ISSN: 1813-4890

Research on the Distribution of Logistics Unmanned Aircraft Operations in the Port Area Considering Customer Timeliness Requirements

Xiaoyu Liu, Zhaoxin Zhou, Zongao Zhang, Jun Jiang, Xiaofan Yuan

School of Shipping, Shandong Jiaotong University, Weihai 264200, China

Abstract

With the continuous advancement of unmanned aerial vehicle (UAV) technology, UAV delivery models are increasingly transforming shore-to-ship material transportation and are expected to become a vital component of future maritime logistics systems. First, a UAV task allocation model considering the customers' timeliness requirements and various constraints was proposed, aiming to simultaneously optimize the two objectives of customer dissatisfaction degree and flight distance. Second, an improved non-dominated sorting genetic algorithm (NSGA-II) is employed to solve the model. By integrating an adaptive crossover and mutation probability calculation method with a 3-opt local search strategy, the improved algorithm demonstrates enhanced performance. Finally, simulation experiments based on randomly generated datasets were conducted. The results demonstrate an 8.7% reduction in customer dissatisfaction and a 5.34% decrease in total flight distance. Therefore, the proposed model can provide both theoretical support and practical guidance for the real-world application of UAVs in maritime material transport and distribution.

Keywords

Unmanned Aerial Vehicle, Customers' Timeliness Requirements, Task Allocation, Time Windows, NSGA-II.

1. Introduction

The UAV refers to aircraft operated without an onboard pilot. They are maneuvered through radio remote-control devices and onboard program-controlled systems, with an integrated computer system enabling autonomous regulation of flight stability[1]. With the rapid development of the global maritime industry and intelligent technologies, using UAVs (Unmanned Aerial Vehicles) for maritime vessel logistics delivery will become one of the research hot spots. The traditional method of vessel replenishment usually relies on the vessel docking at the port or having dedicated personnel and vessels from the port to replenish supplies. This method is not only time-consuming and costly, but also causes certain pollution to the marine environment, and also puts pressure on the operational efficiency of the port. Against this backdrop, using UAVs for maritime delivery is an efficient and flexible solution. UAVs, with their advantages such as rapid response, easy operation and strong mobility, demonstrate significant advantages in reducing logistics costs, minimizing vessel waiting times and enhancing service efficiency. Furthermore, there are still numerous technical and operational challenges in the process of UAV material delivery[2], such as weight capacity limitations, flight distance constraints, energy consumption management, and optimization of delivery routes. Therefore, how to integrate the characteristics of UAVs with the logistics demands of ships, establish an appropriate task assignment model, and enhance delivery efficiency has become a core issue in current research.

ISSN: 1813-4890

However, there are relatively few studies on the logistics model of UAVs delivering supplies from the port distribution center to the ships at the anchorage. Therefore, this paper also draws on the logistics models of UAVs from other fields to provide theoretical support and practical guidance.

In the field of UAV delivery, some scholars have studied the collaborative logistics delivery model involving vehicles and UAVs. Li et al. proposed a UAV collaborative delivery model, which effectively reflects the timeliness requirements of UAVs[3]. The same year, Gu et al.and Moshref-Javadi et al. the system distribution mode of vehicles and unmanned aircraft was studied, and the superiority of this collaborative mode was verified[4, 5]. Furthermore, Zang et al. studied the optimization problem of joint delivery by UAVs and trucks, aiming to minimize costs through collaborative delivery methods[6]. Wang et al. proposed a method for collaborative delivery by vehicles and UAVs. This collaborative delivery system can significantly enhance efficiency and reduce costs[7]. Some scholars have also conducted research on the logistics distribution model for UAV systems. Benarbia et al. found that using logistics UAVs for cargo transportation can reduce distribution costs and delivery time[8]. Li et al. discovered that UAV freight transportation can achieve excellent economic and social benefits[9]. Bridgelall use of UAVs for transporting hazardous materials not only reduces transportation risks, but also cuts costs and alleviates traffic congestion on the ground[10]. Lee et al. conducted a study on using intelligent logistics UAVs to replace delivery personnel for the delivery of small packages[11]. Zhou conducted research on the low-altitude economic efficiency of UAV, proving that it can achieve sustainable development of smart cities[12].

In the aspect of UAV mission allocation, Schwarzrock et al. conducted research indicating that increasing the number of tasks that UAVs can perform can lead to more optimal task allocation[13]. Zhao et al. solved the problem of rapid task allocation for heterogeneous UAVs through reinforcement learning[14]. Wu et al. proposed an approach based on the improved simulated annealing combined with genetic algorithm (ISAFGA) to solve the problem of UAV task allocation[15]. Zhu et al. proposed an improved semi-random Q-learning algorithm to enhance the rationality of UAV task allocation and the success rate of task execution[16]. Hu et al. proposed a pigeon-inspired fuzzy multi-objective optimization algorithm to solve the problem of UAV task allocation for multiple ground tracking targets[17]. Bai et al. reduced the cost and service time of vehicle and UAV collaborative delivery by improving the heuristic algorithm[18]. Zhang et al. proposed a distributed decision-making intelligent framework based on evolutionary game theory to solve the task allocation problem of UAV swarm systems in uncertain scenarios[19]. Park et al. optimization model based on mixed integer linear programming (MILP) enabled multiple heterogeneous UAVs to generate feasible and efficient task allocation schemes[20].

Based on the above literature analysis, the cargo delivery model in urban settings has evolved from the traditional human and vehicle delivery to the UAV collaborative delivery, and finally to the fully unmanned autonomous delivery mode. As an emerging model, UAV delivery, with its flexibility and efficiency, not only improves the delivery time but also reduces the environmental impact of traditional cargo delivery.

Based on this, the experience of delivering daily necessities to ships at offshore anchorages through unmanned aircraft in maritime environments has been gained and supported. Yan et al. proposed an improved particle swarm optimization combined with genetic algorithm (GA-PSO), which enhanced the efficiency of UAV maritime task allocation[21]. Wang et al. provided in-depth guidance for the future development of UAV in the marine field[22]. Pensado et al. conducted a study on using UAVs equipped with a real-time trajectory optimizer for ship-to-shore communication to deliver packages to offshore vessels[23]. Yang et al. developed a mixed integer programming model and a branch-and-price-and-cut (BPC) algorithm to optimize UAV shore-to-ship cargo scheduling[24].

Overall, with the continuous advancement of intelligent UAV technology and the logistics industry, UAVs have broad application prospects as a means of transporting goods. At the same time, as an emerging distribution model, they have gradually attracted attention from various sectors of society and have achieved some success in different fields. However, several issues still need to be resolved. Specifically, existing research mainly focuses on UAV transportation in urban settings, while studies on UAV-based maritime goods transportation are relatively scarce and have neglected the transport of goods between ports and ships.

Based on the above analysis, this study aims to expand the research on material transportation between ports and anchorage areas. Considering the time sensitivity and distance constraints of customers in the port anchorage area, we proposed a dual-objective optimization model and solved it using the NSGA-II algorithm. The contributions of this study are as follows:

(1) This study investigates UAV operation allocation in a port anchorage scenario. The results provide theoretical support and technical assistance for daily necessities distribution via a marine UAV supply system.

(2) A UAV operation allocation model for port anchorages was constructed, with the dual objectives of minimizing customer dissatisfaction and flight distance while considering customer timeliness requirements under multiple constraints.

(3) An improved NSGA-II algorithm was developed, which incorporates a 3-opt local search strategy and adaptive crossover and mutation probabilities. These enhancements strengthen the local search capability and improve the solution quality.

The arrangement of this study is as follows. Section 2 presents a dual-objective model for UAV task allocation considering customer timeliness requirements under multiple constraints; Section 3 introduces a method based on the improved NAGA-II algorithm; Section 4 presents the numerical calculation and analysis of the proposed dual-objective model; Section 5 summarizes the research.

2. Model

2.1. Problem Description and Symbol Explanation

The multi-UAV mission planning mainly consists of two parts: task allocation and path optimization[25]. These two are interrelated and distinct. The purpose of the task allocation is to assign multiple tasks to each UAV and determine the execution sequence The goal of path optimization is to plan a feasible path for the UAVs from the starting point to the target point. The path must have obstacle avoidance and collision avoidance capabilities, and also meet the flight ability requirements of the UAVs.

Suppose there are ships in need of replenishment in a certain anchorage, the port employs multiple UAVs of the same performance to deliver emergency supplies. Each UAV departs from the same port, completes its assigned tasks, and then returns. The UAVs plan their tasks in advance based on the required supply weight and the location of each ship, and they will not alter the original distribution plan during delivery.

Therefore, the objective of this research is to complete the delivery operation within specified soft time windows while minimizing both customer dissatisfaction and the total UAV flight distance. For convenience, the notations used in this paper are explained in Table 2.1.

Table 2.1 Model symbols and parameter Definitions

Parameters	Definition
N	Set of customer nodes $N=\{1,2,\ldots,n\}$
N_0	UAV distribution center (port terminal) nodes $N_0=N\cup\{0\}$

K	The set of UAVs is $K=\{1,2,\ldots,k\}$
$[e_i,\ l_i]$	Time window
t_{ij}	Delivery time of materials
t_{ij}^{-1}	The total time from the arrival of the UAV k at the current customer location until completion
t_s	The maximum hovering service time of the UAV
$T_{\max}$	Maximum flight time of the UAV
$v_{\min}$	Minimum flight speed of the UAV
v_k	Constant flight speed of the UAV

Table 2.1 Model symbols and parameter Definitions(continued)

Parameters	Definition
$v_{\max}$	Maximum flight speed of the UAV
d_{ij}	Distance
$D_{\max}$	Maximum flight distance of UAV
q_i	The cargo capacity required for the ship
$Q_{\max}$	Maximum payload capacity of the UAV
$s(t_{ij})$	The satisfaction level of the i-th customer
S	Customer average satisfaction function
NS	Customer dissatisfaction function
F	UAV flight distance function
x_{ijk}	Decision variable: When the UAV moves from ship i to ship j, its value is 1; otherwise, its value is 0.

2.2. Assumptions

To better meet the emergency supply needs of ships in the anchorage area and facilitate maritime UAV cargo delivery, the following assumptions are made:

(1) The UAV maintains a constant altitude during flight;

(2) The impact of adverse sea conditions is not considered;

(3) The UAV hovers when picking up goods at the distribution point;

(4) The time window for each customer is fixed;

(5) The demand at each customer point is less than the maximum payload capacity of the UAV;

(6) The distance between the distribution center and the ship is the straight-line distance;

(7) The flight speed of the UAV is constant.

Furthermore, to illustrate the maritime UAV cargo delivery process, a specific workflow is presented in Figure 1-1.

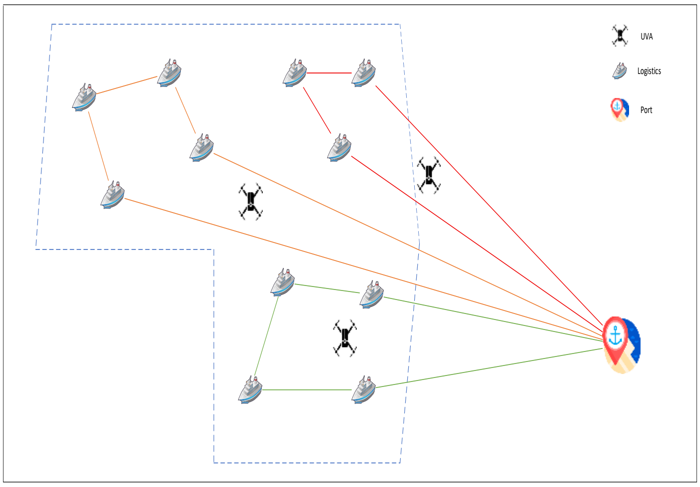


Figure 2-1 Flowchart of Unmanned Aerial Vehicle Operation Allocation

2.3. Optimization of the Model

The maritime UAV logistics distribution system primarily involves three stakeholders: government authorities, customers, and port enterprises. Government authorities are primarily concerned with the safety of UAV operations; customers prioritize the timeliness of delivery; and port enterprises focus on the economic efficiency of the process. To address the demands of all three parties, this study constructs a dual-objective UAV task allocation model under multiple constraints, aiming to minimize both customer dissatisfaction and total flight distance.

2.3.1. Customer Dissatisfaction Model

Customer dissatisfaction mainly depends on the delivery time of the supplies. To evaluate this satisfaction, the degree of matching between the actual delivery time and the customer's expected time window needs to be analyzed. Therefore, the UAV should deliver the supplies to the corresponding vessel within the specified time as much as possible. Due to certain external factors affecting the UAV during flight, a soft time window needs to be set to ensure that the delivery can as closely as possible meet the customer's requirements. If the delivery time of materials is before the ship's expected time window , the customer's satisfaction is 1; if the delivery time of materials is within the ship's expected time window , the customer's satisfaction will decrease as the arrival time increases; if the delivery time of materials is after the ship's expected time window , the customer's satisfaction is 0. Therefore, in this paper, the customer satisfaction is calculated using a linear function to represent it, as follows

$$s(t_{ij}) = \begin{cases} 1 & , t_{ij} < e_i \\ 1 - \dfrac{t_{ij} - e_i}{l_i - e_i} & , e_i \leq t_{ij} \leq l_i \\ 0 & , t_{ij} > l_i \end{cases} \tag{1}$$

The total delivery time is calculated based on three components: firstly, the flight time between two points; secondly, the service time at the previous customer location; thirdly, the arrival time at the previous customer location. The details are as follows

$$t_{ij} = t_{ij}^{-1} + d_{ij} / v_k + t_s \tag{2}$$

As shown in Figure 2-2, the diagram illustrating the calculation of customer satisfaction.

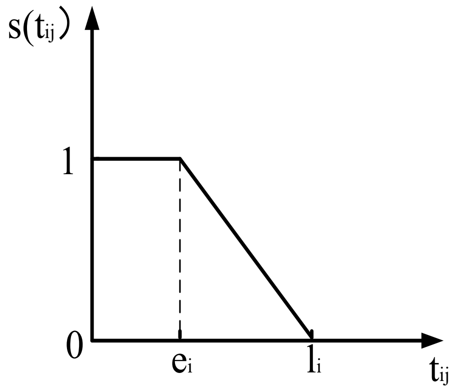


Figure 2-2 Diagram for Calculating Customer Satisfaction

As illustrated in Figure 2-2, the customer satisfaction level for each individual is first calculated. The average of these values, denoted as S, is then computed to quantify the performance of the human-machine job allocation. The function for S is defined as follows

$$S = \frac{\sum_{i=1}^{n} s\left(t_{ij}\right)}{n} \tag{3}$$

Based on this, the paper further defines dissatisfaction as the opposite of satisfaction. Specifically, the objective function NS represents the dissatisfaction with the delivery time when a UAV departs from the distribution center. It is formulated as follows

$$NS = 1 - S = 1 - \frac{\sum_{i=1}^{n} s\left(t_{ij}\right)}{n} \tag{4}$$

2.3.2. Flight Distance Model

In UAV material delivery, the total flight path length is a key metric for evaluating efficiency and transportation costs. The objective is to design a flight route with the shortest total mileage using an efficient heuristic algorithm. The optimization process involves intelligently integrating delivery requirements by considering the geographical distribution of all delivery points, the UAV's flight range, and its maximum payload capacity. By precisely calculating the shortest feasible paths between points and optimizing the visit sequence and task allocation, the system can significantly reduce total flight mileage while ensuring all customers are served. This not only directly reduces the energy consumption of the UAV, extends the service life of the equipment, but also improves the delivery efficiency and shortens the overall delivery time, ultimately achieving the minimization of operating costs and the maximization of the response speed of material delivery. The specific objective function is as follows

$$F = \sum_{i \in N_0} \sum_{j \in N_0} \sum_{k \in K} x_{ijk} \cdot d_{ij} \tag{5}$$

2.3.3 Dual-objective Programming Model under Multiple Constraints

Based on the above analysis, combined with the UAV task allocation model, this paper constructs a dual-target task allocation model under multiple constraints, as follows

$$\min NS = 1 - \frac{\sum_{i=1}^{n} s\left(t_{ij}\right)}{n} \tag{6}$$

$$\min F = \sum_{i \in N_0} \sum_{j \in N_0} \sum_{k \in K} x_{ijk} \cdot d_{ij} \tag{7}$$

Subject to

$$\sum_{k \in K} \sum_{i,j \in N_0} x_{ijk} = 1, \forall i, j \in N_0 \tag{8}$$

$$\sum_{i=1}^{N_0} x_{ijk} d_{ij} \le D_{\max} \tag{9}$$

$$\sum_{i \in N_0} \sum_{j \in N_0} x_{ijk} q_i \le Q_{\max} \tag{10}$$

$$v_{\min} \le v_k \le v_{\max} \tag{11}$$

$$H_{\min} \le h \le H_{\max} \tag{12}$$

$$\sum_{i \in N_0} \sum_{j \in N_0} \sum_{k \in K} t_{ij} \le T_{\max} \tag{13}$$

$$k \ge \left| \frac{\sum_{i=1}^{n} q_i}{Q_{\max}} \right| \tag{14}$$

$$\sum_{j \in N} x_{0jk} = \sum_{i \in N} x_{i0k} = 1, \forall k \in K \tag{15}$$

$$x_{ijk} \in \{0,1\}, \forall i, j \in N_0, \forall k \in K, i \ne j \tag{16}$$

Equations (6) and (7) represent the objective functions. Equation (6) indicates minimizing the customer dissatisfaction during the material distribution process, while Equation (7) indicates minimizing the flight distance of the UAV. Equation (8) represents that each delivery task can only be executed by one UAV once; Equation (9) represents the maximum flight distance constraint for the UAV; Equation (10) represents the maximum load constraint for the UAV; Equation (11) represents the flight speed constraint for the UAV; Equation (12) represents the flight altitude constraint for the UAV; Equation (13) represents the maximum flight time constraint for the UAV; Equation (14) represents the number of UAV; Equation (15) indicates that the UAV departs from the port material distribution center, completes the delivery task and returns to the take-off point. (16) represents the decision variables.

3. Algorithm Design

3.1. Design of NSGA-II Algorithm

Proposed by Srinivas and Deb in 2002, NSGA-II[26] is an advanced multi-objective optimization algorithm. This algorithm introduces non-dominated sorting and crowding distance calculation mechanism based on NSGA to find the Pareto optimal solution set. Taking into account the characteristics of the customer's timeliness requirements in the unmanned aerial vehicle task allocation scenario of the port berthing area, this paper constructs a dual-objective model with multiple constraints, and solves it using the NSGA-II algorithm. To further enhance the performance of the algorithm, this study introduces an adaptive dynamic adjustment mechanism for crossover and mutation probabilities, which enables the algorithm to adjust genetic operator rates in response to population diversity and evolutionary progress during the search process. Additionally, a 3-opt local search strategy is incorporated to refine the solutions by eliminating inefficient routes and exploring more promising neighborhoods within the solution space. These improvements collectively contribute to obtaining higher-quality solutions with accelerated convergence behavior, thereby strengthening both the search capability and computational efficiency of the optimization process. Meanwhile. This research provides a new technical idea and solution approach for the problem of UAV life support material task allocation at sea.

3.2. Principle of NSGA-II Algorithm

The basic process of the NSGA-II algorithm involves initializing the population, performing non-dominated sorting and calculating the crowding distance, and then generating a new population through genetic operations (e.g., selection, crossover, and mutation). The key steps are detailed below:

(1) Encoding and Decoding

This paper employs a real-number encoding strategy to generate the initial solution. Each individual is represented by a vector of real numbers, with its length equal to the total number of customers. Each element in the vector is a random number uniformly distributed in the range [0, 1). Each gene value determines both the UAV assigned to the customer and the customer's service sequence in that UAV's route.

The decoding process transforms the real-number encoded solution into practical UAV delivery routes by first assigning customers to UAVs based on multiplied and rounded gene values, then establishing service sequences through ascending gene value sorting for each UAV's customers, followed by route construction that inserts customers from the distribution center (node 0) while enforcing all operational constraints, and finally representing each validated route as a node sequence that begins and ends at the distribution center, completing the cycle from dispatch to return.

(2) Non-dominated Sorting

During non-dominated sorting, individuals are ranked based on their fitness values to evaluate their dominance relationships within the population. Superior individuals are selected as the parent population to create the next generation. Specifically, if all the objective function values of individual a are less than or equal to those of individual b and at least one is strictly less than, then a dominates b.

(3) Crowding distance calculation

The crowding distance metric serves as a crucial indicator for estimating the density of non-dominated solutions in the vicinity of a particular point on the Pareto front. It quantifies the sparsity of solutions by measuring the average distance between a given solution and its adjacent neighbors along each objective dimension. Solutions with larger crowding distances are situated in less densely populated regions of the front, implying greater diversity contribution. As a result, such solutions are assigned higher selection priority in the evolutionary process to promote uniform Pareto front exploration and representation. The formula for calculating crowding distance is as follows

$$CD_{im} = \frac{f_m(x_{i+1}) - f_m(x_{i-1})}{f_m(x_{\max}) - f_m(x_{\min})}, i = 2, \ldots, (l-1) \tag{17}$$

In the formula, CD_{im} represents the crowding distance of the i-th individual in the m-th objective function; f_m represents the m-th objective function; $x_{\max}$ represents the maximum value of all individuals in the m function; $x_{\min}$ represents the minimum value of all individuals in the m function. For ease of understanding, the crowding distance is shown in Figure 3-1.

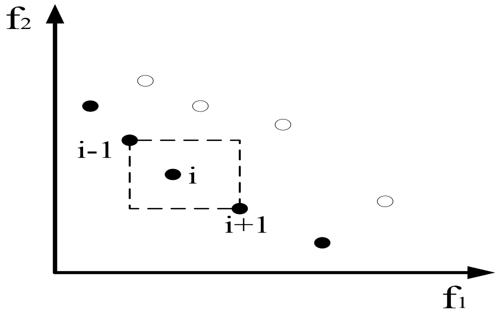


Figure 3-1 Diagram of Calculation for Crowded Distance

(4) Cross-operation

This paper selects the Simulated Binary Crossover[27] (SBX) method. This approach selects parent individuals randomly as the crossover objects, and through steps such as initializing parameters, generating random numbers, calculating crossover probabilities, and performing crossover operations, it exchanges genes between parent individuals to generate new offspring individuals. Compared with the traditional binary crossover, SBX can smoothly search within the real number domain and is suitable for the real number encoding method of this model. The specific crossover process is as follows:

First, two parent individuals are randomly selected from the population for crossover.

Second, for each parent individual, a crossover parameter ζ is generated. This parameter is calculated based on a random number r, which r determines the degree of exchange of the character's genetic information.

Then, two offspring individuals are generated by recombining the genes of the parents based on a probability distribution that simulates single-point crossover. Specifically, the calculation formulas for the offspring x_1 and x_2 derived from the parent generations p_1 and p_2 are as follows

$$\begin{cases} x_1 = \frac{1}{2} * [(1+\zeta) * p_1 + (1-\zeta) * p_2] \\ x_2 = \frac{1}{2} * [(1-\zeta) * p_1 + (1+\zeta) * p_2] \end{cases} \tag{18}$$

Among them, ζ is dynamically and randomly determined by the distribution factor τ according to formula (19).

$$\zeta = \begin{cases} (2r)^{\frac{1}{1+\tau}}, r \le 0.5 \\ \left(2(1-r)\right)^{-\frac{1}{1+\tau}}, r > 0.5 \end{cases} \tag{19}$$

Finally, a boundary constraint handling step is performed on the generated offspring to ensure all variable values lie within the defined feasible range.

For ease of understanding, a simplified schematic of the crossover operation is provided in Figure 3-2.

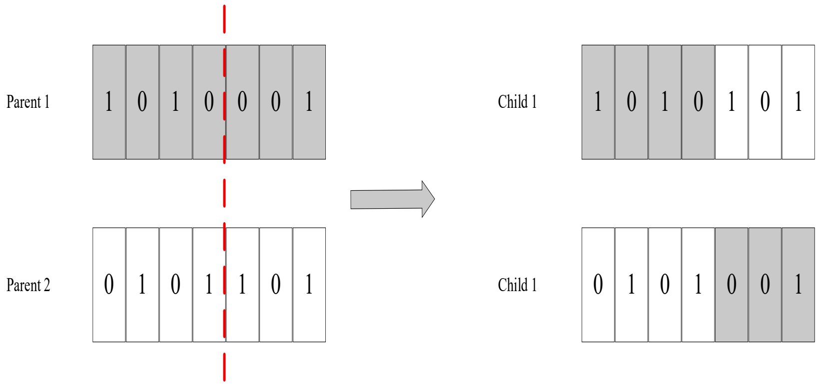


Figure 3-2 Schematic Diagram of Cross-operation

(5) Mutation operation

This study employs polynomial mutation[28], a widely adopted operator for multi-objective optimization problems, to maintain population diversity. The mutation form is $\xi_k^{'} = \xi_k + \phi\left(\xi^u + \xi^l\right)$, where

$$\phi = \begin{cases} \left[2c + (1-2c)(1-\phi_1)^{\eta_m+1}\right]^{\frac{1}{\eta_m+1}} - 1, c \le \frac{1}{2} \\ 1 - \left[2(1-c) + 2\left(c - \frac{1}{2}\right)(1-\phi_2)^{\eta_m+1}\right]^{\frac{1}{\eta_m+1}}, c > \frac{1}{2} \end{cases} \tag{20}$$

In the formula, $\phi_1 = \left(\xi_k - \xi^l\right)/\left(\xi^u - \xi^l\right)$, $\phi_2 = \left(\xi^u - \xi_k\right)/\left(\xi^u - \xi^l\right)$, c are random numbers within the [0,1] range, η_m distribution index, ξ_k the previous generation population, $\xi_k^{'}$ the offspring population after polynomial mutation, ξ^u, ξ^l represents the upper bound and the lower bound.

(6) Elite Retention Strategy

Through non-dominated sorting and crowding distance calculation, the Elite Retention Strategy retains elite individuals to prevent the loss of high-quality solutions, thereby improving the algorithm's convergence and efficiency.

(7) Termination Conditions

In this section, the termination condition is defined as the maximum number of iterations. If the condition is met, the algorithm terminates; otherwise, the iteration continues.

According to the above steps, the algorithm flow of NSGA-II is shown in Figure 3-3.

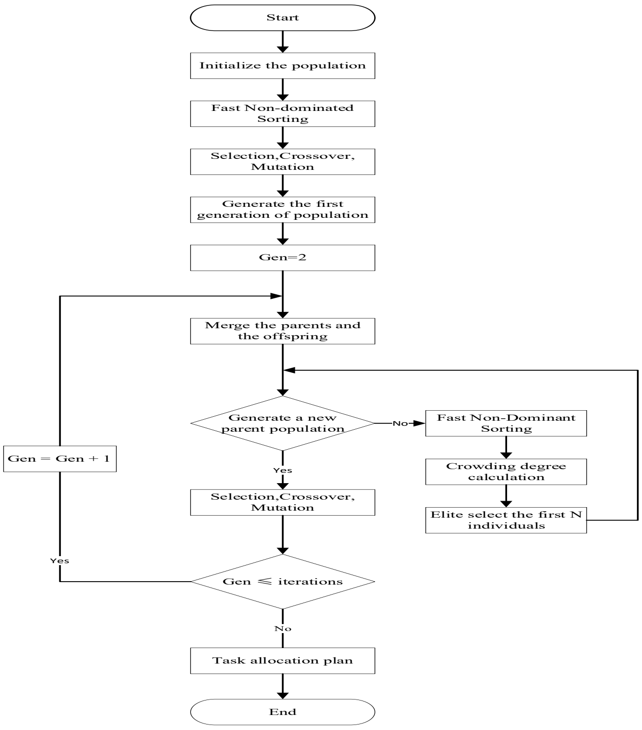


Figure 3-3 Basic Flowchart of NSGA-II Algorithm

3.3. Improving the NSGA-II Algorithm

This paper presents an enhanced NSGA-II algorithm that incorporates dynamically adaptive crossover and mutation probabilities combined with a 3-opt local search strategy. These modifications are introduced to strengthen the algorithm's ability to escape local optima and enhance convergence toward high-quality Pareto fronts. The specific improvements are detailed below:

(1) Adaptive adjustment method for crossover and mutation probabilities

In the traditional NSGA-II algorithm, crossover and mutation probabilities are typically set as fixed values. This approach often limits the algorithm's capacity to balance global exploration in the early stages and local exploitation in the later phases, particularly in solving complex constrained optimization problems such as UAV delivery route planning. To address this limitation, this paper introduces an adaptive parameter control strategy that dynamically adjusts the crossover and mutation rates throughout the evolutionary process. Specifically, higher probabilities are applied in the early evolutionary stage to enhance exploratory diversity and generate new solutions, while these values are gradually reduced in later stages to facilitate convergence and preserve high-quality solutions. The specific adjustment strategy is as follows:

$$cr = cr_{\min} + (cr_{\max} - cr_{\min}) \times (\frac{iter}{iterations}) \tag{21}$$

$$va = va_{\min} + (va_{\max} - va_{\min}) \times (\frac{iter}{iterations}) \tag{22}$$

In the formula, $cr_{\max}$ and $cr_{\min}$ denote the maximum and minimum crossover probabilities, respectively; $iter$ and $iterations$ denote the current and total iteration numbers, respectively. $va_{\max}$ and $va_{\min}$ denote the maximum and minimum mutation probabilities, respectively.

(2) 3-opt Local Search Strategy

This paper employs the 3-opt local search strategy, which enables the algorithm to conduct extensive local exploration, optimize high-quality solutions specifically, and flexibly adapt to changes in path length, thereby significantly enhancing its performance in the unmanned aerial vehicle task allocation problem.

Specifically, the local search operation of 3-opt is as follows:

Step 1: The offspring population generated through tournament selection, SBX and polynomial mutation is merged with the parent population to form a new population.

Step 2: Remove duplicates from the combined population, retaining only the individuals with unique fitness values. Subsequent to non-dominated sorting, the initial solution set for local search is drawn from the first non-dominated layer, to which the 3-opt local search is applied. For a solution with a size (number of customers) greater than or equal to 3, randomly select three different positions and generate a series of candidate solutions through various structural perturbation methods (such as fragment inversion, three-position rotation, etc.); if the dimension is less than 3, perform a two-position exchange operation. Each search samples in the neighborhood through structural perturbation and evaluates the performance of the objective function.

Step 3: Merge the high-quality candidate solutions generated by local search into the original population to form an expanded solution set.

Step 4: Using the elite retention strategy, the best individuals are selected from the new population set to constitute the next generation population.

Specifically, after generating the candidate solutions, the algorithm will compare them with the original solution. A new solution is accepted to replace the incumbent one only if it exhibits Pareto dominance—that is, it demonstrates improvement in both the dissatisfaction function and the total flight distance function. Conversely, if the new solution fails to dominate the original, the latter remains unaltered. This replacement mechanism enables the 3-opt local search strategy to not only strengthen the local exploitation capability of the NSGA-II algorithm, but also synergize with the elite retention strategy. Such integration helps preserve high-quality solutions throughout the evolutionary process, thereby sustaining the overall excellence of the population

4. Numerical experiments

In order to verify the correctness of the model and the effectiveness of the improved NSGA-II algorithm, this study conducted experiments using simulated data of the anchorage in Qingdao Port. In this case, the coordinates of the ships in the anchorage were randomly obtained. Additionally, to ensure the objectivity of the experimental results, this paper used Python 3.10 version for simulation experiment calculations (the experimental environment was Intel(R) Core(TM) i7-14650HX (2.20 GHz)). To ensure the consistency and reliability of the experimental data, all the simulation results below are based on the same environment and parameter settings.

4.1. Introduction of Examples and Parameter Settings

Given the current lack of baseline data on the distribution of ship supplies between ports and anchorage areas, this study selects Qingdao Port as the distribution center and its corresponding anchorage area as the distribution region, with the Ship Information Network serving as the primary data source. To simulate real-world operational scenarios, 25 fixed-position supply ship points were randomly generated within the anchorage area, with their spatial distribution illustrated in Figure 4-1. Since the locations of the port, anchorage area, and ships are expressed in latitude and longitude, all geographic coordinates were converted into a planar coordinate system with Qingdao Port as the origin to simplify subsequent computational

ISSN: 1813-4890

procedures. The detailed coordinate data and corresponding conversion results are provided in Tables 4.1 and 4.2. Furthermore, the mathematical models and algorithm parameters used in this study are systematically summarized in Table 4.3.

Figure 4-1 Distribution center, anchorage, ship schematic diagram

Table 4.1 Latitude and Longitude Coordinates and Planar Coordinates of Anchorage Areas within Qingdao Port

Longitude	Latitude
120°12′40″E	36°06′00″N
120°13′13″E	36°07′36″N
120°16′40″E	36°07′36″N
120°16′50″E	36°06′00″N
120°16′30″E	36°04′18″N
120°14′30″E	36°04′18″N
120°14′30″E	36°06′00″N

Table 4.2 Ship customer information

Number	X	Y	Demand	Number	X	Y	Demand
0	0	0	0	13	-5.666	1.501	1.16
1	-5.291	4.262	1.49	14	-3.020	1.112	1.93
2	-4.393	4.262	1.52	15	-2.995	-0.587	2.56
3	-3.269	3.954	1.38	16	-3.295	-0.596	1.96

Table 4.2 Ship customer information(continued)

4	-4.717	3.768	1.46	17	-4.293	-1.298	7.83
5	-3.744	3.368	3.32	18	-4.868	-0.958	5.32
6	-4.468	3.245	3.96	19	-5.217	-0.185	1.16
7	-3.320	2.780	1.83	20	-5.217	0.371	1.89
8	-5.766	2.812	1.96	21	-4.443	0.371	5.89
9	-4.268	2.441	7.69	22	-3.695	0.68	3.14
10	-3.395	1.761	2.14	23	-4.443	-0.278	4.52
11	-5.217	1.638	9.36	24	-3.445	-1.205	6.78
12	-4.193	1.082	1.69	25	-5.841	-1.236	2.54

Table 4.3 relevant parameter

Description	Parameters	Numerical Value
UAV service time (min)	t_s	10
Maximum payload capacity of the UAV (kg)	$Q_{\max}$	20
Maximum flight radius of the UAV (km)	$L_{\max}$	20
Constant flight speed of the UAV (km/h)	v_k	50
Maximum flight time of the UAV (min)	$T_{\max}$	60
Iterations	/	500
Population quantity	/	200
Crossover probability	cr	0.7
Mutation probability	va	0.01

4.2. Results and Analysis Discussion

To verify the performance of the proposed dual-objective unmanned aerial vehicle task allocation model and the improved NSGA-II algorithm, a case study was conducted using simulated port-anchorage ship data. As all solutions on the Pareto front obtained by the algorithm are non-dominated (meaning no single solution is optimal across all objectives), a trade-off decision is required. This study selects two representative solutions from the Pareto front for detailed comparison. The specific results are presented in Tables 4.4 and 4.5. Furthermore, this section compares the convergence behavior of the the optimization objectives and the Pareto frontier curves between the improved algorithm and the original algorithm, as shown in Figure 4-1.

Table 4.4 Improving the UAV task allocation scheme and compromise solution of NSGA-II

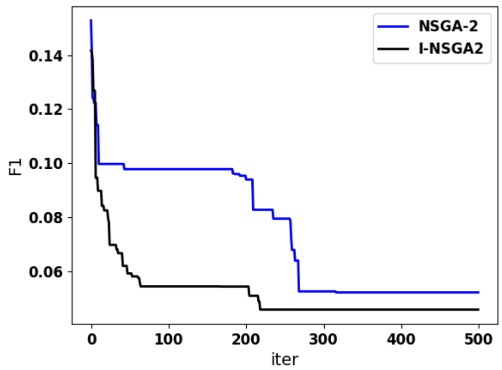
Case	Objective function value		The number of UAVs	Task allocation plan	Compromise solution	
	Distance	Discontent				
1	100.68	0.09	8	0-9-19-16-0 0-20-18-24-0 0-11-8-6-0 0-21-23-17-0 0-14-15-25-0 0-2-4-1-0 0-22-12-13-10-0 0-5-7-3-0	Discontent	0.105
2	91.70	0.12	8	0-22-11-13-0 0-17-23-24-0 0-20-12-0 0-15-16-0 0-2-4-1-3-0 0-14-9-8-6-0 0-21-19-25-18-0 0-5-7-10-0	Distance	96.19

Table 4.5 The UAV task allocation scheme and compromise solution of NSGA-II

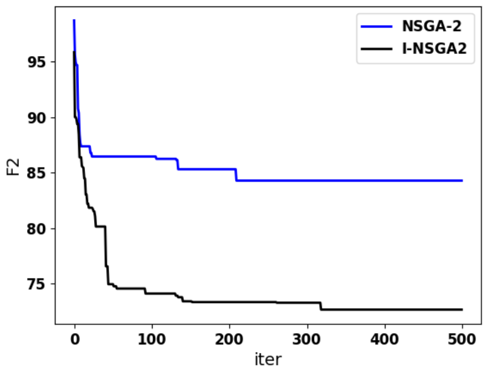
Case	Objective function value		The number of UAVs	Task allocation plan	Compromise solution	
	Distance	Discontent				
1	105.67	0.10	8	0-14-11-13-24-0 0-5-9-17-0 0-15-12-10-7-0	Discontent	0.115

2	97.57	0.13	8	0-16-21-25-0 0-3-4-6-0 0-18-8-1-0 0-23-19-20-0 0-2-22-0 0-11-13-24-0 0-5-3-9-10-0 0-18-17-0 0-15-16-0 0-7-21-25-0 0-6-4-1-8-0 0-23-19-20-22-0 0-14-12-2-0	Distance	101.62

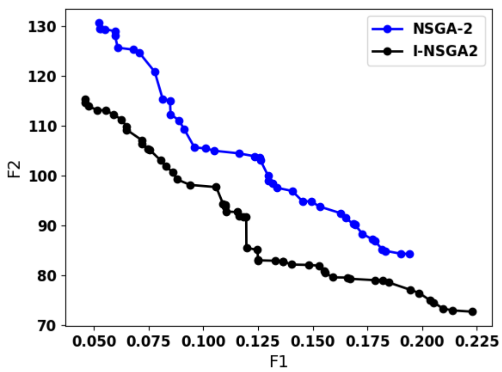
As shown in Tables 4.4 and 4.5, the improved NSGA-II algorithm yields superior results. In this instance, it reduces total flight distance by 5.34% and customer dissatisfaction by 8.7%. This demonstrates the enhanced capability of the improved algorithm to find a better trade-off between these competing objectives, ultimately achieving a higher-quality solution.



(a) Iteration curve graph of customer dissatisfaction target function



(b) Iteration curve graph of flight distance objective function



(c) The Pareto curve diagrams of the improved NSGA-II algorithm and the original algorithm

Figure 4-1 Iteration curves and Pareto curves of the improved NSGA-II algorithm and the original algorithm for the objective functions

As shown in Figures 4-1(a) and 4-1(b), the improved NSGA-II algorithm (labeled as I-NSGA2) demonstrated significant improvements during the optimization process. Specifically, I-NSGA2 achieved a greater reduction in the target value in the early iterations, which reflects its ability to quickly achieve initial convergence. Moreover, in the final iteration stage, the solutions generated by the proposed algorithm had lower customer dissatisfaction and shorter total flight distances compared to the original NSGA-II. Additionally, I-NSGA2 reached outstanding performance earlier in the iteration process. These results confirm that the improved algorithm has a higher convergence speed and optimization accuracy, and prove its effectiveness in solving the bi-objective optimization model introduced in this study.

As evidenced in Figure 4-1(c), the enhanced NSGA-II algorithm exhibits notable superiority across several key aspects. First, I-NSGA2 obtains a larger number of non-dominated solutions with a broader spread along the Pareto front. Second, the solution set demonstrates improved distribution uniformity, reflecting a more consistent and thorough exploration of the objective space. Finally, the Pareto solutions derived from I-NSGA2 achieve superior convergence, approaching closer to the true optimal front compared to the original algorithm. In conclusion, the modified algorithm significantly outperforms the baseline in both the quality and diversity of Pareto-optimal solutions.

5. Conclusion

This study addresses the problem of UAV material transportation and distribution within the port anchorage area. A dual-objective optimization model considering multiple constraints was proposed, with the focus on reducing customer dissatisfaction and total flight distance. The effectiveness of the proposed model was verified through simulation experiments. The main findings of this study are summarized as follows.

(1) This study constructed a dual-objective mathematical model, with the aim of reducing customer dissatisfaction and minimizing the total flight distance of the UAVs. By incorporating a soft time window mechanism and a linear satisfaction function, the model can effectively reflect customers' demands for delivery timeliness, and its feasibility and effectiveness have been verified through practical cases.

(2) The enhanced NSGA-II algorithm, which incorporates an adaptive crossover and mutation probability adjustment mechanism along with a 3-opt local search strategy, demonstrates superior performance over the conventional NSGA-II approach in convergence speed, distribution uniformity of the solution set, and proximity to the true Pareto front. Experimental results indicate a reduction in total flight distance by approximately 5.34% and a decrease in customer dissatisfaction rate by 8.7%.

(3) This research provides specific task allocation and path planning methods for maritime UAV logistics delivery. It has high practical value and broad application prospects especially in emergency material distribution, reduction of vessel waiting time, and lowering of port operation costs.

However, this study also has certain limitations. Further research can improve upon these aspects.

(1) The current study only considers a single distribution center, while actual ports can have multiple distribution centers. Future research can explore the collaborative scheduling model for multiple distribution centers, optimize the task allocation for drones, and thereby enhance transportation efficiency.

(2) The current study does not cover dynamic factors such as sea wind and waves, sudden tasks, and UAV failures. In the future, more comprehensive factors can be considered, combined with real-time monitoring technology, to construct a drone transportation model.

Acknowledgements

Fund Project: This research was funded by the National Natural Science Foundation of China (grant number 52472361).

References

[1] Kuo R J, Lu S H, Lai P Y, et al. Vehicle routing problem with drones considering time windows[J]. Expert Systems with Applications, 2022, 191: 116264.

[2] Murray C C, Chu A G. The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery[J]. Transportation Research Part C: Emerging Technologies, 2015, 54: 86-109.

[3] Li J, Liu H, Lai K K, et al. Vehicle and UAV collaborative delivery path optimization model[J]. Mathematics, 2022, 10(20): 3744.

[4] Gu Q, Fan T, Pan F, et al. A vehicle-UAV operation scheme for instant delivery[J]. Computers & Industrial Engineering, 2020, 149: 106809.

[5] Moshref-Javadi M, Hemmati A, Winkenbach M. A truck and drones model for last-mile delivery: A mathematical model and heuristic approach[J]. Applied Mathematical Modelling, 2020, 80: 290-318.

[6] Zang X, Jiang L, Liang C, et al. Optimization approaches for the urban delivery problem with trucks and drones[J]. Swarm and Evolutionary Computation, 2022, 75: 101147.

[7] Wang Y, Yang S, Wang X V, et al. Research on truck-drone collaborative route planning for rural logistics delivery services[J]. Scientific Reports, 2024, 14(1): 31815.

[8] Benarbia T, Kyamakya K. A literature review of drone-based package delivery logistics systems and their implementation feasibility[J]. Sustainability, 2021, 14(1): 360.

[9] Li Y, Liu M, Jiang D. Application of unmanned aerial vehicles in logistics: a literature review[J]. Sustainability, 2022, 14(21): 14473.

[10] Bridgelall R. Reducing risks by transporting dangerous cargo in drones[J]. Sustainability, 2022, 14(20): 13044.

[11] Lee H W, Lee C S. Research on logistics of intelligent unmanned aerial vehicle integration system[J]. Journal of Industrial Information Integration, 2023, 36: 100534.

[12] Zhou Y. Unmanned aerial vehicles based low-altitude economy with lifecycle techno-economic-environmental analysis for sustainable and smart cities[J]. Journal of Cleaner Production, 2025: 145050.

[13] Schwarzrock J, Zacarias I, Bazzan A L C, et al. Solving task allocation problem in multi unmanned aerial vehicles systems using swarm intelligence[J]. Engineering Applications of Artificial Intelligence, 2018, 72: 10-20.

[14] Zhao X, Zong Q, Tian B, et al. Fast task allocation for heterogeneous unmanned aerial vehicles through reinforcement learning[J]. Aerospace Science and Technology, 2019, 92: 588-594.

[15] Wu X, Yin Y, Xu L, et al. Multi-UAV task allocation based on improved genetic algorithm[J]. IEEE Access, 2021, 9: 100369-100379.

[16] Zhu P, Fang X. Multi-UAV cooperative task assignment based on half random Q-learning[J]. Symmetry, 2021, 13(12): 2417.

[17] Hu C, Qu G, Zhang Y. Pigeon-inspired fuzzy multi-objective task allocation of unmanned aerial vehicles for multi-target tracking[J]. Applied Soft Computing, 2022, 126: 109310.

[18] Bai X, Ye Y, Zhang B, et al. Efficient package delivery task assignment for truck and high capacity drone[J]. IEEE Transactions on Intelligent Transportation Systems, 2023, 24(11): 13422-13435.

[19] Zhang Z, Jiang J, ZHANG W A. Distributed dynamic task allocation for unmanned aerial vehicle swarm systems: A networked evolutionary game-theoretic approach[J]. Chinese Journal of Aeronautics, 2024, 37(6): 182-204.

[20] Park J, Noh G, Park C, et al. Development of mission allocation based on MILP for multi-UAVs with limited resources[J]. Aerospace Science and Technology, 2025, 166: 110598.

[21] Yan M, Yuan H, Xu J, et al. Task allocation and route planning of multiple UAVs in a marine environment based on an improved particle swarm optimization algorithm[J]. EURASIP Journal on Advances in Signal Processing, 2021, 2021(1): 94.

[22] Wang J, Zhou K, Xing W, et al. Applications, evolutions, and challenges of drones in maritime transport[J]. Journal of Marine Science and Engineering, 2023, 11(11): 2056.

[23] Pensado E A, López F V, Jorge H G, et al. UAV shore-to-ship parcel delivery: gust-aware trajectory planning[J]. IEEE Transactions on Aerospace and Electronic Systems, 2024, 60(5): 6213-6223.

[24] Yang Y, Hao X, Wang S. The drone scheduling problem in shore-to-ship delivery: A time discretization-based model with an exact solving approach[J]. Transportation Research Part B: Methodological, 2025, 191: 103117.

[25] Song J, Zhao K, Liu Y. Survey on mission planning of multiple unmanned aerial vehicles[J]. Aerospace, 2023, 10(3): 208.

[26] Deb K, Pratap A, Agarwal S, et al. A fast and elitist multiobjective genetic algorithm: NSGA-II[J]. IEEE transactions on evolutionary computation, 2002, 6(2): 182-197.

[27] Deb K, Beyer H G. Self-adaptive genetic algorithms with simulated binary crossover[J]. Evolutionary computation, 2001, 9(2): 197-221.

[28] Carles-Bou J L, Galán S F. Self-adaptive polynomial mutation in NSGA-II[J]. Soft Computing, 2023, 27(23): 17711-17727.