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An improved adaptive large neighborhood search algorithm on collaborative last mile delivery with roaming customers

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A B S T R A C T

This paper addresses the challenge of rising operational costs in last-mile delivery caused by end-customer no-shows. The study proposes a collaborative operational framework for last-mile delivery that accommodates roaming customers, enabling them to be serviced by multiple depots as they transition between different locations. A mixed-integer programming (MIP) model is formulated to minimize the operational costs of last-mile delivery under the proposed framework. To improve the model's practicality and computational efficiency, an adaptive large neighborhood search (ALNS) algorithm is developed, incorporating tailored neighborhood structures. Furthermore, a late acceptance strategy is embedded within the algorithm to mitigate the risk of premature convergence to local optima. The experimental results demonstrate that, in the absence of depot collaboration, the multi-depot model achieves a 16.9% reduction in operational costs compared to the single-depot model. Moreover, when depot collaboration is enabled, the average cost reduction percentage significantly increases to 40.37%. Notably, under the multi-depot collaborative framework, considering customers' roaming behavior—as opposed to fixed single-location assumptions—leads to a substantial 54.6% reduction in operational costs.

1. Introduction

The investigation by Aized and Srai (2014) shows that urban terminal delivery contributes 13% - 75% of the overall delivery cost, especially in the e-commerce logistics industry. As a result, excelling in this segment is a critical objective for both e-commerce and express service enterprises (Lee & Whang, 2001; F. Zhou, He, Chan, Ma, & Schiavone, 2022). Within last-mile delivery, operational optimization plays a pivotal role, as it directly influences cost reduction and efficiency gains. Although advanced models and technologies offer strategic frameworks, most of them underexplore the intricate, day-to-day operational details. Focusing on these operational layers helps identify hidden bottlenecks, allowing for tailored solutions that deliver crucial improvements in service delivery.

Yet, concentrating solely on operational optimization must also account for the dynamic nature of last-mile logistics, especially with roaming customers whose locations and preferences vary. Addressing this variability requires agile operational responses, and prioritizing adaptive strategies enables faster, more responsive service to meet real-time demands, ultimately improving customer satisfaction and loyalty. Moreover, this approach allows a detailed analysis of resource allocation, scheduling, and route planning, essential factors in minimizing costs and maximizing efficiency. By optimizing these elements, enterprises can unlock synergies across stakeholders, enhancing resource utilization and promoting sustainable last-mile delivery through collaborative efforts. Pooling freight flows among multiple express service enterprises is one such approach, reducing vehicle usage by consolidating deliveries to similar customer clusters. This collaborative model not only lowers operational costs but also supports sustainability initiatives within urban areas (He, Wang, Lin, Zhou, & Zhou, 2017; Wu, Hu, & Gao, 2025; F. Zhou, He, Ma, &

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Mahto, 2020). In addition, digital technology also greatly promotes collaboration between enterprises . For instance, Zhou et al. proposed a two-echelon vehicle routing model integrating shared operational elements—satellites, secondary routes, and terminals—which led to a 16% cost reduction over independent systems (Zhou et al., 2018). A key challenge arises when customers roam across locations during the delivery window, increasing the risk that vehicles may "miss" them as they move from their initially appointed locations (He, Qi, Zhou, & Li, 2020; He, Wang, Zhou, & Lin, 2020). Multiple delivery attempts not only inflate operational costs but also contribute to traffic congestion and other social impacts. Researchers have proposed various delivery models that account for changing delivery points to accommodate roaming customers (Ozbaygin et al., 2017; Ozbaygin & Savelsbergh, 2019; Reyes et al., 2017). Furthermore, He et al. considered the stochastic variant of this issue with stochastic traveling times (He, Qi, Zhou, & Su, 2020). However, these models assume that all roaming destinations remain within the service range of depots, which would generally make additional costs unavoidable when customers move beyond these limits.

In response to this gap, we propose the Collaborative Last-Mile Delivery for Roaming Customers (CLMD-RC) , allowing customers to move freely while enabling vehicles to initiate routes from one depot and conclude at another. This vehicle routing approach for roaming customers, is initially introduced in single-depot contexts by Reyes et al. where it developed trunk routing plans serving only one of locations for each customer (Reyes et al., 2017). One important issue is that the location of the depot exerts substantial impact on the delivery cost in the last mile delivery (Baoxiang Li, Krushinsky, Woensel, & Reijers, 2016). For instance, a customer might roam closer to another depot managed by a different enterprise, inspiring a need for a shared, flexible delivery system. The theoretical innovations of our paper are threefold: firstly, we introduce a novel collaborative operational paradigm to bridge the gap between existing research and real-world application, specifically addressing the issue of customers roaming outside the service area that enhances the efficiency and responsiveness of urban logistics. Secondly, we establish a mixed-integer programming (MIP) model tailored to this collaborative paradigm, which represents a significant theoretical advancement. The model encapsulates the complexities of multi-depot coordination and customer roaming, optimizing operational costs in a way that has not been extensively explored in existing literature. The MIP model's structure and constraints are designed to effectively handle the unique challenges posed by this novel delivery approach, contributing to the theoretical foundation of multi-depot and roaming customer logistics. Thirdly, we design the adaptive large neighborhood search algorithm, enriched with problem-specific neighborhood operators and a late acceptance strategy, tailored to this novel model. Finally, we improve and extend the benchmark instances, in which the experimental results also underscore the practical feasibility and theoretical relevance of our model. These findings provide empirical evidence of the effectiveness of our proposed innovations and highlight their potential to improve urban delivery systems.

The structure of the remaining sections is outlined as follows: Section 2 provides an overview of the existing literature. The model is formulated in Section 3, while Section 4 outlines the proposed research methodology. Section 5 presents the case results, followed by the discussion in Section 6, and finally, Section 7 offers the conclusions.

2. Literature review

This literature review aims to explore the methods for reducing last mile delivery costs from two distinct perspectives: the strategic level and the operational level.

2.1 Strategic level

To effectively reduce last-mile delivery costs, the strategic approach is crucial, focusing on overarching frameworks that reshape logistics networks and service models. Numerous studies highlight how strategic changes, such as network restructuring and technological integration, can reduce cost pressure while adapting to the demands of urban logistics. For instance, centralized distribution hubs and shared logistics networks enable economies of scale, allowing multiple enterprises to pool resources and reduce redundant routes (He, Zhou, Qi, & Wang, 2020). Similarly, emerging technologies—such as autonomous delivery vehicles, drones, and AI-driven demand forecasting—offer strategic value, minimizing costs and enhancing delivery accuracy by reducing dependency on traditional vehicle fleets (Baloch & Gzara, 2020) Together, these strategic innovations demonstrate a shift from isolated logistics systems to integrated, sustainable networks that help address the urban delivery challenges at a broader level. Collaborations among logistics service providers are also indispensable, which relates to the flows of products, services and money, for instance, horizontal strategy among logistics service providers (Vanovermeire et al., 2014). Additionally, Vertical collaborations between upstream and downstream entities in the logistics service supply chain have been extensively studied and are recognized as an effective model for reducing logistics costs (He, Zhou, et al., 2020). The above solutions are innovative approaches designed from the perspective of logistics service models. Additionally, some researchers have proposed solutions for reducing logistics costs and improving service efficiency through logistics network redesign. For instance, some researchers optimized logistics network design to reduce system costs (Wang & Qi, 2020), while others divided the urban delivery system into two tiers: the first tier routes goods from the city distribution center to transfer stations, and the second tier completes delivery to terminal lockers or directly to customers (Zhou et al., 2018; Zhou et al., 2019).

2.2 Operational level

On the operational level, effective management of logistics processes is also indispensable for reducing last mile delivery costs. Strategies such as improving delivery scheduling and enhancing last mile routing can lead to significant efficiency gains.

Moreover, fostering collaboration among various stakeholders in the supply chain can enhance communication and coordination, further streamlining operations. This focus on operational optimization not only addresses cost issues but also contributes to improved service quality and customer satisfaction. The issue of the single depot vehicle routing problem with roaming customers was introduced recently. Reyes et al. initially introduced the concept and formulated a model where each customer is geographically dispersed around their residence. To efficiently address this problem, they devised a two-stage heuristic based on construction and improvement methodologies (Ozbaygin et al., 2017; Ozbaygin & Savelsbergh, 2019; Reyes et al., 2017). As described in that paper, the single-depot vehicle routing problem (VRP) with roaming customers (SDVRPRC) is a challenging variant of the VRPs, the difference between the VRPs and the SDVRPRC is that the SDVRPRC splits a single customer into multiple locations around the customer's home with overlapping time windows during the period. Besides SDVRPRC, our concern on this issue is the collaborative model with roaming customers and shared depots in this paper. For conciseness, we only list the main references closely related to our topic. In the VRP, the task involves delivering parcels to geographically dispersed customers in order to minimize overall costs, achieved by servicing all customers with a single vehicle (Dantzig & Ramser, 1959). In the multiple depots VRP with time windows (MDVRPTW), Du et al. present a joint delivery mode to satisfy customer demand while reducing carbon emission, and a hybrid heuristic is designed to solve this issue (Du, Wang, Wu, Zhou, & Zhou, 2023). In addition, to address the multi-depot problem, many approximation methods are applied to assign customers to the depot and then optimize these routes with the objective minimizing the total cost serving all customers (Dondo & Cerdá, 2007; Giosa et al., 2002; He, Qi, Zhou, & Su, 2020; He, Zhou, et al., 2020; Polacek et al., 2004; Salhi et al., 2014). In another variant of MDVRP, the vehicle may be replenished at an intermediate depot such that only a vehicle can meet the demand of a customer(Crevier et al., 2007). In addition, Zhou et al. focus on the last mile delivery problem with parcel locker location decisions, where customers can pick up their parcels either at home or at parcel lockers (L. Zhou, Li, Hu, & Du, 2024).

We are aware of only three papers that share some similarities with CLMD-RC. One of them is the single depot VRP with roaming customers where a customer is split into multiple locations, but only one of the locations is served (Reyes et al., 2017). The second is the multi-depot vehicle routing problem under shared depots (MDVRP-SD) where customers are associated with distinct depots, allowing the vehicle to initiate its route from one depot and conclude it at another. However, it is noteworthy that each customer is allocated a unique location, ensuring that a single vehicle visits only one location per customer (Baoxiang Li et al., 2016). The last one is the multi-depot vehicle routing problem with roaming delivery locations, although they considered multiple depots, they did not allow vehicles to serve across depots. Specifically, a vehicle must start from one depot, serve the assigned customers, and return to the same depot, rather than being able to return to a closer depot (Jolfaei & Alinaghian, 2024). However, in real-world scenarios, a customer might move to different delivery locations during that time. These existing approaches failed to address cross-depot collaboration within a multi-depot environment when dealing with customers changing their delivery locations.

Regarding the algorithmic dimension, a spectrum of approaches, encompassing both exact and heuristic algorithms, has been devised to address the challenges inherent in VRPs. Some are solved using exact algorithms with small-sized nodes (Baldacci et al., 2012; Battarra et al., 2014; Dayarian et al., 2015; Desaulniers et al., 2016). For example, Ozbaygin et al. design a branch-and-price algorithm for the single-depot vehicle routing problem with roaming delivery locations, which can solve small-scale problems (Ozbaygin et al., 2017). Furthermore, they develop an iterative re-optimization framework to solve dynamic variants that effectively leverage the information gathered from solving previous optimization problems to generate rapid solutions during the operational phase (Ozbaygin & Savelsbergh, 2019). While for instances involving datasets of considerable scale, the heuristic methods are designed to solve many real-life problems; these include tabu search, genetic algorithm, ant colony optimization, local search method, and simulated annealing and the integration of above methods (Baker & Ayechew, 2003; Boschetti & Novellani, 2024; He, Zheng, Li, & Deng, 2024; Ibaraki et al., 2005; Kir & Comert, 2024; Li, He, Xiu, Chen, & Chan, 2024; Reyes et al., 2017; Taş et al., 2013; Zhou et al., 2018). Lombard et al. study the single-depot vehicle routing problem with roaming delivery locations with stochastic travel times and design a greedy randomized adaptive search procedure (GRASP) to solve it (Lombard, Tamayo-Giraldo, & Fontane, 2018). Pham et al design a hybrid genetic algorithm to solve the problem (Pham, Hà, Vu, & Nguyen, 2022). However, some heuristics require great improvement once the original problem is changed. Furthermore, they often exhibit parameter sensitivity that impacts solution consistency. The ALNS is a stable and effective solution for VRPs (Ropke & Pisinger, 2006) and has already been applied to similar problems and has achieved high-quality solutions (Frey, Jungwirth, Frey, & Kolisch, 2023). In addition, to explore the solution space, the late acceptance strategy (Burke & Bykov, 2017) is used to explore better solutions. Regarding this issue, there is currently no suitable framework for solving it. So, this paper tries to design an ALNS heuristic combined with late acceptance (LC) to address this CVRPRDL-SD. Optimizing last-mile delivery from an operational perspective offers distinct advantages that align directly with cost reduction and service improvement goals. First, operational optimization enables a more granular approach to resource allocation and route planning, allowing for immediate, data-driven adjustments that reduce fuel usage, labor costs, and delivery time. Second, focusing on operations facilitates real-time responsiveness to dynamic customer demands, such as sudden changes in delivery locations or time windows—an essential capability in urban environments with high-density logistics activities. Furthermore, operational improvements—such as vehicle load optimization and adaptive scheduling—foster collaborative efficiency among service providers, maximizing asset utilization and minimizing redundant trips. In addition, the literature reveals a significant gap in research regarding collaborative delivery under customer roaming scenarios. Coordinating deliveries among multiple depots is inherently more complex than single-depot delivery and requires targeted, efficient algorithms to address these complexities. Currently, no such specialized algorithms exist in the literature to address collaborative multi-depot delivery under roaming customer demands. This study seeks to bridge this gap by focusing on the optimization of collaborative delivery in customer-roaming scenarios, contributing both practical solutions and academic insights that enhance last-mile delivery efficiency, cost-effectiveness, and customer satisfaction.

3. Formulation

In section 3 we formulated this problem as a mixed-integer programming model (MIP), which was improved based on the models of the two papers (Reyes et al., 2017; He, Qi et al., 2020). One model considered a single depot MIP, while the other offered a two-stage stochastic model considering stochastic travel times. The specific MIP we constructed is as follows:

3.1 Problem description

We describe CLMD-RC as follows: Let (V,A) denote a complete graph, and $V=(N\cup D)$ is the node set, $D=\{v_1,v_2,\ldots,v_m\}$ is a set of a depot, $N=\{v_{m+1},v_{m+2},\ldots,v_{m+n}\}$ is a location set and A represents the set of arcs, with each individual arc associated with a distinct travel time t_{ij} and cost w_{ij}. Specifically, $t_{ij}=w_{ij}=M$ when $i,j\in D$, M is a large number. $C=\{1,2,\ldots c\}$ means the set of customers during a planning period $[0,T]$. The demand of customer c is d_c and each customer has roaming delivery locations $N_c\in N$ and a non-overlapping time window $[e_i^c,l_i^c]$. In addition, in the depot set D, the demand.$d_c=0$, $c\in D$. The vehicle $k\in K$ has a capacity Q_k and each depot has K_d vehicles. The notations are shown in Table 1 and the CLMD-RC constraints must be satisfied as follows:

(1) Each vehicle has the flexibility to initiate its route from one depot and conclude at another depot after fulfilling customer service requirements.
(2) Assignment of a specific depot is exclusive for each customer.
(3) Each customer is allocated to a single vehicle for service provision.
(4) Vehicles are designed to visit only one designated location per customer.
(5) Adherence to designated time windows is mandatory, and vehicles are required to wait if they arrive ahead of schedule.
(6) Vehicles are constrained to operate within their designated maximal capacity.
(7) The deployment of vehicles at each depot is constrained by a predetermined cap on the overall quantity.

Table 1
List of symbols

Sets	Descriptions
D	The set for depots, $D=\{v_1,\ldots,v_m\}$
C	The set for customers, $C=\{1,2,\ldots,c\}$
N	The set for locations, $N=\{v_{m+1},v_{m+2},\ldots,v_{m+n}\}$
N_c	The location set for customer c,
V	The note set, $V=\{v_1,\ldots,v_{m+n}\}$
K	The set for vehicles,
K_d	The set for vehicles at depot $d\in D$
d_{ij}	The distance between i and $j\,(i\in V,\, j\in V\setminus i)$
d_c	The demand quantity for customer c， $c\in C$
t_{ij}	The travel time between node i and j $(i\in V,\, j\in V\setminus i)$
Q_k	The maximal capacity of vehicle k, $k\in K$
e_i^c	The start time at the locations i of customer c
l_i^c	The end time at the locations i of customer c
T	The maximum duration
x_{kij}	1, if vehicle k travels the arc from i to j , for $i\in V, j\in V\setminus i$, 0, otherwise
a_{ki}^c	The departure time after visiting location j of customer c for vehicle k
y_k^c	The remaining cargo quantity after serving customer c with vehicle k.

3.2. The model

Based on 3.1, we establish the formulation for the CLMD-RC as follows:

$$\min \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} w_{ij}x_{ijk} \tag{1.1}$$

subject to (1.2)

$$\sum_{k\in K}\sum_{j\in V\setminus\{i\}} x_{kij} = \sum_{k\in K}\sum_{j\in V\setminus\{i\}} x_{kji} = 1,\quad \forall i\in V \tag{1.3}$$

$$\sum_{k\in K}\sum_{i\in N_c}\sum_{j\in V\setminus\{i\}} x_{ijk} = 1,\ \forall c\in C \tag{1.4}$$

$$\sum_{k\in K}\sum_{j\in N} x_{kdj} \le K_d,\ \forall d\in D \tag{1.5}$$

$$\sum_{d\in D}\sum_{i\in N} x_{kdi} = \sum_{d\in D}\sum_{j\in N} x_{kjd} \le 1,\ \forall k\in K \tag{1.6}$$

$$\sum_{i\in D}\sum_{j\in D} x_{kij} = 0,\ \forall k\in K \tag{1.7}$$

$$e_i^c \le a_{ki}^c \le l_i^c,\ \forall i\in N_c, N_c\subseteq N, k\in K \tag{1.8}$$

$$a_{ki}^c + t_{ij}x_{kij} \le a_{kj}^{c'} + T(1-x_{kij}) \tag{1.9}$$

$$\forall i\in N_c, j\in, N_{c'}, c\in C\cup D, c'\in C\{c\}, k\in K$$

$$0\le y_k^c \le Q - d_c,\ \forall c\in C, k\in K \tag{1.10}$$

$$y_k^c + Q\left(1-\sum_{i\in N_c}\sum_{j\in N_{c'}} x_{kij}\right) \ge d_{c'} + y_k^{c'},\ c\in C\cup D, c'\in C\setminus\{c\}, k\in K \tag{1.11}$$

$$x_{kij}\in\{0,1\},\ \forall i,j\in V \tag{1.12}$$

Expression (1.1) is to minimize the operational cost, specifically focusing on travel times. Constraint (1.2) guarantees flow conservation at each location. To adhere to the principle that vehicles visit a customer only once, Constraint (1.3) is introduced. The total number of vehicles utilized is constrained by Constraint (1.4). Additionally, Constraint (1.5) delineates that vehicles may commence their route from a depot and conclude it at the same or a different depot. Constraint (1.6) ensures that direct travel between two depots is prohibited. Constraint (1.7) ensures the time windows. Constraint (1.8) means consistent constraints and eliminates the sub-tour. Constraints (1.9) and (1.10) ensure the capacity constraints. Constraint (1.11) denotes the range of decision variables.

4. Solution Approach

In this section, we design our effective and efficient ALNS-LA (as shown in Table 2). The best initial solution is generated using a novel and efficient construction heuristic as follows:

(1) Select a customer randomly from unserved customers, for all locations of the selected customer, for each position of all routes (including empty routes) among the solutions, and evaluate the time change of inserting each location into each position of all routes.
(2) Sort the insertions by non-decreasing travel times and keep the best insertion.

The new construction heuristic repeats the above procedure at each step till all customers are served. Through the aforementioned process, 100 initial solutions are generated, and then we select the best one among them as the input for the second-stage algorithm. The result shows that the novel construction heuristic outperformed that designed in existing literature (Reyes et al., 2017) on solution quality and CPU time. The ALNS-LA framework is presented in Algorithm 1.

Table 2
The Framework For ALNS-LA

Algorithm 1: ALNS-LA

Input: an initial solution s
Output: the best solution s_{best}
current solution $s_{curr} := s$
while *stopping criteria are not meet* **do**
Apply destruction operators to destroy the current solution s_{curr}
Apply reconstruction operators to improve the solution and get the improved solution s_{impr}
Apply LA to determine whether to accept this improved solution s_{impr}
if accept s_{impr} **then**
$s_{curr} := s_{impr}$, $s_{best} := s_{impr}$
else
$s_{best} := s_{curr}$
end while
output: s_{best}

4.1 ALNS

In the ALNS, two subroutines are carried out at each iteration: destruction and reconstruction operators. To make the initial solution better and enhance the diversity of operators, seven destruction operators and six reconstruction operators are designed. In addition, two optimization strategies are also used to improve the solution.

(1) Destruction operators

At each iteration, *c* customers will be selected and removed from where they are located. Seven destruction operators are designed, the former two are designed based on the spirit from Ropke and Pisinger (2006), the fifth is motivated by Demir et al. (2012), others are designed based on the ideas described by existing literature (Reyes et al., 2017).

- Random destruction (D1): Remove *c* customers randomly from the current solution.
- Greedy destruction (D2): Remove *c* customers greedily from the current solution.
- Random route destruction (D3): A route is selected randomly from which half customers are removed randomly.
- Costly route destruction (D4): the costly route is selected from which half customers are removed randomly.
- Balance destruction (D5): at iteration *i*, the frequency selected for customer *c* is recorded n_c, then at the next iteration $i+1$ the probability selected for the customer *c* is $p_c = (1-s_c)/(C-s_c)$, where *C* means the total number of customers, and $s_c = n_c / \sum_{c \in C} n_c$. At last, *c* customers are selected according to the roulette strategy and removed.
- Random sequence destruction (D6): at first, a customer is selected randomly, then find the route in which the selected customer is located, and remove the latter customers up to *c* customers, if the number of customers after the first selected customer is less than *c*, then all latter customers are removed.
- Greedy sequence destruction (D7): it is similar to D6, the difference is that the first customer is selected greedily.

(2) Reconstruction operators

After the destruction, six reconstruction operators have been implemented to improve the solution. The first five are inspired by Cordeau and Laporte (Cordeau & Laporte, 2003), Reyes et al. (2017), and Li et al. (2016). In addition, new routes can be generated during the reconstruction process described by the sixth operator.

- Global greedy reconstruction (R1): Remove *c* customers at once, then the reconstruction operator inserts each location of removed customers repeatedly with the least time consumed.
- One-by-one greedy reconstruction (R2): this is similar to R1, and the distinction lies in the immediate insertion, after the removal of a customer, onto the path incurring the least time consumption. Subsequent customers follow the same procedure.
- Balance Route reconstruction (R3): the operator removes *c* customers at once and then inserts them into the route with the least customers incurring the least time consumption. If there exists a violation of vehicle capacity, the unserved customers are handled in the same way with R1.
- Global *K*-random greedy reconstruction (R4): this is similar to R1 except that the customers into one position are selected randomly from the *K* best positions.
- Local inter-route reconstruction (R5): this is similar to R2, and the distinction is restricting the insertion to the original vehicle route.
- Generate new route (R6): the operator is to assign greedily unserved customers to a new and empty route. Those who cannot be inserted into the new route are inserted into other routes of this solution as described in R1. This operator diversifies the search strategy and enhances the solution space.

4.2. Two optimization strategies

Two optimization strategies were developed for handling roaming delivery locations and shared depots during the production process

- Route re-optimization strategy (O1): for each route of the solution, it may not be the best route because each customer is located at a different location. Therefore, each route is re-optimized using Algorithm 1. The customers in one candidate route are stored in the unserved set, and *n* routes are generated using Algorithm 1 from which the best route is opted. If the improved route surpasses the current candidate route in quality, opt to embrace the enhanced option; otherwise, reject it.
- Exchange depot strategy (O2): for each route of the solution, exchange the depot where the vehicle returns. If the cost is reduced, accept the improved route, or reject it.

4.3. Dynamic weighting approach

The choice of destruction and reconstruction operators adheres to the roulette wheel selection principle. More operators result in diversifying the search. However, it is also vital to balance the solution quality and running time. We define P_s^i as the selection probability for operator s at iteration i. The value is updated as $P_s^i = \left(f_s^i / s_s^i\right) / \sum_{s \in S}\left(f_s^i / s_s^i\right)$, where f_s^i is the number of improving the solution for operator s in the last i iterations, s_s^i is the number selected for operator s in the last i iterations.

4.4 Late acceptance strategy

In the course of enhancing a solution, the standard procedure involves accepting the improved solution if it demonstrates superiority or rejecting it if not. However, employing this straightforward strategy may lead to the emergence of local optima. Considering that the sub-optimal solution can introduce more flexibility, the ALNS is integrated with a late acceptance (LA) strategy proposed by Burke and Bykov (2008) . LA has been applied and performs very well in many fields, such as exam timetabling problems (Burke & Bykov, 2008), two-sided assembly line balance problems (Yuan, Zhang, & Shao, 2015), high school timetabling (Fonseca, Santos, & Carrano, 2016) and TSP (Burke & Bykov, 2017). The LA procedure is as follows in Table 3.

Table 3
Late Acceptance Strategy

Algorithm 2: LA
Input: candidate solution s
Output: final solution S
Calculate the objective function $C(s)$ using equation (1.1)
for all $k \in \{0,1,\ldots,L-1\}$ **do**
    $C_k \leftarrow C(s)$
end for
for *any candidate* s' **do**
    Calculate the objective function $C(s')$ using equation (1.1)
    $v \leftarrow iteration\ I \mod L$
    if $C(s') \le C_v$ **then**
        Accept the candidate's solution $s \leftarrow s'$
        Update the list $C_v \leftarrow E(C(s'))$
    end if
end for

5. Computational experiments

5.1 The performance analysis between collaborative and non-collaborative delivery

This section shows the results of the case study to compare the performance of the approach. The ALNS-LA is coded in Java and runs on an Intel Core I5-3337U 1.8GHz CPU 4 GB RAM computer. To analyze the performance, we used five instances with 15, 20, 30, 60, and 120 customers designed by (Reyes et al., 2017). The other depot is generated with coordinates (0, 30) to analyze the performance between collaborative delivery (CD) and non-collaborative delivery (N_CD), the algorithm is run 10000 iterations and the results obtained are presented in Table 4. The first three columns represent the instance ID, number of customers, and number of nodes for each instance. The computational results are shown in column 4 under collaborative delivery, while the first half of the customers are served by the first depot and the latter half by the second depot, the results are presented in columns 5 and 6, the column 7 shows the total delivery cost. The relative difference is shown in column 8. In the last column, the number of unserved customers is shown under non-collaborative delivery. The results show that, in Table 4, the collaborative delivery where customers have roaming delivery locations and depots are shared outperforms the non-collaborative delivery in terms of total completion time across all cases, and the average value across all cases decreased by 40.37%. In addition, in the non-collaborative delivery system, due to the characteristic of roaming, some customers cannot be served, which results in the second or even third delivery. This imposes extra costs on the enterprises, as well as the customer experience is poor.

5.2. The performance comparison between multi-depot and single depot

In this section, we compare the performance between multi-depot (MD) and single-depot (SD). The computational results under a single depot are from (Reyes et al., 2017). The comparisons are shown in TABLE V. Compared with the results under a single depot, the multi-depot greatly reduces the delivery cost when considering roaming delivery locations with a reduction of 16.90% on average. The main reason is that the customers with roaming delivery locations can be served by the nearest depot, while the vehicle sometimes has to travel farther to arrive in the locations of the customers under a single depot, thus resulting in higher delivery costs.

5.3. The Benefit from roaming delivery locations

Table 6 shows the benefit of roaming delivery locations under collaborative delivery. C_R represents the delivery cost with roaming delivery locations and C_S with a single delivery location (such as home delivery). The last column means the unserved customers on the condition that only a single delivery location is considered for each customer. We can conclude that the solutions for five instances considering roaming delivery locations greatly reduce the delivery cost with a reduction of 54.6% on average, and what's more, considering roaming delivery locations can improve the success rate of one-time delivery and avoid the second or even third delivery. A total of 81 customers are missed by vehicles in the first delivery, it is because the vehicles “miss” the customers with a single delivery location and do not arrive before the last starting time.

5.4. Analysis of the impact of initial solutions on algorithm performance

To assess the influence of initial solutions on algorithmic performance, we executed the algorithm using a set of 200 diverse initial solutions as input parameters. The results indicate that the final solution obtained is relatively stable.in these instances. Take instance 21 as an example in Fig. 1. The figure illustrates the variation trends of the final solutions under different initial conditions. We can find that the costs of final solutions vary within a very small range [5330, 5400], which demonstrates that our algorithm is stable.

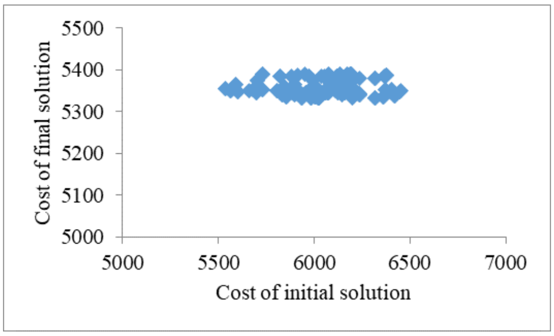

Fig. 1. The Effect of Initial Solutions on Algorithm Performance on Instance 21

5.5. Analysis on iteration times

In Table 7, the algorithm is run for 1000, 2000, and 10000 iterations and the results are shown accordingly. Columns “Average”, and “Best” represent the mean and best results, respectively. By contrasting the average results derived from conducting the algorithm over 10 iterations, the mean values for 1000, 2000, and 10000 stand at 5060.5, 4993.4, and 4903.7, respectively. Furthermore, the best values for 1000, 2000, and 10000 are 4928.6, 4904.2, and 4855.6. This implies that as the number of algorithm iterations increases, the obtained solution is improving, and simultaneously, the algorithm is gradually converging. Fig. 2 and Fig. 3 illustrate the convergence curves of the ALNS-LA and GRASP algorithms for solving Instance 21 and Instance 31, respectively. As shown in Fig. 2, both algorithms tend to converge within fewer than 1,000 iterations; however, the solutions obtained by our proposed algorithm are significantly superior to those of GRASP. In Figure III, for larger-scale instances, GRASP exhibits faster convergence but yields notably inferior results compared to ALNS-LA. This demonstrates that our proposed algorithm is capable of exploring a broader solution space in large-scale instances, thereby achieving more optimal solutions.

Table 4
Performance Analysis between CD and N_CD

Instance	Number of Cus.	Number of nodes	C_{CD}	C_{N-CD}			$\frac{C_{N-CD}-C_{CD}}{C_{CD}}\%$	Customers unserved
				C_1	C_2	C_{total}		
1	15	51	2041	1118	1098	2216	8.57	2
6	20	64	2997	3148	1368	4516	50.68	-
11	30	76	2974	1948	2159	4109	38.10	10
21	60	209	5350	5042	3269	8311	55.34	11,20
31	120	423	11124	7840	7381	15221	36.83	3,8,22,40,60
Overall mean			4897	3819	3055	6874	40.37	9 customers

Table 5
The Performance Comparison between Multi-Depot and Single-Depot

Instance	Number of Cus.	Number of nodes	C_{MD}	C_{SD}	$\frac{C_{SD}-C_{MD}}{C_{MD}}\%$
1	15	51	2041	2128	4.26
6	20	64	2997	3374	12.58
11	30	76	2974	3659	22.86
21	60	209	5350	6049	13.07
31	120	423	11124	13414	20.59
Overall mean			4897	5725	16.90

Table 6
Benefit from Roaming Delivery Locations under Collaborative Delivery

Instance	Number of Cus.	Number of nodes	C_R	C_S	$\frac{C_S-C_R}{C_S}\%$	Customers unserved
1	15	51	2041	3546	73.7%	5, 6, 9, 10, 11, 14
6	20	64	2997	4270	42.5%	2, 6, 8, 9, 15
11	30	76	2974	3880	30.5%	15, 28
21	60	209	5350	13250	147.7%	2,3,4,7,14,15,17,18,19,20 21,23,24,31,37,41,49,51
31	120	423	11124	28998	160.7%	2, 9, 11, 15, 16, 24, 26, 28, 32, 36, 38, 39, 40, 43, 45, 47, 49, 52, 54, 57, 58, 59, 62, 63, 64, 68, 72, 73, 75, 76, 79, 80, 81, 82, 85, 88, 89, 90, 101, 102, 105, 106, 108, 109, 113, 114, 116, 117, 118, 119
Overall mean			4897	10789	54.6%	81 customers

Table 7
Results of 1000, 2000, and 10000 Iterations

Instance	Mean			Best		
	1000	2000	10000	1000	2000	10000
1	2077.0	2057.9	2047.6	2049.0	2041.0	2041.0
6	3000.5	2995.0	2984.6	2966.0	2966.0	2966.0
11	3004.8	3010.9	2978.5	2971.0	2971.0	2971.0
21	5461.3	5381.2	5346.1	5342.0	5342.0	5335.0
31	11758.8	11522.0	11161.6	11315.0	11201.0	10988.0
Average	5060.5	4993.4	4903.7	4928.6	4904.2	4855.6

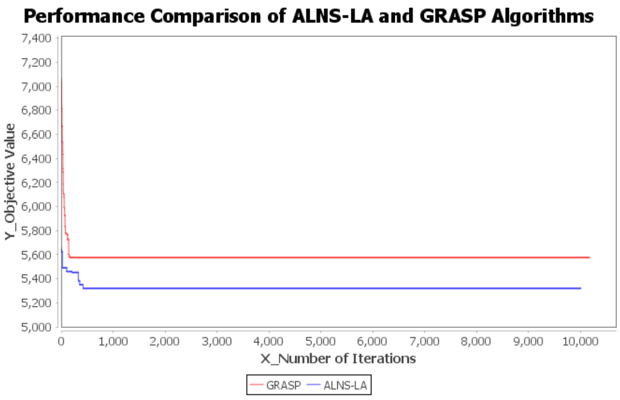

Fig. 2. The Performance Comparison of ALNS-LA and GRASP for Instance 21

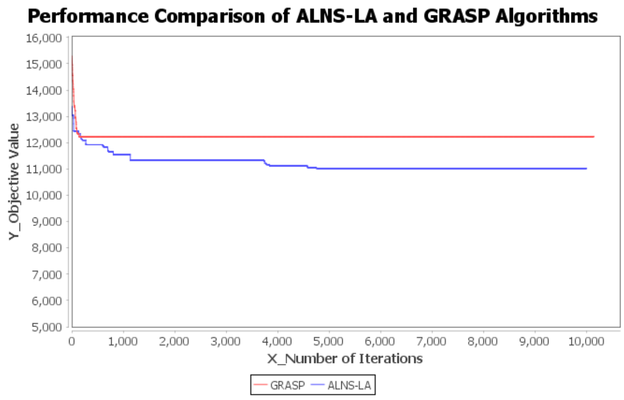

Fig. 3. The Performance Comparison of ALNS-LA and GRASP for Instance 31

6. Discussion

6.1. Analysis on Economic Benefit

The operational mode considering roaming delivery locations of customers can reduce logistics costs significantly, as shown by the extant research findings (He, Qi, Zhou, & Su, 2020; Reyes et al., 2017). However, the roaming customers bring a great challenge to express logistics enterprises. This mode requires express logistics companies to expand the service scope of their terminal delivery stations. In addition, more roaming locations make the scale of the problem even larger which raises higher requirements on the solution approach. We try to redesign the operational mode under the roaming delivery locations, the data analysis of computational experiments shows the obvious potential of this mode in terms of operational cost and service quality. Furthermore, compared with the mode under a single depot (TABLE V), the collaborative operation in the multi-depot environment greatly reduces the logistics cost when considering roaming delivery locations with a reduction of 16.90%

on average. The main reason is that the customers with roaming delivery locations can be served by the nearest depot. For example, one of the leading logistics companies Alibaba has collaborated with multiple express logistics companies to operate, but they have not considered the roaming locations (He, Zhou, et al., 2020), which shows great potential in cost reduction when adopting the proposed model. .

6.2. Analysis on Service Level

Our operational model provides logistics companies and customers with more flexible delivery preference specification capabilities, which can benefit enterprise managers on establishing cutting-edge practices for higher-quality services. For instance, developing flexible operational software for customers that enables them to input multiple delivery addresses can help reduce operational costs and enhance service quality. Furthermore, the development of advanced digital technologies for express logistics companies is essential to support the collaborative operational model (Khan, Piprani, & Yu, 2022). Hence, it is highly suggested that the government should develop relevant policies to promote the mode.

6.3. Analysis on Social Benefit

As demonstrated in Table 4, Table 5 and Table 6, the proposed model not only enhances customer coverage but also significantly reduces transportation distances. It is well known that transportation is a major source of carbon dioxide and related emissions in the logistics industry. Therefore, reducing transportation distances can substantially decrease carbon emissions. Additionally, shorter transportation distances can help alleviate urban traffic congestion and reduce the likelihood of traffic accidents.

7. Conclusions

In this paper, we introduce and consider a collaborative last mile delivery model with roaming customers (CLMD-RC), an innovative operational paradigm addressing dynamic urban logistics challenges. In addition, we propose and develop an adaptive large neighborhood search with late acceptance (ALNS-LA) framework to effectively solve it. Finally, through systematic computational experiments conducted on our newly constructed comprehensive set of benchmark instances, we demonstrate the potential of our proposed solution approach and the benefits of our designed operational mode. The results also show that our algorithm is stable and effective in solving different sizes of CLMD -RC instances, which demonstrates the operational superiority of ALNS-LA across instance scales and its practical viability in the real world.

Future research directions may focus on extending the CLMD-RS to the new variant that considers the split load and crowd-sourcing riders, which is a valuable area. Moreover, advanced algorithm development is crucial to devise efficient solutions capable of managing the complexities arising from dynamic customer movements and multiple depot constraints. Finally, exploring real-time adaptation strategies such as integrating reinforcement learning for real-time route optimization is essential to dynamically adjust vehicle routes based on evolving customer locations and delivery demands, which can also benefit from predictive models and heuristic approaches for enhanced responsiveness. These extensions aim to advance the theoretical foundations and practical implementations of adaptive urban logistics systems in increasingly complex supply chain environments with dynamic operational conditions.

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