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Towards low-carbon e-commerce return logistics: Optimization for simultaneous pickup and delivery

Abstract

Purpose – The rapid expansion of e-commerce platforms has made collaborative logistics networks essential. This study tackles the intricate challenge of optimizing pickup and delivery activities in constrained areas, striving to meet the ever-increasing e-commerce demands while maintaining tight control over distribution costs.

Design/methodology/approach – This study develops a vehicle routing problem with simultaneous pickup and delivery with time windows (VRPSPDTW) model and validates it using simulated annealing (SA) and a hybrid algorithm combining simulated annealing with tabu search (SA-TS). Random pickup and delivery requests were generated following a uniform distribution to evaluate the model's performance.

Findings – This research validates the VRPSPDTW model and the SA and SA-TS algorithms, demonstrating their superior flexibility and comprehensiveness compared to traditional methods. The findings demonstrate their effectiveness in managing dynamic demands, optimizing first-mile and last-mile coordination, and improving efficiency in collaborative e-commerce logistics.

Research limitations/implications – To validate the model, this study employed simplified demand patterns and a uniform distribution. Future research could integrate a broader range of constraints and test scalability across various logistics scenarios to enhance practical applicability.

Practical implications – The proposed VRPSPDTW model optimizes pickup and delivery routes in e-commerce logistics centers, enhancing network coordination, reducing operational costs, and improving delivery efficiency, demonstrating significant practical value.

Originality/value – This research provides an innovative solution for collaborative logistics networks. By addressing first-mile pickups and last-mile deliveries with the VRPSPDTW model and heuristic algorithms, the study fosters operational efficiency and demonstrates practical approaches to dynamic challenges in e-commerce logistics.

Keywords Heuristics, collaborative logistics networks, e-commerce logistics, sustainability, return logistics

Paper type Research paper

1. Introduction

E-commerce logistics returns pose a significant challenge and concern in the thriving e-commerce industry. As the e-commerce sector continues to flourish, returns have become increasingly prevalent, necessitating new demands on the logistics strategies employed by e-commerce platforms. To address the multifaceted challenges posed by e-commerce return logistics, it is imperative for e-commerce platforms to allocate their attention and resources to optimizing the entire returns process. This entails establishing an efficient returns management system to facilitate a seamless returns experience. Additionally, e-commerce practitioners prioritize efforts to minimize the return rate by enhancing product quality and ensuring accurate product descriptions to mitigate returns resulting from customer misuse or dissatisfaction (Mihi Ramírez, 2012). Moreover, attention is directed towards the first-mile pickups within e-commerce reverse logistics (Bergmann et al., 2020). Adhering to this imperative, e-commerce platforms focus on providing convenient and efficient delivery services during the returns process to meet the discerning needs of customers. By effectively addressing the intricacies of e-commerce logistics returns, the e-commerce industry can augment customer satisfaction and loyalty, thereby stimulating sustainable growth in business operations.

Thus, optimizing both forward and reverse logistics paths has become crucial. However, many e-commerce platforms focus primarily on forward logistics, often neglecting the optimization of return logistics. In this study, we distinguish between return logistics and reverse logistics to ensure conceptual clarity. Return logistics specifically refers to the process of handling e-commerce returns, including customer-initiated returns and exchanges, where products are transported back to warehouses or distribution centers for restocking or resale. In contrast, reverse logistics involves processes such as returning goods from consumers to the supply chain, including returns, exchanges, repairs, and recycling (Dixit and Badgaiyan, 2016). To address these challenges, optimizing both forward and reverse logistics is essential for improving efficiency and resource utilization. New technologies, such as Internet of Things (IoT), big data, and smart distribution, enable real-time tracking and path optimization, enhancing logistics performance (He et al., 2024; Zhao et al., 2021). This optimization not only boosts efficiency and customer satisfaction but also minimizes resource wastage, contributing to a better shopping experience, increased consumer loyalty, and the sustainable development of e-commerce.

Nevertheless, building a collaborative logistics network presents significant challenges.

Collaborative logistics refers to the strategic sharing and coordination of resources, such as fleets, infrastructure, and information, between multiple logistics stakeholders—such as e-commerce platforms, third-party logistics providers, and consumers—in order to optimize efficiency and reduce operational costs. First, reverse logistics differs significantly from forward logistics, imposing more stringent requirements on the return time window and return method. Establishing a convenient and transparent return process is essential to meet these strict time requirements, thus cleverly balancing the last-mile delivery with the first-mile of return. Second, the rational use of resources poses another challenge. Optimizing the sharing of fleets and routes for last-mile deliveries and first-mile pickups is necessary to reduce transport costs and meet customer demands, which is a complex optimization problem. Third, as the scale of e-commerce continues to expand, the logistics network must be scalable to accommodate the growing volume of orders and return logistics needs while maintaining efficient operations.

Currently, existing research on last-mile delivery attempts to improve delivery efficiency and reduce costs through order consolidation methods (Zhang et al., 2019). Integrated approaches are introduced to address the issue of doorstep delivery and optimize real-time delivery efficiency (Han et al., 2017). Additionally, route design and customer revisit plans are explored to reduce the number of unsuccessful deliveries (Florio et al., 2018). On the other hand, support for the optimization of real-time mobile crowdsourcing issues in last-mile delivery are proposed by Wang et al. (2016). Allen et al. (2018) also analyze e-commerce logistics challenges in cities, proposing solutions such as infrastructure redesign and cost reduction. Despite significant focus on the e-commerce industry, current research predominantly addresses last-mile delivery and first-mile returns as separate issues, overlooking their synergistic relationship. With limited resources and time windows, the e-commerce industry must balance customer expectations with cost reduction. Consequently, research on integrated logistics networks for both last-mile delivery and first-mile returns has become increasingly urgent.

This paper presents a vehicle routing problem model with time windows for simultaneous pickup and delivery (VRPSPDTW), aiming to obtain efficient vehicle routes that minimize total transportation costs while meeting the time requirements for customer delivery and returns. Specifically, this study addresses three research questions: (1) How can a collaborative delivery network framework be designed to simultaneously consider last-mile delivery and first-mile returns while minimizing total transportation costs? (2) How can timely and reliable services be provided by planning optimal vehicle routes considering the time windows for customer delivery and returns, thereby enhancing customer satisfaction? (3) How can the efficiency of delivery be improved and environmental impact reduced through the construction of a collaborative network, promoting sustainable development and reducing environmental pollution? Being one of the NP-hard problems, VRPSPDTW is challenging to solve exactly within polynomial time. As an effective approach to solving large-scale NP-hard problems, heuristic algorithms can efficiently explore complex solution spaces and provide near-optimal solutions within a reasonable computational time. Their flexibility and adaptability make them particularly suitable for addressing real-world vehicle routing challenges, where problem constraints and dynamic factors significantly increase computational complexity.

To address the aforementioned research questions, two algorithms, simulated annealing (SA) and a hybrid algorithm combining simulated annealing with tabu search (SA-TS), are employed to solve the VRPSPDTW model, leading to the following three research contributions. First, addressing research questions (1), by coordinating the management of forward and reverse logistics processes, this study achieves simultaneous optimization of last-mile delivery and first-mile returns. The application of SA and SA-TS algorithms significantly reduces total transportation costs and enhances the logistics efficiency of e-commerce platforms. Second, in response to research questions (2), the model developed in this paper takes into full consideration the time window requirements of customer orders. By incorporating time constraints into the optimization framework, it provides more timely and reliable services, thereby increasing customer satisfaction. Third, aligned with research questions (3), from the perspective of sustainable development, this research contributes positively to reducing environmental pollution and promoting the sustainable development of logistics. The optimization approach explicitly considers sustainability by minimizing vehicle travel distances, reducing fuel consumption, and decreasing carbon emissions. By designing new algorithms, it reduces vehicle travel distances and effectively decreases carbon emissions. Overall, the proposed model and algorithms contribute to optimizing operations, enhancing customer satisfaction, and promoting environmentally friendly practices in the logistics industry.

The remainder of this paper is organized as follows. Section 2 provides a literature review on return logistics in e-commerce logistics and the vehicle routing problem with simultaneous pickup and delivery. Section 3 presents the problem description, corresponding assumptions, and develops a multi-objective VRPSPDTW mathematical model. The solution methods are introduced in Section 4. Section 5 validates the proposed model and methods through numerical experiments and conducts sensitivity analysis. Finally, Section 6 concludes the study, highlighting the main findings, and suggests future research directions.

2. Literature review

2.1. E-commerce return logistics

Return logistics networks are vital for sustainable e-commerce and supply chain management, with research offering fresh perspectives and solutions. Wang et al. (2020) develop models integrating customer time preferences to address long delivery lead times and high transport costs in B2C cross-border e-commerce. Fried and Goodchild (2023) examine the facility and regional dimensions of e-commerce logistics platform centrality from spatial and statistical perspectives. Wang et al. (2023a) investigate logistics service sharing and carbon pooling in an e-commerce supply chain consisting of two sellers and a platform company. Shahabi-Shahmiri et al. (2021) propose a multi-objective mixed-integer programming model (MIP) and a novel hybrid method to solve the heterogeneous vehicle scheduling problem for transporting perishable goods across cross-docking systems. Bergmann et al. (2020) analyze the route efficiency trade-offs arising from integrating first-mile pickup and last-mile delivery operations in urban distribution systems. Liu et al. (2021) propose an algorithm with efficient local search and extended neighborhood, to solve the VRPSPDTW. Alizadeh Foroutan et al. (2020) investigate the green vehicle routing and scheduling problem, proposing a mixed-integer nonlinear programming (MINLP) model with two meta-heuristics, SA and Genetic Algorithms (GA). Zhang et al. (2020) focus on the multi-cycle multi-warehouse vehicle path problem in a B2C e-commerce logistics system. Sethanan and Jamrus (2020) analyze a multi-trip vehicle path problem in a beverage dispensing system using integer linear programming and a hybrid differential evolutionary algorithm.

In return logistics optimization and closed-loop supply chain network design problems, Reddy et al. (2022) enhance solution efficiency by applying an improved Benders decomposition method. Cárdenas-Barrón and Melo (2021) focus on the used vegetable oil recycling problem in reverse logistics. Das (2012) proposes a MIP model for optimizing supply chain production, distribution, and reverse logistics, focusing on product recovery and cost efficiency. Singh et al. (2023) propose a two-stage hybrid decision-making framework for selecting and optimizing the allocation of orders to qualified third-party reverse logistics providers. Although current research explores return logistics problems from multiple perspectives, such as total cost, carbon emissions, and customer time windows, existing studies have mainly focused on considering the return logistics network in isolation. There has been less attention paid to synergistically integrating last-mile deliveries and first-mile returns of reverse logistics for the collaborative optimization of the logistics network.

2.2. Sustainability in transportation

Sustainable logistics aims to meet business needs while minimizing negative environmental impacts. Camur et al. (2024) address the complexities of the high-volume intermodal freight network faced by General Electric gas power. Shi et al. (2024) introduce an innovative self-contained RLN for managing transportation routes with a mixed-integer planning model to minimize economic and environmental costs. Goswami et al. (2020) explore the relationships between sustainable freight transport performance and the internal and external characteristics of logistics participants. Ju et al. (2023) analyze the impact of e-commerce and green logistics on sustainable development in 21 emerging and developing countries in Asia from 2000 to 2021. Gholizadeh et al. (2022) model the sustainable reverse logistics process of polystyrene disposable electrical appliances as a MINLP with uncertain demand and recycling costs, employing cross-entropy and three heuristics methods. Shrestha et al. (2024) dissect power dynamics in urban logistics and sustainability frameworks using mixed-methods in Oslo, Bergen, and Trondheim. Wang et al. (2024) investigate the impact of customers' dynamic demand on the vehicle routing problem with time window (VRPTW). While existing studies provide valuable insights into sustainable logistics, they often overlook factors such as real-time traffic conditions, vehicle capacity constraints, and dynamic customer demand. This research seeks to bridge these gaps by proposing efficient solutions to enhance e-commerce logistics sustainability in a competitive landscape.

2.3. Vehicle routing problem with simultaneous pickup and delivery

In the current field of vehicle routing problem (VRP) research, significant attentions are given to solving the vehicle routing problem with simultaneous pickup and delivery (VRPSPD) and its related variants. Öztaş and Tuş (2022) employ a hybrid algorithm that combines iterative local search, variable neighborhood descent. Olgun et al. (2021) tackle the green vehicle routing problem using a hyper-heuristic algorithm based on iterative local search and variable neighborhood descent. Zhang et al. (2023) explore carbon emission reduction and sustainability integration in e-commerce logistics by optimizing the multi-depot pollution pathway problem with time window (MDPRPTW). Hosseini-Motlagh et al. (2022) propose a model for pollution routing problem (PRP) with multi-path traffic coverage, incorporating congestion, speed optimization, and cost minimization, solved through a four-stage meta-heuristic algorithm. Koç et al. (2020) provide a comprehensive review of VRPSPD, including mathematical formulations, algorithms, variables, case studies, and industrial applications. Praxedes et al. (2024) propose a uniform branch-cut pricing algorithm to solve VRPSPD, extending it to a heterogeneous location routing problem with time windows. Wu and Gao (2023) create an ant colony optimization algorithm for VRPSPD with time windows, enhancing global search with stochastic rules and repair operators. Bai et al. (2021) addresses the low-carbon Vehicle Routing Problem in cold chain logistics, incorporating the complexity of road networks and real-time traffic conditions. It proposes a low-carbon cold chain logistics routing optimization model aimed at minimizing carbon emissions and costs. Luo et al. (2022) proposes a two-tier city logistics model based on the Physical Internet (PI), featuring a 'Container-as-a-Warehouse' operation mode. A mathematical model is developed, and an Adaptive Large Neighborhood Search (ALNS) algorithm is designed to ensure result consistency and optimization. Kong et al. (2018) systematically reviews the current state of research on physical internet-enabled auction logistics (AL) in perishable supply chain trading, summarizing key themes from the perspectives of auction mechanisms, decision levels, and coordination mechanisms. It explores factors influencing AL performance and proposes future research directions.

Zhao et al. (2023) tackle a green segmented multi-merchandise pickup routing problem, using a two-stage quantum particle swarm optimization to address divisible demand, multiple visits, congestion, and time windows. Chaieb and Ben Sassi (2021) investigate the home healthcare scheduling problem with simultaneous pickup and delivery and time windows,. Hornstra et al. (2020) solve the VRPSPD-H by implementing a heuristic processing strategy and proposing two new myopic strategies. Li et al. (2022) investigate the two-phase vehicle routing problem by a customized branch-down algorithm. Wang et al. (2023b) propose a hybrid multi-objective particle swarm optimization algorithm for the two-stage multi-warehouse multi-period pickup location routing problem. Significant progress has been made in path planning for real-world operations, yet challenges persist in addressing dynamic orders and real-time demand. Enhanced flexibility is essential to accommodate order changes and delivery contingencies, particularly in scenarios lacking fixed time windows.

2.4. Contributions to the literature

Synthesizing the existing literature, it is evident that research has been conducted on return logistics, sustainable transportation, and VRPSPD in e-commerce logistics. However, there still exist gaps that warrant further exploration. Therefore, the innovations of this paper are as follows. (1) Construct a forward-reverse collaborative logistics network to integrate logistics processes, enhancing efficiency and meeting return logistics demands in e-commerce. (2) Develop a heuristic combining SA and TS to boost solution speed and quality, offering a practical approach for network design. (3) Reduce carbon emissions and boost customer satisfaction with the collaborative logistics network, promoting sustainable e-commerce logistics and offering research insights.

3. The model

3.1. Problem description

Given a logistics network $G = (N, E)$, N represents the set of all nodes within the region, where $N = I \cup O$. Here, I is the set of customer orders, $I = \{1, 2, 3, \ldots, N\}$, and O represents the e-commerce logistics center, $O = \{0\}$. The open time window for the e-commerce logistics center is $[OT, CT]$. The center has a fleet of vehicles denoted by $K = \{1, 2, 3, \ldots, K\}$, where each vehicle has a capacity of Q_k (kg). Each vehicle departing from the logistics center incurs a departure cost C_1. The set E consists of all arcs, $E = \{(i,j) | \forall i, j \in N, i \neq j\}$. Each arc $(i,j) \in E$ has an associated delivery distance D_{ij}, and the courier travel time from order i to order j is t_{ij} (minutes). The delivery cost per unit distance is C_2. Each node $i \in N$ has the following attributes: delivery demand d_i, return demand r_i, time window $[ET_i, LT_i]$, service time t_i (minutes), and dispatch time b_i. For the e-commerce logistics center $O = \{0\}$, $d_0 = r_0 = 0$.

To improve customer satisfaction, orders that do not arrive within the specified time window will incur a penalty cost. If a vehicle arrives at order i at time b_i before ET_i, the vehicle must wait, resulting in an early arrival penalty cost, which increases with the waiting time at a rate of C_e. Conversely, if a vehicle arrives at order i at time b_i after LT_i, a tardiness penalty cost will be incurred, which increases with the delay time at a rate of C_l. To achieve sustainable logistics supply chain development, environmental factors are integrated into the total cost function through the inclusion of the carbon tax and carbon emission factors. Furthermore, since vehicle travel generates carbon emissions, the carbon emission cost is divided into two parts, i.e., carbon tax cost and carbon trading cost. In this paper, the fuel consumption per unit distance is denoted by P, and the carbon emission factor W is related to fuel consumption. A carbon emission quota L is implemented, wherein carbon emissions below this quota only incur the carbon tax, which is charged at a unit carbon tax cost C_E. When carbon emissions exceed the quota L, additional emission units must be purchased at a cost of C_T per unit.

The summarized notation is shown in Table 1.

<<<Insert Table 1>>>

3.2. Assumptions

To facilitate the construction of the mathematical model, the following assumptions are proposed.

(1) Delivery orders start at the outbound warehouse of the e-commerce logistics center, while return orders are sent back to the e-commerce logistics center.

(2) Each order has a service time window, and penalty costs are incurred when the service vehicle arrives early or late.

(3) Each order will be fulfilled by a single vehicle in a single service, and the service task cannot be split into multiple executions.

(4) The service time of a vehicle at order point i is t_i.

(5) All vehicles depart from the e-commerce logistics center and return to the e-commerce logistics center after completing their routes.

(6) The load of a vehicle cannot exceed its capacity at any point in time from its departure through its work journey.

(7) The capacity of the e-commerce logistics center is unlimited.

3.3. Model description

In the process of transport service, each vehicle incurs a fixed departure cost from the e-commerce logistics center. This fixed departure cost is proportional to the number of vehicle departures, which is defined as G_1 in this paper. The introduction of G_1 serves to limit the number of vehicle departures. By optimizing G_1, the capacity usage of each vehicle can be ensured. The fixed cost of vehicle departure G_1 in all scenarios can be defined as equation (1):

$$G_1 = C_1 \sum_{k=1}^{K} z_k. \tag{1}$$

Vehicles in the distribution process will also incur certain costs, which we define as G_2. This cost is positively proportional to the distance traveled by the vehicle. Previously, we defined the distribution cost per unit distance in the distribution process as G_2. In various scenarios, the vehicle distribution cost G_2 can be expressed as equation (2):

$$G_2 = C_2 \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} D_{ij} x_{ijk}. \tag{2}$$

Limiting the carbon emissions of logistics service providers solely through a carbon tax is challenging. To achieve sustainable development in the supply chain, this paper divides the carbon emission cost into carbon tax cost and carbon trading cost. The carbon tax cost is positively correlated with the distance traveled by the vehicle. Additionally, any emissions exceeding the carbon emission limit L require the purchase of additional carbon trading volume. Thus, the carbon emission cost G_3 can be expressed as equation (3):

$$G_3 = C_T \max\{[(\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} D_{ij}x_{ijk})PW - L], 0\} + C_E \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} D_{ij}x_{ijk}. \tag{3}$$

To enhance customer satisfaction, it is essential that vehicles arrive within the specified time window requested by the customer. Deviations from this expectation, whether arriving early or late, inconvenience the customer and incur a penalty cost when orders are not fulfilled within the required timeframe. The default cost G_4 for failing to meet the required time window in various scenarios can be expressed as equation (4):

$$G_4 = C_e \sum_{i=1}^{N} \max\{ET_i - b_i, 0\} + C_l \sum_{i=1}^{N} \max\{b_i - LT_i, 0\}. \tag{4}$$

In this paper, we consider not only the fixed cost of vehicle departure G_1 and the cost of vehicle travel G_2, but also the cost of carbon emissions G_3 and the penalty cost for failing to arrive at the specified time G_4. To address these considerations, we construct a VRPSPDTW model as follows.

$$min\ G = G_1 + G_2 + G_3 + G_4 \tag{5}$$

s.t.

$$OT \le w_{0k}, \forall k \in K, \tag{6}$$

$$w_{0k} \le CT, \forall k \in K, \tag{7}$$

$$w_{ik} + t_i \le w_{jk}, \forall i, j \in I, k \in K, \tag{8}$$

$$\sum_{i \in I} (d_i - r_i)\, y_{ik} \le Q_k, \forall k \in K, \tag{9}$$

$$\sum_{j \in I, j \ne i} x_{ijk} = 1, \forall i \in I, \forall k \in K, \tag{10}$$

$$\sum_{j=1}^{N} x_{jik} - \sum_{j=1}^{N} x_{ijk} = 0, \forall k \in K, i \in I, \tag{11}$$

$$\sum_{i=1}^{N} x_{0ik} = 1, \forall k \in K, \tag{12}$$

$$\sum_{i=1}^{N} x_{i0k} = 1, \forall k \in K, \tag{13}$$

$$\sum_{k=1}^{K} z_k \le |K|, \tag{14}$$

$$\sum_{j \in I, j \ne i} \sum_{k \in K} x_{ijk} = 1, \forall i \in I, \tag{15}$$

$$\sum_{k=1}^{K} x_{ijk} = 1, \forall i, j \in N, i \neq j, \tag{16}$$

$$x_{ijk} \in \{0,1\}, \forall i, j \in N, i \neq j, \forall k \in K, \tag{17}$$

$$y_{ik} \in \{0,1\}, i \in I, k \in K, \tag{18}$$

$$z_k \in \{0,1\}, k \in K. \tag{19}$$

Equation (5) serves as the optimization objective of the model, aiming to minimize the overall cost of the entire transportation process. This total cost comprises four main components: the fixed cost of vehicle departure, the travel cost of the vehicle, the cost of carbon emissions, and the contractual penalty incurred for failing to arrive at the designated time. Inequality (6) imposes the opening time constraint of the e-commerce logistics center, ensuring that all vehicles depart after the logistics center's opening. Similarly, inequality (7) enforces the closing time constraint, guaranteeing that all vehicles return before the logistics center closes. Inequality (8) represents the service time constraint, stipulating that vehicles can only proceed to the next order point for service upon completing the order of a single customer. Inequality (9) addresses the vehicle capacity constraint, ensuring that the total carrying capacity of each vehicle during transportation does not exceed its maximum capacity. This constraint explicitly accounts for both forward and reverse logistics flows. Equation (10) functions as vehicle routing constraint, ensuring that if a vehicle arrives at an order location, it must also leave that location, thereby preventing infeasible route configurations. This is necessary to maintain route continuity. Equation (11) enforces the vehicle path connectivity constraint, preventing the formation of closed loops during the service of all vehicles. Equation (12) represents the vehicle departure constraint, stipulating that all vehicles must depart from the e-commerce logistics center. Equation (13) enforces the vehicle return constraint, mandating that vehicles return to the logistics center upon completing all order services. Inequality (14) imposes the departing vehicle number constraint, limiting the number of departing vehicles to no more than the number of vehicles owned by the e-commerce logistics center. Equation (15) ensures that each order is visited only once, while Equation (16) guarantees that every order is accessible. Finally, Constraints (17)-(19) define the binary decision variable domains, specifying that x_{ijk}, y_{ik}, and z_k are binary variables representing routing, service, and vehicle dispatch decisions, respectively.

4. Solution methodology

4.1. Real-time solution strategy

Traditional single-objective optimization methods often oversimplify or reduce multi-objective problems, which may not adequately address the complexity of real-world scenarios. It lacks flexibility, adaptability, and real-time performance when dealing with dynamic environments, particularly in complex and evolving e-commerce logistics networks. In contrast, the VRPSPDTW multi-objective model proposed in this paper aligns closely with the realities of e-commerce logistics centers, avoiding the pitfalls of oversimplification inherent in single-objective approaches. The model employs a multi-stage solution method to address the problem in greater detail and comprehensively considers the dynamics of continuous optimization. Special emphasis is placed on real-time optimization capabilities, enabling the model to swiftly adapt to changing environments by regularly updating parameters based on new order requirements. This ensures the model's ability to cope effectively with the complexities and dynamics inherent in e-commerce logistics operations.

The collaborative logistics network in this study introduces a two-stage model, i.e., initial optimization and real-time optimization, which divides the dynamic sequential optimization problem into distinct phases. This approach allows for a more comprehensive consideration of the problem's complexity while ensuring real-time performance. As depicted in Fig. 1, within the collaborative logistics network, an initial heuristic algorithm is employed to generate delivery routes based on available order information such as customer locations, order demands, and service time windows. Following this initial phase, delivery routes are optimized within a predefined time interval. Subsequently, orders that arrive after this optimization phase but before the closing time of the e-commerce logistics center are consolidated. In response to these newly arrived orders, a heuristic algorithm is again applied in real-time to adjust and optimize delivery routes dynamically.

<<<Insert Fig. 1>>>

The staged solution approach not only enhances problem-solving efficiency but also closely aligns with real-world logistics scenarios. By integrating heuristic algorithms and real-time optimization strategies, the model exhibits exceptional flexibility in responding dynamically to logistics environments. Focusing on multi-stage optimization and real-time capabilities improves distribution efficiency and lowers logistics costs.

4.2. Simulated annealing algorithm

The SA algorithm, a global optimization heuristic search technique, is rooted in the analogy of the physical annealing process. By simulating the gradual cooling of metals from high temperatures, this algorithm combines a stochastic search with the systematic reduction of the ‘system temperature’ to locate a globally optimal solution. In addressing the complex VRPSPDTW problem, SA proves especially effective. It facilitates the discovery of optimal vehicle routes that cater to customer demand, abide by time window restrictions, and adhere to vehicle capacity limits, all while minimizing the overall cost. To further illustrate the structure and execution of the proposed algorithms, Fig. 2 presents the flowcharts of the SA. The implementation of this algorithm in solving the VRPSPDTW problem involves several key steps.

<<<Insert Fig. 2>>>

Step 1. Parameter initialization. Set initial parameters: initial temperature T_0, final temperature T_f, and temperature decay rate ΔT, with T_0 typically set high (i.e., 8000) for thorough initial exploration.

Step 2. Data reading. Retrieve essential data, such as customer node coordinates and demands, and compute necessary distance and time matrices for route planning.

Step 3. Generate an initial solution. Create a starting solution by randomly assigning customer nodes to routes, ensuring time window and capacity constraints are met.

Step 4. Temperature iteration. Conduct iterative stochastic operations (i.e., node insertion, deletion, swapping) while gradually lowering the temperature to refine the solution towards global optima.

Step 5. Calculate cost change and acceptance decision. Compare the new solution’s cost to the current one. If the new solution is better, accept it. If worse, accept with probability based on temperature and cost difference, balancing search strategies.

Step 6. Update current solution and reduce temperature. Replace the current solution with accepted new ones and lower the temperature to enhance solution quality progressively.

Step 7. Termination condition. Conclude the algorithm when a termination condition, such as a low temperature threshold, is met, yielding a global or near-optimal solution. The pseudo-code for the SA algorithm is shown in Algorithm 1.

Algorithm 1 Algorithm SA

Input: parameter (T_0, T_f, ΔT, Q, v, etc)

Output: sol_best, obj_best

Initialize model with demand and depot data from files

Calculate distance and time matrices based on the data

Initialize sol with a randomly generated initial solution

$sol \leftarrow initial\_sol$

$sol\_best \leftarrow sol$

$obj\_best \leftarrow obj(sol)$

$T_k \leftarrow T_0$

While $T_k \geq T_f$ **do**

    repeat

    Generate a new solution sol_new by applying a random action to sol

        Calculate Δf as $obj(sol\_new) - obj(sol)$

    if $\Delta f < 0$ or $random() < exp(-\Delta f / T_k)$ **then**

        $sol \leftarrow sol\_new$

        if $obj(sol\_new) < obj(sol\_best)$ **then**

        $sol\_best \leftarrow sol\_new$

        $obj\_best \leftarrow obj(sol\_new)$

        end if

    end if

Update T_k using ΔT

end while

plot objective value history

plot routes based on sol_best

end

4.3. SA-TS algorithm

The SA algorithm, a probability-based global search method, avoids local optima by occasionally accepting inferior solutions, with this acceptance probability decreasing to ensure convergence to the global optimum. Despite its effectiveness in global searches, its stochastic nature can still lead to local optima. Conversely, the TS algorithm, a local search method, uses a tabu list to avoid revisiting similar solutions, helping it escape local optima and quickly enhance solution quality. However, it might fail if the initial solution is poor. To address these limitations, we introduce a hybrid SA-TS algorithm for the VRPSPDTW problem, leveraging SA's global search to generate a strong initial solution and TS's local search to refine it further. This hybrid approach allows for effective solution space exploration and rapid escape from local optima, improving robustness and performance for global optimization problems. The stepwise process of the SA-TS algorithm is depicted in Fig. 3, providing a clear visualization of its iterative improvement mechanism. The algorithm is detailed below.

<<<Insert Fig. 3>>>

Step 1. Parameter initialization. Set initial parameters such as the initial solution, tabu length, and search strategy to guide the solution space exploration and process.

Step 2. Data reading. Read data on node coordinates, demand, service times, and time windows to form the solution space for the hybrid SA-TS algorithm.

Step 3. Initial solution generation. Use the SA algorithm to generate an initial solution. At high temperatures, explore the solution space randomly to escape local optima. As the temperature decreases, gradually converge toward a near-optimal solution.

Step 4. Tabu iteration phase. Progressively approach the global optimal solution by executing random operations (i.e., node swaps, insertions) and evaluating solution quality in each iteration.

Step 5. Evaluate solution quality and break Tabu constraints. Assess the new solution's quality; if superior, adopt it as the current optimal solution. Otherwise, potentially accept an inferior solution with a probability linked to search depth and quality difference to explore more of the solution space.

Step 6. Update the Tabu List. Revise the tabu list after each iteration to avoid repeating similar operations, preventing convergence to local optima.

Step 7. Termination Condition Fulfillment Phase. Conclude the algorithm when the termination condition, like a set number of iterations, is met, yielding the global or near-optimal solution.

The hybrid SA-TS algorithm combines the strengths of both the SA and TS algorithms. It effectively balances the trade-off between exploration and exploitation, allowing it to escape local optima. This approach yields relatively strong solutions, making it well-suited for addressing complex combinatorial optimization problems. The pseudo-code of the SA-TS algorithm is shown in Algorithm 2.

Algorithm 2 Algorithm SA-TS

Input: parameter ($epochs$,v_cap,$tabu\_tenure$, etc)

Output: $best\_sol$, $best\_obj$

Initialize $tabu\_list$

```
Initialize model with demand and depot data from files
Calculate distance and time matrices based on the data
Generate initial solution with SA
current_sol ← initial_sol
best_sol ← current_sol
L ← tabu_list
for each iteration (epoch) in range (epochs) do
        Generate a set of neighbor solutions
 neighbors ←set of neighbor solutions
        for neighbor in neighbors do
        if obj(neighbor) < obj(current_sol) and neighbor is not in L then
                current_sol ← neighbor
                L.append(current_sol)
                if obj(current_sol) < obj(best_sol) then
                        best_sol ← current_sol
                end if
        else
                L.pop(0)
                if current_sol not in L then
                        L.append(current_sol)
                end if
        end if
 end for
end for
return best_sol
plot objective value history
plot routes based on best_sol
end
```

5. Numerical experiment

In this section, we provide an in-depth description of the numerical setup for the experiment and present the computational outcomes of two algorithms within the VRPSPDTW framework, considering variable demands. To validate our proposed model, we initially generate random demands using a uniform distribution, which facilitates the creation of a demand file and corresponding orders, as illustrated in Table 2, Table 3, Table 4. The algorithms employed were crafted using Python 3.9.13 and executed on a Windows 11 operating system. The computational device is equipped with a 12th Gen Intel(R) Core (TM) i9-12900H processor clocked at 2.50 GHz, accompanied by 16GB of RAM.

<<<Insert Table 2>>>

<<<Insert Table 3>>>

<<<Insert Table 4>>>

5.1. Benchmark instance

We introduce benchmark instance I0, with the e-commerce logistics center operating 24 hours (1440 minutes). Orders arrive uniformly, starting with 100 orders consolidated every 8 hours, prompting route adjustments. Each delivery vehicle incurs a fixed cost of 100 yuan, with a 2-ton capacity, and travels at 1 km/h. Vehicles consume 1 liter of fuel per kilometer, emitting 5 kg of CO2, with a carbon emission quota of 50 kg per vehicle. Exceeding this quota results in a carbon tax of 3 yuan per liter. Penalties apply for early or late arrivals, costing 10 yuan per minute outside specified customer time windows. Through multiple experiments, we fine-tuned the parameters of the SA algorithm to optimize its performance. Specifically, we set the initial temperature T_0 to 8000 and the final temperature T_k to 0.001, with a temperature reduction rate ΔT of 0.9.

To further optimize the solution process, we introduced a hybrid SA-TS algorithm. This approach initially generates the initial solution using the SA algorithm. During the initial solution generation phase, we applied similar parameter settings: T_0 = 8000 for the initial temperature, T_k = 0.001 for the termination temperature, and ΔT = 0.9 for the temperature decrease rate. In the main part of the SA-TS hybrid algorithm, we established an empty tabu list and initialized its length to 30 to maintain search diversity. The hybrid algorithm was iterated for 300 cycles. This design ensures rapid convergence of the algorithm while enhancing global search effectiveness.

The performances of the SA algorithm, the SA-TS algorithm, and CPLEX are compared in this chapter. CPLEX was selected as a benchmark for comparison because it is a widely recognized optimization solver known for its ability to provide optimal solutions for complex combinatorial optimization problems. As one of the leading commercial solvers, CPLEX is widely used in both academia and industry for solving large-scale and NP-hard problems, such as vehicle routing problems, that require exact solutions. Its robustness and proven performance in delivering high-quality results make it an ideal reference point for assessing the performance of heuristic approaches. Furthermore, CPLEX's ability to handle a wide range of problem instances and guarantee optimal solutions allows us to evaluate how well our proposed heuristic algorithms (SA and SA-TS) approximate optimality in comparison, especially in cases where exact methods may be computationally expensive or time-consuming for large problem sizes.

We utilize the CPLEX solver, renowned for its capability in solving a diverse array of problem types, particularly general linear programming (LP) problems. Given CPLEX's computational demands, we initially assessed its challenges with large-scale problems, noting significant increases in solution time as problem size grows. To ensure feasibility and efficiency, experiments in Table 2 are limited to the first 30 client nodes, allowing a practical comparison between exact and heuristic methods and highlighting their performance on small-scale problems. The experimental outcomes are presented in Table 5.

<<<Insert Table 5>>>

According to Table 5, CPLEX provides the optimal solution with the lowest total cost but at the cost of high CPU time. In contrast, both SA and SA-TS are significantly faster, with SA-TS achieving the best trade-off between solution quality and efficiency. While the total cost for SA is higher, SA-TS comes closer to the optimal solution while reducing computation time to just 0.71 seconds. Thus, SA-TS strikes a balance between solution quality and speed, making it more practical for large-scale problems.

Fig. 4 shows the iterative plots of the objective values of the SA algorithm over three-time intervals, while Fig. 5 displays the iterative plots of the objective values of the SA-TS algorithm over the same intervals. The results indicate that both algorithms' objective values converge after several iterations, demonstrating the convergence of the algorithms.

<<<Insert Fig. 4>>>

<<<Insert Fig. 5>>>

Table 6 presents the optimal solutions obtained by both algorithms. Analysis of the data reveals that, on average, the SA-TS algorithm demonstrates a 3.62% improvement in cost reduction and a 4.89% decrease in carbon emissions compared to the SA algorithm alone. However, there is a slight increase in average CPU time by 9.58% with the SA-TS algorithm. Particularly when aiming to optimize both cost and carbon emissions, the SA-TS algorithm emerges as the preferred choice. Despite its slightly longer runtime, SA-TS achieves superior optimization performance compared to the SA algorithm.

<<<Insert Table 6>>>

5.2. Sensitivity analysis

In this section, we present the results of the sensitivity analysis to assess the impact of the fixed cost of vehicle departure (C_1), the distribution cost per unit distance (C_2), the price per unit of carbon traded (C_T), and the default cost coefficients (C_e, C_l) for early and late arrival of the vehicle on the total cost and customer satisfaction.

Based on the benchmark instance I0, we introduce 12 different instances divided into 4 groups, each varying only one key parameter from I0, named G1, G2, G3, and G4. For statistical convenience, we assume that the default cost coefficients for early and late arrivals are equal, i.e., $C_e = C_l$. To comprehensively evaluate the impact of each parameter on customer satisfaction, we introduce an important metric: average order delay time (ADT). The average order delay time is calculated by dividing the sum of the early and late arrival times of delivery vehicles by the total number of delivery orders. In general, the more on-time the order arrival, the higher the customer satisfaction. Therefore, a smaller average order delay time (ADT) indicates higher customer satisfaction. The calculation of ADT is defined as follows:

$$ADT = \frac{\sum_{i=1}^{N} \max\{ET_i - b_i, 0\} + \sum_{i=1}^{N} \max\{b_i - LT_i, 0\}}{|I|}. \tag{20}$$

The results of the sensitivity analysis are shown in Table 7. Based on the data in Table 7, Fig. 6 has been developed to visualize the specific impact of each parameter's variation on the total cost under different algorithms. It is clearly observed from the figure that when the SA-TS algorithm is applied, the calculated total cost is consistently slightly lower than when the SA algorithm is used. Therefore, when comprehensively considering the influence of each parameter on the total cost, we particularly emphasize the performance advantages of the SA-TS algorithm. To explore the specific role of each parameter on ADT in depth, we further present Fig. 7, which details the specific impact of each parameter's variation on ADT under the SA-TS algorithm.

<<<Insert Table 7>>>

<<<Insert Fig. 6>>>

<<<Insert Fig. 7>>>

In the initial sensitivity analysis (G1), we analyzed the impact of C_1 on the total cost and average delay time (ADT), while maintaining the other parameters of instance I0 constant. Specifically, we set the fixed cost C_1 for each vehicle departure to (100,200,300,400) respectively. The experimental outcomes reveal a gradual increase in the total cost as the fixed cost C_1 escalated. This suggests a positive correlation between the rise in fixed cost and the total cost. Notably, the average order delay time (ADT) exhibited a downward trend with the augmentation of fixed cost, indicating that an increase in fixed cost may contribute positively to reducing order delays, thereby enhancing customer satisfaction.

In the second set of sensitivity analyses (G2), we investigate the effect of the distribution cost per unit distance C_2 on the total cost by setting the value of C_2 to (10,15,20,25). The experimental results show that the total cost increases significantly with the rise in the distribution cost per unit distance C_2, indicating that C_2 is a crucial factor affecting the total cost. Meanwhile, the average order delay time (ADT) also tends to increase with higher unit distance distribution costs, suggesting that higher C_2 may lead to longer order delay times, thereby reducing customer satisfaction.

The third set of sensitivity analyses (G3) sets the unit carbon trading price C_T to (3,4,5,6), respectively. The experimental results show that the total cost gradually increases as the unit carbon trading price C_T rises, suggesting that an increase in C_T prompts the optimisation process to reduce fuel consumption as much as possible, thereby decreasing carbon emissions. Additionally, the ADT gradually decreases with the increase in C_T, indicating that a higher unit carbon trading price may help to reduce order delay time, though the impact on ADT is not significant.

The fourth group of sensitivity analysis (G4) examines the effect of the default cost coefficient C_e, which is set to (5,10,15,20). The results show that as C_e increases, there are slight fluctuations in the total cost, but the overall change is not significant. This indicates that variations in the default cost coefficient have a relatively minor impact on the total cost. Meanwhile, the average order delay time (ADT) shows a decreasing trend with an increase in C_e, suggesting that raising the default cost coefficient may help reduce order delay time, thereby improving customer satisfaction.

6. Conclusion

This study addresses the last-mile delivery and first-mile return issues in e-commerce logistics by constructing a collaborative logistics network for both forward and reverse logistics and designing a VRPSPDTW model. By incorporating time windows, we successfully capture the time-sensitive demands of e-commerce logistics while considering return logistics, comprehensively optimizing the entire supply chain. However, multi-objective problems typically belong to the NP-hard category, making the search for global optimal solutions challenging. To solve this multi-objective problem, we employ a heuristic approach. We first utilize the SA algorithm and then design a hybrid heuristic algorithm that combines SA with TS to further improve solution efficiency. The application of this algorithm enables us to better cope with the time-varying delivery demands in practical operations.

Experimental results demonstrate that our model and algorithms provide a feasible solution for e-commerce logistics, offering strong support for improving operational efficiency and reducing carbon emissions. By effectively addressing multi-objective optimization problems, our model and algorithms offer a viable solution for e-commerce logistics. In practical applications, our algorithm performs exceptionally well in handling the complex characteristics of e-commerce return logistics. Our algorithm excels in both small and large-scale e-commerce logistics, optimizing multi-vehicle routing, time windows, and delivery efficiency while reducing costs and carbon emissions, thereby providing a comprehensive, sustainable solution.

The sensitivity result show that an increase in fixed costs leads to an increase in total costs. However, this is accompanied by a decrease in average order delay time, thus improving customer satisfaction. An increase in unit distance delivery costs significantly raises total costs while also causing an increase in order delay time and a decrease in customer satisfaction. Analysis of changes in unit carbon trading prices shows that an increase leads to higher total costs but has a positive effect on average order delay time, potentially enhancing customer satisfaction. Changes in the default cost coefficient have a relatively small impact on total costs, and increasing this coefficient helps reduce order delay time and improve customer satisfaction.

The contribution of this paper lies in filling the research gap in the field of e-commerce logistics regarding collaborative logistics networks for both forward and reverse logistics and providing an innovative multi-objective routing model. Future research will explore dynamic demands and traffic conditions in e-commerce logistics using real-time data and intelligent scheduling. Additionally, we will delve into multi-party collaboration strategies, optimizing logistics network efficiency in collaboration with e-commerce platforms and delivery service providers, to achieve resource integration and cost reduction. Furthermore, by analyzing and learning from historical data, we can predict future demand trends and traffic conditions, enabling better planning of logistics networks and vehicle routes. These new research directions aim to drive efficient operations and sustainable development in e-commerce logistics.

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Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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