APEM journal

Advances in Production Engineering & Management
Volume 21 | Number 1 | March 2026 | pp 139–155
https://doi.org/10.14743/apem2026.1.566

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

A human-robot collaborative delivery model for instant orders in metropolitan areas

Xie, X.L.[a,*], Chen, X.[a], Wu, J.Y.[a], Zhang, X.F.[a], Kong, L.K.[a], Xiao, Y.[b]

[a]Logistics School, Beijing Wuzi University, Beijing, P.R. China
[b]School of Economics and Management, Suqian University, Suqian Jiangsu, P.R. China

A B S T R A C T

In metropolitan instant delivery systems, rising operational costs and poor delivery timeliness pose significant challenges. This study addresses these issues by investigating optimal order allocation and route optimization in a hybrid delivery system that integrates autonomous delivery vehicles (ADVs) with human riders. Analysis of historical order data indicates that inefficient order assignment between ADVs and riders is a major operational bottleneck. To address this problem, a collaborative human-ADV delivery model is formulated with the objective of minimizing total logistics costs under constraints related to delivery time windows, vehicle capacity, and routing requirements. The proposed model is applied to a real-world case involving QX Fresh Supermarket, comprising 80 orders and 16 community transfer points. An improved genetic algorithm is developed to solve the optimization problem efficiently. Empirical results for off-peak, normal, and peak periods show that the collaborative delivery approach significantly improves ADV utilization and reduces total delivery costs by more than 30 % without compromising timeliness. These findings provide both a sound theoretical basis and practical guidance for the advancement of human-machine collaborative logistics.

A R T I C L E I N F O

Keywords:
Instant delivery;
Unmanned delivery vehicle;
Human-robot collaboration;
Order allocation;
Route optimization;
Genetic algorithm;
Last-mile logistics

**Corresponding author:*
xiexiaoling@bwu.edu.cn
(Xie, X.L.)

Article history:
Received 1 December 2025
Revised 7 April 2026
Accepted 10 April 2026

1. Introduction

The global retail sector is undergoing a profound transformation toward the "New Retail" model, integrating online and offline channels to prioritize experiential consumption. The fresh grocery segment leads this trend, having demonstrated remarkable resilience in the post-pandemic period. In 2024, the global fresh food retail market reached approximately USD 1.35 trillion, with projected annual growth of around 6 %. This surge is evident worldwide: in North America, platforms such as Instacart and Amazon Fresh are reshaping consumption; in Europe, Ocado's automated warehouses set new efficiency standards; and in Asia, Hema Fresh pioneers data-driven logistics. China, with a fresh grocery online penetration rate of 14.6 % in 2022, exemplifies this shift yet still faces the universal "last-mile" bottleneck: fragmented, high-frequency orders with tight delivery windows make traditional centralized distribution inefficient.

Consequently, the logistics industry is transitioning toward Autonomous Delivery Vehicles (ADVs). In China, enterprises like Meituan and JD.com have achieved rapid growth in delivery volumes, supported by policies promoting "vehicle-road-cloud integration." However, full commercialization faces a severe "cost trap." While ADVs offer superior payload capacity and operational continuity compared to riders, the marginal cost of resolving the final 1 % of complex driving scenarios (the "long-tail problem") remains prohibitive. Furthermore, the industry currently struggles with "diseconomies of scale," where current fleet sizes cannot yet offset high R&D and hardware costs. Fully autonomous systems still falter in complex urban environments, while traditional human delivery is constrained by rising labor costs and limited scalability.

Therefore, a collaborative delivery model that integrates the flexibility of human riders with the cost-efficiency of ADVs presents a critical strategic direction. This study investigates order allocation and route optimization in a hybrid human-ADV delivery system in Chinese metropolitan areas. By constructing a multi-constraint optimization model and solving it using an improved genetic algorithm, this study addresses the gap in operationalizing human-machine collaboration. It provides a theoretical framework for hybrid fleet management and offers actionable strategies to enhance efficiency and reduce operational costs by over 30 %, contributing to the sustainable development of urban logistics systems globally.

2. Literature review

This section systematically reviews and synthesizes the literature concerning three core research issues: human-machine collaboration, order allocation, and delivery route optimization, with the objective of identifying current research progress, limitations, and future directions. First, the human-machine collaboration perspective examines effective coordination mechanisms between human operators and intelligent systems. Second, order allocation strategies are analyzed with respect to their impacts on delivery efficiency. Finally, delivery route optimization approaches are evaluated, with particular emphasis on algorithmic applications for enhancing distribution performance. Through this comprehensive literature review, the current study establishes a theoretical foundation for subsequent model development and methodological improvements.

2.1 Human-machine collaboration (HRC)

HRC, which focuses on synergistic task execution between humans and robotic systems, is foundational to modern logistics. Early research laid the theoretical groundwork, and recent advances have been driven by developments in artificial intelligence and sensor technologies.

A critical challenge in HRC is dynamic task allocation. Traditional models often rely on predefined rules, but recent studies emphasize adaptability. For instance, Alirezazadeh and Alexandre [1] developed a dynamic task scheduling framework that allows for real-time task reallocation in response to environmental changes. Furthermore, Wu *et al*. [2] presented a trust-based task allocation method for human-robot collaboration, optimizing the assignment process by establishing a trust model between humans and robots. Ranz *et al*. [3] proposed a capability-based task allocation approach that dynamically assigns tasks according to human and robot capabilities, thereby improving collaboration efficiency.

Decision-making methodologies in HRC have evolved to support complex joint actions. Cai *et al*. [4] investigated collaborative decision-making for resource-constrained field inspection tasks, optimizing task execution under limitations.

Ensuring safety and adaptability remains paramount. Studies have moved beyond physical safeguards to cognitive models. Yao *et al*. [5] developed a task reallocation algorithm incorporating dynamic fatigue assessment, enhancing operator safety by adjusting workloads based on real-time states. Faccio *et al*. [6] further contributed by modeling variable robot speeds within task allocation, enabling finer control over collaborative efficiency. Zhao *et al*. [7] further emphasized the importance of safety in HRC and proposed an integrated task allocation framework balancing both safety and efficiency. Bruno and Antonelli [8] developed a dynamic task classification and allocation method that adapts task assignments based on task requirements and team capabilities to enhance collaborative performance.

The application of HRC in industrial logistics is well-documented. Vahedi-Nouri *et al*. [9] extended this to reconfigurable manufacturing systems, presenting an optimized scheduling method for dynamic production needs.

While HRC has advanced significantly, it still faces limitations, including oversimplified human factor models, a lack of studies in multi-robot environments, and underexplored cross-domain applications. Xu *et al*. [10] investigated fairness concerns in symmetric manufacturing enterprises and found that such concerns exhibit heterogeneity, directionality, and reinforcement, which significantly affect the stability of resource-sharing strategies. This provides a useful reference for understanding human-machine collaboration in manufacturing contexts. To overcome these limitations, future research should focus on deeply integrating human cognition with machine intelligence, thereby facilitating broader adoption across diverse and complex scenarios.

2.2 Order allocation

Order allocation, as a specific instantiation of task allocation in logistics, is critical for operational efficiency. Research has evolved from static models toward dynamic, multi-objective optimization frameworks.

Multi-objective optimization is central to modern approaches, balancing conflicting goals such as cost, time, and service level. Sodenkamp *et al*. [11] incorporated collaborative effects into a multi-criteria decision model for supplier selection and order allocation. Xiang *et al*. [12] developed a multi-objective optimization model for order allocation within clustered multi-supply-and-demand networks, optimizing for cross-network resource utilization.

The application of intelligent algorithms has revolutionized this field. Zhang *et al*. [13] proposed an improved adaptive variable neighborhood search algorithm to solve stochastic order allocation problems, enhancing robustness and solution efficiency.

Dynamic and real-time allocation is essential for contemporary on-demand logistics. Huq *et al*. [14] utilized Long Short-Term Memory (LSTM) models to predict cross-regional food delivery demand, informing real-time order allocation decisions to optimize service quality. In crowdsourced delivery, which is a highly flexible model, studies mainly focus on real-time matching. As emphasized by Silva *et al*. [15], optimizing last-mile operational models is key to reversing the trend of rising fuel costs and emissions caused by high delivery volumes.

Seghezzi and Mangiaracina [16], and Seghezzi *et al*. [17] conducted in-depth economic analyses comparing crowdsourced logistics against traditional delivery models for B2C e-commerce. Their studies, utilizing cost models applied to Milan, demonstrated that crowdsourcing significantly reduces per-delivery costs for both express and multi-parcel services. Specifically, they identified cost savings of approximately 11 % compared to traditional vans, attributing this advantage to the operational flexibility and higher delivery success rates inherent in the crowdsourcing model.

This study builds upon these foundations by formulating the order allocation problem between riders and ADVs as a dynamic, multi-objective optimization solved with a metaheuristic algorithm.

2.3 Delivery route optimization

The Vehicle Routing Problem (VRP) is the cornerstone of delivery optimization. This research focuses specifically on VRP with Time Windows (VRPTW), which is paramount for time-sensitive fresh grocery delivery.

Research on VRP with Time Windows has diversified to model various real-world constraints. A key distinction is made between hard (infeasible to violate) and soft (violatable with penalty) time windows. Errico *et al*. [18] addressed a VRPTW with stochastic service times using a two-stage stochastic programming model solved by a branch-cut-and-price algorithm, providing exact solutions for medium-scale problems. Ghannadpour *et al*. [19] tackled uncertainty by introducing fuzzy time windows in a multi-objective dynamic VRP solved with a genetic algorithm.

The rise of collaborative and multi-modal delivery has introduced new VRP variants. Wang *et al*. [20] studied a two-stage location-routing problem with hard time windows, solved with an improved NSGA-II algorithm.

In the context of two-echelon distribution network optimization, Jiao *et al*. [21] investigated the low-carbon multimodal vehicle logistics route optimization problem with timetable limits using Particle Swarm Optimization, demonstrating the synergistic effects of multimodal transportation in reducing both carbon emissions and costs. Furthermore, Xiao and Lan [22] proposed a two-echelon drone-truck collaborative TSP-based routing model for humanitarian logistics with time windows and stochastic demand, providing important methodological references for the two-echelon human-robot relay delivery network in this study.

Solving algorithms for these complex NP-hard problems are predominantly metaheuristic or hybrid in nature. Mohammed *et al*. [23] applied an improved genetic algorithm for campus bus routing. Huang *et al*. [24] used a genetic algorithm hybridized with local search (IGALS) for a VRPTW with simultaneous pickup and delivery. Hybrid approaches are particularly effective. Zhang *et al*. [25] combined an artificial bee colony algorithm with tabu search for cold chain logistics VRP. Zhang *et al*. [26] established a single-objective model to minimize the maximum delivery time for emergency rescue, demonstrating that reducing waiting and transport times is essential for system effectiveness. Similarly, our study prioritizes strict delivery time windows to ensure the freshness and punctuality of instant orders.

Li *et al*. [27] developed a cost model for drone-rider collaborative food delivery. By optimizing transfer station locations using genetic algorithms and conducting comprehensive cost analysis, they identified specific service radii where the total cost of collaboration undercuts the rider-only mode, providing crucial quantitative support for human-robot collaboration strategies. In metropolitan environments, static path planning often fails to meet the strict timeliness requirements of instant delivery due to fluctuating traffic conditions. Li *et al*. [28] demonstrated the effectiveness of integrating real-time traffic flow prediction into path planning algorithms. Similarly, our collaborative model accounts for dynamic travel times to optimize the interaction between riders and ADVs. To effectively manage the complexity of large-scale logistics networks (e.g., 120 nodes), decomposing the problem is often necessary. Zhang *et al*. [29] proposed a two-stage algorithm design that utilizes K-means clustering to group demand points before applying a genetic algorithm for routing.

Recently, Zhao *et al*. [30] published a study on synchronized deliveries with a bike and a self-driving robot (TSPBR), a problem setting highly similar to the human-ADV collaborative model in this paper. Beyond this comparison, the novelty of our work lies in two aspects. First, operationally, we address the practical limitations of current ADVs (short range, high empty-load rate, chaotic routes) by integrating them with riders into a unified delivery system that leverages complementary strengths. Second, algorithmically, we improve the genetic algorithm by redesigning the chromosome encoding scheme: unlike traditional encoding that includes only one rider type and uses the store as the separator, our scheme sequentially incorporates full-route riders, relay riders, and ADVs within one chromosome, with relay rider sub-paths separated by transfer points instead of the store. These distinctive features constitute the main novelty of this paper compared to existing two-echelon, relay, and collaborative routing studies.

Recent studies have also explored customer-centric last-mile delivery optimization. Wang and Huang [31] investigated urban end-delivery paths considering consumers' delivery time preferences using an ALNS algorithm, showing that personalized delivery time services increase delivery costs by approximately 20 % while generating additional revenue. Zhao *et al*. [32] further studied the vehicle routing problem considering customers' multiple preferences (delivery time, location, and mode) and demonstrated that preference constraints significantly affect total delivery costs when the average preference probability exceeds 0.5. These studies highlight the importance of incorporating customer preferences into last-mile delivery optimization, which aligns with the time window constraints considered in our human-robot collaborative model.

In summary, while extensive literature exists on HRC, order allocation, and VRP individually, their intersection in the context of a human-ADV hybrid delivery system for fresh supermarkets remains underexplored. This research synthesizes concepts from these three streams to develop an integrated model and solution methodology for this emerging logistics paradigm.

2.4 Unmanned delivery policies and development trends

The global regulatory framework for unmanned delivery is rapidly evolving as nations seek to balance innovation with public safety concerns. The United States has adopted a decentralized approach in which the National Highway Traffic Safety Administration provides federal guidance while states like California and Texas have developed their own specific regulations governing autonomous delivery vehicle testing and deployment. The European Union has implemented a comprehensive Strategy on Automated Mobility that emphasizes standardization and cross-border testing compatibility, though its strict privacy regulations under the GDPR create additional compliance requirements for drone operations. Japan stands out for its proactive legislative approach, having formally revised its Road Traffic Act to explicitly accommodate unmanned delivery vehicles in public spaces. Singapore has emerged as a particularly progressive testing ground through initiatives like the TRUST trial framework and National Drone Initiative that actively encourage real-world commercialization and even cross-border drone logistics experiments. These international policy developments demonstrate a spectrum of regulatory philosophies, ranging from cautious permission to active promotion, while addressing core concerns about safety, privacy, and integration with existing transportation systems. Some other countries have adopted a relatively loose regulatory approach, leaving the development of driverless and unmanned delivery to autonomous exploration by enterprises or local organizations, with the relevant policies, as shown in Fig. 1.

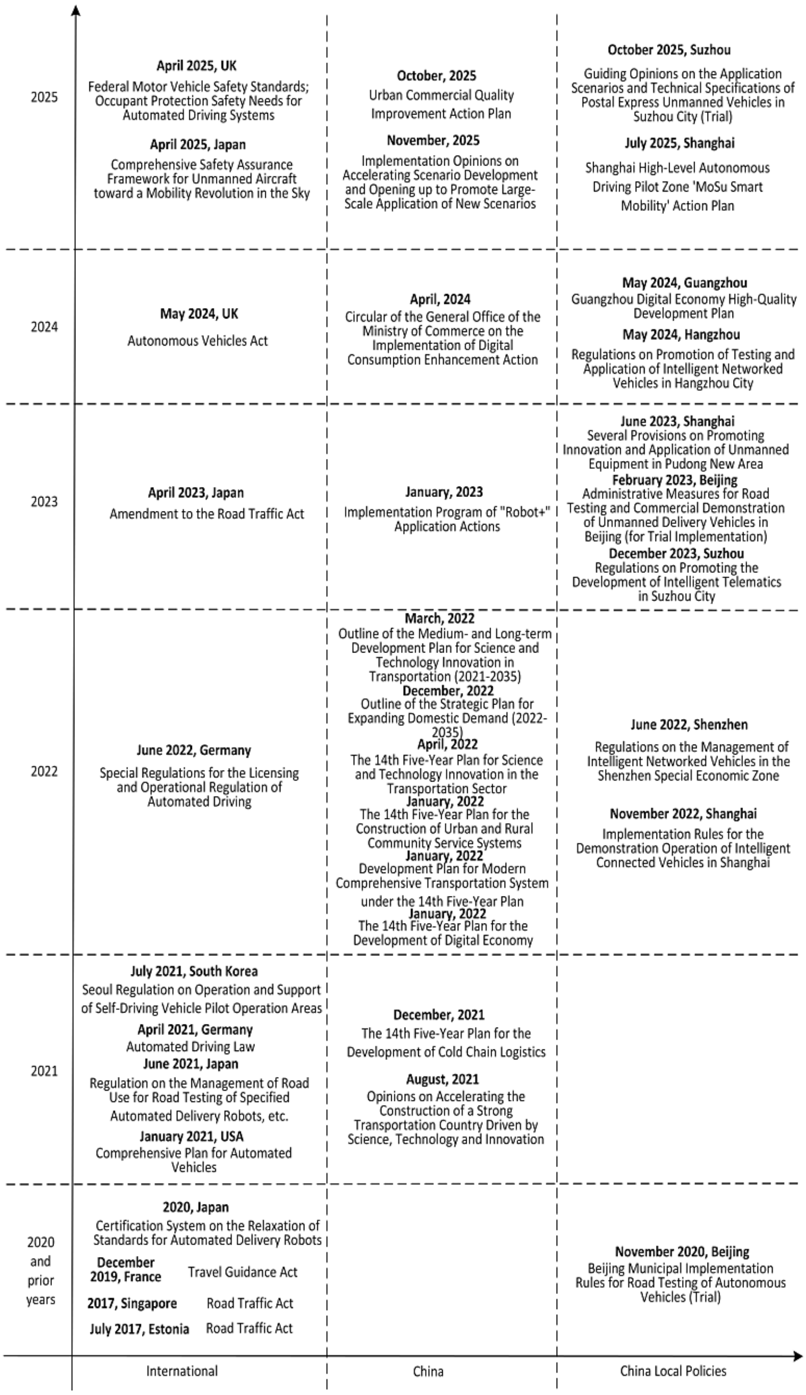

Fig. 1 Domestic and foreign policies related to unmanned delivery industry

China has demonstrated a strong national commitment to developing its unmanned delivery sector through coordinated policy support and local implementation. The central government has established a clear strategic direction through a series of top-level policies that provide both guidance and standards for industry development. Ji *et al*. [33] developed an evolutionary game model between government and automobile enterprises, demonstrating that reward and punishment policies significantly influence firms' transition to new energy production and that erroneous policy implementation can alter equilibrium outcomes. This finding highlights the importance of policy design in guiding industrial transformation. This national framework has been effectively operationalized at the local level, with key cities including Beijing, Shanghai, and Shenzhen creating detailed implementation rules and designated zones for testing and demonstration operations. This multi-level governance approach has created a structured yet adaptable environment that supports technological advancement while maintaining oversight, reflecting China's methodical strategy for nurturing emerging technologies through policy-enabled ecosystems.

Driven by falling costs and tech upgrades like V2X, the unmanned delivery market is surging, particularly in China. Application scenarios are expanding from food delivery to medical and campus logistics. Meanwhile, policymakers worldwide are refining regulations to support safe, large-scale deployment.

3. Mathematical model

3.1 Problem statement and assumptions

The optimization of last-mile delivery in China's major cities, characterized by high order density and complex logistics networks, presents significant challenges for contemporary retail models. To investigate these challenges in a concrete operational context within the Chinese market, this study selects QX Fresh Supermarket as a representative case for empirical analysis. This research addresses the last-mile delivery optimization problem for QX Fresh Supermarket within the new retail context. The supermarket operates on an "online order, offline delivery" model, featuring a hierarchical distribution network with a "single distribution center – multiple transfer points – multiple customers" structure, as shown in Fig. 2. Customers place orders via an online platform, specifying their expected delivery time windows, which are then fulfilled by the nearest store.

Fig. 2 Schematic diagram of the distribution network structure

Currently, QX Fresh Supermarket employs two delivery modes:

1. Direct Rider Delivery: Riders collect orders from the store and deliver them directly to all customers before returning to the store.
2. Human-Robot Relay Delivery: Unmanned delivery vehicles transport batches of orders to designated transfer points, where relay riders subsequently complete the delivery from the transfer point to the final customers.

However, significant issues exist in the current operation: order allocation between riders and unmanned vehicles relies heavily on experience, lacking systematic optimization. This results in low loading rates for unmanned vehicles, resource idling, and a failure to fully leverage their inherent cost advantages. Consequently, the core research problem is to scientifically allocate orders to riders or unmanned vehicles while simultaneously optimizing their respective delivery routes, aiming to minimize the total distribution cost, all under the constraints of customer time windows and vehicle capacity.

3.2 Parameters and decision variables

The following fundamental assumptions are made to formulate the mathematical model:

1. The travel speeds of unmanned vehicles and riders are constant and unaffected by traffic congestion.
2. The demand, delivery location, and time window for all customer orders are known.
3. A single order cannot be split and must be completed by the same delivery unit.
4. Relay riders are immediately available for handover when unmanned vehicles arrive at transfer points, resulting in zero waiting time.
5. The service time at customer points and transfer points is a fixed constant.

Table 1 Parameters and decision variables

Type	Symbol	Definition
Model Parameters	M	Set of customer points to be served, $g, h \in M$
	N	Set of transfer points, ($i, j = 0$ denotes the store) $i, j \in N$
	K	Set of autonomous delivery vehicles， $k \in K$
	P	Set of full-route riders, $p \in P$
	U	Set of relay riders, $u \in U$
	Q_1	Maximum order capacity per autonomous vehicle
	Q_2	Maximum order capacity per rider
	q_j	The quantity of delivery orders reaching the transfer point j
	v_k	Average delivery speed of autonomous vehicles
	v_p	Average delivery speed of riders
	e_1	Per-kilometer delivery cost for autonomous vehicles
	e_2	Per-order delivery cost for full-route riders
	e_3	Per-order delivery cost for relay riders
	e_4	Loading cost per order for autonomous vehicles
	D_{ij}	the distance of the unmanned delivery vehicle from transfer point i to transfer point j
	d_{gh}	the distance from customer point g to customer point h for the rider
	ET_g	Earliest delivery time at customer
	LT_g	Latest delivery time at customer
Auxiliary Variables	t_{ij}	the time it takes for the unmanned delivery vehicle to travel from transfer point i to transfer point j,t_{0i}represents the time it takes to travel from the store to transfer point i
	t_{gh}	the time it takes for the rider to travel from customer point g to customer point h,t_{og}Indicates the time it takes to travel from the store to customer point g
	t_λ	Service time required by the rider at a single customer point
	t_μ	Service time required by the unmanned delivery vehicle at a single transfer point
Decision Variables	X_{ij}^k	Binary variable: $X_{ij}^k = 1$ if unmanned delivery vehicle k travels from transfer point i to transfer point j; $X_{ij}^k = 0$otherwise
	Y_{gh}^p	Binary variable:$Y_{gh}^p = 1$ if full-route rider p travels from customer point g to customer point h; $Y_{gh}^p = 0$ otherwise
	Z_{gh}^u	Binary variable: $Z_{gh}^u = 1$ if shuttle rider u travels from customer point g to customer point h; $Z_{gh}^u = 0$otherwise
	W_{ig}	Binary variable: W_{ig}if customer point g is served by transfer point i; W_{ig} otherwise
	V_{ug}	Binary variable: $V_{ug} = 1$ if shuttle rider u serves customer point g; $V_{ug} = 0$ otherwise
	R_i^k	Binary variable: $R_i^k = 1$ if unmanned delivery vehicle k serves transfer point i; $R_i^k = 0$ otherwise

It should be noted that Assumption 4 (zero waiting time at transfer points) is an idealized simplification of reality. In practice, the temporal uncertainty of human behavior can significantly affect collaboration efficiency. A potential approach to address this issue is to adopt a two-layer optimization framework combining offline pre-optimization with online reactive adjustment. In future research, such a framework can be explored to incorporate stochastic waiting times at transfer point handovers into our model, enhancing its applicability in real dynamic environments.

The model parameters, auxiliary variables, and decision variables are listed in Table 1.

3.3 Model formulation

The objective of this study is to minimize the total distribution cost, which primarily consists of three components:

1. Unmanned vehicle transportation cost C_1: Proportional to the total travel distance.

$$C_1 = \sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} e_1 D_{ij} X_{ij}^{k}\ (1) \tag{1}$$

2. Unmanned vehicle loading cost C_2: Proportional to the total number of orders delivered by unmanned vehicles.

$$C_2 = \sum_{i=1}^{N}\sum_{g=1}^{M}\sum_{k=1}^{K} e_4 W_{ig}\, R_i^k \tag{2}$$

3. Rider delivery cost C_3: Includes the costs of both direct riders and relay riders.

$$C_3 = \sum_{p=1}^{P}\sum_{g=0}^{M}\sum_{h=0}^{M} e_2 Y_{gh}^{p} + \sum_{u=1}^{U}\sum_{g=0}^{M}\sum_{h=0}^{M} e_3 Z_{gh}^{u} \tag{3}$$

Thus, the total objective function is:

$$C = C_1 + C_2 + C_3 = \sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} e_1 D_{ij} X_{ij}^{k} + \sum_{i=1}^{N}\sum_{g=1}^{M}\sum_{k=1}^{K} e_4 W_{ig}\, R_i^k + \sum_{p=1}^{P}\sum_{g=0}^{M}\sum_{h=0}^{M} e_2 Y_{gh}^{p} + \sum_{u=1}^{U}\sum_{g=0}^{M}\sum_{h=0}^{M} e_3 Z_{gh}^{u} \tag{4}$$

Eqs. 5-7 enforce flow conservation for unmanned delivery vehicles, ensuring they originate from and return to the distribution center while maintaining flow balance at transfer points. Similarly, routing logic and path continuity for full-route and relay riders are defined by Eqs. 8-13. Service completeness is guaranteed by Eqs. 14-15, which mandate that each customer order is fulfilled exactly once by a single rider. Capacity constraints for ADVs, full-route riders, and relay riders are formulated in Eqs. 16-18, respectively. Eqs. 19-22 govern the temporal aspects, ensuring arrival times fall within customer time windows and calculating travel duration between nodes. Finally, the logical dependencies between order assignment and routing variables are established in Eqs. 23-24.

$$\sum_{i=1}^{N} X_{i0}^{k} = 1, k \in K \tag{5}$$

$$\sum_{j=1}^{N} X_{0j}^{k} = 1, k \in K \tag{6}$$

$$\sum_{i=1}^{N} X_{ij}^{k} = \sum_{i=1}^{N} X_{ji}^{k}, j \in N, k \in K \tag{7}$$

$$\sum_{g=1}^{M} Y_{g0}^{p} = 1, p \in P \tag{8}$$

$$\sum_{h=1}^{M} Y_{0h}^{p} = 1, p \in P \tag{9}$$

$$\sum_{g=1}^{M} Y_{gh}^{p} = \sum_{g=1}^{M} Y_{hg}^{p}, h \in M, p \in P \tag{10}$$

$$\sum_{g=1}^{M} Y_{gh}^{p} = \sum_{g=1}^{M} Y_{hg}^{p}, h \in M, p \in P \tag{11}$$

$$\sum_{h=1}^{M} Z_{0h}^{u} = 1, u \in U \tag{12}$$

$$\sum_{g=1}^{M} Z_{gh}^{u} = \sum_{g=1}^{M} Z_{hg}^{u}, h \in M, u \in U \tag{13}$$

$$\sum_{i=1}^{N} W_{ig} + \sum_{p=1}^{P} \sum_{h=1}^{M} Y_{hg}^{p} = 1, g \in M \tag{14}$$

$$\sum_{g=0}^{M} \sum_{p=1}^{P} Y_{gh}^{p} + \sum_{g=0}^{M} \sum_{u=1}^{U} Z_{gh}^{u} = 1, h \in M \tag{15}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} q_j X_{ij}^{k} \leq Q_1, k \in K \tag{16}$$

$$\sum_{g=0}^{M} \sum_{h=0}^{M} Y_{gh}^{p} \leq Q_2, p \in P \tag{17}$$

$$\sum_{g=1}^{M} \sum_{h=0}^{M} Z_{gh}^{u} \leq Q_2, u \in U \tag{18}$$

$$ET_g \leq t_{0g} \leq LT_g, g \in M \tag{19}$$

$$t_{0j} = \left(t_{0i} + t_{\mu} + t_{ij}\right) X_{ij}^{k}, i, j \in N, k \in K \tag{20}$$

$$t_{0h} = \left(t_{0g} + t_{\lambda} + t_{gh}\right) Y_{gh}^{p}, g, h \in M, p \in P \tag{21}$$

$$t_{0h} = \left(t_{0g} + t_{\lambda} + t_{gh}\right) Z_{gh}^{u}, g, h \in M, u \in U \tag{22}$$

$$\sum_{g=1}^{M} \sum_{h=1}^{M} \sum_{p=1}^{P} Y_{gh}^{p} + \sum_{g=1}^{M} \sum_{h=1}^{M} \sum_{u=1}^{U} Z_{gh}^{u} = M \tag{23}$$

$$\sum_{g=1}^{M} \sum_{k=1}^{K} X_{ji}^{k} \cdot W_{ig} = \sum_{g=1}^{M} \sum_{u=1}^{U} V_{ug} \cdot W_{ig}, i \in N \tag{24}$$

This formulation constitutes a complex Mixed-Integer Linear Programming (MILP) model, which is computationally intractable for large-scale instances when using exact methods. Therefore, Section 4 presents an efficient metaheuristic algorithm to obtain high-quality solutions.

4. Solution algorithm

In terms of algorithm design, Ostermeier and Huf [34] studied the multi-vehicle truck-and-robot routing problem and proposed a specialized heuristic based on a novel neighborhood search. Their algorithmic framework provides a useful reference for the design of our Improved Genetic Algorithm (IGA).

To build a suitable solution methodology, this section conducts an adaptability analysis of various intelligent optimization algorithms for the complex human-robot collaborative delivery problem. Han and Song [35] applied hybrid metaheuristic algorithms to robot path planning problems in shop-floor environments. Given the multiple nonlinear constraints in this problem, the genetic algorithm demonstrates greater applicability to the route optimization problem in this study than other intelligent algorithms, such as particle swarm optimization and simulated annealing, owing to its population-based search mechanism and strong global optimization capability.

Accordingly, the main procedure of the Improved Genetic Algorithm is illustrated in Fig. 3. It iteratively evolves a population of solutions by simulating the processes of natural selection and genetics, ultimately converging towards an optimal or near-optimal solution.

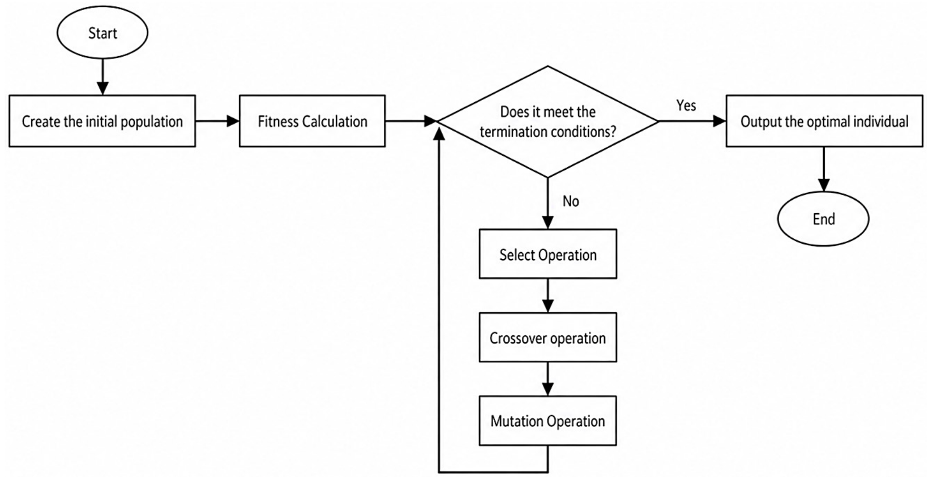

Fig. 3 Flowchart of the Improved Genetic Algorithm

Step 1: Encoding and decoding

Natural number encoding is adopted to represent the solution. The chromosome structure is defined as a sequence, where [symbol] represents the distribution center, [symbol] denotes customer nodes, and [symbol] denotes transfer points. During decoding, the algorithm sequentially reads the gene sequence and assigns tasks to full-route riders, ADVs, or relay riders by strictly verifying capacity and time window constraints.

Step 2: Population initialization

To ensure both population diversity and solution quality, a hybrid initialization strategy is implemented comprising four sub-strategies:

- Spatiotemporal clustering: Grouping orders with close geographical locations and overlapping time windows.
- Loading rate optimization: Prioritizing sequences that maximize vehicle capacity utilization.
- Transfer point constraints: Ensuring relay orders are mapped to their feasible transfer service scopes.
- Random permutation: Introducing randomness to prevent the algorithm from getting trapped in local optima early.

Step 3: Fitness function

Since the objective is to minimize the total delivery cost, the fitness function is defined as the reciprocal of the objective function value to convert the minimization problem into a maximization one.

Step 4: Genetic operators

Selection: A hybrid mechanism combining tournament selection and roulette wheel selection is employed. This approach maintains sufficient selection pressure to preserve elite individuals while ensuring population diversity.

Crossover: The Order Crossover (OX) operator is utilized to generate offspring. By preserving the relative order of genes from parent chromosomes, OX helps maintain valid permutations in permutation-based encoding, although additional decoding and feasibility checks are still required to satisfy problem-specific constraints. The crossover probability is set to 0.8.

Mutation: An adaptive Inversion Mutation operator is applied. Two gene loci are randomly selected, and the sequence between them is reversed. This operation enhances the algorithm's local search ability. The mutation probability is initially set to 0.2 and adjusts adaptively based on population diversity. Păun *et al*. [36] successfully applied an improved multi-objective genetic algorithm to optimize power consumption in flexible manufacturing systems.

Although Zhang and Zhou [37] focused on factory AGV systems rather than urban instant delivery, their AIGC-enhanced MPC framework for dynamic congestion management still provides a useful methodological reference for extending our static IGA model toward dynamic, real-time scheduling.

5. Numerical experiments

5.1 Case setup

To validate the effectiveness of the proposed model and algorithm, this study employs real operational data from an offline store of QX Fresh Supermarket in Beijing. The store's delivery service covers an area within a 3-kilometer radius. Experimental data consists of 80 orders placed within a 15-minute time window (10:00 – 10:15 AM) on a specific Saturday. This period ensures sufficient order volume and wide geographical distribution, effectively covering the entire delivery area. For computational convenience, all time data were converted into timestamp format using Eq. 26.

$$T_n = [T_0] + \frac{(T_0 - [T_0]) \times 100}{60} \tag{26}$$

The store's delivery network includes 16 pre-set transfer points. Travel distances and times between any two points were obtained using the Amap API to reflect real road conditions, rather than approximating them with Euclidean or Manhattan distances. The spatial distribution of the store, transfer points, and the 80 customer points is visualized in Fig. 4, where the red square represents the store, blue triangles represent transfer points, and green circles represent customer points.

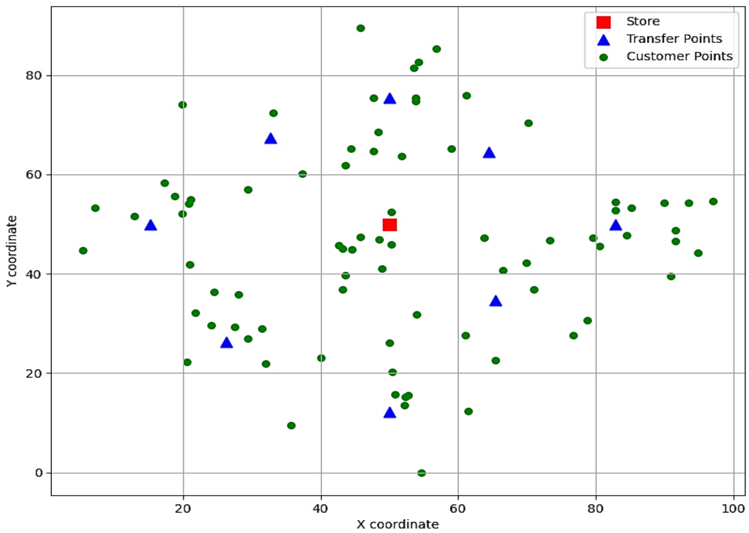

Fig. 4 Customer point distribution diagram

5.2 Parameter setting

Experimental parameters were set based on field research and are categorized into model parameters and algorithm parameters, as detailed in Table 2.

Table 2 Model and algorithm parameters

Parameter type	Parameter name	Parameter value
Model parameters	Unmanned vehicle speed	11km/h
	Full-route rider speed	25km/h
	Shuttle rider speed	25km/h
	Unmanned vehicle capacity	16orders
	Rider electric vehicle capacity	6orders
	Unmanned vehicle loading cost	¥0.5/order
	Unmanned vehicle travel cost	¥0.2/km
	Full-route rider delivery fee	¥6/order
	Shuttle rider delivery fee	¥3/order
Algorithm parameters	Population size	80
	Crossover probability	0.8
	Mutation probability	0.2
	Iteration count	200

5.3 Solution process and results

The model was implemented in Python 3.11 and executed on a PC with a 13th Gen Intel i5 processor and 16 GB of RAM. The convergence process of the Improved Genetic Algorithm is shown in Fig. 5. The algorithm converged after approximately 20 generations, with the objective function value (total delivery cost) stabilizing at 341.9 CNY, demonstrating satisfactory convergence performance.

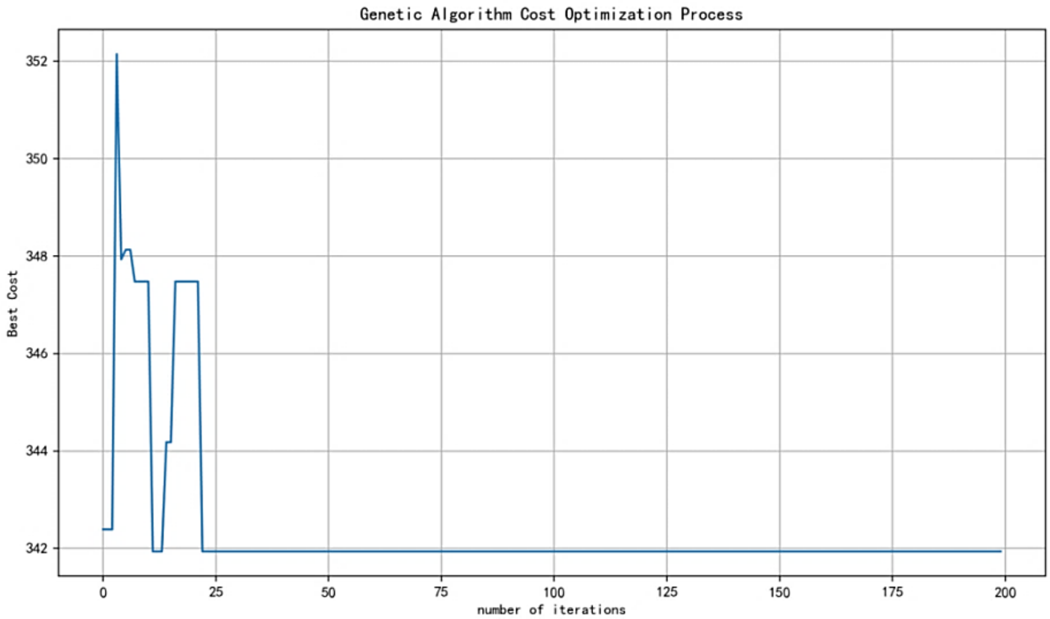

Fig. 5 Cost iteration graph

The optimized delivery plan for the 80 orders is as follows: the task is completed collaboratively by 7 full-route riders, 19 transfer riders, and 6 unmanned delivery vehicles. Among these, 20 orders are delivered directly by full-route riders, while the remaining 60 orders are delivered via the human-robot relay mode. Fig. 6 illustrates the final delivery routes, where cool-colored dashed lines represent full-route rider paths and warm-colored dotted lines represent transfer rider paths.

The specific routes for the unmanned delivery vehicles are listed in Table 3. The results indicate a relatively balanced order allocation across transfer points. The proposed scheme satisfies all customer time window constraints while achieving optimized delivery costs.

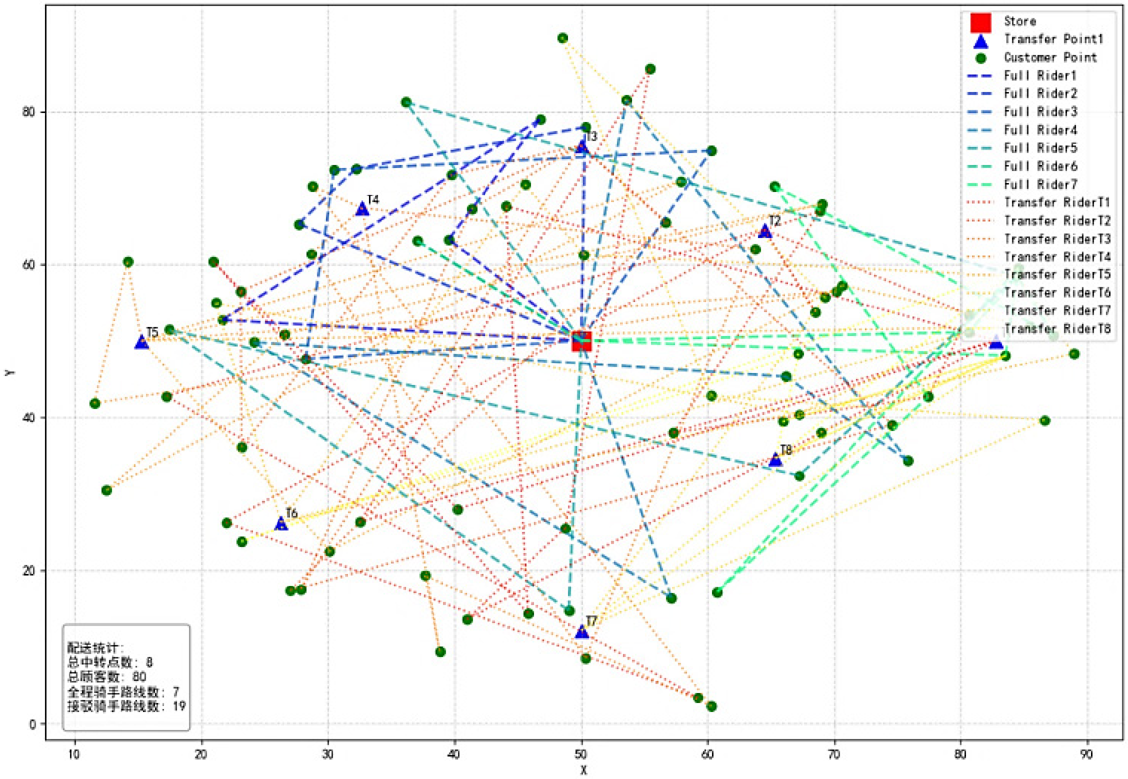

Fig. 6 Order delivery routes

Table 3 Delivery routes of unmanned delivery vehicles

Vehicle ID	Delivery Route
1	0-1-8-0
2	0-2-3-0
3	0-4-5-0
4	0-6-7-0

5.4 Sensitivity analysis

To comprehensively evaluate the model's performance, additional scenarios with low (30 orders), regular (60 orders), and peak (120 orders) order volumes were tested. The human-robot collaborative delivery mode was compared with the traditional full-route rider delivery mode. The results are summarized in Table 4.

Key findings include:

- The human-robot collaboration mode effectively reduces delivery costs by 30-34 % across all order volume scenarios.
- As the order volume increases, the average loading rate of unmanned vehicles significantly improves from 36 % during the low period to 70 % during the peak period, highlighting the economies of scale.
- During the peak period, the average delivery load per transfer rider reaches 4 orders, indicating optimized resource utilization.

Table 4 Statistics on delivery conditions for different order volumes

Order volume	Original delivery cost (¥)	Human-robot collaborative cost (¥)	Cost reduction (%)	Full-route rider orders	Shuttle rider orders	Unmanned vehicles deployed	Vehicle utilization rate
30 orders	180	117.2	34	7	23	4	0.36
60 orders	360	244.8	32	15	45	6	0.47
120 orders	720	504.5	30	30	90	8	0.7

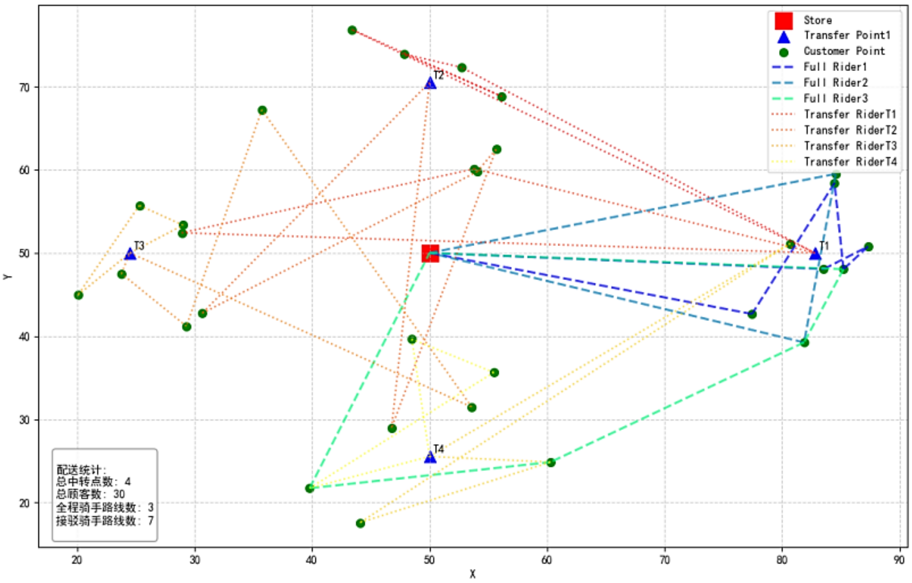

Fig. 7 Delivery routes for low volume (30 orders)

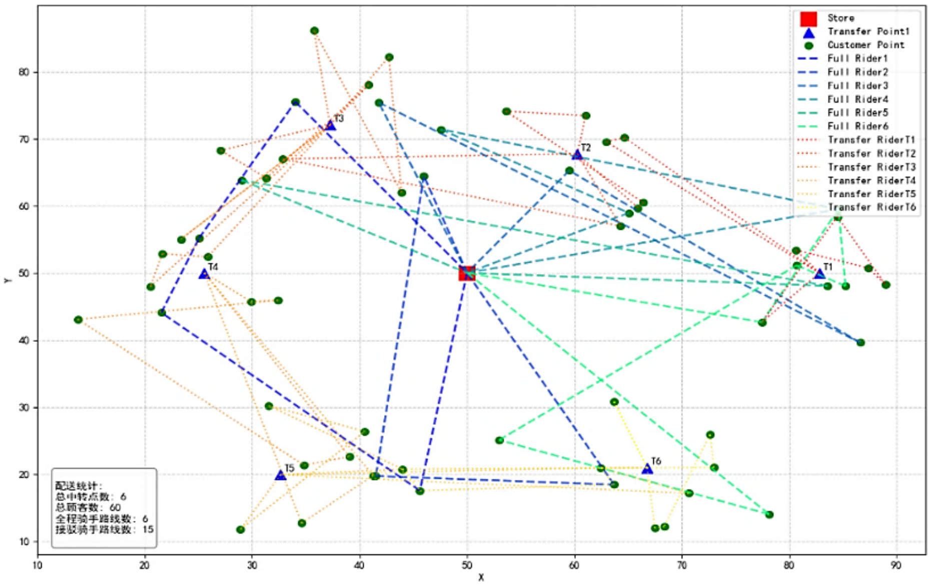

Fig. 8 Delivery route map for regular volume (60 orders)

The visualized delivery routes for the three scenarios are shown in Fig. 7 (Low), Fig. 8 (Regular), and Fig. 9 (Peak), respectively.

This section investigates the impact of key resource configurations (number of transfer points, number of unmanned vehicles) on the total cost. Sensitivity analyses were conducted by varying these two parameters under different order volumes.

Low Order Volume (30 orders): As shown in Table 5, the lowest total cost (117.2 CNY) is achieved with 4 transfer points and 4 unmanned vehicles. Considering resource conservation, using 4 transfer points and 2 vehicles slightly increases cost but significantly improves the vehicle loading rate.

Regular Order Volume (60 orders): Table 6 shows that configuring 6 transfer points with 6 vehicles, or 8 transfer points with 8 vehicles, are both cost-effective options. The key is to ensure that the number of vehicles is not less than the number of transfer points, while avoiding a significant surplus of vehicles.

Peak Order Volume (120 orders): According to Table 7, configuring 8 transfer points and 8 unmanned vehicles achieves the optimal cost (504.5 CNY) and the highest vehicle loading rate.

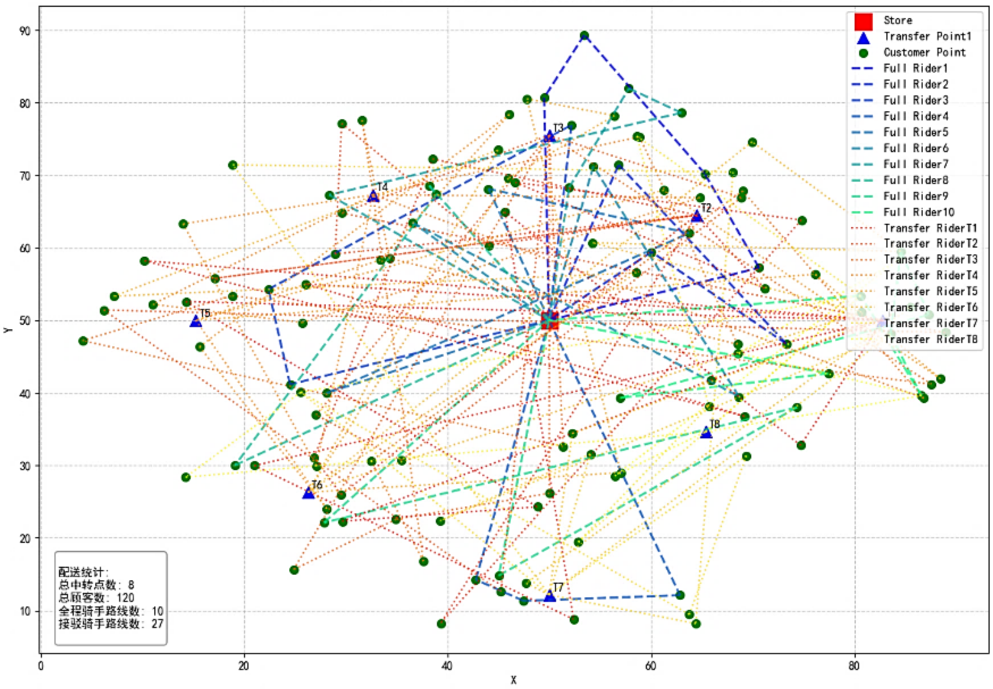

Fig. 9 Delivery route map for peak volume (120 orders)

Table 5 Delivery cost for low order volume

Cost of delivery for 30 orders	Unmanned vehicles deployed		
Number of transfer points	2	3	4
2	121.4	121.4	121.4
4	119.7	119.3	117.2
6	-	120.1	118.4

Table 6 Delivery cost for regular order volume

Cost of delivery for 60 orders	Unmanned vehicles deployed		
Number of transfer points	4	6	8
4	264	260.6	260.1
6	251.5	244.8	246.4
8	254	246.8	243.4

Table 7 Delivery cost for peak order volume

Cost of delivery for 120 orders	Unmanned vehicles deployed		
Number of transfer points	6	8	10
6	523.4	521.6	517.2
8	518.3	504.5	506.2
10	515.6	517.3	512.3

6. Conclusion

This study establishes the core mechanism of human-robot collaborative delivery under static conditions, thereby providing a theoretical foundation for more complex dynamic extensions. Specifically, we address the last-mile delivery optimization problem for the fresh food retail sector by constructing a human-robot collaborative delivery model. Taking QX Fresh Supermarket as a case study, we formulate a multi-constraint optimization model that incorporates customer time windows, vehicle capacity constraints, and hybrid order allocation. To solve this NP-hard problem, we design an Improved Genetic Algorithm (IGA) that employs a natural number encoding scheme and adaptive genetic operators.

Empirical experiments demonstrate that the proposed collaborative mode significantly outperforms traditional rider-only models. Specifically, the hybrid approach achieves a total cost reduction of over 30 % across low, regular, and peak order volume scenarios. Sensitivity analysis further reveals that the optimal configuration of unmanned vehicles and transfer points varies with demand density, highlighting the necessity of dynamic resource scheduling.

The findings provide actionable strategies for urban logistics management. First, the adoption of Autonomous Delivery Vehicles (ADVs) effectively mitigates the "diseconomies of scale" associated with high labor costs in pure manual delivery, particularly for medium-distance, batch transport. Second, managers should move beyond static fleet sizing; dynamic deployment based on historical order density is crucial to balancing cost and efficiency. Finally, investing in intelligent decision support systems is essential to replace experience-based scheduling, ensuring precise coordination between riders and ADVs.

While this study validates the efficacy of human-robot collaboration, several avenues warrant further investigation. First, the current model focuses on one-way delivery; future research should integrate reverse logistics (e.g., returns) to better reflect complex operational realities. Second, although the IGA proved effective, this study does not include a systematic comparison with other metaheuristics. Comparative studies involving other metaheuristics (e.g., Ant Colony Optimization and Large Neighborhood Search) could further validate the robustness of the algorithm. Lastly, extending the model from static, single-period optimization to dynamic, real-time scheduling under stochastic demand remains a critical direction for future work.

Acknowledgment

The authors acknowledge the financial support from the Jingdong Modern Industry Institute Open Fund of Suqian University.

References

[1] Alirezazadeh, S., Alexandre, L.A. (2022). Dynamic task scheduling for human-robot collaboration, *IEEE Robotics and Automation Letters*, Vol. 7, No. 4, 8699-8704, doi: 10.1109/LRA.2022.3188906.

[2] Wu, B., Hu, B., Lin, H. (2017). Toward efficient manufacturing systems: A trust based human robot collaboration, In: *Proceedings of 2017 American Control Conference (ACC)*, Seattle, USA, 1536-1541, doi: 10.23919/ACC.2017.7963171.

[3] Ranz, F., Hummel, V., Sihn, W. (2017). Capability-based task allocation in human-robot collaboration, *Procedia Manufacturing*, Vol. 9, 182-189, doi: 10.1016/j.promfg.2017.04.011.

[4] Cai, H., Mostofi, Y. (2019). Human-robot collaborative site inspection under resource constraints, *IEEE Transactions on Robotics*, Vol. 35, No. 1, 200-215, doi: 10.1109/TRO.2018.2875389.

[5] Yao, B., Li, X., Ji, Z., Xiao, K., Xu, W. (2024). Task reallocation of human-robot collaborative production workshop based on a dynamic human fatigue model, *Computers & Industrial Engineering*, Vol. 189, Article No. 109855, doi: 10.1016/j.cie.2023.109855.

[6] Faccio, M., Granata, I., Minto, R. (2024). Task allocation model for human-robot collaboration with variable cobot speed, *Journal of Intelligent Manufacturing*, Vol. 35, No. 2, 793-806, doi: 10.1007/s10845-023-02073-9.

[7] Zhao, R.H., Tao, S.C., Li, P.Z. (2025). Safety-efficiency integrated assembly: The next-stage adaptive task allocation and planning framework for human-robot collaboration, *Robotics and Computer-Integrated Manufacturing*, Vol. 94, Article No. 102942, doi: 10.1016/j.rcim.2024.102942.

[8] Bruno, G., Antonelli, D. (2018). Dynamic task classification and assignment for the management of human-robot collaborative teams in workcells, *The International Journal of Advanced Manufacturing Technology*, Vol. 98, No. 9, 2415-2427, doi: 10.1007/s00170-018-2400-4.

[9] Vahedi-Nouri, B., Tavakkoli-Moghaddam, R., Hanzálek, Z., Dolgui, A. (2024). Production scheduling in a reconfigurable manufacturing system benefiting from human-robot collaboration, *International Journal of Production Research*, Vol. 62, No. 3, 767-783, doi: 10.1080/00207543.2023.2173503.

[10] Xu, W., Xu, S., Liu, D.Y., Awaga, A.L., Rabia, A.C., Zhang, Y.Y. (2024). Impact of fairness concerns on resource-sharing decisions: A comparative analysis using evolutionary game models in manufacturing enterprises, *Advances in Production Engineering & Management*, Vol. 19, No. 2, 223-238, doi: 10.14743/apem2024.2.503.

[11] Sodenkamp, M.A., Tavana, M., Di Caprio, D. (2016). Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading, *European Journal of Operational Research*, Vol. 254, No. 3, 859-874, doi: 10.1016/j.ejor.2016.04.015.

[12] Xiang, W., Song, F.S., Ye, F.F. (2014). Order allocation for multiple supply-demand networks within a cluster, *Journal of Intelligent Manufacturing*, Vol. 25, No. 6, 1367-1376, doi: 10.1007/s10845-013-0735-0.

[13] Zhang, Z.Z., Zhang, L., Li, W.C. (2025). An improved adaptive variable neighborhood search algorithm for stochastic order allocation problem, *Scientific Reports*, Vol. 15, Article No. 481, doi: 10.1038/s41598-024-84663-y.

[14] Huq, F., Sultana, N., Roy, P., Razzaque, M.A., Huda, S., Hassan, M.M. (2025). Cross regional online food delivery: Service quality optimization and real-time order assignment, *Computers & Operations Research*, Vol. 173, Article No. 106877, doi: 10.1016/j.cor.2024.106877.

[15] Silva, K.O.A.N., Lima, R.S., Alves, R. (2024). The impacts of the pandemic on urban freight deliveries: A case study in a Brazilian carrier, *International Journal of Simulation Modelling*, Vol. 23, No. 1, 65-76, doi: 10.2507/IJSIMM23-1-672.

[16] Seghezzi, A., Mangiaracina, R. (2021). Investigating multi-parcel crowdsourcing logistics for B2C e-commerce last-mile deliveries, *International Journal of Logistics Research and Applications*, Vol. 25, No. 3, 260-277, doi: 10.1080/13675567.2021.1882411.

[17] Seghezzi, A., Mangiaracina, R., Tumino, A., Perego, A. (2021). 'Pony express' crowdsourcing logistics for last-mile delivery in B2C e-commerce: An economic analysis, *International Journal of Logistics Research and Applications*, Vol. 24, No. 5, 456-472, doi: 10.1080/13675567.2020.1766428.

[18] Errico, F., Desaulniers, G., Gendreau, M., Rei, W., Rousseau, L.M. (2016). A priori optimization with recourse for the vehicle routing problem with hard time windows and stochastic service times, *European Journal of Operational Research*, Vol. 249, No. 1, 55-66, doi: 10.1016/j.ejor.2015.07.027.

[19] Ghannadpour, S.F., Noori, S., Tavakkoli-Moghaddam, R., Ghoseiri, K. (2014). A multi-objective dynamic vehicle routing problem with fuzzy time windows: Model, solution and application, *Applied Soft Computing*, Vol. 14, 504-527, doi: 10.1016/j.asoc.2013.08.015.

[20] Wang, Y., Assogba, K., Liu, Y., Ma, X.L., Xu, M.Z., Wang, Y.H. (2018). Two-echelon location-routing optimization with time windows based on customer clustering, *Expert Systems with Applications*, Vol. 104, 244-260, doi: 10.1016/j.eswa.2018.03.018.

[21] Jiao, Z.H., Duan, H.W., Zhou, Y.J., Xiang, X. (2025). Low-carbon multimodal vehicle logistics route optimization with timetable limit using Particle Swarm Optimization, *Advances in Production Engineering & Management*, Vol. 20, No. 2, 173-190, doi: 10.14743/apem2025.2.534.

[22] Xiao, N., Lan, H. (2025). Two-echelon drone–truck collaborative TSP-based routing for humanitarian logistics with time windows and stochastic demand, *Advances in Production Engineering & Management*, Vol. 20, No. 3, 351-368, doi: 10.14743/apem2025.3.545.

[23] Mohammed, M.A., Abd Ghani, M.K., Hamed, R.I., Mostafa, S.A., Ahmad, M.S., Ibrahim, D.A. (2017). Solving vehicle routing problem by using improved genetic algorithm for optimal solution, *Journal of Computational Science*, Vol. 21, 255-262, doi: 10.1016/j.jocs.2017.04.003.

[24] Huang, W., Zhang, T. (2016). An improved genetic algorithm for vehicle routing problem with simultaneous pickups and deliveries and time windows, In: *Proceedings of 2016 35th Chinese Control Conference (CCC)*, Chengdu, China, 9639-9643, doi: 10.1109/ChiCC.2016.7554885.

[25] Zhang, D.F., Cai, S.F., Ye, F.R., Si, Y.-W., Nguyen, T.T. (2017). A hybrid algorithm for a vehicle routing problem with realistic constraints, *Information Sciences*, Vol. 394-395, 167-182, doi: 10.1016/j.ins.2017.02.028.

[26] Zhang, H.K., Zheng, Q.M., Yang, S., Ojsteršek, R. (2025). Bare-bones particle swarm optimization for emergency scheduling in public events, *International Journal of Simulation Modelling*, Vol. 24, No. 2, 273-284, doi: 10.2507/IJSIMM24-2-726.

[27] Li, Y., Liu, M., Hu, H., Jiang, X. (2025). A cost analysis of the collaborative delivery mode of drones and riders in food delivery scenarios, *International Journal of Logistics Research and Applications*, 1-30, doi: 10.1080/13675567.2025.2480636.

[28] Li, J., Li, J., Fang, H., Jiang, J. (2024). Dynamic energy-efficient path planning for electric vehicles using an enhanced Ant Colony Algorithm, *Tehnički Vjesnik – Technical Gazette*, Vol. 31, No. 2, 434-441, doi: 10.17559/TV-20230510000618.

[29] Zhang, Y., Chen, Y., Yu, P., Li, X., Wang, Y., Zhang, J., Pang, J. (2024). Optimization of multi-temperature joint distribution paths for convenience store chains, *Tehnički Vjesnik – Technical Gazette*, Vol. 31, No. 5, 1734-1746, doi: 10.17559/TV-20230812000875.

[30] Zhao, Y., Cattaruzza, D., Kang, N., Roberti, R. (2024). Synchronized deliveries with a bike and a self-driving robot, *Transportation Science*, Vol. 58, No. 1, 219-239, doi: 10.1287/trsc.2023.0169.

[31] Wang, W., Huang, Q. (2023). Research on urban end-delivery paths considering the consumer's delivery time demand, *Tehnički Vjesnik – Technical Gazette*, Vol. 30, No. 4, 1209-1216, doi: 10.17559/TV-20221212144331.

[32] Zhao, S., Li, P., Li, Q. (2024). The vehicle routing problem considering customers' multiple preferences in last-mile delivery, *Tehnički Vjesnik – Technical Gazette*, Vol. 31, No. 3, 734-743, doi: 10.17559/TV-20230717000807.

[33] Ji, X., Xu, W., Aslam, R., Yin , Y. (2024). The influence of government on automobile enterprise's production methods: An evolutionary game based study, *Economic Computation and Economic Cybernetics Studies and Research*, Vol. 58, No. 4, 223-240, doi: 10.24818/18423264/58.4.24.14.

[34] Ostermeier, M., Huf, T. (2026). The truck-and-robot routing problem with pickups and deliveries, *European Journal of Operational Research*, Vol 333, No. 1, 174-191, doi: 10.1016/j.ejor.2025.11.034.

[35] Han, Y., Song, T. (2024). Path planning for shop-floor material transfer robots incorporating particle swarm and ant colony algorithms, *Studies in Informatics and Control*, Vol. 33, No. 3, 49-59, doi: 10.24846/v33i3y202405.

[36] Păun, M.-A., Coandă, H.-G., Mincă, E., Iliescu, S.S., Duca, O.G., Stamatescu, G. (2024). Improved multi-objective genetic algorithm used to optimizing power consumption of an integrated system for flexible manufacturing, *Studies in Informatics and Control*, Vol. 33, No. 1, 27-36, doi: 10.24846/v33i1y202403.

[37] Zhang, X.R., Zhou, J.N. (2025). Simulation of AIGC-enhanced congestion management in factory autonomous driving, *International Journal of Simulation Modelling*, Vol. 24, No. 4, 718-729, doi: 10.2507/IJSIMM24-4-CO19.