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Optimization of Vehicle-UAV Collaborative Delivery Path Based on Improved Genetic Algorithm

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ABSTRACT

As urban demand for last-mile logistics grows rapidly, vehicle-UAV collaborative delivery has drawn widespread interest as an efficient distribution mode. To address the path optimization problem in the collaborative delivery of a single vehicle with two UAVs, this study proposes an optimization approach based on an improved genetic algorithm. Multi-chromosome hybrid encoding is employed to simultaneously represent the collaborative paths of the vehicle and UAVs. The algorithm's global search capability and convergence speed are enhanced by integrating elitism preservation, adaptive crossover and mutation, neighborhood transformation, and task perturbation strategies. A multi-objective optimization model is established to comprehensively consider delivery time, energy consumption, and cost, with simulation experiments conducted in the MATLAB. The experimental results demonstrate that the improved algorithm significantly reduces total delivery time, energy consumption, and costs compared to traditional single-vehicle delivery and standard genetic algorithms, while also enabling reasonable task allocation and path planning. Additionally, the algorithm shows good stability and robustness under different parameter conditions. This research offers an effective approach and theoretical reference for optimizing vehicle-UAV collaborative delivery routes in intelligent logistics systems, and has practical significance for improving the efficiency of urban last-mile delivery.

KEYWORDS

Vehicle-UAV collaboration; Path optimization; Improved genetic algorithm; Energy consumption model; Collaborative scheduling

1 Introduction

With the rapid development of e-commerce and instant logistics, last-mile delivery has become a critical factor constraining the overall efficiency of logistics systems. Traditional delivery methods primarily rely on vehicles for centralized transportation. However, against the backdrop of urban traffic congestion, dispersed delivery nodes, and increasingly stringent customer time requirements, the single-vehicle delivery model faces challenges in both time cost and economic efficiency. In recent years, the Vehicle-UAV (V-UAV) collaborative delivery model has emerged as a significant research direction in intelligent logistics systems due to its combination of the large capacity of vehicles and the high flexibility of drones [1].

In Vehicle-UAV (V-UAV) collaborative delivery systems, vehicles serve as mobile platforms responsible for trunk transportation and the deployment/recovery of drones, while drones perform short-distance, rapid last-mile delivery tasks, thereby significantly enhancing overall delivery efficiency and reducing transportation costs. However, the path optimization problem of this system (Vehicle-UAV (V-UAV) Routing Problem, VDRP) exhibits complex combinatorial characteristics, requiring consideration not only of task allocation between vehicles and drones, range constraints, energy consumption constraints, and time synchronization issues, but also seeking the optimal delivery solution under multi-objective optimization [2].

Traditional heuristic algorithms are prone to falling into local optima when solving VDRP, making it difficult to balance global search and local optimization performance. The Genetic Algorithm (GA) is widely applied to path optimization problems due to its strong global optimization capability, but issues such as slow convergence speed and insufficient precision persist. To address this, this paper introduces adaptive parameter adjustment and a local search mechanism based on the standard genetic algorithm to improve the algorithm, aiming to achieve efficient optimization of collaborative delivery paths for vehicles and drones [3].The purpose of this study is to: construct an efficient vehicle–UAV collaborative delivery model by improving the genetic algorithm, achieve the comprehensive optimization of total delivery cost, time, and energy consumption, and provide a reference for route scheduling in intelligent logistics systems.

2 Vehicle-UAV (V-UAV) Collaborative Delivery Model Establishment

This paper studies a vehicle-UAV collaborative delivery system composed of one truck and two drones, as shown in Figure 1. The truck departs from the distribution center and transports packages along a predetermined path. Under conditions satisfying load capacity and endurance constraints, drones can take off from truck docking points to execute short-range delivery tasks and return to the truck or designated recycling points after completing the delivery. The objective is to minimize the system's total delivery time, total cost, and energy consumption while warranting task completion.

In this system, the vehicle is primarily responsible for trunk transportation and drone trunk support, while the drones undertake flexible delivery tasks for endpoint nodes.Vehicles and drones must maintain task time coordination, meaning the takeoff and recycle of the drone's task execution must be completed within the time window of the truck's arrival at the corresponding node [4].

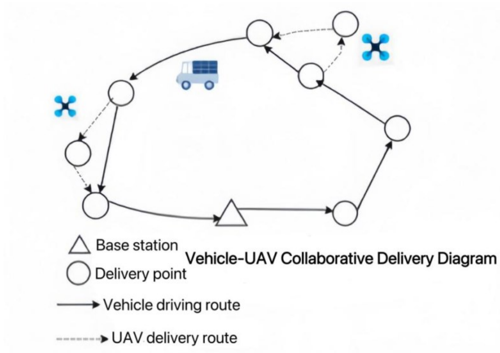

Figure 1 Schematic diagram of Vehicle-UAV collaborative delivery

2.1 Model Assumptions

To simplify the model and facilitate problem-solving, this paper makes several reasonable assumptions when establishing the vehicle–UAV collaborative delivery path optimization model. First, all delivery tasks are assumed to be known before scheduling begins, with fixed and unique coordinates for delivery points, ensuring that location data remains unchanged during path planning. Second, both trucks and drones depart from the same distribution center and return to it after completing all delivery tasks, forming closed-loop delivery paths. Regarding drone operations, it is assumed that the truck must charge or replace the battery of each UAV before takeoff to ensure no energy depletion during flight, while the drone's flight distance must not exceed its maximum range constraint to ensure path feasibility. Furthermore, the model assumes real-time communication between the truck and the drone with no delayed interference to simplify the Information synchronization problem. To spotlight the path optimization problem, this paper does not consider the impact of external interference factors such as environmental wind speed and obstacles on the drone's flight. In terms of delivery method selection, each customer node is served by only one delivery method—either by truck or by drone—to avoid redundant delivery and task conflict. Based on the above assumption, this paper systematically sets the parameters involved in the entire collaborative delivery process, including vehicles, drones, and delivery nodes, providing fundamental conditions for subsequent path optimization and algorithm design [5].

Table 1 Node Parameter Settings Table

Symbol	Meaning
N	Number of customer points
$V = \{0,1,2,\ldots,N\}$	Collection of nodes, with one node being the distribution center
$D_{i,j}$	Distance between node (i) and node (j)
C_T, C_D	Cost per unit distance for truck and drone
E_T, E_D	Energy consumption per unit distance for truck and drone
v_T, v_D	Average speed of truck and drone
R_D	Maximum flight range of drone
$T_{i,j}$	Transportation time from node (i) to (j)

2.2 Objective Function

To comprehensively consider efficiency, cost, and energy consumption during the delivery process, this paper constructs the following multi-objective optimization model. By adopting a weighted approach, the model simultaneously minimizes the total delivery time, total transportation cost, and system energy consumption, thereby achieving the overall optimization of vehicle and drone collaborative delivery [6]. The specific objective function is as follows:

$$\operatorname{Min} F = \alpha T_{\text{total}} + \beta C_{\text{total}} + \gamma E_{\text{total}} \tag{1}$$

Among them, the total delivery time T_{total} is composed of the vehicle travel time T_T and the maximum time taken by the drones to complete their tasks, $\max(T_{D1}, T_{D2})$:

$$T_{\text{total}} = T_T + \max\left(T_{D1}, T_{D2}\right) \tag{2}$$

The total transportation cost C_{total} includes the sum of the transportation costs of vehicles and drones on their respective delivery paths:

$$C_{\text{total}} = \sum_{(i,j)\in R_T} C_T d_{ij} + \sum_{(i,j)\in R_D} C_D d_{ij} \tag{3}$$

The total system energy consumption is obtained by accumulating the energy consumption of vehicles and UAVs along their delivery routes:

$$E_{total} = \sum_{(i,j)\in R_T} E_T d_{ij} + \sum_{(i,j)\in R_D} E_D d_{ij} \tag{4}$$

where, α, β, γ are the weight coefficients of time, cost price, and energy consumption, used to reflect the importance of different factors in the optimization objective.

2.3 Constraints

While constructing the multi-objective optimization model, it is necessary to impose several constraints on the path planning procedure to ensure the feasibility of vehicle–UAV collaborative delivery [7]. The first is the integrity constraint, which requires each customer point to be visited only once, and the paths of both the vehicle and the drone must form closed loops to warrant that all delivery tasks are covered:

Path Integrity Constraint:

$$\sum_{j=1}^{N} x_{ij} = 1, \sum_{i=1}^{N} x_{ji} = 1 \tag{5}$$

Among them,

x_{ij} indicates whether node j is directly reached from node i in the delivery path.

Next is the drone range constraint, which requires that the total flight distance of the drone in a single takeoff task must not exceed its maximum range R_D, to warrant the feasibility of the flight task:

$$\sum_{(i,j)\in R_D} d_{ij} \leqslant R_D \tag{6}$$

For vehicles, the load capacity constraint must also be met, which requires that the total cargo carried by a vehicle does not exceed its maximum capacity:

$$\sum_{i\in R_T} q_i \leqslant Q_T \tag{7}$$

where q_i is the customer demand, and Q_T is the maximum vehicle capacity.

Finally, the time synchronization constraint requires that the UAV's takeoff and recovery times must fall within the vehicle's parking time interval. This ensures that the UAV can be recharged or have its battery replaced by the vehicle during the delivery process, while guaranteeing real-time coordination and task continuity in the collaborative delivery system.

3 Improved Genetic Algorithm Design

3.1 Genetic Algorithm Overview

The Genetic Algorithm (GA) is a global optimization method inspired by natural selection and genetic mechanisms [8]. It exhibits strong parallelism and robustness, making it particularly suitable for addressing complex combinatorial optimization problems such as the Vehicle Routing Problem (VRP). In the context of vehicle–UAV collaborative delivery, traditional genetic algorithms tend to converge prematurely to local optima or suffer from slow convergence when handling multiple competing objectives. To address these limitations, this paper incorporates multidimensional encoding, neighborhood transformation, elite preservation, and adaptive crossover and mutation strategies into the basic GA framework, thereby improving both global search capability and convergence efficiency.

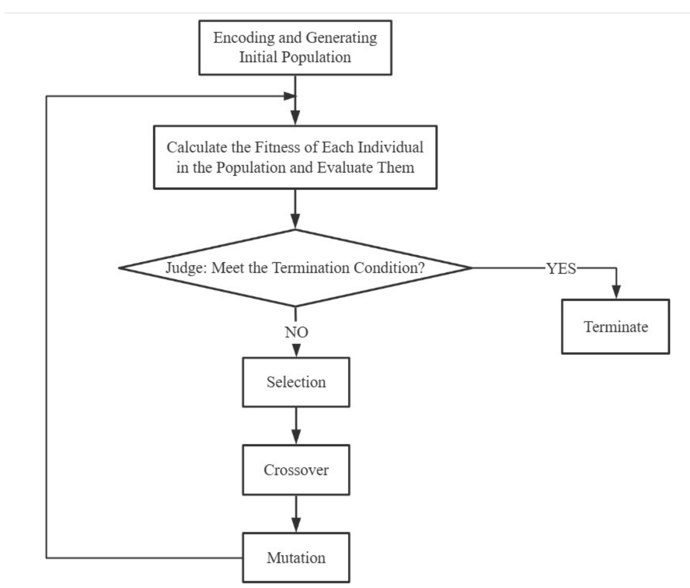

Figure 2 Genetic Algorithm Flowchart

3.2 Encoding Design

To represent the coordinated paths of both trucks and drones, this paper employs a multi-chromosome hybrid encoding structure, in which each individual is composed of five parts:

$$\text{Individual}=[\text{Route},\text{Ops},\text{Truck},\text{Drone1},\text{Drone2}] \tag{8}$$

Route: The sequence in which nodes are visited is stored.

Ops: Each node ' s task assignment (truck or drone) is marked.

Truck: The sub-path carried out by the truck is represented.

Drone1,Drone2：Denote the task node sequences assigned to the two drones, respectively.

The collaborative relationship between trucks and drones is effectively represented through this multi-layer encoding approach, which ensures precise computation of time, energy consumption, and cost during the decoding process.

3.3 Fitness Function Design

The objective of the algorithm is to minimize the overall system cost. The fitness function is formulated as follows:

$$f=\omega_1\frac{T_{total}}{T_{max}}+\omega_2\frac{C_{total}}{C_{max}}+\omega_3\frac{E_{total}}{E_{max}} \tag{9}$$

Where ω_1,ω_2, and ω_3 denote the weighting coefficients assigned to time, cost, and energy consumption, respectively; T_{max}, C_{max}, and E_{max} represent the normalized upper bounds for the corresponding performance metrics. The smaller the final fitness value is, the better the distribution plan is.

3.4 Improvement Strategies

To address the premature convergence and local optima issues of traditional genetic algorithms in multi-objective optimization, the following enhancements are implemented in the algorithmic operations:

3.4.1 Elitist preservation strategy

A set of the best individuals in each generation is directly passed to the next generation, preserving high-quality solutions and accelerating convergence [9].

3.4.2 Adaptive crossover and mutation operators

The crossover probability P_c and mutation probability P_m are dynamically adjusted according to the fitness of individuals.

$$P_c=P_{c0}\left(1-\frac{f-f_{min}}{f_{avg}-f_{min}}\right),\ P_m=P_{m0}\left(1-\frac{f_{best}-f}{f_{avg}-f_{min}}\right) \tag{10}$$

This adaptive mechanism enables robust global exploration during the initial phase and improves local search accuracy in the later phase.

3.4.3 Neighborhood Transformation Operations

Three neighborhood operations are introduced in this study to enhance solution diversity and global search capability beyond the standard genetic algorithm. The Flip operation reverses the order of nodes in a randomly selected segment of an individual path, generating new path combinations. In the Swap operation, two nodes are randomly chosen and their positions are exchanged, thereby disrupting the original path structure and broadening the exploration of the solution space. The Slide operation shifts an entire path segment by one position and reassembles the path to form new solutions. Through the integration of these three neighborhood operations, population diversity is effectively improved while preserving the core mechanisms of the genetic algorithm. This enhancement strengthens the ability to search for the global optimum and thus improves the overall performance of collaborative delivery path optimization [10].

3.4.4 Task Assignment Random Perturbation

After each iteration, minor perturbations are introduced to the task assignments of UAVs and vehicles by randomly reassigning a subset of nodes. This process helps avoid convergence to fixed allocation patterns and improves the algorithm's ability to explore diverse routing solutions.

3.5 Algorithm Flow

The main flowchart of the improved genetic algorithm introduced in this study is presented in Figure 3. Initially, population initialization is carried out by randomly generating a set of feasible individuals to form the initial solution pool, thereby offering diverse starting points for the iterative process. Subsequently, fitness evaluation is conducted using the established multi-objective optimization function, which assesses delivery time, transportation cost, and energy consumption for each individual, thereby ranking their performance within the population. Crossover and mutation are executed based on adaptive probabilities, preserving the essential search mechanism of genetic algorithms while adaptively enhancing exploration and exploitation across different search phases. To further strengthen global search performance and diversify solutions, neighborhood transformation and perturbation operations—such as Flip, Swap, and Slide—are incorporated. These strategies facilitate local path refinement and generate new feasible solutions, effectively avoiding convergence to local optima.Meanwhile, an elite retention strategy is implemented to retain the best individual in each iteration, thereby preventing the loss of the optimal solution. After every iteration, the termination criteria are evaluated, and the process halts once either the maximum number of iterations or the convergence threshold is met, with results being output accordingly. The algorithm ultimately derives the optimal cooperative delivery route involving the vehicle and two drones, achieving an integrated minimization of time, cost, and energy consumption. This offers a practical and efficient scheduling strategy for collaborative delivery operations.

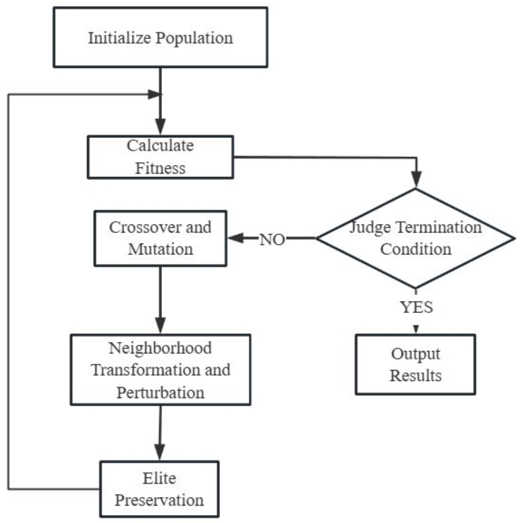

Figure 3 Flowchart of the Improved Genetic Algorithm

4 Experiments and Analysis

4.1 Simulation Environment and Parameter Settings

Simulations were carried out in MATLAB R2023b to evaluate the performance of the proposed vehicle – UAV cooperative delivery path optimization model, which incorporates an improved genetic algorithm. The experimental setup used in this study is detailed below:

Processor: Intel Core i7-12700H

Memory: 16 GB RAM

Operating System: Windows 11 64-bit

Programming Environment: MATLAB R2023b

In the simulation setup, the delivery area contains multiple delivery nodes, such as customers or receiving points, along with a central distribution center that serves as both the start and end point. Vehicles are assigned to main route transportation, while drones perform short-range deliveries within their operational flight limits. Task coordination between the vehicle and drone occurs at predefined nodes, which support drone takeoff, landing, and recharging operations.The primary parameters are listed in Table 2.

Table 2 Table of Experimental Parameter Settings

Parameter	Symbol	Value	Description
Total Number of Nodes (Including Distribution Center)	n	20	Including distribution centers
UAV endurance range	range	10 km	If exceeded, it is not feasible
Vehicle speed	v_t	35 km/h	Constant speed
UAV speed	v_d	70 km/h	Constant speed
Vehicle energy consumption	E_t	8.0×10^6 J/km	Unit energy consumption of the truck
UAV energy consumption	E_d	5.0×10^4 J/km	UAV unit energy consumption
Vehicle cost	C_t	1.5 USD/km	Fuel cost and depreciation cost
UAV cost	C_d	0.3 USD/km	Electricity consumption and maintenance cost
Population size	popSize	60	Initial number of individuals
Maximum number of iterations	numIter	200	Algorithm iteration upper limit

4.2 Algorithm Convergence Analysis

To evaluate the optimization performance of the algorithm, the convergence curve of the total delivery time during the iteration of the improved genetic algorithm was recorded, as illustrated in Figure 4.

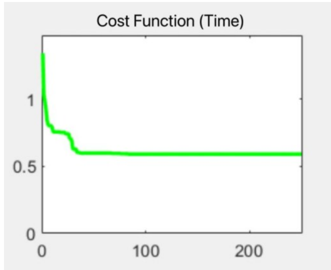

Figure 4 Relationship between Delivery Time and Number of Iterations

The graph illustrates that the total time decreases rapidly during the first 50 iterations, indicating strong global search capability of the algorithm. After 100 iterations, the curve stabilizes, suggesting convergence to a near-optimal solution. Compared to the standard genetic algorithm, the improved version achieves approximately 30% faster convergence, along with reduced fluctuation and enhanced stability in the final results.

4.3 Comparative Experiments of Different Algorithms

To evaluate the performance of the improved algorithm, a comparison was conducted with the standard genetic algorithm, and the results are presented in Table 3.

Table 3 Experimental Results Comparison

Algorithm Type	Description	Optimal Time (h)	Total Distance (km)	Number of Iterations
Standard Genetic Algorithm (GA)	Traditional selection + fixed crossover and mutation	0.8	93.56	176
Improved Genetic Algorithm (IGA)	Elite retention + adaptive neighborhood perturbation	0.7	90.40	118

As shown in Table 3, the improved genetic algorithm demonstrates superior performance over the standard genetic algorithm across all three metrics: time, distance, and number of iterations. The total delivery time is reduced by approximately 12.5% compared to the standard GA, indicating that the algorithm excels in coordinating Vehicle – UAV collaboration. Additionally, the total delivery distance is shortened from 93.56 km to 90.40 km, which reflects more efficient route planning and contributes to improved economic and energy performance in logistics distribution. In terms of number of iterations, the improved genetic algorithm achieves the optimal solution in only 118 iterations, substantially fewer than the 176 iterations required by the standard GA, highlighting its faster convergence and enhanced search efficiency. The experimental results confirm that the improved genetic algorithm, integrating elite preservation, adaptive neighborhood perturbation, and local optimization strategies, offers significant advantages in optimizing vehicle – UAV cooperative delivery routes. It not only reduces both delivery time and path length but also increases iterative efficiency and global search capability, providing a practical and effective optimization method for real-world logistics distribution.

4.4 Collaborative Path Visualization Results

The optimal collaborative paths derived from the improved genetic algorithm are illustrated in Figure 5, with the following detailed information:

Truck route: 11-18-8-6-12-3-4-15
Drone 1 route: 11-9-18-8-19-10-6-14-3-7-4-15
Drone 2 route: 11-17-18-20-8-5-6-2-16-3-1-4-13-15
Total energy consumption for the truck and drones: 157495591.0302
Average energy consumption of the truck and drones: 50000
Total cost: 15.8527 USD
Total travel time: 0.59065
Total travel distance: 81.0198

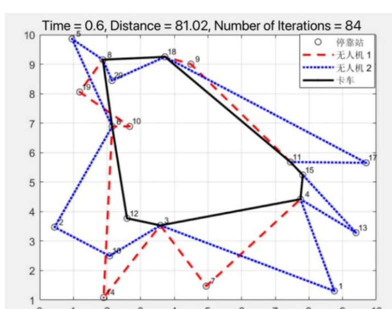

Figure 5 Visualization of Optimal Collaborative Delivery Paths

Figure 5 illustrates that the truck is assigned to serve the more distant backbone nodes, while two drones perform rapid deliveries in separate local regions. The layout of takeoff and landing points for both the truck and drones is well organized, resulting in minimal overlap across the overall routes. This cooperative strategy leads to a significant reduction in total travel time.

5 Conclusion

This paper proposes an optimization method based on an improved genetic algorithm for the vehicle – UAV cooperative delivery routing problem. In the model design, a multi-objective optimization function is established, comprehensively considering total delivery time, total cost, and energy consumption, while employing multi-chromosome hybrid encoding to simultaneously represent the cooperative routes of the vehicle and two drones. In terms of algorithm design, this paper introduces elite preservation, adaptive crossover and mutation, neighborhood transformation, and task perturbation strategies on the basis of the traditional genetic algorithm, effectively enhancing global search capability and convergence speed, and avoiding premature convergence to local optima. The effectiveness of the algorithm is verified through MATLAB simulation experiments. The results show that Parameter sensitivity analysis further demonstrates that the algorithm maintains good stability and robustness under variations in population size, number of UAVs, and endurance range, while also demonstrating reasonable route planning and clear task allocation. The visualization results intuitively reflect the benefits of cooperation.Parameter sensitivity analysis further demonstrates that the algorithm maintains good stability and robustness under variations in population size, number of UAVs, and endurance range, indicating its adaptability and generalizability across different delivery environments. Although this study primarily focuses on static scenarios with fixed nodes and deterministic demands, future research could extend to large-scale delivery networks, dynamic orders, and uncertain environments, as well as explore integration with other intelligent optimization algorithms to enhance the algorithm's global optimization capability and practical application value. Overall, the proposed model and improved genetic algorithm provide an effective methodology and theoretical foundation for route optimization in urban last-mile intelligent logistics systems, laying the groundwork for practical applications of vehicle–UAV collaborative delivery.

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