Research on Rural Logistics Path Optimization Based on Collaborative Delivery with Electric Vehicles and Drones

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Abstract. The rural logistics distribution system faces significant pressure due to the complexity of the terrain and the widespread dispersion of delivery points. To address this challenge, this study innovates upon the traditional single-mode delivery system by proposing a “Electric Vehicle + Drone” collaborative delivery model, which takes into consideration factors such as carbon emissions and customer satisfaction with the goal of minimizing total costs. Initially, the k-means clustering method is used to determine the stopping points of electric vehicles and effectively categorize customer points. Subsequently, an improved ant colony algorithm is employed for route planning. The model's effectiveness and practicality were verified using the Solomon dataset. Experimental results show that compared to traditional vehicle-only delivery models, the collaborative delivery model excels in reducing total costs by 14.52% and significantly enhances delivery efficiency, with an improvement of 21.86%.

Keywords: Rural Logistics; Drones; Path Optimization; Improved Ant Colony Algorithm

1 INTRODUCTION

With the rapid development of internet technology and the booming rise of e-commerce, the rural market has become a new growth point for online retail. However, due to its unique geographical environment, rural areas pose greater challenges to the logistics distribution system, especially in achieving efficient and low-cost "last-mile" delivery services. These challenges not only inhibit the potential growth of rural e-commerce but also significantly affect the shopping experience and satisfaction of rural consumers. Therefore, it is particularly urgent to explore and implement a new model of rural logistics distribution that is both efficient and economical. Against this backdrop, technological innovations in drones and electric vehicles offer fresh perspectives and possibilities for logistics distribution in rural areas.

Numerous scholars have conducted research on drone delivery. Sawadsitang[1] and colleagues considered the various challenges and random events that might occur during drone delivery, proposing a multi-objective drone delivery system and a three-stage stochastic optimization model. Ye Liwei[2] and others utilized an improved

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hybrid particle swarm optimization algorithm to study the problem of drone and vehicle collaborative path scheduling with time windows. Du Pengfei[3] addressed the issue of incomplete factors in drone delivery modeling, constructing a multi-warehouse logistics drone delivery model based on energy consumption changes, hybrid time windows, and simultaneous pickup and delivery. Xia[4] and colleagues designed an improved adaptive large neighborhood search algorithm, creating an integer programming model to address the impact of drone weight on costs. Kitjacharoenchai[5] and others explored the last-mile delivery problem of drones, solving it through a formulated mixed-integer programming approach.

In recent years, the application of electric vehicles (EVs) has expanded the range of options for logistics transportation strategies, making the efficient dispatch of EVs a hot topic among scholars. Mavrovouniotis[6] and colleagues have considered EV charging strategies and utilized an improved ant colony algorithm for planning EV routes. Vani[7] and others have modeled electric vehicle routes based on time-of-use electricity pricing, proposing an optimization using a bat algorithm. Wen Hsin[8] and colleagues, under the premise of considering carbon emissions, have developed an optimization model for multi-temperature joint distribution paths for electric vehicles in a time-varying network with soft time windows. Jia[9] and others have framed the EV routing problem as a bi-level optimization issue and introduced an innovative bi-level ant colony optimization algorithm for solving it.

In summary, despite significant progress in the field of delivery models, current research still has certain shortcomings: (1) Most studies analyze drones, electric vehicles, and time windows separately, lacking a comprehensive consideration of these key factors. (2) Research on carbon emissions caused by the use of drones and electric vehicles remains scarce. (3) Although some studies have mentioned the collaborative delivery model of drones and vehicles, in-depth discussions on its application in rural logistics are relatively insufficient. In light of this, this paper innovatively proposes a "Electric Vehicle + Drone" collaborative delivery model for rural logistics that integrates considerations of time windows and carbon emissions. Compared to existing literature, the innovations of this study are primarily reflected in several aspects: First, it cleverly combines the complementary advantages of electric vehicles and drones, providing a comprehensive solution strategy for the logistics challenges faced by rural areas. Second, the model incorporates carbon emissions and customer satisfaction as core considerations, demonstrating how to reduce environmental impact while enhancing delivery efficiency. Furthermore, after k-means clustering, a hybrid binary search is introduced to solve the initial pheromone setting issue of the ant colony algorithm, optimizing the delivery route planning. These innovative measures not only fill the gaps in existing research but also offer new perspectives and strategies for the field of rural logistics delivery.

2 MATHEMATICAL MODEL

2.1 Problem Description and Hypothesis

The problem studied in this paper can be specifically described as follows: A distribution center reasonably plans delivery routes with the goal of minimizing total delivery costs, taking into account customer demand. An electric vehicle carrying a drone departs from the distribution center and, upon reaching a designated electric vehicle stopping point, releases the drone. The drone then delivers goods to a fixed receiving point in the village and returns to the electric vehicle, which ultimately returns to the distribution center with the drone (as shown in Figure 1). To ensure the integrity of the model constructed in this paper, the following assumptions are made:

(1) This paper only considers the delivery scenario involving a single distribution center and multiple customer points;

(2) Each village's fixed receiving point can only be serviced once;

(3) The starting and stopping points for the electric vehicle are always the distribution center, and for the drone, they are the respective electric vehicle;

(4) The demand type for all customers is delivery, and the demand volume for each customer is known;

(5) All roads between the electric vehicle's temporary stopping points and the distribution center are bidirectional and passable.

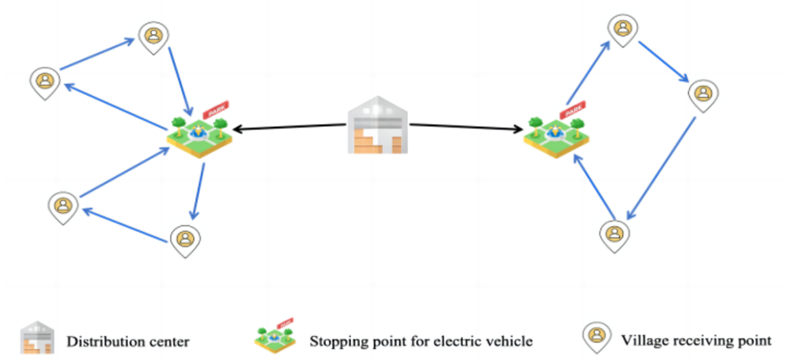

Fig. 1. "Electric vehicle + drone" distribution mode

2.2 Symbol Description

The symbols and meanings of the problems in this paper are shown in Table 1.

Table 1. Problem symbol and meaning description

Symbol	Meaning description
A	Distribution center set, A has only one element, A=0
T	Electric vehicle temporary parking point collection, T={1,2⋯,T}
N	Village fixed receiving point collection, N={1,2⋯,N}
H	Drone assembly, H={1,2⋯,H}
F	Electric vehicle collection, {1,2⋯,F}
d_{ij}	Distance from node i to node j
u	Time window penalty factor
Q_H	Maximum payload of the drone
Q_F	Maximum load of electric vehicle
x_{ijk}	Variable 0-1, vehicle or drone k traveling from i to j is 1; Otherwise zero
y_{ik}	Variable 0-1, vehicle or drone k at point i for service is 1; Otherwise zero

2.3 Objective Function

The fixed costs are directly proportional to the number of electric vehicles and the number of drones equipped with them. As the quantity of electric vehicles and drones increases, the corresponding fixed costs also rise accordingly.

$$C_1 = m_1 \sum_{k \in F} \sum_{j \in T} x_{0jk} + m_2 \sum_{k \in H} \sum_{i \in T} \sum_{j \in N} x_{ijk} \tag{1}$$

Among them, m_1 and m_2 respectively represent the unit fixed costs of electric vehicles and drones.

Transportation costs are primarily determined by the cost of electricity consumed by electric vehicles and drones during the delivery process, and are proportional to their travel distance. Given that this portion of the cost constitutes a significant proportion of the total cost, finding a relatively shortest delivery route is particularly important for effectively reducing transportation costs.

$$C_2 = m_3 \sum_{k \in F} \sum_{i \in (A \cup T)} \sum_{j \in (A \cup T)} d_{ij} x_{ijk} + m_4 \sum_{k \in H} \sum_{i \in (A \cup T)} \sum_{j \in (A \cup T)} d_{ij} x_{ijk} \tag{2}$$

Among them, m_3 and m_4 represent the unit transportation cost of electric vehicles and drones, respectively.

Time windows can be categorized into three types: hard time windows, soft time windows, and mixed time windows. In this paper, based on the actual situation, a mixed time window constraint function as shown in Figure 2 is designed.

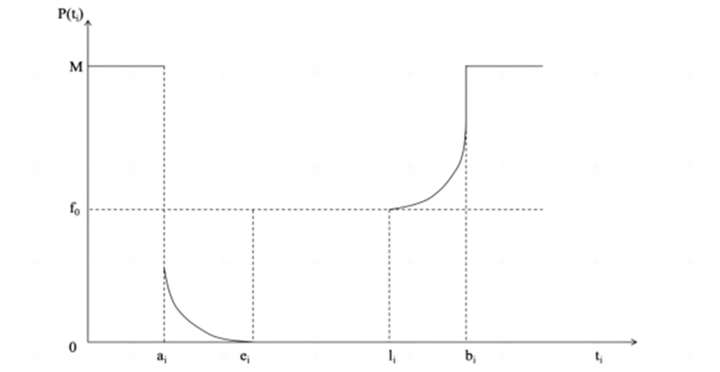

Fig. 2. Function of improved hybrid time window

In the illustration,[e_i, l_i] represents the accepted delivery time window. If the goods arrive within the [a_i, e_i] timeframe, i.e., earlier than the scheduled time, the penalty cost for this period will increase quadratically with the early arrival time. Conversely, if the goods arrive within the[l_i, b_i] timeframe, i.e., later than the scheduled time, this may lead to customer dissatisfaction due to the prolonged wait. Therefore, in addition to bearing a penalty cost similar to that for early arrival, a fixed cost f_0 must also be assumed. For goods arriving between [0, a_i] and [b_i, +∞) since they have exceeded the acceptable earliest or latest arrival time, they will be considered unacceptable, and a significantly large value M is used to represent the cost of this scenario.

$$P(t_i)=\begin{cases} M, & t_i \le a_i \\ u(t_i-e_i)^2, & a_i < t_i \le e_i \\ 0, & e_i < t_i \le l_i \\ f_0+u(t_i-l_i)^2, & l_i < t_i \le b_i \\ M, & t_i > b_i \end{cases} \tag{3}$$

Drones and electric vehicles do not directly produce carbon emissions during their usage. Their primary carbon footprint originates from the electricity consumption and the production of materials required for maintenance and upkeep. Therefore, the carbon emission costs for drones and electric vehicles are composed of two parts.

$$C_{use}=\frac{(FC_1+FC_2)\times\frac{d_{ij}}{100}}{\mu}\bullet k\bullet C_{tax} \tag{4}$$

$$C_p=\sum m_i\bullet k_i \tag{5}$$

$$C_3=C_{use}+C_p \tag{6}$$

Among them, FC_1 and FC_2 respectively represent the power consumption of electric vehicles and drones traveling 100 kilometers, μ represents the charging efficiency, k represents the carbon emission factor of power consumption, m_i represents the quality of substance i that needs to be supplemented, and k_i represents the carbon emission factor of substance i that needs to be used.

2.4 Model Establishment

Objective function:

$$minZ=C_1+C_2+P(t_i)+C_3 \tag{7}$$

Constraints:

$$\sum_{i\in T} q_{ik}\le Q_k,\quad (k\in F) \tag{8}$$

$$\sum_{i\in N} q_{ik}\le Q_k,\quad (k\in H) \tag{9}$$

$$\sum_{k\in H}\sum_{i\in N} x_{ijk} = 1, \quad (j \in N) \tag{10}$$

$$\sum_{k\in H}\sum_{j\in N} x_{ijk} = 1, \quad (i \in N) \tag{11}$$

$$\sum_{i\in A} x_{ijk} = \sum_{j\in T} x_{jik}, (i \in A, j \in T, k \in F) \tag{12}$$

$$\sum_{i\in T} x_{ijk} = \sum_{j\in N} x_{jik}, (i \in T, j \in N, k \in H) \tag{13}$$

In the model described above, equations (8) and (9) indicate that the total load of goods carried by the electric vehicle or drone is less than its maximum carrying capacity; equations (10) and (11) specify that each drone will provide delivery service to each village's fixed receiving point only once; equation (12) signifies that the electric vehicle departs from and eventually returns to the distribution center; and equation (13) denotes that the drone departs from the electric vehicle's temporary stopping point and ultimately returns to this stopping point.

3 ALGORITHM DESIGN

This paper addresses the issue of collaborative distribution logistics in rural areas, taking into consideration multiple factors such as customer satisfaction and carbon emissions, and proposes an effective distribution optimization scheme. Initially, the k-means clustering algorithm is utilized to determine the stopping point locations for electric vehicles, optimizing the distribution network layout for efficient resource utilization. Subsequently, an improved ant colony algorithm is introduced to optimize the delivery routes, aiming to further reduce delivery costs, shorten delivery times, and decrease carbon emissions, thereby enhancing the environmental friendliness of the overall logistics system.

3.1 k-Means Clustering to Determine the Position of Stopping Point of Electric Vehicle

The k-means algorithm, with its straightforward implementation, efficient computational performance, and wide applicability, has been universally applied in the fields of data classification and cluster analysis. Faced with the challenges of rural logistics distribution, especially the complexity of the terrain and the widespread distribution of delivery points, the k-means algorithm can effectively determine the stopping points for electric vehicles, crucially reducing logistics costs and significantly enhancing delivery efficiency.

Step 1: Data Preparation. Set $D=\{d_1,d_2,...,d_n\}$ as the collection of all fixed receiving points in the villages. Where, $d_1=(x_1, y_1)$ represents the coordinates of the distribution center.

Step 2: Selecting the Number of Clusters k. The number of clusters is predetermined, This paper sets k according to the actual situation.

Step 3: Assigning Cluster Centers. For each village's fixed receiving point d_i, calculate its distance to each cluster center and assign it to the nearest cluster center.

$$d_{(x_i,x_j)} = \sqrt{\sum_{k-1}^{d} (x_{ik} - x_{jk})^2} \tag{14}$$

Step 4: Updating Cluster Centers. For each cluster, recalculate the average position of all member delivery points and set this average position as the new cluster center.

$$c_j = \frac{1}{|S_j|} \sum_{d_i \in S_j} d_i \tag{15}$$

Where, S_j is the set of fixed receiving points of all villages assigned to clustering center c_j, and

$|S_j|$ is the number of fixed receiving points of villages in the set.

Step 5: Repeat the iteration. Repeat Step3 and Step4 until the clustering center no longer changes or a preset upper limit of iterations is reached.

Step 6: Output clustering results.

3.2 Improved Ant Colony Algorithm

In addressing the rural logistics distribution problem, considering the complexity of delivery routes and the diversity of demands, this study opts for the ant colony optimization (ACO) algorithm for route optimization. The ACO algorithm is a heuristic algorithm that simulates the foraging behavior of ants in nature and is suitable for solving combinatorial optimization problems. However, in the application of the ACO algorithm, the setting of the initial pheromone level significantly affects the algorithm's performance. Too high or too low initial pheromone concentration can lead to premature convergence or inefficient search processes, impacting the quality of the final solution. To address this issue, this paper obtains a superior initial solution through a hybrid binary method, providing a better foundation for the subsequent iterations of the ACO algorithm. This effectively enhances the algorithm's performance and stability in solving practical logistics distribution route optimization problems.

Step 1 involves using a hybrid binary algorithm to find initial solutions and update pheromone levels[10]. The first method, Variable Neighborhood Search, starts with an initial solution, searches within different neighborhood structures for improved solutions, and updates the current solution if a better one is found. If not, it moves to the next neighborhood structure. The second method, Greedy Search, begins with the distribution center initiating delivery, selecting the nearest electric vehicle stopping point within the maximum load capacity of both the electric vehicle and drones.

Drones are then deployed from these points, prioritizing the nearest customer points and ensuring each delivery does not exceed the drone's weight limit. This process continues until all customers are served, with drones eventually returning to the electric vehicle, which then returns to the distribution center.

Step 2: Calculate the path selection probability. Calculating route selection probability is the core mechanism of ant colony algorithm, which guides ants to make decisions when constructing distribution routes. Specifically, when the ants choose the next distribution point to travel, they calculate the probability based on the pheromone concentration and distance from the current location to other distribution points.

$$P_{ij} = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{s\in allowed_k}[\tau_{is}(t)]^{\alpha}[\eta_{is}(t)]^{\beta}}, & j \in allowed_k \\ 0, & j \notin allowed_k \end{cases} \tag{16}$$

Here, $allowed_k$ is a collection of cities that the KTH ant has not visited.

Step 3: Update pheromone concentration. Updating the pheromone concentration is a crucial step in the iterative process of the algorithm. The purpose is to enhance the pheromone on the superior paths, thereby guiding ants to prefer these paths in subsequent iterations. This step ensures that the algorithm progressively converges towards the most efficient routes by reinforcing positive feedback on successful paths, which is a fundamental principle of the ant colony optimization algorithm.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m}\Delta\tau_{ij}^{k} \tag{17}$$

$$\Delta\tau_{ij}^{k} = \frac{Q}{f_k} \tag{18}$$

Where f_k represents the total cost of the ant's route.

Step 4: Repeat iterations. Repeat Steps 2 and 3 until the optimal solution no longer changes or until the preset maximum number of iterations is reached. This iterative process allows the algorithm to refine the solutions continuously by exploring new paths and reinforcing the pheromone on the most successful ones, gradually converging towards the most efficient and cost-effective delivery routes.

Step 5: Output the optimal route.

4 EXPERIMENTAL SIMULATION AND RESULTS ANALYSIS

4.1 Experimental Case Study

In this study, we utilize the renowned Solomon[11] benchmark dataset to validate the effectiveness and efficiency of the proposed algorithm. Specifically, we carefully selected two different instances from the dataset: C101, R101, and RC101, each representing different delivery scenarios. To construct the experimental case study, we chose the first 30 delivery points from each instance for analysis. This selection is designed to demonstrate the versatility and adaptability of our algorithm in handling different types of routes (C-type for clustered routes, R-type for random routes). By testing on these classic experimental instances, our aim is to comprehensively assess the algorithm's performance in practical applications, especially its capability in route optimization and cost reduction.

4.2 Algorithm Parameters

This study uses k-means clustering algorithm and improved ant colony algorithm, and the specific parameters are as follows:

The number of iterations G=50, the number of clusters k=3, the number of ants m=50, the pheromone evaporation rate ρ=0.5, the pheromone influence factor α=1, the heuristic influence factor β=2, and the updating pheromone concentration Q=100.

4.3 Model Parameters

The model parameter Settings are shown in Table2.

Table 2. Model parameter table

Argument	Numerical value	Argument	Numerical value
Q_E	4t	m_2	100RMB/piece
Q_t	80kg	m_3	0.65RMB/km
V_E	60km/h	m_4	0.40RMB/km
V_D	40km/h	k_i	2.50RMB/kg
m_1	500RMB/vehicle		

4.4 Algorithm Analysis

In order to fully evaluate the effectiveness of the proposed improved algorithm, detailed tests will be performed on two selected instances of the Solomon dataset, C101, R101. These examples represent different types of customer distributions, providing us with rich test scenarios to examine the applicability and performance of the algorithm. The focus of the test will be on the optimal solution that the algorithm can achieve and the number of iterations required to achieve this optimal solution.The specific results are shown in Figure 3 and Figure 4.

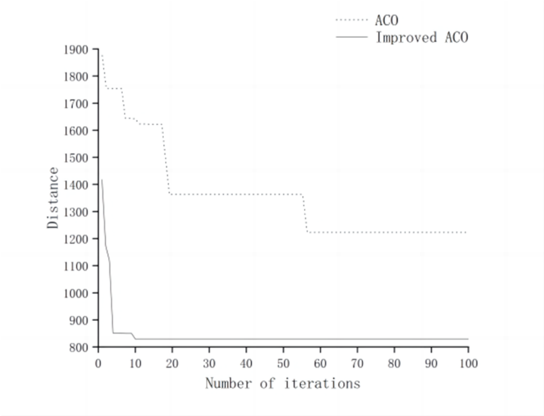

Fig. 3. C101 iteration diagram

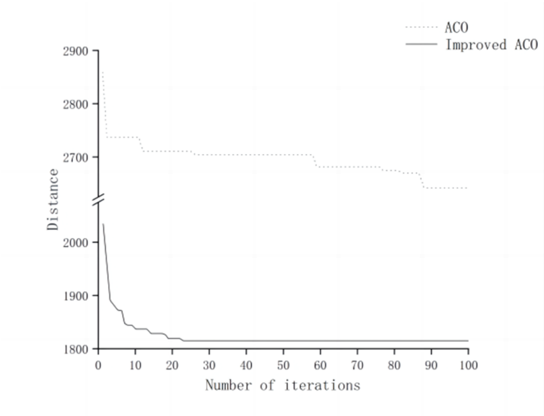

Fig. 4. R101 iteration diagram

According to the data in Table 3, it is clear that the improved ant colony algorithm outperforms the traditional ant colony algorithm in terms of obtaining the optimal solution, the average quality of solutions, and the number of iterations. Specifically, the performance of the improved ant colony algorithm has increased by 33.06% in terms of optimal solution, by 31.28% in the quality of average solutions, and the number of iterations has been reduced by 36.93%. These data not only prove the effectiveness of the improved algorithm but also highlight its efficiency in solving specific problems.

Further analysis of these results reveals several key factors that have positively impacted the performance of the improved ant colony algorithm. Firstly, the optimization of the algorithm may involve improvements in the search strategy, such as more effective use of heuristic information, enabling the algorithm to focus more quickly on high-quality solutions. Secondly, the refinement of parameter adjustments may also have a positive effect on the convergence speed and stability of the algorithm, thereby more effectively finding the optimal or near-optimal solutions during the iteration process.

Table 3. Results of ant colony algorithm and improved ant colony algorithm are obtained

Data set	Standard ant colony algorithm			Improved ant colony algorithm		
	Optimal solution	Mean solution	Mean frequency of convergence	Optimal solution	Mean solution	Mean frequency of convergence
C101	1218.56	1332.35	45.85	845.63	953.32	25.70
R101	2537.75	2758.68	61.34	1621.84	1843.29	38.59

4.5 Cost Analysis

In the cost analysis of the logistics distribution system, this study focuses on comparing three different distribution modes: the electric vehicle (EV) + drone combination mode, the pure electric vehicle mode, and the traditional fuel vehicle mode. This analysis aims to delve into the differences between each mode in terms of operational costs, carbon emissions, and customer satisfaction. Figures 5 to 6 are the optimal route maps for the EV + drone mode under C101, R101(each selecting 30 customer points), respectively.

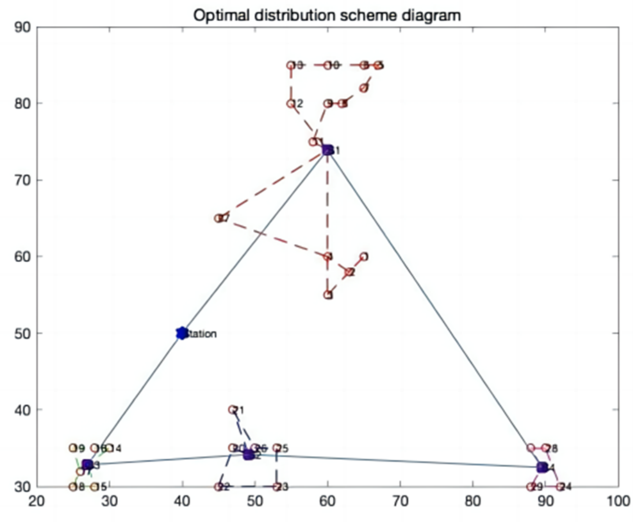

Fig. 5. C101 Optimal roadmap

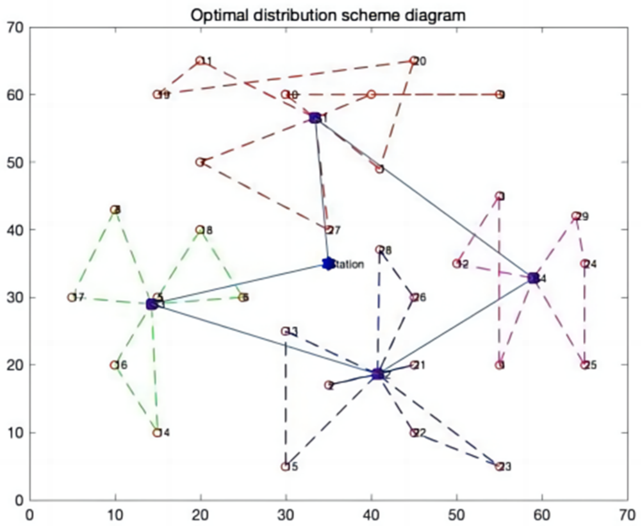

Fig. 6. R101 Optimal roadmap

According to Table 4, it is observed that compared to conventional fleets, the total cost under the drone + electric vehicle delivery mode has significantly decreased, with a reduction rate of 13.72%, 13.10%, and 16.73% across the three datasets, respectively. In terms of environmental protection, the carbon emissions of the drone + electric vehicle mode are also lower than those of conventional fleets, with reductions of 43.51%, 40.55%, and 39.40%. Additionally, due to the efficiency of collaborative delivery, penalties for violating time windows have decreased by 46.30%, 24.75%, and 21.46%, respectively.

Analyzing the above experimental results, the combined delivery mode of drones and electric vehicles has demonstrated exceptional performance in reducing delivery costs and lowering carbon emissions through its efficiency, flexibility, and environmentally friendly approach. This mode fully leverages the advantage of drones for direct delivery of goods and the characteristic of electric vehicles for efficient energy conversion, effectively avoiding congestion in ground traffic and unnecessary long-distance transportation.

Table 4. Comparative statement of costs

Data set	Regular fleet			Electric vehicle + drone fleet		
	Total cost	Carbon emission	Time window penalty	Total cost	Carbon emission	Time window penalty
C101	2840.32	193.38	261.34	2450.52	109.24	132.32
R101	3321.19	227.19	249.15	2885.95	135.07	187.48

5 CONCLUSIONS

This study has constructed and validated a rural logistics route optimization model based on the collaborative delivery of electric vehicles and drones, clearly demonstrating the significant advantages of this innovative delivery mode in reducing total costs, cutting carbon emissions, and enhancing delivery efficiency. The experimental results show that, compared to traditional vehicle-only delivery modes, the electric vehicle + drone collaborative delivery mode achieves an average total cost reduction of 14.52%, a mean decrease in carbon emissions of 41.15%, and a significant reduction in penalties for time window violations, averaging a decrease of 30.83%. These achievements not only confirm the dual advantages of this mode in economic and environmental sustainability but also highlight the potential of collaborative delivery in improving rural logistics efficiency and customer satisfaction.

Moreover, the k-means clustering algorithm and the improved ant colony algorithm used in this study have shown strong performance in optimizing delivery routes, enhancing the layout of the delivery network, and effectively reducing carbon emissions and costs during the delivery process. The successful practice of this innovative delivery mode provides not only an effective solution for rural logistics distribution systems but also offers new ideas and methods for the logistics industry when facing complex geographical environments and widely distributed delivery points.

In conclusion, the introduction of the electric vehicle and drone collaborative delivery mode provides reliable technical support for achieving efficient, low-cost, and environmentally friendly rural logistics services, which is of significant importance for promoting the development of rural e-commerce and optimizing rural logistics systems. Future research could further explore the adaptability and optimization strategies of this mode in different geographical environments and scales of application, providing theoretical and practical guidance for a wider range of application scenarios.

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