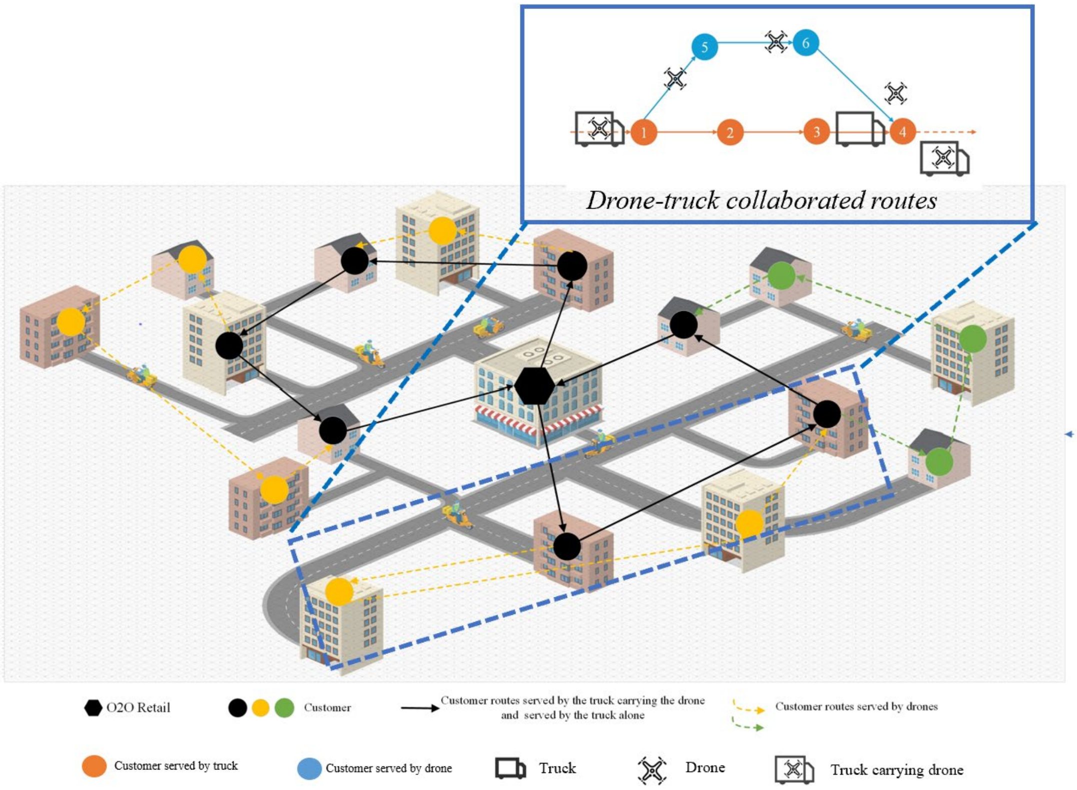
Ma, H., Tsang, Y. P., & Lee, C. K. M. (2025). Optimizing multi-objective instant logistics with trucks and drones for the quick commerce order fulfilment. Journal of Industrial and Production Engineering, 42(5), 516–532. https://doi.org/10.1080/21681015.2025.2468201

Optimizing Multi-Objective Instant Logistics with Trucks and Drones for the Quick Commerce Order Fulfilment

Quick commerce (Q-commerce) is an emerging online retail model that demands near-instant order fulfilment and adapts to delivering goods with varying environmental requirements, including temperature-sensitive items. Addressing the complex optimization challenges in distribution, a gap in effective delivery route planning and tool utilization has been identified. This study introduces three innovations: (1) a formulation that reduces drone sub-route path computations for real-time decision-making, (2) a multi-objective instant delivery model employing both vehicles and drones, and (3) a multi-objective memetic algorithm that accounts for time windows and temperature variations. Computational experiments demonstrate that this approach outperforms traditional models, significantly enhancing delivery time satisfaction, product quality, and overall service efficiency. The model scales effectively to large order quantities while maintaining high customer satisfaction rates of 97%. This research contributes to the industrial engineering literature by presenting a novel Q-commerce logistics model and offering insights into multi-objective optimization for last-mile delivery.

Keywords: q-commerce; instant logistics; temperature-sensitive goods; drone; memetic algorithm

Graphical Abstract



Note: Blue wireframe simplifies the simulated routing graph in order to illustrate in detail the routes for the realisation of simultaneous drone and truck deliveries

1. Introduction

Online-to-offline (O2O) retails are facing remarkable challenges driven by changes in customer expectations and business models. Since the early 2010s, E-commerce and business-to-consumer (B2C) services have exhibited consistent growth [1]. Building upon this trend, on-demand food delivery has emerged as an indispensable component of modern consumers' lifestyle choices [2]. Subsequently, propelled by rapid advancements in Internet and transportation technologies, O2O has evolved into a pivotal profit model for retail enterprises [3]. However, contemporary customers pay more attention to the efficiency of delivery, including preservation of perishables, diverse delivery schemes, and reasonable margins [4]. The delivery time for some renowned retail supermarkets, such as Amazon Fresh, Shipt and Freshippo, can be customized based on customer preferences, with the fastest possible delivery occurring within 30 minutes after placing an order. Consequently, the Quick Commerce (Q-commerce) has emerged [5]. This model not only redefines the shopping experience but also has far-reaching implications for routing management and the competitive strategies of retail businesses. Ideally, the optimal shopping experience for customers entails immediate access to goods akin to that of a physical store. Therefore, under the Q-commerce business model, the core competitiveness of the enterprise is to improve the efficiency and safety of instant delivery by exploring the innovative delivery tools and delivery strategies [6-7].

In addition, orders of Q-commerce are frequently characterized by a diverse range of products and unpredictable location. O2O retails are no longer limited to providing packaged snacks, convenience foods, household items, or other general commodities. The stringent time criticality of Q-commerce complicates the practicality of distributing temperature-sensitive goods, which poses a huge gap in the market and research. iiMedia Research shows that Chinese consumers have a high demand for fresh food online, with 89.7% of them consuming it one to four times a week and 81.7% of people spend between 50 and 200 RMB at a time. It is estimated that the scale of China’s grocery market will reach 630.2 billion RMB in 2026 [8]. Moreover, the demand of pre-cooked meals with thermal insulation has emerged as a popular commodity in the retail market. According to statistics, the prefabricated meal industry in China has a scale of 419.6 billion RMB in 2022, reflecting a remarkable growth rate of 21.3%. This sector is expected to sustain its trajectory in the future, attaining a market size of 1,072 billion RMB by 2026. In addition, an increasing number of enterprises are implementing a new business—they offer cooking services wherein staff select the necessary ingredients and prepare the dishes upon customer orders. To ensure the quality and taste of the food, it necessitates an efficient delivery system to mitigate the negative impacts of temperature changes during transit. Therefore, improving the supporting facilities and rules of Q-commerce is important, especially to improve the efficiency of instant delivery. Dissecting the root causes, compared to the instant delivery of regular goods, the transportation of temperature-sensitive goods must not only adhere to customers' specified time windows but also ensure product quality. In simpler terms, while customer satisfaction remains high for timely delivery, it drops for temperature-sensitive goods if their quality is compromised by temperature fluctuations, even if delivered on time. Therefore, in pursuit of efficient distribution speed, it is crucial to devise a rational sequential distribution plan.

The search for an alternative to autonomous delivery equipment, like drones, has also attract the attention from academic and industry. Drones offer attractive advantages over regular delivery trucks, such as avoiding congestion on the road network, faster delivery, and much lower transport costs per kilometer [9]. As early as 2013, Amazon introduced its "Amazon Prime Air" project, showcasing the possibilities of drone-based deliveries within urban areas [10]. Between 2023 and 2027, substantial growth is projected for the global drone delivery market with an expected market size of $4.35 billion by the end of this period [11]. However, uncertainties remain regarding the practicality of utilizing drones for load distribution due to their limited power capacity [10]. For addressing these negative possibilities, the utilization of drones and vehicles for hybrid delivery holds boundless potential. Wurray and Chu [12] conducted experimental research that demonstrated the feasibility of simultaneous drone-truck integration, while proposing a novel heuristic algorithm to optimize flight speed and endurance. Subsequently, several major online retailers, including Amazon, Google, DHL, and Walmart, highlighted the potential of integrating drones into their package delivery operations alongside trucks to enhance delivery efficiency [13]. The allocation of mixed delivery routes is evidently a critical factor in enhancing the efficiency of Q-commerce.

In view of this, it is very important to make an optimization on drone-vehicle hybrid delivery routes for improving instant delivery efficiency. This paper proposes a multi-objective route selection strategy for hybrid delivery, which represents a significant milestone in future distribution. Unlike the traditional model that solely focuses on controlling distribution distance, this strategy aligns more closely with real-world application scenarios and offers greater economic benefits. At the same time, the paper employs a multi-objective memetic algorithm, which conducts global scope search for the optimal solution while simultaneously performing local optimization for specific locations [14]. Among them, the local search section greatly optimized the drone delivery route, leading to a substantial improvement in customers' satisfaction with instant delivery of temperature-sensitive goods. The contributions of this paper are as follow: Firstly, the study aims to focus on the comprehensive delivery satisfaction of temperature-sensitive commodities in Q-commerce for the first time. Secondly, the study enables the integration of unlimited drones in hybrid distribution to establish an automated distribution process, mitigating challenges associated with manual distribution and facilitating sustainable development of enterprise O2O distribution. Additionally, it supports multiple take-offs for a single drone to enhance service efficiency. Thirdly, the proposed model aims to integrate the branching routes of drones into vehicle routes, streamline the objectives of multi-objective optimization, and introduce the travel time of vehicles as a novel objective. In comparison with traditional models, it exhibits superior performance in optimizing both customer satisfaction and quality satisfaction. Lastly, the solution algorithm is proposed, which is more efficient than the genetic algorithm in optimizing delivery routes in practical applications.

2. Literature review

In this section, first we briefly cover the literature on multi-objective logistics models mainly about delivery optimization. Then we review the most recent works on drone-based routing planning including the mathematical models and algorithms.

Extensive research efforts have been dedicated to path optimization, with scholars striving to establish a fundamental principle of optimization by defining clear goals and tailoring strategies for specific problems. For exploring green logistics, the emphasis lies in path reduction, aligning with the objective of maximizing environmental sustainability by minimizing carbon emissions. Additionally, this path optimization contributes to less cost, thereby promoting long-term economic sustainability for enterprises. In Sherif's study, the optimization of a heterogeneous fleet of vehicles focuses on minimizing inventory holding costs, transportation expenses, and carbon emission expenses in the efficient recycling of industrial materials. The proposed optimized simulated annealing algorithm exhibits commendable computational performance in this regard [15]. Jabir et al. [16] proposed a combined approach for addressing the economic and environmental objectives in the context of single echelon capacitated multi-depot green vehicle routing problem (MDGVRP). Their objective is to minimize a common objective function. To tackle large-scale instances of this problem, the authors integrates the Ant Colony Optimization algorithm with Variable Neighbourhood Search. Additionally, they conduct an analysis using various models to assess the impact on economic factors, emissions, and overall cost reduction. Furthermore, cold chain distribution is a widely discussed topic which concerns the transportation of perishable goods under low temperatures [17]. Tsang et al. [18] have not only focused on finding the shortest path in transportation but also emphasized reducing the consumption of packaging materials during the delivery process. To tackle these challenges, genetic algorithms have been employed to gain a comprehensive understanding of how delivery efficiency and packaging impact product quality within cold chain logistics activities. In addition, to transition from the cold chain logistics model with the fixed-temperature characteristics and achieve a socio-economically balanced interplay of cost and carbon emission, a multi-temperature combined distribution model has been proposed. This strategy notably enhances the flexibility of cold chain logistics while concurrently bolstering operational efficiency across various logistics activities, such as storage, loading and unloading, sorting, and distribution [19]. For “Same-day delivery” or “Instant delivery” has primarily focused on investigating the shortest delivery path or minimizing delivery time [20]. An instance of this is the successful application of the optimized fuzzy-based Ant Colony Optimization algorithm, which effectively addresses the shortest path problem with varying fuzzy weights [21]. This algorithmic approach holds significance for determining distribution paths in instant delivery. Additionally, scholars have proposed viable and efficient solutions that consider economic factors, particularly in situations where customer demand is uncertain and round-trip replenishment is permitted [22]. Based on these, the increasing demands of customers for higher service standards have necessitated the consideration of multiple factors including delivery speed, product quality and even the sustainability of transportation—in the emerging “Q-commerce” logistics. Unfortunately, within the Q-commerce model, various objectives exhibit inverse effects and mutual influences, posing challenges for decision-making in enterprise development. However, thus far, there is a lack of scholarly guidance from this perspective to assist enterprises in making informed choices.

In fact, hybrid delivery with vehicles and drones has great potential in instant delivery [23]. Firstly, its exceptional performance in last-mile delivery efficiency aligns perfectly with customers’ growing demand for immediate delivery [24]. Secondly, it enables multifunctional services, including delivery, pick-up, and simultaneous delivery and pick-up operations. Theses versatile options not only significantly enhance the utilization of time and facilities but also provide customers with a more convenient, flexible and comprehensive service experience [25]. Drone-based routing problem can be grouped into two types according to the number of the trucks: the traveling salesman problem with drone in which a single truck is employed and the vehicle routing problem with drones (VRPD) in which multiple trucks are employed [26]. In reviewing the existing literature, two types of layouts can be identified based on the movement of vehicles during drone flights: static and dynamic layouts. In the static layout, researchers employ a divide and conquer approach to segment customer locations into multiple zones. Subsequently, a distribution centre is established at the centre of each zone. In this setup, the vehicle halts at each distribution centre, dispatches the drone, and awaits its return to the same location. Only after the drone has returned does the vehicle proceed to the next distribution centre. Leon-Blanco et al. [27] proposed an alternative method for collaboration between multiple drones and vehicles, where the vehicles remain stationary while launching drones to customer locations with parcels until all drones return. They employ the k-means algorithm to dynamically determine optimal parking spots based on customer distribution, and utilize a genetic algorithm to optimize vehicle routes considering these designated parking areas in order to solve the traveling dealer problem. In order to maximize the utilization of vehicle resources for distribution, Gu et al. [28] proposed a capacitated set covering location model to determine the parking position of vehicles carrying drones. Followed by the use of a multilevel model to optimize decisions on remaining processes and ultimately determine locations for vehicle stops while minimizing dispatched vehicles and total travel time. In an ideal scenario, achieving optimal distribution efficiency would involve having an ample number of vehicles and drones that synchronize their arrival at the distribution centre. However, this approach entails substantial costs and fails to align with the practical requirements of real-world business applications. As previously discussed, the static model fails to fully optimize the vehicle return time to the warehouse, resulting in inevitable idle waiting periods at locations where services are not required. This inefficiency not only undermines the efficacy of instant logistics but also jeopardizes the quality of heat-sensitive food products. Therefore, the dynamic layout presents distinct advantages by addressing these challenges including maximizing time utilization. Gonzalez-R et al. [23] propose an iterated greedy heuristic based on a process of iterative solution destruction and reconstruction. They evaluate the efficacy of hybrid truck and drone delivery in a large-scale setting. Additionally, drones can be integrated with other ground-based autonomous mobile robots to accomplish deliveries. Even in densely populated urban areas, delivery robots offer distinct advantages [29]. Freitas [30] propoed a novel Mixed Integer Programming (MIP) formulation with better linear relaxation bounds and a hybrid heuristic based on the General Variable Neighborhood Search metaheuristic combining Tabu Search concepts to improve over 80% of the best-known solutions. The classical literature in this field has made significant research contributions, as outlined in Table 1. A notable objective of optimization, observed in both single-objective and multi-objective models, is the minimization of the overall transportation distance for vehicles and drones. However, by employing clever modelling, it is possible to achieve the same outcome by optimizing the operational time of vehicles during a single delivery. Additionally, the time windows play a crucial role in dynamic programming. While it may be feasible to disregard customer’s delivery time requirements in simplistic scenarios, accounting for diverse consumer preferences becomes essential when evaluating service quality. When considering the deployment locations for drones, they can be broadly categorized into two types: customer locations and docking hubs. The choice of deployment largely relies on the availability of hardware facilities. However, within the realm of Q-commerce, which primarily serves areas within a 3-5-kilometer radius of a store, utilizing customer locations as temporary “depots” proves cost-effective by reducing fixed costs. Moreover, this paper distinguishes itself by offering reasonable simulations and assumptions concerning both the drone’s service capacity and the vehicle’s carrying capacity. In summary, the model presented in this study aims to replicate real-world business conditions and provides valuable recommendations for the development of Q-commerce in enterprises.

Table 1. Comparisons between classical drone-based delivery studies and this research

	Objective(s)	Time window	Practical assumption	Launch and reconvening on the same node for drones	N^1	N^2	Algorithm
[31]	Min. Total Cost	Hard	With service time	No	1	1	Variable neighborhood search
[32]	Min. Total arrival time	-	With service time	Yes	1	2	Adaptive tabu search-simulated annealing
[33]	Min Total cost	-	-	No	n	1	Ant colony optimization
[34]	Min. Total cost +Min. Reduced cost of a drone path	-	With service time	No (with docking hub)	n	1	Branch-and-price-and-cut algorithm
[35]	Min. Total cost +Min. Value loss of perishable products	Soft	With service time	No (with distribution site)	n	1	Two-phase hybrid heuristic algorithm
This work	Min. max(vehicle return time) +Max. Customer satisfaction +Max. Quality satisfaction	Soft	With service time	No	n	n	Multi-objective memetic algorithm

$N^{1:}$ Number of nodes served by each drone; $N^{2:}$ Number of drones carried by one vehicle.

3. Research Methodology

3.1 Problem Description

In this section, we describe the assumption of the Multi-Objective Instant Delivery based on Vehicle and Drone (MOIDVD) and present the corresponding mathematical model of the problem. First, we explain the operational process of Q-commerce. Online-to-Offline (O2O) stores and dark stores have fixed delivery schedules, and the orders in the same batch have different delivery requirements. As shown in Figure 1, the vehicle equipped with drones departs from the store, and according to the delivery strategy, the drones and vehicles visit their respective customers. After completing all delivery tasks, they return to the starting point, i.e. depot. This study considers the presence of customer time windows and the freshness time window for food delivery, as well as the capacity constraints of trucks and drones when planning routes. The delivery strategy aims to optimise customer satisfaction with service time and product quality, and minimize the delivery time for a single delivery task. In order to build the mathematical model, primary assumptions are considered and listed as follows.

- The vehicle routes must start and end at the store, while the drone routes must start and end at the customer locations.
- The route distances associated with vehicles and drones are calculated based on Euclidean distance, ignoring the impact of obstacles (e.g., tall buildings) encountered by drones along their routes.

- Within a single vehicle route, drones can be launched multiple times without considering recharging time, because the battery replacement can be completed in the mobile drone airports.
- The weight of the cargo carried by trucks and drones has no impact on their respective operating speeds.
- The service time at each point for both vehicles and drones is fixed.
- The time used to launch and retrieve drones, as well as supply batteries and parcels to drones is slight and covered by the service time of the truck.
- The drone service is accepted by all customers by default.

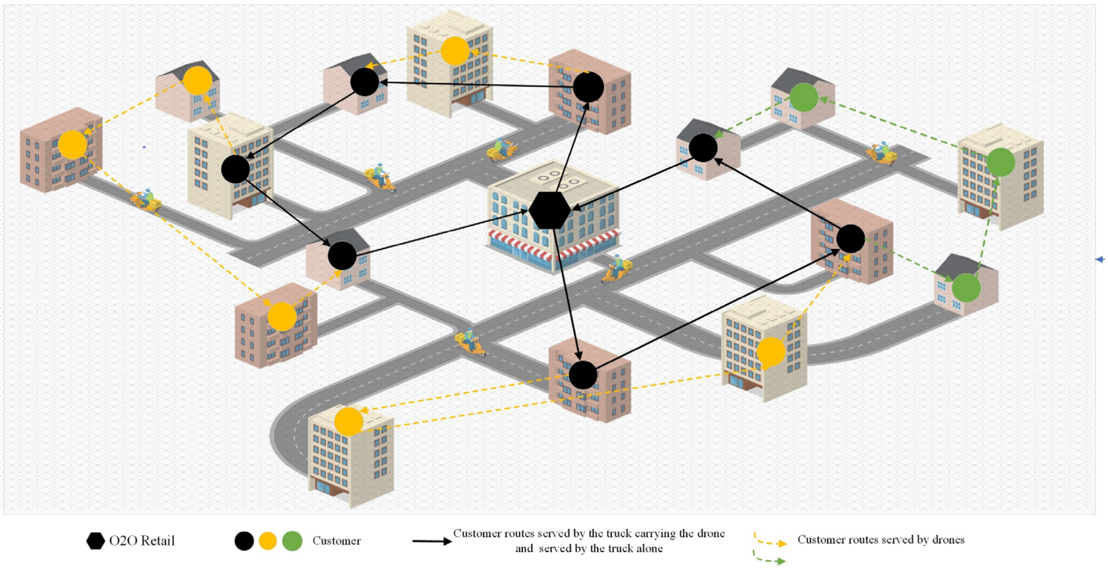


Figure 1. Illustration of the MOIDVD

For the remainder of this work, the term '*vehicle tour*' is used to refer to a sequence of customer visits by a delivery vehicle that starts and ends at the same location (usually the sore), while the term '*vehicle route*' and '*drone route*' are used to refer to a sequence of customer serviced by vehicles or drones.

3.2 Mathematical Model

In this problem, there are a set of human-driving vehicles $k \in K$ (i.e. $K = \{1, 2, \dots, |K|\}$) with identical speed v_k and capacity Q_k, as well as a set drones $d \in D$ (i.e.$D = \{1,2, \dots, |D|\}$) with the identical capacity Q_d , flight speed v_d, maximum flight time T_d with a full load available at the decision time to perform specific delivery task to customers and own weight is q_d. Each customer can only place one parcel using the same box for delivery, so q_i represents the weight of each parcel for the customer node $i \in C$ (i.e. $C = \{1,2, \dots, |C|\}$). This two-dimensional map N consists of the locations of stores and customers where $i, j \in N$ and $N = \{0\} \cup C$. Node $\{0\}$, namely (0, 0), represents the store or depot, while nodes $i \in N$ represent the customers who placed the orders with expected service time windows. The distance of two customers is calculated by using the Euclidean distance and described as Δ_{ij}, where $i, j \in N$. In addition, the travel time between two customers can be described T_{ij}. The decision variables are defined as follows:

- y_{ij}^k: Equals 1 if vehicle k is dispatched at customer i to serve customer j, and 0 otherwise.
- x_{ij}^d: Equals 1 if drone d is dispatched at customer i to serve customer j, and 0 otherwise.

In this model, to achieve optimal efficiency in instant delivery, the delivery strategy based on three objectives is formulated. Firstly, goods that are dispatched simultaneously for delivery are referred to as a batch order. The delivery task is considered complete once all customer orders have been fulfilled, at which point the vehicles return to the depot along with the drones. Therefore, the delivery time for the same batch of deliveries is minimized, which involves optimizing the vehicle tour with the longest delivery time. Secondly, customer satisfaction on delivery services S_c is maximized, as shown in Equation (1), where a_i denotes time spent on delivery for a customer $i \in C$. Delivery satisfaction primarily depends on whether the delivery time falls within the customer's expected time window. In practice, the generation pattern of O2O orders results in varying customer expectations regarding delivery time windows and tolerance levels for delivery time. In this model, these expectations are represented by trapezoidal functions. They have own most desired time window $[e_i, u_i]$ for delivery services, where e_i, u_i represent the lower and upper bounds of a desired time window of a customer $i \in C$. Customer satisfaction with delivery outside the specific time window is gradually decreasing until to 0 at e_i' (where $0 < e_i' < e_i$) and u_i' (where $u_i < u_i'$), as shown in Figure 2 and Equation (2). Similarly, customer satisfaction on received product quality, called as quality satisfaction, S_q is also maximized, as shown in Equation (3). Research indicates that temperature variation during handling may result in a decline in its taste, quality, and other aspects [36]. Typically, in commercial orders, thermal passive packaging, e.g. insulated bags, is used to maintain the ideal temperature of goods for a specified duration [37-38]. Therefore, this study formulates the quality satisfaction based on the delivery time, where f and f' denote the desired and maximal time allowed for delivery, specified by the thermal passive packaging design. The relationship between each customer's quality satisfaction S_q and delivery time is shown in Figure 2 and Equation (4).

$$\text{Maximize} \sum_{i\in C} S_{ci}(a_i) \tag{1}$$

$$S_{ci}(a_i) = \begin{cases} \dfrac{t_i - u_i'}{u_i - u_i'}\text{, where } u_i < a_i \leq u_i' \\ 1\text{, where } e_i \leq a_i \leq u_i \\ \dfrac{t_i - e_i'}{e_i - e_i'}\text{, where } e_i' \leq a_i < e_i \\ 0\text{, Otherwise} \end{cases} \tag{2}$$

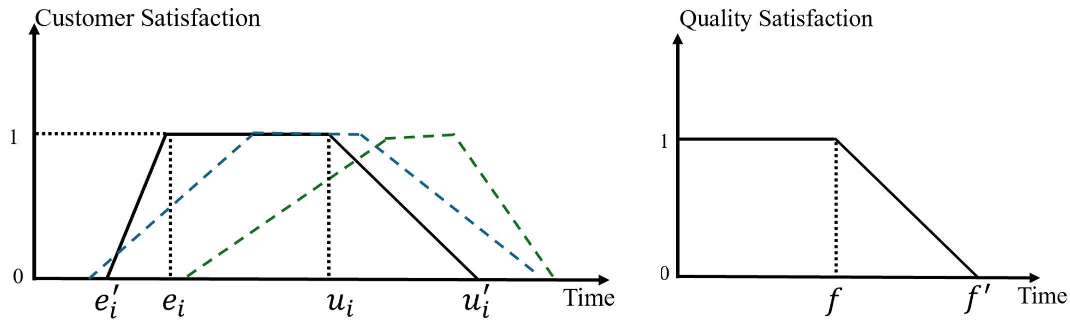


Figure 2. Soft constraints of customer satisfaction (solid and dash lines in black, blue and green representing different customer time windows) and quality satisfaction

$$\text{Maximize} \sum_{i\in C} S_{qi}(a_i) \tag{3}$$

$$S_{qi}(a_i) = \begin{cases} 1, 0 < a_i \leq f, \\ \dfrac{t_i - f'}{f - f'}, f < a_i \leq f' \\ 0, a_i > f' \end{cases} \tag{4}$$

The third objective function of this model is to minimize the longest delivery time across all vehicles, as in Equation (5), where a_0^k is the arrival time of vehicle k back at the depot. In other words, the make-span of the vehicle-based tour, including drones returning, can be minimized.

$$\text{Minimize } \max_{k\in K}\{a_0^k\} \tag{5}$$

When formulating delivery routes, it is essential to consider capacity constraints for both drones and vehicles. Specifically, the logic of the formulas is noteworthy here as parameters from drone routes are aggregated into vehicle paths. This study considers the departure and assembly positions of each drone route within the vehicle paths. For instance, as illustrated in the Figure 3, a vehicle transports with a drone to customer 1, where the vehicle serves customer 1 and launches the drone. The drone completes deliveries for customers 5 and 6, while the vehicle handles deliveries for customers 2 and 3. Finally, the vehicle serves customer 4 and assembles with the drone. During this delivery sequence, the drone's payload at customer 5 includes parcels for both customers 5 and 6, whereas at customer 6, it only includes parcels for customer 6, with no task to deliver to customer 4. Therefore, at any point serviced by a drone, its payload is determined solely by that point and the subsequent point in the route, constrained not to exceed the drone's maximum capacity, as outlined in Equations (6) and (7). To avoid counting the weight at the assembly position, an intermediate binary variable α_{ij}^{d} is considered where its value is equal to 1 if $x_{ij}^{d} = 1$ and $y_{i'j}^{k} = 0$, and 0 if $x_{ij}^{d} = y_{i'j}^{k} = 1$, where $i' \in C \backslash \{i\}$. For vehicles, it is necessary to restrict the combined weight of drones carried upon departure and all parcels serviced by the vehicle to remain within its capacity limit, as formulated in Equation (8), where the value $\mathcal{M}$ refers that all trucks carry the same number of drones.

$$w_j^d = q_d + \sum_{i \in C} (\alpha_{ji}^{d} \cdot q_i) \text{ , } \forall j \in C, \forall d \in \mathrm{D} \tag{6}$$

$$w_j^d \leq Q_d, \forall j \in C, \forall d \in \mathrm{D} \tag{7}$$

$$\sum_{i \in \mathrm{C}} \sum_{j \in \mathrm{C}} [q_j \cdot (y_{ij}^{k} + x_{ij}^{d})] + \mathcal{M} \cdot q_d \leq Q_k, \forall k \in K \tag{8}$$

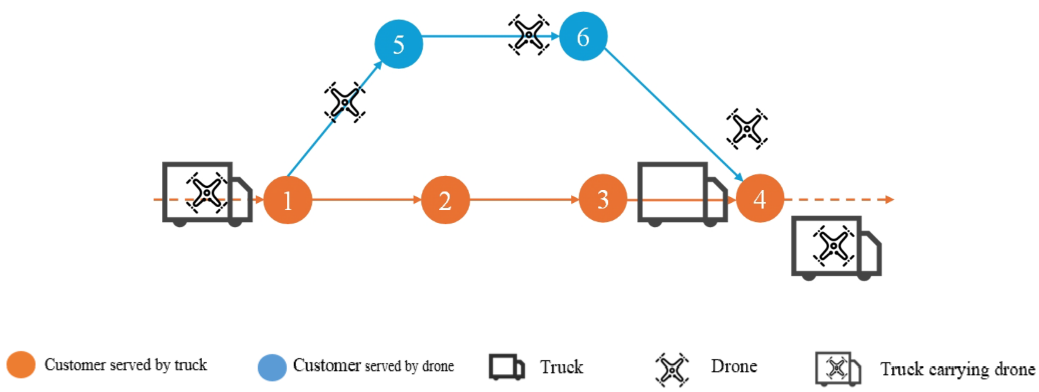


Figure 3. Logic for merging drone routes to vehicle routes

The time of arrival a_i at customer i serves as a critical variable to ensure the feasibility of the delivery, which is extended to vehicles and drones in this model. Mathematically, the arrival time and departure time at node i are defined as a_i^d and l_i^d for drone d, while a_i^k and l_i^k for vehicle k. The below big-M constraints, using M_1 and M_2, are formulated to link travel arcs with arrival and departure time. Constraint (9) ensures that drone d arrives at node j no earlier than it leaves node i plus the travel time $T_{ij}^d = \frac{\Delta_{ij}}{v_d}$ if $x_{ij}^d = 1$, where v_d denotes the speed of a drone. When the drone d arrives at node j, the corresponding service time is c_d, plus a possible waiting time σ if node j is a location to re-assemble with the vehicle as in Constraint (10). An intermediate variable δ_j^d is used, where $\delta_j^d = 1$ when a synchronization or waiting is needed, and thus drone d can depart at node j at time l_j^d. Moreover, Constraints (11) limits that the overall operating time of drones does not exceed its flight-time capacity (where the maximum flight time is defined as T_d) per each drone trip.

$$a_j^d \geq l_i^d + T_{ij}^d - M_1 \cdot (1 - x_{ij}^d), \forall i, j \in N, \forall d \in D \tag{9}$$

$$l_j^d \geq a_j^d + c_d + \sigma \cdot \delta_j^d - M_1 \cdot (1 - x_{ij}^d), \forall i, j \in N, \forall d \in D \tag{10}$$

$$\sum_{i,j \in N} \left(T_{ij}^d \cdot x_{ij}^d\right) \leq T_d, \forall d \in D \tag{11}$$

Similarly, the arrival and departure time for vehicles are defined in Constraints (12) and (13). In Constraint (12), the arrival of vehicle k at node j depends on when it leaves at node i plus the vehicle travelling time T_{ij}^k, where $T_{ij}^k = \frac{\Delta_{ij}}{v_k}$ and v_k denotes the speed of a vehicle. In Constraint (13), vehicle k completes the delivery service at node j at time $a_j^k + c_k$ plus the waiting time to assemble with drones if any.

$$a_j^k \geq l_i^k + T_{ij}^k - M_2 \cdot \left(1 - y_{ij}^k\right), \forall i, j \in N, \forall d \in D \tag{12}$$

$$l_j^k \geq a_j^k + c_k + \sigma \cdot \delta_j^k - M_2 \cdot (1 - y_{ij}^k), \forall i, j \in N, \forall d \in D \tag{13}$$

Lasty, several routing constraints are considered to ensure that vehicles and drones can form proper routes. Constraint (14) ensures that the vehicles must leave the depot as many times as they return. Constraint (15) limits that each customer is visited exactly once by either a vehicle or a drone. Constraints (16) and (17) guarantee that the in-degree is equal to the out-degree for vehicle routes and drone routes at customer j, respectively. Constraint (18) secures that each vehicle can be used at most once, namely it can only leave the depot once. In Constraint (19), each vehicle k does not visit the same customer j more than once, such that the vehicle assignment at node j is not duplicated. Constraint (20) limits the usage of drone d to precisely $\mathcal{P}$ flights, such that the drone can serve at most $\mathcal{P}$ pairs of customers along the vehicle route.

$$\sum_{j \in C} y_{0j}^k = \sum_{j \in C} y_{i0}^k, \forall k \in K \tag{14}$$

$$\sum_{k \in K} \sum_{i \in C} y_{ij}^k + \sum_{d \in D} \sum_{i \in C} x_{ij}^d = 1, \forall j \in C \tag{15}$$

$$\sum_{i \in N} y_{ij}^k = \sum_{m \in N} y_{jm}^k, \forall j \in C, \forall k \in K \tag{16}$$

$$\sum_{i \in N} x_{ij}^d = \sum_{m \in N} x_{jm}^d, \forall j \in C, \forall d \in D \tag{17}$$

$$\sum_{j \in C} y_{0j}^k \leq 1, \forall j \in C, k\forall \in K \tag{18}$$

$$\sum_{i \in C} y_{ij}^k \leq 1, \forall j \in C, \forall k \in K \tag{19}$$

$$\sum_{i \in C} \sum_{j \in C} x_{ij}^{d} \leq \mathcal{P}, \forall d \in D \tag{20}$$

4. Proposed Algorithm

This section describes the proposed solution method in detail. Section 4.1 presents the solution scheme developed in this study and the encoding–decoding process of this scheme. Section 4.2 provides a complete explanation of the proposed algorithm.

4.1 Framework of the MOMA

To address the problem of distributing temperature-sensitive goods in Q-commerce, as described in Section 3, we propose a multi-objective enhanced memetic algorithm. In general, the multi-objective genetic algorithm (MOGA) is commonly recognized as an effective approach for addressing multi-objective routing problems [39-41]. However, in the context of this study, the delivery of commercial orders involves two specific constraints, namely “customer time windows” and “geographical locations”. It is imperative to contemplate whether local optima within each closed loop formed by trucks and drones hold greater significance. Therefore, this paper considers the memetic algorithm as an initial choice. Traditional memetic algorithms typically involve a two-stage process: the initial stage employs evolutionary algorithms for optimizing non-linear objective functions with mixed-integer constraints, while the subsequent stage utilizes local search method to refine solutions for increased efficiency [35]. This multi-objective model adopts a population-based strategy inspired by the well-established NSGA-II framework to achieve superior global solutions. Notably, the algorithm introduces innovative “enhanced problem-specific encoding, decoding, and recombination operators” in comparison to traditional approaches. The pseudocode for the resulting multi-objective enhanced memetic algorithm (MOMA) is presented in Algorithm 1. During each iteration, the pool is updated in step 5 through a non-dominated sorting process, followed by the creation of a mating pool using tournament selection. Elitism is integrated in Step 8, preceding crossover and mutation operations. Notably, Step 12 introduces the possibility of employing local search to enrich the understanding and effectiveness of the algorithm.

Algorithm 1 Multi-Objective Memetic Algorithm(MOMA)

Input: MOIDVDinstance,MA parameters($POP_s, C_R, M_R, EL_R, POOL_s$),$N_{LIST}$

Result: S, Z

1: $P \leftarrow \emptyset$
2: $P \leftarrow$ initialize Population (POP_s)
3: **while** *termination criterion is not met* **do**
4:     $P \leftarrow$ fitness Evaluation (P)
5:     $P \leftarrow$ non-dominated sorting (P)
6:     $M\ P \leftarrow$ create Mating Pool(P,$Pool_s$)//based on tournament selection
7:     $P_{new} \leftarrow \emptyset$
8:     $P_{new} \leftarrow$ elitism(P, EL_R)
9:     $Parent_A$, $Parent_B \leftarrow$ parent Selection(M,P)
10:     $S \leftarrow$ order Crossover(C_R,$Parent_A$,$Parent_B$)
11:     $S \leftarrow$ swap Mutation(M_R,S)
12:     S,Z $\leftarrow$local Search(S,N_{LIST})
13:     $P_{new} \leftarrow P_{new} \cup S$,$Z$
14:     $P \leftarrow P_{new}$
15: **end while**
16: $P \leftarrow$ fitness Evaluation (P)
17: $P \leftarrow$ non-dominated sorting (P)
18: $S, Z \leftarrow$ find Best Solution(P

4.1 Solution Representation

First, the encoding scheme of the solution representation will be explained. In general, our scheme consists of two constituent components, as depicted in Figure 4. The uppermost row, designated as the ‘vehicle part’, reflects the number of vehicles utilized. By amalgamating this with the lower section denoting the ‘drone part’, it can concurrently express the route of customer nodes serviced by each vehicle, as well as the customer nodes served by the drones. Nonnegative integer numbers are used here, in which the value of '0' indicates the beginning of a new vehicle route and/or the end of the current route, while the non-zero values represent the customer nodes. Therefore, the total length of the vehicle part of the solution vector is $K + C + 1$, where $C + 1$ nodes take the value of '0'. On the other hand, the rest part of the solution vector has the same length as the upper part, but comprises binary numbers. This solution can support the specification of multiple drone paths. For every drone, the codes can be divided into two lines that express information about the position of the drone for takeoff and landing and the customer nodes served by the drone respectively. These codes work in the following way:

- If the i-th number of the second line takes the value of '0', then the customer node depicted in the i-th number of the vehicle part will be served by a truck.
- Else, if the i-th number of the second line takes the value of '1', then the customer node depicted in the i-th number of the vehicle part will be served by a drone.
- If the i-th number of the first line takes the value of '1', and the $(i-1)$-th number of the first line (previous number) takes the value of '0', then the drone will take off at the customer node depicted in the $(i-1)$-th number of the vehicle part.
- If the i-th number of the first line takes the value of '1', and the $(i+1)$-th number of the first line (previous number) takes the value of '0', then the drone

will land at the customer node depicted in the $(i+1)$-th number of the vehicle part.

A simple example of the solution scheme is depicted in Figure 4. In this case, 11 customers are served by two vehicles each carrying two drones. According to the vehicle part, customers 1 to 6 are served by vehicle 1 and the drone carried by it, and the rest is the distribution task of vehicle 2. Since the second line code of drone 1 is displayed as ‘1’ at customer 2 and 4, and the second line code of drone 2 is displayed as ‘1’ at customer 5, vehicle 1 only needs to deliver customers 1, 3 and 6. For drone 1, its first line of code is ‘1’ from nodes 2 to 5. According to the above rules, it takes off from customer 1, serves customers 2 and 4, then lands on the vehicle at customer 6, at last returns to deport with vehicle 1. At the same time, ‘1’ is shown on customer 4 and 5 of drone 2’s first line, so it takes off from customer 3 to serve customer 5 and lands at customer 6. For vehicle 2, all the codes of drone1 carried by it are ‘0’, which means that drone1 is not involved in this mission. Drone 2 departs from the location of customer 7, travels to customer 8 and completes a delivery, then lands at the site of customer 9. The drone subsequently takes off again, flies to customer 10 and performs another delivery, finally lands at the location of customer 11. Therefore, the full delivery route for vehicle 2 is customer 7 - 9 - 11.

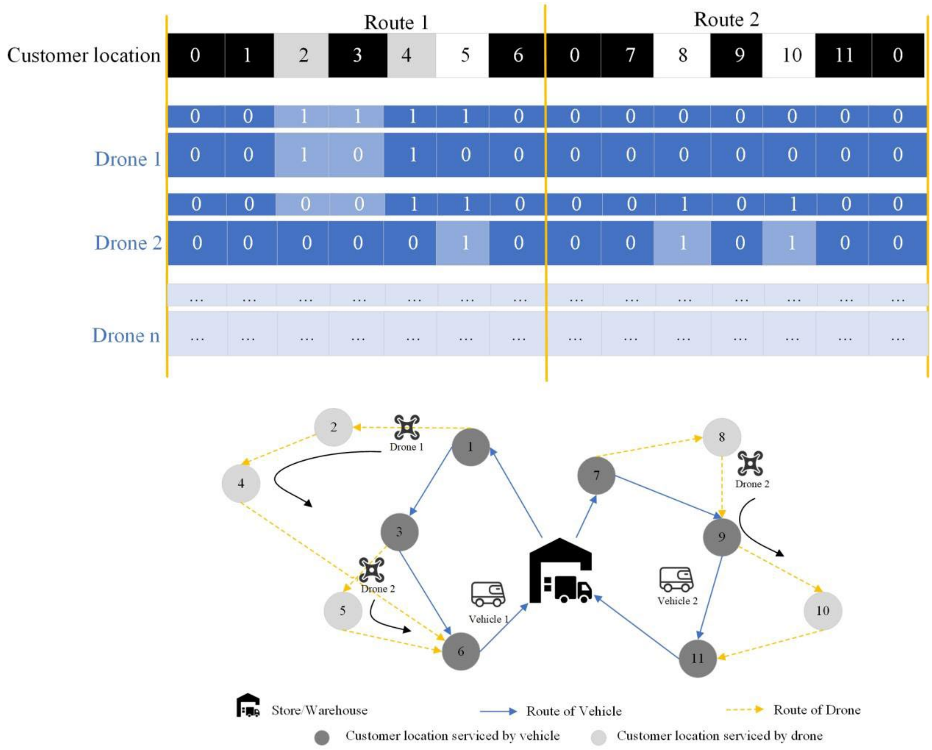


Figure 4. Logic of encoding and decoding in the proposed algorithm

4.2 Evolutionary operators

There are three primary operators in combinatorial optimization: the initialization operator, the crossover operator, and the mutation operator. The initialization operator begins by generating a random permutation to determine the path order for the vehicle component. For the drone component, more than 30% of the positions are set to true in the first line, and over 50% are set to false in the second line. These proportions are determined empirically to identify feasible solutions. The crossover operator employs an order crossover (OX) technique. It first randomly selects a chromosome segment from the vehicle component chromosome of one parent, retaining its order and position. The complementary segment is then taken from the other parent. The two offspring chromosomes are created by merging these segments and their inverted counterparts. For example, given parent chromosomes [0, 1, 2, 3, 4, 5] and [5, 4, 3, 2, 1, 0], along with a randomly generated segment mask [0, 1, 0, 0, 1, 1], the resulting offspring chromosomes are [3, 1, 2, 0, 4, 5] and [0, 5, 2, 3, 4, 1]. For the drone component chromosome, a uniform binary crossover scheme is employed. The mutation operator begins by randomly generating a binary mask to indicate which values will be shuffled. If more than one value is masked, a random shuffle is performed, resulting in a mutated chromosome. For drone component chromosomes, mutation is carried out by randomly flipping the binary values. Finally, constraints are applied to the drone component chromosomes based on the mutated permutation to prevent infeasible solutions.

4.3 Local search

The local search process in this study adheres to two-neighborhood-move rules: exhaustive swapping for integer encodings and exhaustive mutation for binary encodings (Figure 5). The former is employed in the vehicle part of the code to examine various sequences of vehicle services. Additionally, it influences the order of service for the vehicles and drones. On the other hand, the latter is utilized in the drone part of the code. Specifically, it is employed in even lines to alter the service tasks of the drones and in odd lines to explore optimal takeoff and landing positions. By employing these neighborhood-move rules, the study aims to iteratively improve the solution quality. Specifically, the swapping of positions between customers 6 and 11 results in changes to the distribution tasks of the two vehicles. In the drone’s code, an essential principle is followed: ‘1’ cannot appear in the same position in even lines (mutations that violate this principle are disregarded). This principle ensures that each node is visited only once by a distribution tool. For instance, when the code of drone 1 on vehicle 1 changes from ‘1’ to ‘0’, and the code of drone 2 on vehicle 1 is also ‘0’, it indicates a transfer of the delivery task for customer 4 to vehicle 1. Conversely, if the code of drone 2 on vehicle 2 mutates from ‘0’ to ‘1’ at customer 9, it implies the addition of a distribution task at that specific location for drone 2. Examining the odd rows, the mutation between ‘0’ and ‘1’ explores the impact of drones taking off and landing at different locations on the objective. Drone 1 on vehicle 1 lands at customer 5, while drone 2 on vehicle 2 takes off from customer 7, serves three consecutive customers, and eventually lands at customer 6.

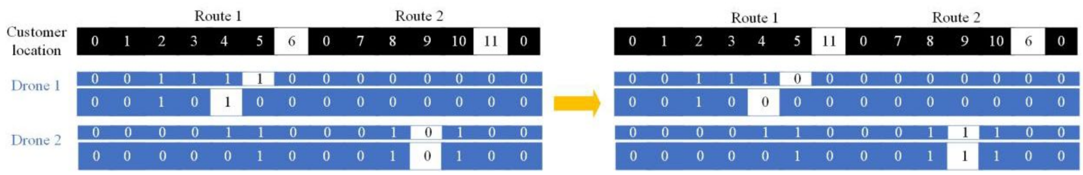


Figure 5. Logic of the local search in the proposed algorithm

5. Computational Experiments and Analysis

To evaluate the effectiveness of the proposed model and algorithm, we conduct computational experiments and analyses in this section. Initially, we compare the performance of the proposed model against traditional drone-based delivery models in solving the problem of distributing temperature-sensitive goods in Q-commerce. Additionally, we examine the effectiveness and robustness of the Multi-Objective Memetic Algorithm (MOMA) in optimizing the hybrid delivery paths of vehicles and drones.

This experiment simulates the delivery operations of a supermarket within a 5000m x 5000m area. Although the proposed model can theoretically accommodate an unlimited number of drones, practical considerations necessitate that stores determine the number of vehicles and drones based on their infrastructure capabilities. For the purposes of this experiment, we set the upper limit of vehicles at six, with each vehicle capable of carrying up to three drones (allowing for some to remain idle). The fixed parameters for the vehicles and drones used in these experiments are detailed in Table 2. To replicate the uncertainty of real-world conditions, customer delivery locations and desired time windows are randomly generated (random seed = 1234). The experiment examines scenarios involving 8, 20, and 50 customers to assess the performance of the proposed model under varying customer demands. Table 3 shows the problem parameters.

Table 2. Parameters of the computational experiments

Parameters	**Values**
Map	5000m*5000m
Drone speed	1300m/min
Drone weight	30kg
Endurance of drone	40min
Drone service time	5min
Truck speed	800m/min
Truck capacity	5kg
Truck capacity	300kg
Truck service time	10min

Table 3: Hyperparameters for the experiments

Parameters	**Values**
Maximum generation	50
Population size	100
Crossover rate	1.00

Mutation rate	0.01

5.1 Case 1: Comparison with the Traditional Model

First, the computational logic of traditional models is explained. Typically, in the hybrid delivery of vehicles and drones, the optimization focuses solely on minimizing the overall delivery distance, which can be expressed as 'Minimizing sum of vehicle distance and drone distance' in this paper. While this approach ensures instant delivery efficiency, aligning with the quick delivery objectives of Q-commerce, it overlooks the customers' requirements for specific delivery time windows. This oversight may negatively impact customer satisfaction. Therefore, this experiment demonstrates the performance of traditional models in terms of customer satisfaction and quality satisfaction when the objective is to optimize the overall delivery distance. The experimental data are presented in Table 3. In comparison with the MOIDVD model proposed in this paper, it is evident that the traditional model falls significantly short of meeting the current market demands for the instant delivery of temperature-sensitive goods.

Table 4. Comparison between MOIDVD and the traditional model

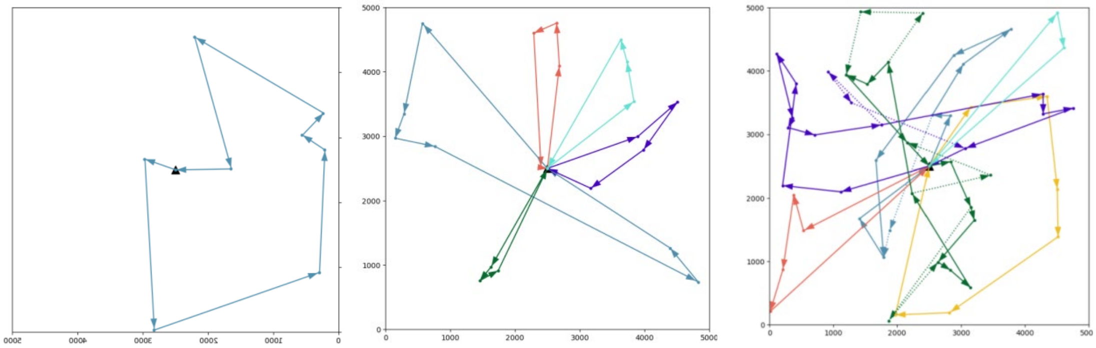
Customer number	Customer Satisfaction		Quality Satisfaction	
	Traditional	MOIDVD	Traditonal	MOIDVD
8	3.33	4.45	6.93	7.75
20	3.36	9.95	19.51	19.71
50	18.46	25.31	41.83	49.10

The delivery path is shown in Figure 6. It is evident that, compared to the delivery routes generated by traditional models, the routes produced by the MOIDVD model lack regularity in terms of distance and appear more disordered. This is attributable to the MOIDVD model's greater emphasis on fulfilling customers' time requirements. This multi-objective model thoroughly accounts for the high demand for instant delivery in modern society.

5.2 Case 2: Effectiveness of MOMA compared to MOGA

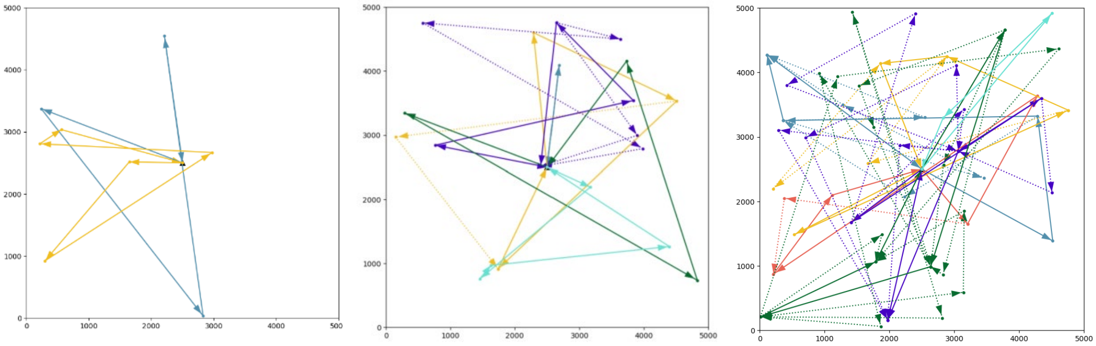
In this case, the optimization performance of MOMA and MOGA is primarily compared. By varying the number of orders, the study demonstrates both the computational efficiency of the algorithms in practical applications and their adaptability to uncertain demands. The delivery routes and Pareto solutions are illustrated in the Figure 7.

To provide a more intuitive comparison of the effectiveness of the two algorithms, the two sets of Pareto solutions are plotted on the same coordinate system, as shown in Figure 8. To facilitate an objective comparison, the negative value of the total time is utilized as the y-axis coordinate, thereby associating solutions nearer to the origin on the coordinate axis in the graph with smaller objective values. When the number of orders is 8, the two Pareto frontiers' curves are nearly overlapping. However, as the number of orders increases, the curve of the MOMA gradually surpasses that of the MOGA. Additionally, MOMA exhibits a broader range of solutions, indicating a higher diversity of optimal outcomes. Particularly, when the number of orders reaches 50, there is a significant discrepancy between the two solution sets both diversity and objective value. It is evident that the results from MOMA are superior.



$N = 8$ $N = 20$ $N = 50$

(a) Traditional Model



$N = 8$ $N = 20$ $N = 50$

(b) MOIDVD

Remark: Solid lines show vehicle delivery routes while dashed lines indicate drone paths, with matching colors signifying which drone is carried by which vehicle.

Figure 6. Visualization of delivery routes by using (a) traditional model and (b) MOIDVD (Remark: N refers to the size of customers)

5.3 Case 3: Robustness of MOMA compared to MOGA

Many researchers have tried to find the local points or regions with special significance on the Pareto Front [42][43]. The knee point or knee region has been of particular interest to researchers. The knee point on the pareto optimal front refers to the point with the maximum marginal rates of return. It means that there is a small improvement in one objective, accompanied by severe degradation of at least one other objective. In addition, it is proved that the knee point is better than the other points on the pareto front (PF) in the metric of hypervolume indicator (HV) [44]. The higher the HV, the better the convergence and distribution of the population. This metric is used in this experiment to clearly and fully illustrate the superiority of MOMA. The robustness of MOMA is tested by varying the random seed to simulate the randomness in real order generation. The performance of three targets was observed in this experiment using 5 randomly selected seeds, with order numbers of 8, 20, and 50 respectively. The corresponding results are presented in Table 4.

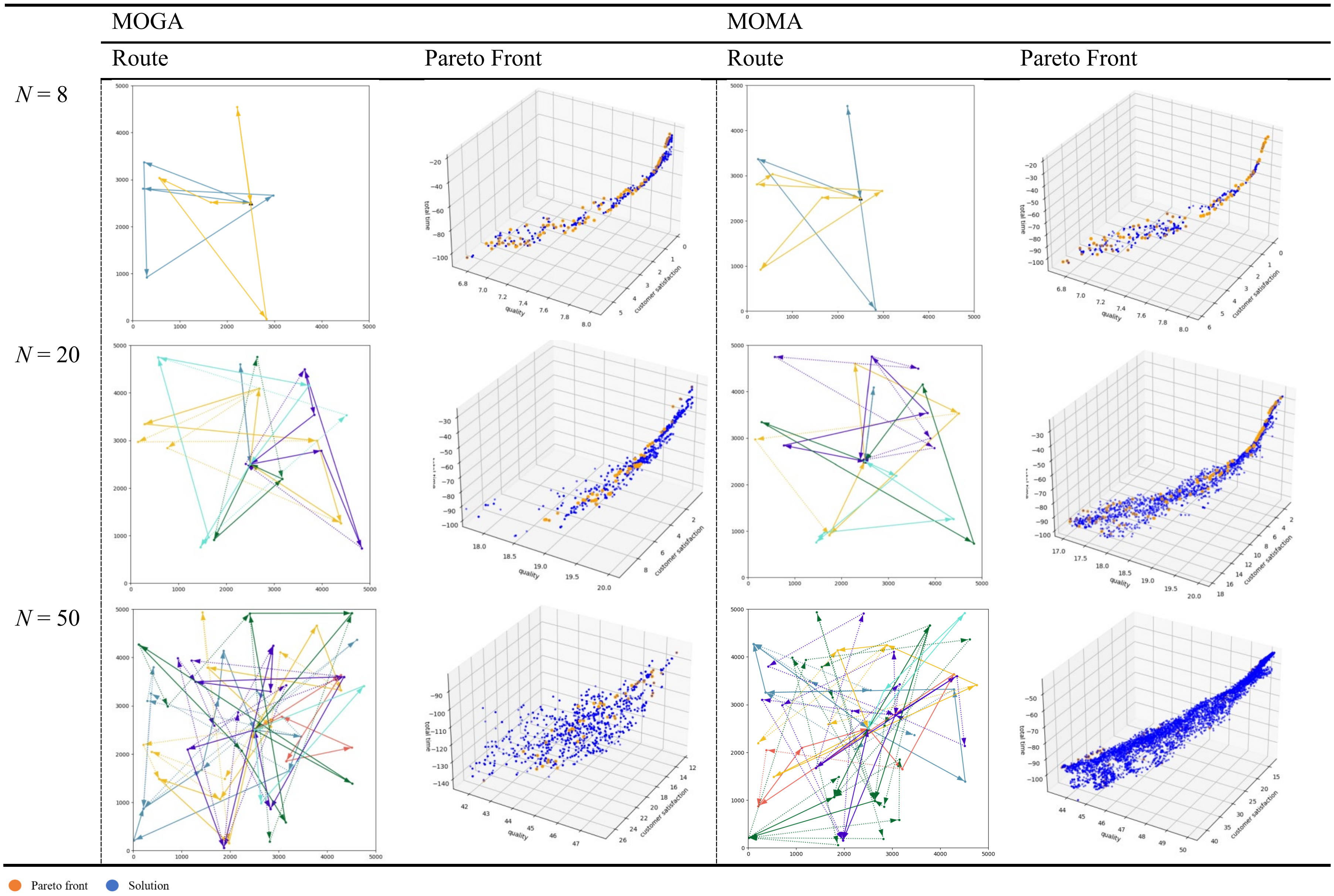


Figure 7. Routes and Pareto solutions from MOGA and MOMA

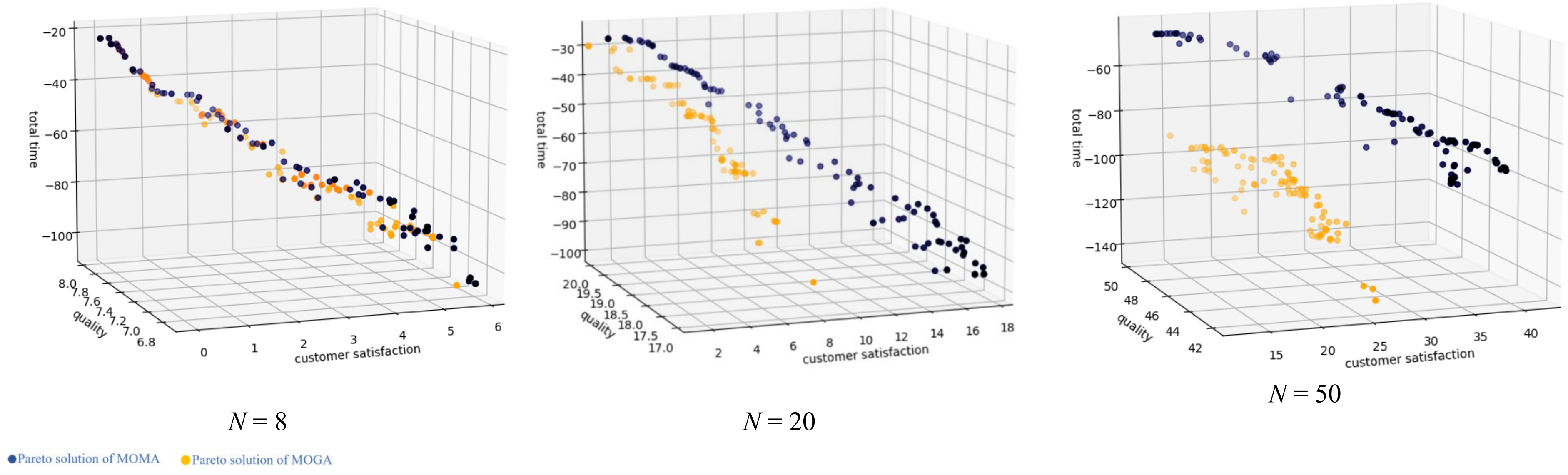


Figure 8: Comparison of Pareto solutions from MOMA and MOGA

Table 5: Knee solution of random environment

Random Seed	‘1234’		‘2453’		‘8752’		‘4964’		‘3721’	
$N = 8$	MOMA	MOGA	MOMA	MOGA	MOMA	MOGA	MOMA	MOGA	MOMA	MOGA
Customer Satisfaction	3.33	2.63	2.01	2.29	3.00	2.31	3.33	2.47	2.59	2.62
Quality Satisfaction	7.54	7.82	7.93	7.91	7.79	7.87	7.75	7.87	7.83	7.83
Return Time	64,15	56.42	47.16	51.96	59.33	52.52	64.15	56.36	55.21	53.90
$N = 20$										
Customer Satisfaction	9.95	7.19	9.75	7.72	10.26	7.09	10.88	8.85	11.12	8.28
Quality Satisfaction	19.71	19.77	19.70	19.84	19.66	19.80	19.55	19.66	19.52	19.73
Return Time	51.22	54.77	51.14	51.29	53.58	53.14	53.29	64.23	53.90	55.17
$N = 50$										
Customer Satisfaction	25.31	22.32	29.23	21.51	29.23	21.37	27.33	21.35	28.53	18.94
Quality Satisfaction	49.10	46.26	48.34	46.46	48.34	45.95	48.58	46.83	48.26	46.81
Return Time	56.14	92.87	69.81	91.60	69.81	87.67	64.15	97.06	64.68	90.99

6. Results and Discussion

Based on the computational experiments as above, the results are further discussed in this section so as to elaborate the phenomenon of different experimental cases. Moreover, the insights to the Q-commerce are explicitly elaborated to guide the sustainable development.

6.1 Discussion on Experimental Cases

In Case1, the capabilities of the MOIDVD are compared with those of traditional models. It is found that the number of orders did not affect customer satisfaction regarding delivery time and quality in the MOIDVD model, with results significantly surpassing those of traditional models. Historically, commercial models prioritized delivery speed and distance at the expense of the customer experience. With the rise of Q-commerce, consumers increasingly prefer companies offering superior shopping experiences. The study observes an average increase of 36% in delivery satisfaction and 15% in quality satisfaction, which is crucial for building a strong brand image.

In Case 2, the computational efficiency of the MOMA algorithm is compared with that of the MOGA algorithm. Results show that when the number of orders was 20 and 50, MOMA's Pareto solutions were generally superior to those of MOGA. However, with 8 orders, the performance of both algorithms was similar. The MOMA algorithm is more suitable for larger order quantities, leveraging the advantages of local search. Conversely, for smaller order sizes, global algorithms can achieve optimal results. Although the equipment used in the experiment limits larger-scale testing, the trends observed with these three order quantities suggest that MOMA has stronger adaptability in handling large-scale orders in practical applications.

In Case 3, the Knee point is selected to demonstrate the robustness of the algorithm, so the random seed was altered to simulate different order generation scenarios. The MOMA algorithm outperforms MOGA in customer satisfaction, achieving average improvements of 35.65%, 51.96%, and 55.85% for order quantities of 8, 20, and 50, respectively, with growth rates ranging from 4.85% to 13.66%. However, quality satisfaction shows superiority only when the order quantity is 50. This can be attributed to the interaction between customer satisfaction and quality satisfaction. The quality of goods deteriorates over time from the store to delivery, so faster delivery increases quality satisfaction. However, this may conflict with customers who prefer later delivery times, resulting in a trade-off between the two metrics. Nevertheless, regardless of order quantity or generation method, 97.43% of customers' quality requirements are met. Return time, from another perspective, controls the variable costs of transportation. MOMA reduces distribution time by up to 39.55%, indicating a high turnover rate. This metric reflects the time taken for the latest vehicle in a batch to complete its delivery tasks; the shorter this time, the higher the overall efficiency of the delivery operation. Furthermore, the quicker the current delivery task is completed, the sooner resources can be allocated to the next task. As vehicles and drones depart from the store simultaneously, shorter return times for the latest vehicles reduce idle time for other tools, improving utilization rates and thereby achieving greater economic benefits under the same fixed costs.

6.2 Managerial Implications

The experiment in this study thoroughly demonstrates the effectiveness of the model in guiding the development of Q-commerce enterprises, particularly in balancing cost and customer satisfaction. Historically, minimizing transportation costs has been a primary objective in supply chain management. However, with the emergence of integrated warehousing and Q-commerce, metrics such as customer satisfaction have gradually become focal points for businesses. Enterprises are required to align their business objectives, which have become crucial in shaping corporate image. For instance, companies like Freshippo in China have expanded their delivery services, particularly in handling various temperature-sensitive goods, thereby adjusting their transport strategies to prioritize enhancing customer satisfaction in delivery rather than solely pursuing speed [45][46].

Moreover, enhancing corporate sustainability is no longer confined to reducing transportation costs but increasingly emphasizes service quality, which is critical for economic sustainability. Through continuous technological innovation and strategic adjustments, enterprises can continuously enhance product added value, such as improving customers' immediate shopping experiences, thereby promoting sustainable consumption. Simultaneously, by minimizing losses of temperature-sensitive goods, companies have also made strides in promoting green consumption patterns, effectively reducing resource wastage and environmental pollution. Hence, the model presented in this paper achieves a win-win situation of economic growth and efficient resource utilization, offering valuable experiential guidance for Q-commerce enterprises.

7. Conclusion

This study highlights the enhancement of the delivery of temperature-sensitive goods in the Q-commerce business environment. The model's impact is analyzed from three key perspectives: meeting customer delivery time expectations, ensuring satisfaction with the quality of goods, and managing transportation time. Compared to the traditional model, the findings demonstrate that the proposed models and algorithms perform exceptionally well, particularly in large-scale environments. This superior performance is crucial for guiding the sustainable development of O2O stores in practical applications. In addition, the novelty of the model points out the direction of optimizing the vehicle routing problem of mixed distribution of drones and vehicles. The subsequent calculation can be simplified by merging the branch routes into the main routes, which is feasible according to logical reasoning. However, there are still areas for improvement, particularly in incorporating uncertainties into the model, such as traffic jams, and dynamic characteristics, like order insertion. In future work, a distributionally robust optimisation approach could be adopted to develop more resilient optimal solutions that address these concerns. Additionally, incorporating more real-life case studies will enhance the ability to quantitatively assess the sustainability value derived from the proposed model.

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Appendix A. List of notations

Symbol	Description
	Sets
K	Set of human-driving vehicles indexed by $k \in K$
D	Set of drones indexed by $d \in D$
C	Set of customer nodes indexed by $i \in C$
N	Set of nodes, $N = \{0\} \cup C$, where node 0 is the depot
	Parameters
v_k	Speed of vehicle k
Q_k	Capacity of vehicle k
v_d	Speed of drone d
Q_d	Capacity of drone d
T_d	Maximum flight time of drone d
q_d	Weight of drone d
q_i	Weight of the parcel for customer i
Δ_{ij}	Euclidean distance between nodes i and j
T_{ij}	Travelling time between nodes i and j, where $T_{ij}^k = \frac{\Delta_{ij}}{v_k}$ and $T_{ij}^d = \frac{\Delta_{ij}}{v_d}$
e_i	Lower bound of desired delivery time window for customer i
u_i	Upper bound of desired delivery time window for customer i
e_i'	Lower bound of maximal delivery time window for customer i
u_i'	Upper bound of maximal delivery time window for customer i
f	Desired delivery time based on thermal passive packaging
f'	Maximal allowable delivery time based on thermal passive packaging
c_d	Service time for drone d
c_k	Service time for vehicle k
σ	Waiting time buffer for synchronization between vehicle and drone
$\mathcal{M}$	Number of drones carried by each vehicle
M	A large constant used in those big-M constraints, i.e. M_1 and M_2
$\mathcal{P}$	Maximum number of flights that a drone can perform
	Decision variables
y_{ij}^k	Binary variable where 1 if vehicle k serves customer j after customer i, else 0
x_{ij}^d	Binary variable where 1 if drone d serves customer j after customer i, else 0
α_{ij}^d	Binary intermediate variable where 1 if $x_{ij}^d = 1$ and $y_{i'j}^k = 0$, else 0.
a_i^d	Arrival time at customer i by drone d
l_i^d	Departure time at customer i by drone d
a_i^k	Arrival time at customer i by vehicle k
l_i^k	Departure time at customer i by vehicle k