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Research on Path Planning for Rural Truck-Drone Combined Delivery

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ABSTRACT
In order to solve the truck and drone cooperative distribution path planning problem that simultaneously picks up and delivers goods and reduces carbon emissions, this paper establishes a joint path planning model considering carbon emissions by taking the minimisation of the total transport cost as the goal and combining the constraints of load and range. The model is solved by designing an improved genetic algorithm and compared with the PSO algorithm to verify the effectiveness of the model and algorithm. The results show that the model can significantly reduce the logistics cost, especially in the medium-sized case, the cost reduction reaches 52.1%. The improved genetic algorithm outperforms PSO in terms of path planning, convergence performance and cooperative logic, and can effectively shorten the distance travelled by trucks by 36.2%-52.9%, and achieve the complementary advantages of trucks and drones. The model and algorithm have good adaptability in different scale rural e-commerce logistics scenarios, which provides theoretical support for cost reduction and efficiency.

Keywords: *Route planning; Carbon emissions; Combined delivery*

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I. INTRODUCTION

With the development of e-commerce, improving distribution efficiency and reducing logistics costs have become key topics in the industry. Technological progress and demand upgrading have pushed drone distribution to become a research hotspot, but due to the limitations of small loads and short flight distances, it is difficult for drones to independently complete large-scale distribution tasks. Therefore, the joint distribution mode of trucks and drones has become an effective choice to improve efficiency and reduce costs.

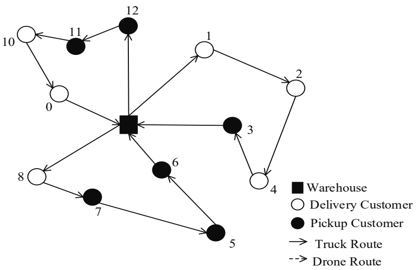
The integrated planning of pickup and delivery is the key to reduce the empty rate, cut cost and improve efficiency of express enterprises, and thus becomes the focus of research. Liu Jiansheng et al[1] proposed an adaptive brainstorming algorithm to solve the simultaneous pickup and delivery problem with time windows; Xu Ning et al[2]proposed to solve the path optimisation problem for larger scale simultaneous pickup and delivery in logistics and distribution.KARAK et al[3] considered the hybrid vehicle-drone path problem for pickup and delivery services. The research on cooperative distribution of drones and trucks mostly revolves around carbon emission. Drone-truck cooperative distribution research mainly focuses on carbon emissions.Chiang[4]and Kuo[5]et al. incorporate emission reduction objectives in path optimisation to prove the advantages of drone-assisted distribution; GOODCHILD et al.[6] compare the differences in carbon emissions between trucks and drones and find that the co-operative distribution advantage is more significant in the overall framework.In terms of solution algorithms, Deng Yongrui et al[7] constructed a cold chain logistics model and solved it using an improved genetic algorithm; Cao Yingying et al[8]solved the joint truck-drone delivery problem under clustering with a two-stage algorithm of genetic simulated annealing.Han et al[9]optimised the system's operating cost by using an improved artificial bee colony algorithm.

Although existing studies have proposed joint drone-truck pickup and delivery services, most of them have not considered carbon emissions or have only focused on delivery but neglected pickup. In this paper, based on previous studies, we design a model that is closer to the actual scenario, considering pickup and delivery services and carbon emissions, and construct a path planning model with the objective of minimising transport costs.

II. PROBLEM DESCRIPTION AND MODEL

2.1 Problem description

At present, rural e-commerce logistics terminal distribution is usually carried out by vehicles from the logistics outlets in townships or core villages to deliver parcels to customers, as shown in Figure 1. Due to the problems of ‘long logistics chain and low consumption density’, the distribution cost is high and the efficiency is low, and even in remote areas, the parcels need to be picked up by the users themselves. Therefore, this paper investigates the cooperative distribution mode of drones and vehicles, as shown in Figure 2. Vehicles carry drones and parcels, start from logistics outlets, and complete distribution tasks in collaboration with drones according to planned routes. Specifically, the truck departs from the distribution centre, carries the drone to complete the task and returns, customers beyond the load or distance limit are distributed by the truck, and customers on the collaborative path are completed by the truck and the drone together.



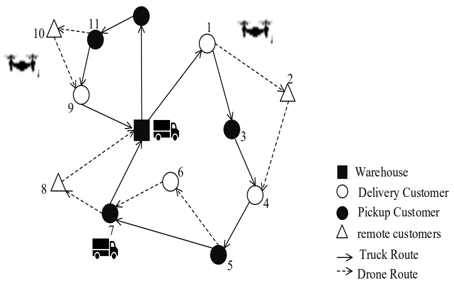


Figure 1.Traditional delivery model.Figure 2.Drone-Vehicle Collaborative Delivery Model.

For further quantitative study and mathematical modelling of the problem, the scenarios and the problem are simplified and the following assumptions are made:

(1) All customer locations and demand are known, enabling drone takeoff and landing;(2) The drone carries multiple parcels each time, and each drone can make multiple deliveries, exceeding the maximum load capacity of the drone customers are delivered by the vehicle, and can only return to the vehicle docking point to replace the battery or charge after the delivery is completed;(3) Both trucks and drones travel at a constant speed during the delivery process ;(4) Trucks and drones cannot revisit any customer; each customer receives service only once.

2.2 Model construction

2.2.1 Parameter and Variable Description

N is the set of nodes, $N = \{1, 2, ..., n+1\}$, where node 1 is the distribution center;q_iRepresents delivery demand for the distribution center (q_1=0) and customer demand ($q_i \geqslant 0$);(x_i, y_i) are the coordinates of node i;d_{ij} is the distance from node i to node j,;Q_t is the maximum load of the truck;Q_d is the maximum load limit of the drone.;$R$is the maximum distance of single flight (round trip) of drone;$v_t$andv_d are the travelling/flying speeds of the truck and drone, respectively;C_{ft},C_{fd},C_{dt},C_{dd},C_{ct},$C_{cd}$are the fixed cost, distribution cost per unit distance and carbon emission cost per unit distance for trucks and drones, respectively. Variable:$x_{ij}$is 1 when the path from node i to node j is selected by the truck, and 0 otherwise;$x_{ik}$is 1 when the truck from node i meets the drone at node k, and 0 otherwise;y_{ijk} indicates whether the drone is launched by the truck at node i, proceeds to customer j, and then rendezvouses with the truck at node k. y_{ijk}= 1 if this occurs, otherwise 0;g_i represents the current payload of the truck upon arrival at node i (non-negative continuous variable);Auxiliary variable $u_i$is used to eliminate truck sub-loop (applies only to customer nodes $i \geqslant 2$).Note: i, k may represent distribution centers (node 1) or customer nodes; j: represents customer nodes only(2~n+1).

2.2.2 Model Construction

Objective function:

$$minZ = C_{ft} + C_{fd} \sum_{i,j,k} y_{ijk} + C_{dt} \sum_{i,j} d_{ij} x_{ij} + C_{dd} \sum (d_{ij} + d_{jk}) y_{ijk} + C_{ct} \sum_{i,j} d_{ij} x_{ij} + C_{cd} \sum (d_{ij} + d_{jk}) y_{ijk} \quad (1)$$

$$\sum_{j \in N \ , \ \{1\}} x_{1j} = 1 \quad (2)$$

$$\sum_{i \in N \ , \ \{1\}} x_{i1} = 1 \quad (3)$$

$$\sum_{i \neq j} x_{ij} + \sum_{i,j} y_{ij} = 1, \forall i \in N \ , \ \{1\} \quad (4)$$

$$u_i - u_j + (n+1) x_{ij} \leq n, \quad \forall i, j \in N \ , \ \{1\}, i \neq j \quad (5)$$

$$1 \leq u_i \leq n, \quad \forall i \in N \ , \ \{1\} \quad (6)$$

$$\sum_{j \in N} q_j x_{ij} \leq Q_t, \quad \forall i \in N \quad (7)$$

$$q_j \le Q_d + M(1 - y_{ijk}), \quad \forall i,j,k \in N \qquad (8)$$

$$\sum_{i \in N}\sum_{k \in N} y_{ijk} \le 1, \quad \forall j \in N\ ,\ \{1\} \qquad (9)$$

$$y_{ijk} \le x_{ij}, \quad \forall i,j,k \in N \qquad (10)$$

$$y_{ijk} \le x_{ik}, \quad \forall i,j,k \in N \qquad (11)$$

$$d_{ij} + d_{jk} \le R, \quad \forall i,j,k \in N,\ \text{且} y_{ijk} = 1 \qquad (12)$$

$$\sum_{i \in N} x_{ij} = 1, \quad \forall j \in N, p_j > 0 \qquad (13)$$

$$\sum_{j \in N} x_{ij} = 1, \quad \forall i \in N\ ,\ \{1\} \qquad (14)$$

$$g_1 = \sum_{j \in N} q_j x_{1j} \qquad (15)$$

$$g_j = g_i - q_j + p_j, \quad \forall i,j \in N, x_{ij} = 1 \qquad (16)$$

$$g_i \le Q_t, \quad \forall i \in N \qquad (17)$$

The objective function (Eq. (1)) minimises the total transportation cost, including the fixed costs of trucks, drones, path costs and carbon emission costs; Eqs. (2) and (3) ensure that the truck traffic in the distribution centre is balanced and at least one truck enters and exits the logistic centre; Eq. (4) restricts each customer node to be serviced once by a truck or a drone; Eqs. (5) and (6) eliminates the sub-loops and avoids the path loops; Eq. (7) ensures that the truck load does not exceed its capacity; Eq. (8) ensures that the total customer deliveries serviced by the drone satisfy the load constraint; Eq. (9) ensures that each customer node is serviced by the drone at most once; Eq. (10) ensures that the drone launching node is in the path of the truck; Eq. (11) denotes that the drone meets with the truck after completing its service; Eq. (12) restricts the total drones service distance from the drones to not exceeding the maximum voyage distance R; Eqs. (13), (14) ensure that the pickup node is visited by the truck and the drone is not involved in picking up the goods; Eq. (15) sets the initial load of the truck and there is no pickup demand in the distribution centre; Eq. (16) defines the change of the truck load, where the delivery node load is reduced and the pickup node load is increased; and Eq. (17) restricts the truck load not to exceed the capacity limit.

III. ALGORITHM DESIGN

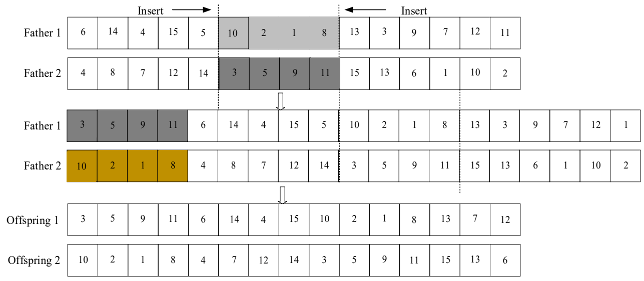
The GA-ALNS algorithm combines the global search capability of genetic algorithm with the local optimisation capability of Adaptive Large Neighbourhood Search (ALNS), which reduces ineffective searches and optimises the joint truck and drone delivery paths by quickly removing inefficient path segments through the destruction operator and accurately inserting customer points through the repair operator. In this study, adaptive large neighbourhood search (ALNS) is performed after the variable operations of the traditional genetic algorithm to obtain the optimal solution.

3.1 Encoding Scheme

The chromosome is generated using integer coding form, encoding customer nodes with integers 2,3,...,n and distribution centres with 1. Randomly arrange the customer points and insert 1 into the arrangement based on constraints such as truck load and drone load.

3.2 Constructing Initial Solutions

Initial solutions are constructed using a genetic algorithm (GA) through the following steps.step 1: Randomly generate the initial population p_t;step 2: Selection operation. Employ a roulette wheel selection method to screen individuals with higher fitness values based on their fitness scores, which are then used for subsequent crossover, mutation, and local search operations. Step 3: Crossover Operation. In this section, the sequential crossover (OX) operator is designed as shown in Fig. 3. This operator generates crossover segments by randomly selecting the start and end positions of the chromosomes of the two parents, moving the crossover segment of parent 1 to the front end of parent 2 and vice versa. In the new parent, the duplicate coding within the non-crossover fragment is removed to form a new offspring. Step 4: Mutation operation. Randomly select a chromosome as a mutated individual, generate multiple mutation points and perform the exchange operation, as shown in Figure 4.



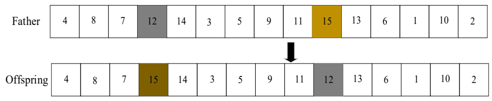


Figure 3. Cross-section diagram   Figure 4. Schematic diagram of mutatio

3.3 ALNS Algorithm

To overcome the limitation of GA algorithms prone to local optima due to insufficient search strategies, this study employs the multi-neighborhood search mechanism of the ALNS algorithm. By alternately applying destruction and repair operators, it effectively generates new feasible solutions within the domain, helping the algorithm escape local optima.

Destruction operators and repair operators： (1) Random destruction operator: randomly delete m customer points in the path of the drone or truck in the current solution. (2) Maximum saving point destruction operator: delete m customer points in the current path that increase the total cost the most. (3) Lowest relevant match destruction operator: remove m customer points in the current path with the lowest match according to the distance between customers.Greedy repair operator reduces the cost by selecting appropriate locations to insert customer points. Stochastic repair operator which mainly includes vehicle-first repair operator and drone-first repair operator.Adaptive weight adjustment is the dynamic adjustment of the weights according to the effect of the operator on the improvement of the solution quality.

3.4 Algorithm Termination Criteria

When the set maximum number of iterations is reached, the algorithm stops iterating and outputs the final solution, as shown in Figure 5.

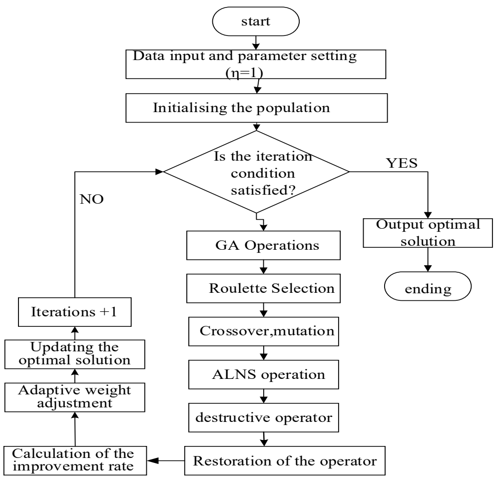


Figure 5.Flowchart of the improved genetic algorithm

IV. CASE STUDY ANALYSIS

4.1 Experimental Environment and Parameter Settings

This study is implemented using Matlab 2024a programming with a computer configuration of Intel(R) Core(TM) i7-10510U CPU @ 1.80GHz 2.30 GHz and Windows 11 as the operating system.Due to the lack of standard arithmetic libraries, this paper generates arithmetic examples of random customer points based on actual data and references to related literature to demonstrate the model and algorithmic to demonstrate the optimisation characteristics of the model and algorithm. The model parameters are shown in Table 1.

Table 1. Parameters and values in this model

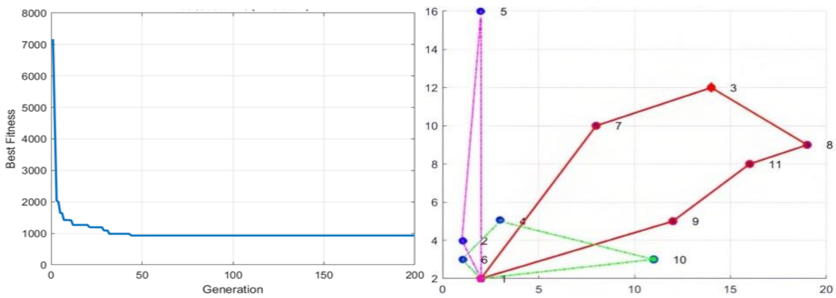
Parameters	value	Parameters	value
C_{ft}/(yuan·vehicle^{-1})	100	Q_t/kg	50
C_{fd}/(Yuan·Frame^{-1})	30	Q_d/kg	5
C_{dt} /(yuan·km$^{-1)}$	1.5	v_t/(km • h^{-1})	30
C_{dd}/(yuan·km^{-1})	0.15	v_d/(km • h^{-1})	60
C_{ct}/(yuan·km^{-1})	1	M	1000
C_{cd}/(yuan·km^{-1})	0.3	R/km	40

4.2 Applicability Analysis

To validate the universality of the model and algorithm, a small-scale case study was conducted by generating 10 customer points within a 20×20 grid. The coordinate point (1,1) was designated as the distribution center. The Particle Swarm Optimization (PSO) algorithm was selected as the benchmark due to its widespread application in path optimization problems, fast convergence speed, and shared heuristic nature with the Genetic Algorithm (GA), making the comparison results more persuasive. Therefore, the results obtained by the improved genetic algorithm in this study were compared with those of the PSO algorithm, as shown in Table 2.

Table 2: Solution Paths of GA-ALNS Algorithm and PSO Algorithm

Solution result		GA-ALNS algorithm	PSO algorithm
	truck	1→7→3→8→11→9→1	1→4→11→6→3→9→2→8→1
Solution path	Drone 1	1→6→4→10→1	1→7→1
	Drone 2	1→2→5→1	1→5→10→1
Solution time/s		3.11	3.51



(a) GA-ALNS algorithm solving iterative graphs (b) GA-ALNS algorithm solving optimal paths
Figure 6. GA-ALNS Algorithm Results for Small-Scale Example

As seen in Table 2, the GA-ALNS algorithm outputs shorter truck paths and more compact nodes than the PSO algorithm. The drone path achieves 'multi-client tandem service' and improves the utilisation rate (e.g. path 1→6→4→10→1, 1→2→5→1), whereas the drone path (1→7→1) in the PSO algorithm serves only one client and suffers from a high idling rate problem. The solution time is 3.11s for GA-ALNS and 3.51s for PSO, with 11.4% efficiency improvement. Although PSO converges faster, it is easy to fall into the local optimum, and increasing the number of iterations will prolong the computation time. From Fig. 6(b), it can be seen that the drone gives priority to serve customers far away from the distribution centre (e.g, Customer 5), which effectively reduces the truck mileage and saves cost.

In order to verify the universality of the model and algorithm, this paper is tested by multi-scale cases, respectively constructing small-scale, medium-scale and large-scale cases with 10, 30 and 70 customer points. All customer points are randomly generated in the grid, and the medium-scale and large-scale cases use a 100×100 grid to simulate township-level distribution scenarios with more dispersed customer points, which is in line with the distribution characteristics of the rural 'long logistics chain and low consumption density'. The coordinates of the distribution centre are set as (1,1) for the small-scale example and (50,50) for the medium- and large-scale examples. The results are shown in Table 3.

Table 3 Comparison of solution results of GA-ALNS and PSO

Example	GA-ALNS algorithm				PSO algorithm			
	Total cost /yuan	Truck driving distance/km	Drone travel distance/km	Numberof termination iterations	Total cost /yuan	Truck driving distance/km	Drone travel distance/km	Number of termination iterations
small-scale	284.82	40.96	49.82	48	341.38	64.2	46.4	78
medium scale	1665.57	570.5	109.6	79	3475.76	1213.81	158.3	89
large-	3848.73	1238.74	448..63	496	5805.78	1965.17	961.89	325

scale

The experimental results show that the GA-ALNS algorithm reduces the cost by 16.6%, 52.1%, and 33.7% in the small-scale, medium-scale, and large-scale cases, respectively, with the medium-scale effect being the most significant; in terms of the path optimisation, the medium-scale truck travelling distance is reduced by 52.9% compared with the PSO algorithm. Meanwhile, GA-ALNS converges faster and more stable, and the total cost and distance travelled are better than PSO algorithm.

V. CONCLUSION

In this paper, we constructed a joint truck-unmanned aircraft distribution model considering pickup and delivery demand, carbon emission, load and range constraints, and solved the model by improved genetic algorithm with the objective of minimising the total transportation cost. The example results show that the model can significantly reduce logistics costs, which meets the needs of rural e-commerce cost reduction and efficiency; the improved GA-ALNS algorithm outperforms the PSO algorithm in terms of path optimisation, convergence performance, and collaborative efficiency; the model is applicable to village, township, and county scenarios, with the township level having the most prominent effect on cost reduction. Future research can further extend the joint transport path optimisation in dynamic environments.

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