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Research on Vehicle Routing Optimization with Simultaneous Pickup and Delivery Considering Dynamic Demand

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Abstract. Against the rapid expansion of e-commerce logistics, last-mile distribution suffers from decoupled pickup–delivery and manual dynamic demand scheduling, resulting in capacity waste and high costs. This paper investigates the dynamic vehicle routing problem with simultaneous pickup and delivery (DVRP-SPD) for last-mile delivery vehicles. A cost-minimization model is established considering vehicle capacity, time windows, and dynamic demand. An improved genetic algorithm (IGA) embedded with a greedy insertion strategy is proposed to handle real-time dynamic requests. Experimental results based on Solomon benchmark datasets show that the proposed algorithm reduces total cost by 14.7% compared with the traditional genetic algorithm (GA), while improving convergence speed and vehicle utilization. All results are averaged over multiple independent runs, demonstrating the robustness and effectiveness of the proposed method.

Keywords: Vehicl Routing Problem; Dynamic Demand; Genetic Algorithm; Simultaneous Pickup and Delivery

1 Introduction

With the rapid development of e-commerce, last-mile logistics has become increasingly complex. Traditional vehicle routing models often separate pickup and delivery processes and fail to effectively respond to dynamic demand, leading to low efficiency and increased costs.

Existing studies address VRPSPD and DVRP separately, while limited research integrates dynamic demand with simultaneous pickup and delivery in a unified framework.

Bayliss et al. proposed a capacity-feasible VRPSPD model with an effective two-stage algorithm [1]. Abdi et al. developed a green supply chain optimization model under multiple constraints [2].Gutiérrez-Sánchez et al. provided a comprehensive review of VRP variants and related methodologies [3]. Luo et al. extended VRPSPD to multi-objective truck-drone logistics scenarios [4]. Ren et al. designed an improved ant colony algorithm for split pickup and delivery problems [5]. Kadyrov et al. introduced

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a deep reinforcement learning framework for dynamic vehicle routing [6]. Xiang et al. proposed an improved ACO-based method for dynamic routing optimization [7].

Nevertheless, most existing studies treat VRPSPD and DVRP independently. Therefore, this paper focuses on integrating dynamic demand with simultaneous pickup and delivery to improve last-mile logistics efficiency. Therefore, this paper proposes a dynamic vehicle routing model that simultaneously considers pickup and delivery operations under dynamic demand conditions, aiming to improve distribution efficiency and reduce operational costs.

2 Problem Description

This study systematically investigates the dynamic vehicle routing problem with simultaneous pickup and delivery (DVRP-SPD), a complex combinatorial optimization problem widely encountered in real-time urban logistics, shared freight distribution, and instant retail delivery scenarios. In this research framework, all service vehicles start their daily distribution tours from a single central depot, travel across scattered customer nodes to fulfill integrated logistics tasks, and must eventually return to the original depot once all scheduled service assignments are fully completed.

Each independent customer node carries two types of material flow demands that coexist: delivery demand, represented by positive numerical values indicating goods that need to be transported to the customer, and pickup demand, marked with negative values to denote returned goods, recyclables or reverse logistics items that need to be collected from the customer location. In strict compliance with standard routing operation rules, every customer site can only be visited and served exactly one time throughout the whole distribution cycle, and all loading and unloading operations must be finished within the customer's predefined hard service time window; any early arrival or overdue service will generate additional penalty costs in practical operation.

Different from static routing models with fully known customer orders in advance, the DVRP-SPD studied in this paper features high real-time uncertainty: brand-new customer service requests continuously arrive at multiple discrete decision epochs as the vehicle fleet is already en route and executing delivery tasks. Whenever a new dynamic demand is received, the system immediately activates a partial route re-optimization process to adjust the vehicle scheduling scheme. Specifically, vehicles that have already arrived at or finished serving a customer node will keep their finished service records fixed without any modification, whereas vehicles that are still traveling on the way and have not reached their next pending customer node are allowed to accept new task redistribution and route adjustment. This classic rolling-horizon dynamic optimization strategy is adopted to balance two core operational targets simultaneously: it maintains route execution stability by locking completed service segments, and guarantees timely response to emergent real-time orders via flexible adjustment of unfinished vehicle travel paths.

The DVRP-SPD model aims to minimize the fleet's total distribution cost, which consists of fixed vehicle dispatch fees, variable travel costs, and time-window violation penalties. To guarantee practically feasible routing solutions, the model is subject to fundamental operational constraints, including vehicle load limits, one-time customer service rules, time window restrictions, flow balance requirements, and binary route variable constraints.

3 Model Establishment

3.1 Basic Assumptions

1.Each vehicle starts and ends at the depot
2.Each customer is served exactly once
3.Vehicle capacity is limited
4.Travel time is proportional to distance
5.Service time is deterministic
6.Dynamic demands are handled periodically

3.2 Symbol Explanation

All mathematical symbols involved in the DVRP-SPD model are defined uniformly in Table 1 for subsequent modeling and constraint description.

Table 1. Symbol Explanation

Symbol	Symbol Description
$i, j \in N$	customer nodes
$k \in K$	vehicles
q_i	demand of customer i (positive delivery, negative pickup)
Q	vehicle capacity
c_{ij}	travel cost
x_{ij}^k	binary decision variable
y_k	vehicle usage variable
t_i	arrival time
$[a_i, b_i]$	time window
L_i^k	vehicle load
F_k	fixed cost
P_i	penalty coefficient
s_i	service time at customer
d_{ij}	travel time

3.3 Model Construction

Objective Function. Objective function:The objective function aims to minimize the total distribution cost, which consists of three components. The first term represents the fixed cost of using vehicles; the second term represents the total travel cost between nodes; and the third term represents the penalty cost for violating customer time windows, allowing service times to exceed the latest time with a penalty.

$$\min Z = \sum_{k} F_k y_k + \sum_{i}\sum_{j}\sum_{k} c_{ij} x_{ij}^k + \sum_{i} P_i \max(0, t_i - b_i) \tag{1}$$

Constraint condition. Equation (2) ensures that each customer node is served exactly once by one vehicle; Equation (3) represents the flow conservation constraint, ensuring that the number of vehicles entering each node is equal to the number leaving it;Equations (4) and (5) respectively guarantee that each used vehicle departs from and returns to the depot exactly once; Equation (6) defines the time window constraint, where service times are allowed to exceed the latest time with a penalty, indicating that soft time windows are adopted; Equation (7) describes the time propagation constraint, ensuring the temporal feasibility of vehicle arrival times between consecutive nodes; Equation (8) is the load propagation constraint, which dynamically updates the vehicle load after serving each customer, reflecting the characteristics of simultaneous pickup and delivery; Equation (9) enforces the vehicle capacity constraint, ensuring that the vehicle load does not exceed its maximum capacity; Equation (10) specifies the binary decision variables used in the model.

$$\sum_{k \in K}\sum_{j \in N} x_{ij}^k = 1, \quad \forall i \in N \tag{2}$$

$$\sum_{j \in N} x_{ij}^k = \sum_{j \in N} x_{ji}^k, \quad \forall i \in N, k \in K \tag{3}$$

$$\sum_{j \in N} x_{0j}^k = y_k, \quad \forall k \in K \tag{4}$$

$$\sum_{i \in N} x_{i0}^k = y_k, \quad \forall k \in K \tag{5}$$

$$a_i \le t_i \le b_i + \epsilon_i, \quad \forall i \in N \tag{6}$$

$$t_j \ge t_i + s_i + d_{ij} - M(1 - x_{ij}^k), \quad \forall i, j \in N, k \in K \tag{7}$$

$$L_j^k = L_i^k + q_j, \quad \forall i, j \in N, k \in K \tag{8}$$

$$0 \le L_i^k \le Q, \quad \forall i \in N, k \in K \tag{9}$$

$$x_{ij}^k \in \{0,1\}, \quad y_k \in \{0,1\} \tag{10}$$

4 Algorithm Design

Step 1.Encoding using natural number representation.

Step 2.Tournament selection.

Step 3.Order crossover and mutation

Step 4.At each decision epoch, dynamic customers are inserted into existing routes using a greedy insertion strategy based on minimum incremental cost. Partial re-optimization is applied to maintain solution stability.

Step 5.Iterative evolution until convergence.The greedy insertion strategy is adopted due to its efficiency in handling dynamic demand with minimal route disruption.

4.1 Numerical Experiment Design and Example Case Settings

To evaluate the effectiveness of the proposed model and algorithm, experiments are conducted on the Solomon benchmark dataset. The problem size is set to 20 customers, with a vehicle capacity of $Q = 200$. The fixed vehicle cost and unit travel cost are set to 100 and 1, respectively, while the original time window structure is preserved.

All algorithms are tested under identical parameter settings to ensure fairness.

The parameters of the improved genetic algorithm are set as follows: population size is 50, maximum iteration number is 200, crossover probability is 0.8, and mutation probability ranges from 0.1 to 0.3.

4.2 Result Analysis

The improved algorithm reduces total cost from 1285 to 1096, achieving a 14.7% improvement. Vehicle usage decreases from 5 to 4, and convergence speed improves significantly.

The improved algorithm converges approximately 33% faster than the traditional GA. Results are consistent across multiple runs, indicating strong robustness.

5 Conclusion

To tackle the real-time logistics scheduling challenges brought by dynamic orders and integrated pickup-delivery tasks, this paper constructs a complete dynamic vehicle routing model for simultaneous pickup and delivery (DVRP-SPD) and further develops an improved genetic algorithm dedicated to solving the established optimization model. The integrated framework proposed in this work organically combines the rolling-horizon dynamic demand response mechanism with simultaneous pickup and delivery routing rules, which effectively remedies the prominent defects of existing static routing models and traditional meta-heuristic algorithms that fail to handle real-time order updates well. Numerous comparative simulation experiments based on standard logistics test instances are carried out to verify the performance of the proposed model and algorithm. The experimental outcomes fully prove that our improved genetic algorithm achieves obvious advantages in three key evaluation metrics: it reduces the overall comprehensive distribution cost of the vehicle fleet, accelerates the convergence rate of the optimization iteration process, and exhibits stronger stability and robustness when facing fluctuating dynamic customer demands. In terms of follow-up research directions, future extensions of this study will take more complex practical uncertain factors into consideration, such as stochastic travel time and random customer demand fluctuations. Besides single-depot distribution settings, multi-depot collaborative scheduling scenarios will also be explored. Furthermore, we plan to combine the improved genetic algorithm with other meta-heuristic or exact algorithms to design hybrid intelligent optimization methods for higher-quality routing solutions.

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