(A,B)=1$ shows that all solutions in the set B are dominated by some solutions in the A (for instance $\varsigma\in A$). And $C(A,B)=0$ means that there does not exist any one solution $\psi\in B$ dominated by a solution in the set A.

2) IGD metric

This metric calculates the average Euclidean distance between each solution in the actual Pareto front and the non-dominated solution identified by the optimization algorithm[15]. A lower IGD value signifies a closer proximity of the non-dominated solution set to the genuine Pareto front, indicating a more even distribution and improved convergence and diversity within the solution set.

$$IGD\left(X,P^*\right)=\frac{\sum_{x\in P^*}d(x,X)}{|P^*|}, \tag{26}$$

where, X denotes the points set obtained by the algorithm X, P^* is the set of points on the real Pareto front.

3) Hypervolume metric

This metric calculates the volume of the hypercube formed by all non-dominated solutions and a reference point, which comprehensively evaluates the convergence and distribution of the non-dominated solution set[63,64]. The calculation method is shown in Equation (27).

$$\text{Hypervolume }=\bigcup_{i=1}^{\bar{P}_1} v_i, \tag{27}$$

where v_i represents the volume of the hypercube formed by the i-th non-dominated solution and a reference point. For multi-objective optimization problems where all objectives are minimized, a larger value of this metric indicates better algorithm performance. Hence, through the computation and comparison of the aforementioned indicators, it is feasible to ascertain the efficiency of solutions attained by different algorithms and obtain Pareto optimal vectors distributed uniformly along the Pareto front.

After comparing the C indicators as presented in Table 4, it is evident that MOFFO surpasses other multi-objective optimization algorithms notably by achieving a higher quantity of non-dominated solutions. For example, this is supported by the observation that the value of $C(a,b)$ approaches 1 in numerous instances, while $C(b,a)$ tends to approach 0.

According to the IGD index results outlined in Table 5, it is clear that MOFFO surpasses other algorithms with statistically significant outcomes across all instances. This is evident from the consistently low IGD index values attributed to MOFFO, underscoring its remarkable convergence capability.

Table 5 IGD of the MOFFO and other MOEAs

Instance	MOFFO	NSGA-II	SPEA2	MOEA/D	MOABC
	Mean/std	Mean/std	Mean/std	Mean/std	Mean/std
P01	8.04e-03/4.2e-03	2.78e-02/5.1e-03	1.18e-02/3.7e-03	1.73e-02/5.4e-03	1.36e-02/5.3e-03
P02	1.23e-02/5.9e-03	1.62e-02/2.4e-03	2.23e-02/4.9e-03	1.69e-02/7.8e-03	1.04e-02/6.5e-03
P03	1.18e-02/3.7e-03	1.36e-02/5.3e-03	2.34e-02/5.2e-03	1.63e-02/7.8e-03	1.03e-02/5.4e-03
P04	1.23e-02/5.9e-03	1.44e-02/6.5e-03	1.43e-02/6.1e-03	1.78e-03/6.1e-03	1.52e-02/5.6e-03
P05	1.34e-02/3.2e-03	1.43e-02/5.4e-03	1.54e-02/5.9e-03	1.73e-02/5.4e-03	2.23e-02/4.9e-03
P06	1.26e-02/3.2e-03	2.52e-02/5.6e-03	2.06e-02/4.2e-03	1.69e-02/7.8e-03	2.34e-02/5.2e-03
P07	1.16e-03/6.4e-03	2.23e-02/3.4e-03	1.96e-02/8.5e-03	1.63e-02/7.8e-03	1.43e-02/6.1e-03
P08	2.12e-02/9.3e-03	2.23e-02/5.8e-02	2.63e-02/5.9e-03	2.92e-02/6.4e-03	1.54e-02/5.9e-03
P09	1.94e-02/7.4e-03	1.02e-02/6.5e-03	2.68e-02/2.7e-03	2.42e-02/5.3e-03	2.18e-02/3.7e-03
P10	1.65e-02/5.5e-03	2.09e-02/2.2e-03	2.60e-02/7.2e-03	2.10e-02/6.1e-03	2.23e-02/5.9e-03
P11	1.96e-02/5.3e-03	2.46e-02/3.2e-03	3.61e-02/6.2e-03	1.99e-02/5.4e-03	2.34e-02/3.2e-03
P12	1.83e-02/7.6e-03	2.36e-02/3.9e-03	3.50e-02/2.8e-03	1.92e-02/5.8e-03	2.26e-02/3.2e-03
P13	1.75e-02/7.4e-03	2.28e-02/3.6e-03	1.93e-02/5.4e-03	2.03e-02/6.4e-03	2.62e-02/2.4e-03
P14	1.74e-02/5.8e-03	1.94e-02/2.6e-03	1.89e-02/2.8e-03	1.99e-02/4.8e-02	2.36e-02/5.3e-03
P15	1.19e-02/5.9e-03	1.36e-02/2.50e-03	1.83e-02/5.8e-03	1.73e-02/5.4e-03	2.44e-02/6.5e-03
P16	1.53e-02/6.3e-03	1.65e-02/3.6e-02	2.78e-02/5.1e-03	1.69e-02/7.8e-03	2.43e-02/5.4e-03
P17	1.45e-02/4.0e-03	1.78e-02/4.6e-03	1.73e-02/5.4e-03	1.63e-02/7.8e-03	2.52e-02/5.6e-03
P18	1.27e-02/5.6e-03	1.66e-02/2.5e-03	1.69e-02/5.0e-03	1.62e-02/8.9e-02	2.08e-02/7.2e-03
P19	1.64e-02/5.8e-03	1.65e-02/5.5e-03	2.53e-02/3.8e-03	1.67e-2/1.6e-02	2.01e-02/6.2e-03
P20	1.57e-02/5.9e-03	1.72e-02/6.7e-03	1.68e-03/4.1e-03	1.73e-02/5.4e-03	2.50e-02/2.8e-03

Furthermore, Table 6 offers a comparative analysis of MOFFO's average CPU time (in seconds) in relation to competing methods across three columns. Notably, the use of black font in the second column of Table 7 signifies that MOFFO exhibits a lower average CPU time compared to the other three algorithms.

Table 6 Hypervolume of the MOFFO and other MOEAs

Instance	MOFFO	NSGA-II	SPEA2	MOEA/D	MOABC
P01	3.17e+02	2.78e-01	3.70e-01	2.70e-01	2.36e-02
P02	1.93e+02	1.32e-01	5.00e-01	3.06e-01	4.10e-01
P03	3.18e+01	1.16e-01	2.71e-01	1.82e-01	3.12e-01
P04	1.23e+02	2.32e-01	4.00e-01	2.56e-01	4.79e-01
P05	2.18e+02	3.56e+01	1.58e+01	1.88e+01	5.12e+01
P06	1.67e+02	2.42e+01	3.05e-01	2.16e-01	2.17e+01
P07	3.18e+01	6.12e-01	2.11e+01	1.92e-01	3.92e-01
P08	4.79e+02	2.05e-01	3.80e-01	6.12e-01	1.79e+02
P09	2.17e+01	3.07e-01	4.62e-01	2.82e-1	6.18e-01
P10	5.23e+01	2.32e+01	1.05e+01	2.38e+01	2.79e-01
P11	4.18e+02	5.54e+01	3.58e+01	2.38e+01	4.12e+01
P12	1.97e+02	2.02e+01	3.15e-01	2.26e-01	2.91e+01
P13	4.08e+01	5.14e-01	2.19e+01	1.02e-01	2.92e-01
P14	2.15e+01	3.19e-01	2.31e-01	2.89e-01	4.12e-01
P15	1.27e+02	2.12e-01	6.00e+01	2.56e+01	4.09e-01
P16	5.13e+01	2.56e+01	2.85e+01	1.80e-01	3.12e+01
P17	4.61e+02	2.02e+01	6.05e-01	6.10e-01	4.17e+01
P18	2.96e+02	3.95e-01	4.89e-01	6.12e-01	1.79e+02
P19	2.19e+01	4.08e-01	4.02e-01	5.82e-1	2.18e-01
P20	4.11e+01	5.09e-01	6.32e-01	2.02e-1	6.38e-01

As shown in Table 6, based on the calculation results of the Hypervolume indicator mentioned above, it can be observed that the algorithm designed in this paper generally obtains non-dominated solutions with significant benefits. Therefore, this validates the superiority of the algorithm proposed in this paper.

In conclusion, our computations of the C-metric, IGD value, and CPU time demonstrate that the solution algorithm employed in this study has yielded notable advantages in terms of convergence and the overall performance of the non-dominated solutions[3,15].

Table 7 CPU time of the MOFFO and other MOEAs

Instance	MOFFO	NSGA-II	SPEA2	MOEA/D	MOABC
P01	5.29	4.25	7.26	8.36	6.25
P02	**6.82**	7.53	9.52	9.52	7.63
P03	**3.34**	4.23	15.68	5.68	5.21
P04	6.47	5.26	12.25	7.25	9.52
P05	5.86	6.52	10.18	9.18	6.89
P06	**4.52**	5.68	17.53	7.95	7.96
P07	**7.63**	12.25	14.23	12.59	8.12
P08	**5.05**	10.18	26.20	17.53	5.18
P09	**6.05**	7.95	10.14	14.23	7.08
P10	8.12	7.52	16.89	15.26	11.20
P11	9.15	6.52	12.39	16.52	10.92
P12	**12.25**	19.14	25.06	25.68	13.25
P13	**16.72**	21.89	36.47	19.51	19.25
P14	**17.89**	32.39	25.86	29.52	22.39
P15	**21.54**	54.06	41.52	35.68	24.08
P16	28.54	14.15	27.63	47.25	34.75
P17	**16.72**	28.95	45.05	29.18	21.95
P18	**22.67**	45.25	26.52	37.95	**26.01**
P19	34.06	25.12	35.68	22.25	35.09
P20	29.48	21.52	42.25	21.89	32.85

5.3 An Example

In order to assess the discrepancy between the two objectives outlined in this study, a numerical simulation is conducted using a computer-generated example as per Li[3], which is detailed in Table 8. The scenario involves an e-commerce company operating three distribution centers in a specific area of a city. Each refrigerated delivery truck has a maximum load capacity of 1300 kg and can travel up to 800 km. The rental cost for each refrigerated truck amounts to \$500, encompassing fees for third-party cold chain logistics or outsourced delivery services. Variable costs per kilometer amount to \$5 for mileage and \$7 for fuel, with a fuel price of \$5 per liter. Cooling expenses are calculated at \$3 per kilometer traveled, while unloading incurs a cost of \$0.2 per minute. Any delays in delivery beyond the stipulated timeframe result in a penalty of \$3 per hour per unit.

Besides, the task at hand involves three depots which need to provide service to 30 customers, with location information being randomly generated within the specified range $[-50, 50]$ (as shown in Figure 10 and Table 9). The distance between any two points is determined using Euclidean distance. The positions of the depots and customers are predetermined and visualized in Figure 10. In a hypothetical scenario where a refrigerated vehicle commences a distribution assignment at a designated time and is constrained to deliver perishable goods to customers within a 5-hour timeframe, the vehicle's average speed is estimated at approximately 60 km/h[3]. We utilized MOFFO to address the aforementioned issue and obtained various Pareto solutions, which form the Pareto front of the multi-objective problem.

Table 8 The depot information

No.	x-coordinate (km)	y-coordinate (km)	The number of vehicles
1	−15.54	−5.80	2
2	34.40	18.23	2
3	−29.73	33.10	2

Table 9 30 customer information

	1	2	3	4	5	6	7	8	9	10
x	−36.12	−30.66	22.64	−13.17	−17.41	32.90	38.24	−45.00	−4.18	−14.16
y	43.68	15.46	−5.47	19.34	43.32	−6.27	32.26	27.23	−1.57	3.90
Service time	22	18	16	15	12	25	23	20	19	26
Demand	250	270	200	250	280	270	260	295	200	330

	11	12	13	14	15	16	17	18	19	20
x	−36.67	−30.67	−33.04	−15.38	−21.94	−10.25	18.60	−10.94	−3.76	23.77
y	10.14	−8.89	6.56	−33.82	27.59	26.21	26.72	43.21	−32.20	29.08
Service time	29	19	16	25	25	27	30	26	25	21
Demand	150	160	190	180	130	250	230	200	190	210

	21	22	23	24	25	26	27	28	29	30
x	−43.03	−35.30	−4.76	−0.33	30.40	37.40	−38.56	−16.78	−8.55	16.23
y	20.45	−24.90	11.37	33.37	41.82	13.82	−13.71	21.54	15.19	9.32
Service time	12	19	14	16	10	14	23	10	19	22
Demand	160	320	280	240	200	210	230	270	250	220

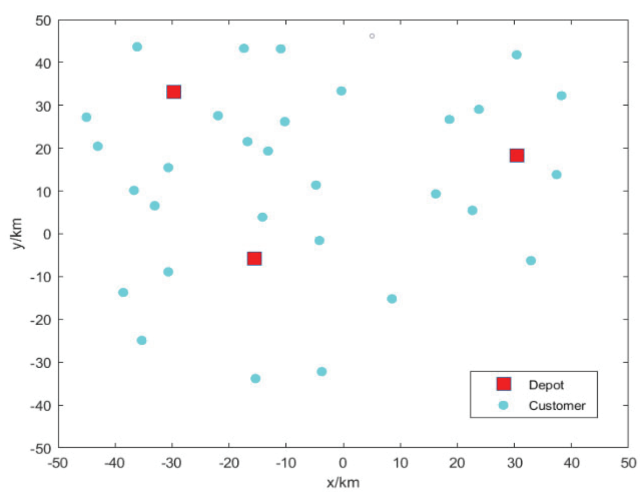

Figure 10 Scatter plot of depot and customer locations

5.3.1 Pareto Front

Upon analyzing the outcomes depicted in Figure 11, the Pareto front is graphically represented to optimize penalty costs (x-axis) against delivery costs (y-axis). While multiple strategies can be employed for the delivery service, it is essential to acknowledge the inverse correlation between penalty costs and delivery expenses, as illustrated in Figure 11. Enhanced logistics satisfaction necessitates increased investment in logistics costs, suggesting a delicate balance between logistical expenditure and service advantages.

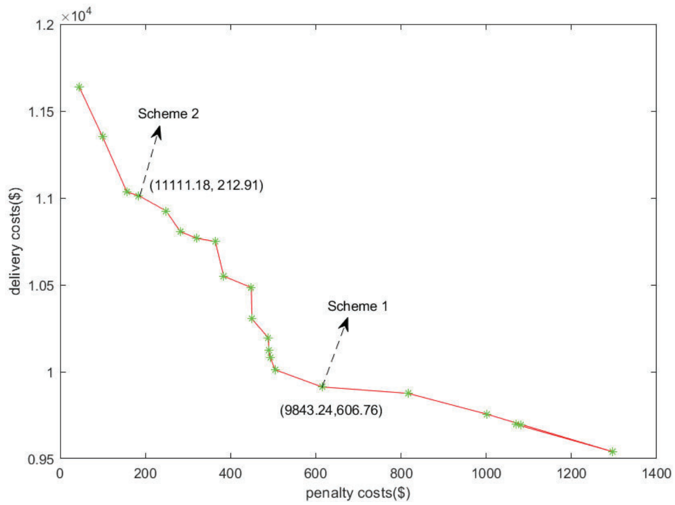

Figure 11 The Pareto front of the multi-objective problem

Tables 10 and 11 illustrate notable disparities in the logistics cost breakdown for each delivery route. Specifically, in Route 1, the comprehensive cost to service 30 customers amounts to \$9,843.24, inclusive of a \$606.76 penalty provision for potential delays in deliveries. Conversely, for Route 2, the corresponding expenses stand at \$11,111.18 and \$212.91, respectively. This discrepancy arises from the imperative for e-commerce platforms to optimize customer satisfaction by increasing the number of refrigerated trucks to mitigate delivery delays, consequently raising logistical costs while concurrently enhancing consumer contentment.

Table 10 The cost composition of each vehicle of the delivery scheme 1

Vehicle	Route	delivery costs	penalty costs
D.1	Vehicle (1) : I → 10 → 9 → 19 → 14 → 22 → 27 → 12 → I	2101.56	193.19
D.2	Vehicle (2) : II → 17 → 20 → 25 → 7 → 26 → II	2002.69	143.83
	Vehicle (3) : II → 24 → 29 → 23 → 30 → 3 → 6 → II	1876.33	72.63
D.3	Vehicle (4): III → 18 → 5 → 1 → 8 → 21 → III	2053.15	89.20
	Vehicle (5): III → 15 → 16 → 4 → 28 → 13 → 11 → 2 → III	1809.51	107.91
	Total Cost	9843.24	606.76

Table 11 The cost composition of each vehicle of the delivery scheme 2

Vehicles	Route	delivery costs	penalty costs
D.1	Vehicle (1) : I → 29 → 4 → 15 → 28 → 9 → 23 → 10 → I	2047.02	19.98
	Vehicle (2) : I → 27 → 12 → 13 → 22 → 19 → 14 → I	1864.43	22.39
D.2	Vehicle : (3): II → 3 → 6 → 3 → 26 → II	1632.78	32.46
	Vehicle (4): II → 20 → 7 → 25 → 17 → II	1897.34	45.00
D.3	Vehicle (5) : III → 24 → 5 → 18 → 16 → 2 → III	1966.93	32.42
	Vehicle (6): III → 1 → 8 → 11 → 21 → III	1702.68	60.66
	Total Cost	11111.18	212.91

Moreover, we conducted an analysis of the costs associated with fuel and carbon emissions. Our findings reveal that under Scheme 1, the total expenditure on fuel and carbon emissions stands at 1835.59, whereas for Scheme 2, it amounts to 1785.25. These values differ from the previously mentioned logistics expenses.

The traditional assumption that a higher utilization of logistics vehicles results in increased carbon emissions and fuel usage is not universally valid. In the present context, in order to enrich customer satisfaction levels, e-commerce platforms are advised to expand their fleet of vehicles dedicated to the delivery of fresh goods. This strategic approach mandates that each depot caters to customers in close proximity, thereby reducing the average distance traveled by vehicles. As a result, vehicles can optimize their routes without needing to make extensive diversions to reach distant customers, ultimately leading to reduced fuel consumption and carbon emissions. Ultimately, the strategic establishment of depots in a methodical and rational manner can significantly augment the timeliness of delivery services, thereby minimizing customer waiting times for product receipt and consequently enhancing overall customer satisfaction. This practice underscores the pragmatic nature of operational decisions. For instance, within the realm of fresh food e-commerce enterprises like Hema Xiansheng operated by Alibaba, the selection of locations with dense customer populations for depot placement, the conversion of storefronts into front-end warehouses, and the optimization of delivery routes are employed to guarantee swift order fulfillment within as little as 30 minutes from the time of order placement.

5.3.2 Sensitivity Analysis

As stated in study of Zhang and Li[6], the number of the weight vectors in the neighborhood of each weight vector T is a major control parameter in MOEA/D. As such, we syudy the sensitivity of the performance to T in MOEA/D in our example, we have tested different settings of T in the implementation of MOEA/D with the weighted sum approach. All other parameter settings are the same as the above section, except the settings of T.

As clearly shown in Figure 12, our proposed algorithm performs very well with all the values of T except very small one. Thus, we can claim that our algorithm is not very sensitive to the setting of T. And, the algorithm does not work well when T is very small. This could be due to the fact that when the size of neighborhood T is too small, it can result in poorer exploration. Besides, we also note that, a decision maker can not want to have a huge number of Pareto optimal solutions at high computational cost. As such, they are often interested in obtaining a smaller number of evenly distributed solutions at low computational cost. In what follows, we will show that our algorithm using small population could serve this purpose. All other parameter settings are the same as in the above section except the population size $K = 15$. Thus, we can obtain the final solutions in a single sun with $K = 15$. By comparing these 15 Pareto solutions with the Pareto solutions of the aforementioned three algorithms, it can be observed that the efficiency and accuracy of our proposed algorithm still surpass those of the three comparative algorithms.

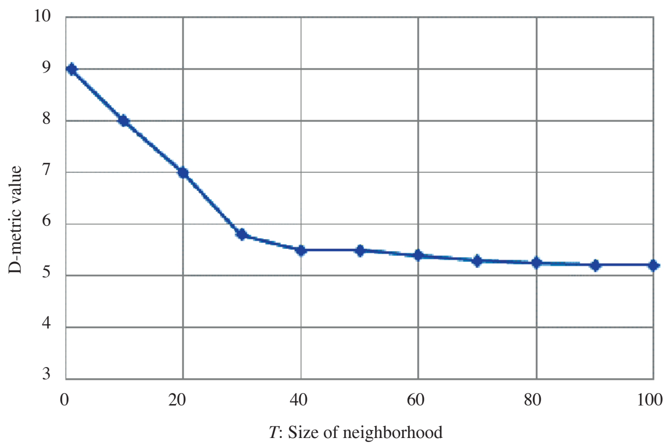

Figure 12 The average D-metric value versus the value of T in MOFFO algorithm

6 Conclusion

The optimization of the vehicle routing problem is a crucial aspect of fresh food e-commerce and platform economics. This paper examines the vehicle routing problem in fresh food e-commerce, focusing on the consumer's time loss aversion, the fuel consumption cost, carbon emissions, and other related factors. The study establishes a fuel consumption model that identifies the driving distance and load capacity of the delivery vehicle as crucial factors affecting fuel consumption, and proposes a new low-carbon logistics optimization model that includes multiple depots under the constraints of consumers' receiving time, to optimize cost and customer-based compensation. We utilize a decomposition-based multi-objective algorithm framework that leverages the benefits of the fruit fly optimization algorithm to avoid local optimal solutions. This approach enables us to solve the proposed multi-objective problem and provide a reference for addressing fresh product logistics vehicle routing problems with time windows.

6.1 The Main Findings

Our research has led to the following conclusions. Firstly, our computation of the C-metric, IGD value, and CPU time showcases the notable advantages yielded by the algorithm employed in this study in terms of convergence and overall performance of the non-dominated solutions. Secondly, we discover that achieving higher logistics satisfaction necessitates a significant investment in logistics costs, thereby demanding a delicate balance between expenditure and service advantages. Lastly, through a typical example analysis of cost modules in cold chain distribution, we establish that vehicles can optimize routes without extensive diversions to reach distant customers, resulting in reduced fuel consumption and carbon emissions. Furthermore, the conventional assumption that increased logistics vehicle utilization invariably leads to heightened carbon emissions and fuel usage proves to be invalid universally. Our research contributes to the current equilibrium between cold chain costs and consumer satisfaction in the field of cold chain distribution. Additionally, by leveraging multi-objective algorithm design, we offer feasible solutions for existing cold chain delivery operations. Moreover, by incorporating the consumer time loss aversion model, we facilitate a better understanding of the impact of consumer behavior on cold chain delivery solution design.

6.2 Management Insights

The management implications of the above conclusions are as follows: Firstly, logistics service providers need to balance multiple objectives, such as logistics costs, consumer satisfaction, and low-carbon considerations. Specifically, managing logistics costs is essential for the financial sustainability of a logistics service provider. By optimizing routes, transportation modes, inventory management, and warehousing strategies, companies can minimize operational expenses and improve profitability. However, solely focusing on cost reduction may impact service quality and customer satisfaction. Besides, customer satisfaction is a key driver of business success in the logistics industry. Satisfied customers are more likely to become repeat buyers and brand advocates, leading to increased loyalty and positive word-of-mouth referrals. With a growing emphasis on sustainability and environmental responsibility, integrating low-carbon considerations into logistics operations is becoming increasingly important. Adopting eco-friendly practices such as using electric vehicles, optimizing delivery routes to reduce emissions, and implementing green packaging solutions not only helps mitigate environmental impact but also aligns with regulatory requirements and enhances brand reputation. Thus, it is essential to prioritize these objectives based on their impact on customer satisfaction, company costs, and logistics expenses.

Secondly, by leveraging path planning strategies, companies can align their operational activities with corporate social responsibility (CSR) goals and make a positive contribution to society. Through the modification of operational strategies to reduce carbon emissions, businesses can effectively demonstrate their commitment to sustainability and environmental stewardship. This approach not only showcases a proactive response to environmental challenges but also helps build a positive brand image, foster stakeholder trust, and meet regulatory requirements. Furthermore, by embracing sustainable practices, companies can play a significant role in addressing global environmental concerns, promoting resource efficiency, and contributing to the well-being of present and future generations. Overall, these efforts not only benefit the environment but also position the company as a responsible and forward-thinking entity within its industry and community.

Finally, achieving a delicate balance between logistics costs and customer satisfaction is paramount for e-commerce platforms, necessitating strategic investments in infrastructure enhancements. To effectively meet the evolving needs of customers, platforms may need to expand their distribution vehicle fleets, enabling faster and more reliable order fulfillment. Increasing warehouse capacities can improve inventory management and reduce order processing times, leading to enhanced customer satisfaction through timely deliveries. Implementing efficient same-day delivery services further elevates the customer experience by offering convenience and quick turnaround times. Besides, by investing in infrastructure upgrades, e-commerce platforms can optimize their logistics operations, reduce overhead costs in the long run, and ultimately strengthen customer loyalty and retention. This proactive approach not only enhances operational efficiency but also positions the platform competitively in the market by meeting customer expectations promptly and effectively.

6.3 Future Research Directions

The research in this article has limitations. Firstly, as it only examines the scenario of purchasing at a single production location with predetermined consumer demand. Next, it is necessary to investigate the optimization of logistics and delivery for fresh food e-commerce when purchasing from multiple production locations with unpredictable consumer demand. Secondly, this paper assumes that consumer market demand is fixed, whereas in reality, consumer market demand may fluctuate in real-time, and consumers may also have return issues. Therefore, future research could focus on optimizing fresh product delivery with uncertain demand and consumer returns. Finally, this paper assumes that the delivery vehicles primarily use chemically fueled vehicles, while advancements in current new energy vehicle technology make it feasible to utilize new energy vehicles for delivering fresh products. Hence, future research could explore the optimization of fresh product delivery routes by combining the use of new energy vehicles and traditional fuel vehicles.

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