Postprint: A Study on Customer-Value-Aware Time-Dependent Route Optimization Methods for Collaborative Truck-Drone Delivery

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Date: 2022-05-18T16:08:25+00:00

Abstract

To address the problems of low delivery timeliness and poor customer value in the logistics industry resulting from increasing vehicle ownership and escalating traffic congestion, this study proposes a time-varying routing optimization method for truck-drone collaborative delivery, comprehensively considering factors such as customer value and cost. Accounting for traffic congestion during different time periods in the delivery process, a speed distribution function is utilized to characterize vehicle travel speeds, while incorporating constraints including customer time windows, vehicle payload capacity, and drone payload capacity to establish a cost-minimization mathematical model. According to the characteristics of the model, k-means clustering is introduced to group customer locations, and a hybrid particle swarm optimization algorithm is designed to solve the model. Finally, simulation experiments are conducted using Solomon data to verify the effectiveness of the model and algorithm. The experimental results indicate that, compared with the static road network model that neglects customer value, the proposed model reduces costs by 9.32% while simultaneously increasing customer value by 16.83% and customer satisfaction by 21.28%, demonstrating the effectiveness of the proposed algorithm in reducing delivery costs and improving enterprise economic benefits.

Full Text

Research on Time-Varying Route Optimization Method for Truck and UAV Joint Delivery Considering Customer Value

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Abstract: Aiming at the problems of low timeliness and customer value in logistics delivery caused by increasing vehicle ownership and traffic congestion, this paper proposes a time-varying route optimization method for truck and UAV joint delivery that comprehensively considers customer value and cost factors. Taking into account congestion conditions across different time periods during delivery, the method employs speed distribution functions to characterize vehicle travel speeds and incorporates constraints such as customer time windows, vehicle load capacity, and UAV load capacity to establish a mathematical model minimizing total cost. According to the model characteristics, k-means clustering is introduced to cluster customer locations, and a hybrid particle swarm optimization algorithm is designed to solve the model. Finally, simulation experiments using Solomon data verify the effectiveness of the model and algorithm. Experimental results show that compared with the static road network model without considering customer value, the proposed model reduces costs by 9.32% while increasing customer value by 16.83% and customer satisfaction by 21.28%, demonstrating the effectiveness of the algorithm in reducing distribution costs and improving enterprise economic benefits.

Keywords: vehicle-mounted UAV; customer value; time-varying road network; k-means clustering; joint distribution; hybrid particle swarm optimization

0 Introduction

With the development of e-commerce, improving product delivery efficiency and reducing logistics costs have become critical challenges for the logistics industry. In this context, the use of high-efficiency, low-cost UAVs for logistics delivery has emerged as a research hotspot. However, UAVs have limitations such as small load capacity and short flight range, making it impossible for them to independently complete large-scale logistics distribution tasks. Consequently, the truck-UAV joint delivery model has become an inevitable choice for cost reduction and efficiency improvement in the logistics industry.

In recent years, research on truck-UAV joint delivery routing problems has focused on two aspects: model establishment and algorithm design. Regarding model establishment, Murray et al. [1] first combined trucks and UAVs to establish a mixed-integer programming model for the flying sidekick traveling salesman problem. Building on this, Semiz et al. [2] incorporated customer time windows as constraints to develop a truck-UAV routing model with time windows. Zhu et al. [3] embedded regional restriction factors into model construction according to vehicle restrictions and no-fly zones. Peng et al. [4] designed a hybrid neighborhood search algorithm to solve the UAV routing problem for contactless delivery to multiple customers during the pandemic, with the shortest delivery time as the optimization objective. Zhang et al. [5] established a multi-objective model from the perspectives of low carbon and stochastic demand. Du et al. [6] incorporated multi-depot scenarios as environmental factors in the model under actual logistics distribution requirements.

To solve these mathematical models, most scholars employ improved heuristic intelligent optimization algorithms. Salama et al. [7] proposed an unsupervised machine learning-based heuristic algorithm to accelerate solution speed for optimizing truck-UAV delivery routes. Wang et al. [8] established a problem model minimizing total cost while comprehensively considering UAV station locations and customer time window requirements to improve customer satisfaction, and designed an adaptive large neighborhood search algorithm. Deng et al. [9] established a cold chain logistics optimization model for truck-UAV joint delivery in natural disaster scenarios, employing evolutionary reversal operations and designing an improved genetic algorithm. Tang et al. [10] utilized the concept of Thiessen polygons to improve the ant colony algorithm for solving a UAV path model considering route safety in mountainous areas. Li et al. [11] improved the variable neighborhood search algorithm to solve the split-delivery routing problem. Cao et al. [12] employed a genetic-simulated annealing two-stage algorithm to solve the truck-UAV joint delivery problem under clustering. Xiong et al. [13] proposed a novel optimization iterative algorithm for route planning in two steps with the shortest delivery time as the objective. Han et al. [14] adopted an improved artificial bee colony algorithm to minimize the overall system operation cost. Phan et al. [15] extended the problem to scenarios combining one truck with multiple UAVs, employing greedy randomized adaptive search procedure (GRASP) and adaptive large neighborhood search (ALNS) heuristic algorithms.

Although the above studies start from objectives of minimum cost and shortest distance, none consider customer value factors. Moreover, these studies explore route optimization in static road network environments, largely ignoring the impact of time-varying road networks on logistics distribution optimization. The resulting models have poor robustness and increase distribution costs for logistics enterprises.

Based on this, this paper establishes a truck-UAV joint delivery route optimization model considering customer value and time-varying road networks under constraints of vehicle load capacity, customer time windows, UAV flight range, and UAV load capacity. K-means clustering is introduced, and a hybrid particle swarm optimization algorithm is designed for simulation analysis of the case study.

1.1 Problem Description

The problem studied in this paper can be specifically described as follows: A logistics enterprise has a distribution center. To save distribution costs and improve efficiency, the enterprise adopts trucks and UAVs as delivery tools to serve its customers. Trucks depart from the distribution center carrying a sufficient number of UAVs and return to the distribution center after completing delivery tasks for both truck and UAV customers. UAVs must take off and land at customer points or the distribution center. Based on customer location information, k-means clustering is used to form initial truck delivery routes. Finally, UAV customers are arranged according to UAV load capacity and flight range constraints. UAVs can serve multiple customers in a single flight. Customers beyond UAV load and range limits are served by trucks. Customers on the same route are served collaboratively by trucks and UAVs, as illustrated in Figure 1.

Figure 1. Schematic diagram of truck and UAV joint distribution route

1.2 Model Assumptions and Symbol Description

Basic Assumptions: a) The locations and demands of distribution centers and customer points are known, with distribution center demand being 0. b) Each truck carries only one UAV and packages for both truck and UAV customers. c) The maximum flight range and maximum load capacity of UAVs are known. d) Each UAV can carry multiple packages and serve multiple customers, with each UAV capable of multiple delivery trips. e) Both trucks and UAVs travel at constant speeds, with UAV speed exceeding truck speed. f) UAV endurance time is constant, without considering the impact of flight speed and load on endurance time. g) Customer service time and UAV pickup/battery replacement time are not considered. h) Trucks carry sufficient UAV batteries. i) Trucks and UAVs cannot revisit any customer, and each customer can only be served once. j) All trucks and UAVs are of the same model.

Model Parameters and Variables:

Sets: - N: Set of all customer points - $N_0 = N \cup \{0\}$: Set of all road network nodes, where 0 represents the distribution center - H: Set of all trucks - R: Set of all UAVs

Model Parameters: - Q^T: Maximum load capacity of trucks - Q^D: Maximum load capacity of UAVs - L: Maximum flight distance of UAVs - f_1: Unit fixed cost of trucks - f_2: Unit usage cost of UAVs - b_1: Unit transportation cost of trucks - b_2: Unit transportation cost of UAVs - l_{ij}: Travel distance of trucks from customer i to customer j - d_{ij}: Flight distance of UAVs from customer i to customer j - t_i: Arrival time at customer point i - t_i^h: Arrival time of trucks at customer point i - t_i^k: Arrival time of UAVs at customer point i - S^T: Set of customers served by trucks - S^D: Set of customers served by UAVs - S^S: Set of UAV launch/landing sites - q_i: Goods demand of customer i - v_i: Travel speed of trucks - λ_1: Value per unit product - λ_2: Profit per unit product - V_i: Total value of customer point i - V_i^g: Potential value brought by customer point i - V_i^c: Current value brought by customer point i - p_j: Number of potential customers - ψ: Information diffusion intensity - ζ: Information diffusion depth - η: Influence scale - $[a_i, b_i]$: Customer time window - α, β: Early and late delivery penalty cost coefficients for time windows - ε, θ: Waiting cost coefficients for trucks and

UAVs, respectively

Decision Variables: - $x_{ij}^h = \begin{cases} 1 & \text{if truck travels from node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$ - $y_{ij}^r = \begin{cases} 1 & \text{if UAV flies from node } i \text{ to node } j \\ 0 & \text{otherwise} \end{cases}$

1.3.1 Customer Value Analysis

Customer value includes current value and potential value. Current value is related to customer demand and is calculated as:

$$V_i^c = q_i \cdot \lambda_2 \cdot \eta_i$$

where q_i is the demand of customer i, λ_2 is the profit per unit product, and η_i is the demand proportion coefficient of customer i.

Customer potential value is mainly related to factors such as business capability, corporate reputation, and technological innovation capability. Delivery efficiency and scheme quality affect corporate reputation. Moreover, when customer satisfaction is high, the probability of acquiring potential customers increases, leading to more potential customers and higher potential value. The potential value calculation formula is:

$$V_i^g = p_i \cdot \psi \cdot \zeta$$

where p_i is the satisfaction of customer i, ψ is the importance of customer i, and ζ is the number of potential customers stimulated by customer i.

Since customer importance affects the number of potential customers, formula (2) can be rewritten as formula (3):

$$V_i^g = p_i \cdot \psi \cdot \zeta \cdot \eta_i$$

Total customer value is the sum of current value and potential value, calculated as:

$$V_i = \omega \cdot V_i^c + (1 - \omega) \cdot V_i^g$$

where ω is the customer weight. Higher customer importance leads to higher weight, which can enhance customer value and promote sustainable enterprise development.

1.3.2 Time-Varying Road Network Analysis

In time-varying road networks, truck travel speed changes with traffic flow, and truck transportation costs increase significantly with congestion. Increased transportation time due to congestion may prevent meeting customer time window requirements. Traffic congestion includes recurrent and non-recurrent congestion. Recurrent congestion is regular and predictable, allowing optimization of delivery time slots and routes.

Traffic flow changes are generally represented by explicit speed distribution functions. Building on previous research, this paper assumes that during free-flow periods, speed follows a log-normal distribution $v(t) \sim \mathrm{LN}(\mu, \sigma^2)$. During moderate traffic (general periods) and peak periods, speed follows a normal distribution $v(t) \sim N(\mu, \sigma^2)$.

The speed distribution functions for three traffic flow periods are defined as:

$$f(v,t) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_1 v} \exp\left(-\frac{(\ln v-\mu_1)^2}{2\sigma_1^2}\right), & v \in [v_{\min}, v_{\max}], t \in tw_1 \\ \frac{1}{\sqrt{2\pi}\sigma_2} \exp\left(-\frac{(v-\mu_2)^2}{2\sigma_2^2}\right), & v \in [v_{\min}, v_{\max}], t \in tw_2 \\ \frac{1}{\sqrt{2\pi}\sigma_3} \exp\left(-\frac{(v-\mu_3)^2}{2\sigma_3^2}\right), & v \in [v_{\min}, v_{\max}], t \in tw_3 \end{cases}$$

where tw_1, tw_2, tw_3 represent the three traffic flow time periods, and $\sigma_1, \sigma_2, \sigma_3$ represent speed standard deviations.

1.4 Objective Function

The objective function for the truck-UAV joint delivery time-varying route problem considering customer value is: **minimization of total cost**.

1.4.1 Cost Function Components

The total cost in the objective function consists of the following components:

1) **Transportation Cost**
Vehicles incur transportation costs during travel, and UAVs incur flight costs during operation. This cost is calculated as:

$$Z_1 = \sum_{h\in H} \sum_{i\in N_0} \sum_{j\in N_0} b_1 \cdot l_{ij} \cdot x_{ij}^h + \sum_{r\in R} \sum_{i\in N_0} \sum_{j\in N_0} b_2 \cdot d_{ij} \cdot y_{ij}^r$$

2) **Fixed Cost**
In logistics distribution, enterprises incur vehicle dispatch costs and UAV usage costs. This is calculated as:

$$Z_2 = \sum_{h\in H} \sum_{i\in N_0} \sum_{j\in N_0} f_1 \cdot x_{ij}^h + \sum_{r\in R} \sum_{i\in N_0} \sum_{j\in N_0} f_2 \cdot y_{ij}^r$$

3) **Time Window Penalty Cost**
Under time-varying road network constraints, to improve customer satisfaction and value, penalty costs may occur for early or delayed deliveries. This is calculated as:

$$Z_3 = \sum_{i \in S^T \cup S^D} [\alpha \cdot \max(0, a_i - t_i) + \beta \cdot \max(0, t_i - b_i)]$$

4) **Waiting Cost**
Due to different delivery speeds and road conditions, waiting costs for trucks and UAVs may occur during delivery. This is calculated as:

$$Z_4 = \sum_{h \in H} \sum_{i \in S^T} \varepsilon \cdot w_i^h + \sum_{r \in R} \sum_{i \in S^D} \theta \cdot w_i^r$$

where w_i^h represents the waiting time of trucks at point i for UAVs, and w_i^r represents the waiting time of UAVs at point i for trucks.

1.4.2 Mathematical Model

The complete mathematical model is formulated as:

Objective Function:

$$\min Z = Z_1 + Z_2 + Z_3 + Z_4$$

Subject to:

$$\sum_{i \in S^T} q_i + \sum_{i \in S^D} q_i \leq Q^T \quad \forall h \in H$$

$$\sum_{i \in S^T} \sum_{j \in S^D} x_{ij}^h \leq \sum_{i \in S^T} \sum_{j \in S^D} y_{ij}^r \quad \forall h \in H, r \in R$$

$$\sum_{h \in H} \sum_{i \in N_0} x_{ij}^h + \sum_{r \in R} \sum_{i \in N_0} y_{ij}^r = 1 \quad \forall j \in N$$

$$\sum_{i \in S^D} q_i \cdot y_{ij}^r \leq Q^D \quad \forall r \in R$$

$$y_{ij}^r = 0 \quad \forall i, j \notin S^D, r \in R$$

$$\sum_{j \in N_0} d_{ij} \cdot y_{ij}^r \leq L \quad \forall r \in R$$

$$a_i \leq t_i \leq b_i \quad \forall i \in N$$

$$x_{ij}^h \in \{0, 1\} \quad \forall i, j \in N_0, h \in H$$

$$y_{ij}^r \in \{0, 1\} \quad \forall i, j \in N_0, r \in R$$

where formula (9) is the objective function minimizing total cost (including transportation cost, fixed cost, time window penalty cost, and waiting cost).

Constraint (10) ensures total demand served by trucks and UAVs does not exceed truck maximum load capacity. Constraint (11) ensures UAVs can only deliver after trucks reach launch points. Constraint (12) ensures each customer is served only once by either truck or UAV. Constraint (13) ensures UAV delivery demand is within UAV load capacity. Constraint (14) ensures customers inaccessible to UAVs are served by trucks. Constraint (15) ensures UAVs cannot exceed distance limits. Constraint (16) enforces customer time window constraints. Constraints (17) and (18) define decision variables.

2.1 Improved k-means Clustering Algorithm

Traditional k-means clustering algorithms require specifying the number of clusters k in advance. With unknown delivery vehicle requirements, the exact number of vehicles cannot be predetermined. This paper employs an improved k-means clustering algorithm to cluster customer points using distance as the similarity metric. The Euclidean distance between two data objects δ_i and δ_j is calculated as:

$$\mathrm{dist}(\delta_i, \delta_j) = \sqrt{\sum_{p=1}^{m} (\delta_{ip} - \delta_{jp})^2}$$

where m is the total number of data objects.

2.2 Determination of k-means Clustering Centers

Traditional clustering centers are randomly generated. This paper adopts a location encoding method for clustering center selection [16]. Assuming a sample data scale of n, each data object has p feature attributes, the number of clusters is k, and clustering centers are $e_j (j = 1, 2, \dots, k)$. A total of M particles are generated, where each particle' s position consists of k clustering centers. The position encoding structure is:

$$\mathrm{particle}_i = [e_1, e_2, \dots, e_k] = [x_1, x_2, \dots, x_{k\times p}]$$

2.3 Algorithm Design

Based on the above clustering algorithm, the number of vehicles and their served customers can be initially determined. To further optimize vehicle delivery routes, concepts of crossover and mutation from genetic algorithms are introduced to design a hybrid particle swarm optimization algorithm for model solution.

2.3.1 Hybrid Particle Swarm Optimization Algorithm

Particle swarm optimization is a heuristic optimization algorithm that simulates birds randomly searching for food. Through experience and communication, they adjust their search direction and velocity to find the optimal solution [17].

Assuming a D-dimensional target search space with a swarm of τ particles, the position of particle i is represented as a D-dimensional vector $X_i = (X_{i1}, X_{i2}, \dots, X_{iD})$. The historical best position of particle i is $P_i = (P_{i1}, P_{i2}, \dots, P_{iD})$. The best position found by the entire swarm is $P_g = (P_{g1}, P_{g2}, \dots, P_{gD})$. The velocity of particle i is also a D-dimensional vector $V_i = (V_{i1}, V_{i2}, \dots, V_{iD})$. For particle i, the velocity and position at iteration $k+1$ are:

$$V_{id}^{k+1} = w \cdot V_{id}^{k} + c_1 \cdot \mathrm{rand}() \cdot (P_{id}^{k} - X_{id}^{k}) + c_2 \cdot \mathrm{rand}() \cdot (P_{gd}^{k} - X_{id}^{k})$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1}$$

where w is the inertia weight, c_1 and c_2 are individual and global learning factors respectively, rand() is a random number between 0 and 1, i represents the i-th particle, k represents the iteration number, and d represents the dimension.

2.3.2 Algorithm Flow

The particle swarm optimization algorithm's convergence can be affected by particle update speed. To help the algorithm escape local optima quickly, crossover and mutation concepts from genetic algorithms are introduced to prevent premature convergence, resulting in a hybrid particle swarm algorithm (HPSA). The implementation steps are:

Step 1: Initialize the particle swarm (with N particles). Assign random initial positions and velocities to each particle.

Step 2: Calculate fitness values. Compute each particle' s fitness according to the fitness function.

Step 3: Find individual best fitness. For each particle, compare its current fitness with its historical best position' s fitness, and update the individual optimal particle.

Step 4: Find global best fitness. For each particle, compare its current fitness with the global best position' s fitness, and update the global optimal particle.

Step 5: Perform OX crossover on individual and global optimal particles.

Step 6: Conduct mutation operations on particles with a certain probability.

Step 7: Update particle positions and velocities.

Step 8: Check termination condition. If not satisfied, return to Step 2; if satisfied, output the global optimal particle.

2.3.3 Algorithm Flowchart

The hybrid particle swarm algorithm flowchart is shown in Figure 2.

Figure 2. Flow chart of hybrid particle swarm optimization

2.3.4 Local Search for UAV Routes

Through the improved k-means clustering hybrid particle swarm algorithm, all customers are assigned to trucks to obtain an optimal delivery scheme. After completing customer assignment, local search is performed on these customers to form UAV delivery routes.

The UAV route local search procedure is as follows: First, from each truck' s delivery route, select from left to right the customer points that meet UAV delivery conditions (maximum load and maximum flight range). Then, from the remaining truck route, select the two points closest to the customer as UAV launch and landing points. If a point is already used as a launch point by another UAV, select from other customers. Customer points not selected by UAVs in the route are served by trucks. Trucks serve customers from left to right, finally forming optimal delivery routes for both trucks and UAVs.

3.1 Experimental Environment and Parameters

The case tests in this paper were conducted on a computer with Intel(R) Core(TM) i7-1065G7 CPU @ 1.50 GHz, Windows 10 (64-bit), and MATLAB R2018b programming environment for the hybrid particle swarm algorithm. Truck real-time speeds are determined through speed distribution functions. In the solution parameters: customer current value threshold is 120, customer potential value threshold is 20, information propagation intensity is 0.1, information diffusion depth is 0.125, influence scale is 20, unit product value is 6 yuan, unit product profit is 3 yuan, maximum vehicle load is 100, maximum UAV load is 10. The population size is set to $N = 100$, maximum iterations to 200, inertia weight $w = 1$, individual learning factor $c_1 = 1.5$, and global learning factor $c_2 = 2$.

3.2 Case Verification

Taking a logistics transportation enterprise as an example (data obtained from http://chairedistributique.com/data/), the enterprise needs to deliver goods to 20 customers. Distribution center and customer information is shown in Table 1, where ID 0 is the logistics distribution center and others are customer points. The average vehicle speed is assumed to be 50 km/h, with 4 vehicles total. Based on vehicle route arrangement and under UAV load constraints, truck and UAV routes are reasonably planned.

Table 1. Related information of customer points

Customer ID	Coordinates	Demand	Time Window
0	(30, 50)	0	-
1	(40, 50)	7	[7, 18]
2	(45, 68)	18	[18, 20]
...	...	...	...
20	(15, 80)	7	[17, 19]

A survey of traffic conditions during the enterprise' s delivery process shows specific daily traffic conditions in Table 2. This paper assumes truck unit fixed cost is 100 yuan, UAV fixed cost is 15 yuan, truck unit transportation cost is 3 yuan/km, UAV unit transportation cost is 1 yuan/km, truck waiting cost is 3 yuan/h, UAV waiting cost is 1.5 yuan/h, truck early penalty coefficient is 1, and late penalty coefficient is 2.

Table 2. Velocity distribution function

Time Period	Traffic Condition	Speed Distribution
7:00-9:00	Congested	$v(t) \sim N(15, 0.5)$
9:00-12:00	General	$v(t) \sim N(32, 0.5)$
12:00-14:00	Free-flow	$v(t) \sim \text{LN}(3.8, 0.12)$
14:00-17:00	General	$v(t) \sim N(32, 0.5)$
17:00-18:00	Congested	$v(t) \sim N(15, 0.5)$
18:00-20:00	General	$v(t) \sim N(32, 0.5)$

Based on the above model, MATLAB programming is used to incorporate speed parameters from different time periods into the hybrid particle swarm algorithm. Through UAV local search, truck and UAV delivery routes are obtained as shown in Table 3. After optimization, the total cost is 1257.53 yuan.

Table 3. Path planning results

Route	Truck-UAV Delivery Path
1	$0 \to 1 \to 2 \to 3 \to 4 \to 5 \to 0$
2	$0 \to 6 \to 7 \to 8 \to 9 \to 10 \to 0$
...	...

Note: Solid lines represent truck transportation; dashed lines represent UAV transportation.

3.2.1 Comparative Experiment 1

To verify the rationality of dynamic road networks and customer value for truck-UAV delivery routes, this paper compares the static model without considering customer value with the proposed dynamic model considering customer value. The results are compared and analyzed in Table 4.

Table 4. Comparison between static road network model without considering customer value and the proposed model

Metric	Static Model (No Customer Value)	Proposed Model	Improvement
Total Cost (yuan)	1386.78	1257.53	-9.32%
Total Customer Value (yuan)	856.32	1000.45	+16.83%
Customer Satisfaction (%)	68.45	83.01	+21.28%

The comparative results in Table 4 show that: First, in terms of total cost, the proposed model reduces costs by 9.32% compared to the static network model, decreasing logistics company expenses and improving economic benefits. Second, regarding total customer value and satisfaction, the proposed model increases total customer value by 16.83% and customer satisfaction by 21.28% compared to the static network model. These results demonstrate that the model considering customer value and time-varying network factors better reflects reality, enhances company competitiveness, maximizes enterprise benefits, and promotes sustainable development.

3.2.2 Comparative Experiment 2

Different scholars have proposed various algorithms for solving vehicle-UAV joint delivery routing problems, such as: Hybrid Tabu Search with Short-path Algorithm (SPTS) [3], Adaptive Large Neighborhood Search (ALNS) [8], Greedy Randomized Adaptive Search Procedure (GRASP) [15], and Hybrid Genetic Algorithm (HGA) [18]. However, these algorithms have certain limitations in different aspects. To verify the effectiveness and rationality of the proposed algorithm, the above four methods are used to solve the truck-UAV joint delivery time-varying route model considering customer value, and the results are compared and analyzed in Table 5.

Table 5. Performance comparison of algorithms

Algorithm	Average Cost	Best Cost	Computation Time (s)	Convergence Iterations
SPTS	1325.67	1289.45	45.2	160

Algorithm	Average Cost	Best Cost	Computation Time (s)	Convergence Iterations
ALNS	1356.23	1312.78	38.7	110
GRASP	1298.45	1267.89	42.1	95
HGA	1278.92	1259.34	35.8	85
HPSA	1265.43	1257.53	32.4	75

The experimental results in Table 5 show that: (a) SPTS converges at iteration 160, while ALNS converges at iteration 110. Although ALNS has faster convergence speed, its optimal solution performance is worse than SPTS. (b) Comparing GRASP and HPSA, GRASP has faster convergence but slightly longer computation time than HPSA, with both average and optimal values higher than HPSA results. (c) Comparing HPSA and HGA, HPSA shows stronger solution precision in both average and optimal values, with faster computation time, enabling quicker acquisition of optimal solutions.

In summary, compared with other algorithms, the hybrid particle swarm algorithm adopted in this paper demonstrates higher computational accuracy and faster speed when solving the proposed model, effectively avoiding local optima limitations, with faster convergence and global search performance, saving logistics enterprise distribution costs and improving economic benefits.

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4 Conclusion

This paper conducts the following research on the time-varying route problem for truck-UAV joint delivery considering customer value:

1) In terms of delivery mode, this paper adopts truck-UAV joint delivery, incorporating customer value and road network time-varying characteristics as constraints to establish a mathematical model minimizing total cost. Compared with the static model without considering customer value, the proposed model better increases customer value and satisfaction, thereby expanding enterprise economic benefits.

2) To improve algorithm performance, a hybrid particle swarm optimization algorithm is designed to solve the model. Comparative analysis with different algorithms shows that the hybrid particle swarm algorithm exhibits good performance in convergence speed, computation time, and optimal solution quality, proving to be an effective intelligent optimization algorithm for solving truck-UAV joint delivery problems.

3) This paper only considers UAV load capacity factors when studying truck-UAV routing problems. Future research could comprehensively consider delivery time and energy consumption, as well as incorporate weather

uncertainty factors to build more realistic models combined with practical problems.

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Note: Figure translations are in progress. See original paper for figures.