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Master Computer Science

[Charging-Aware Routing Problem for Multi-UAV Wildfire Detection with Station Deployment]

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Master's Thesis in Computer Science

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Abstract

With the increasing frequency of extreme weather events, wildfires pose an escalating threat to ecosystems. As an efficient aerial inspection tool, Unmanned Aerial Vehicles (UAVs) have attracted growing attention in wildfire monitoring applications. To address the challenges of complex path planning and limited energy capacity in multi-UAV cooperative missions, this thesis proposes an innovative Mixed-Integer Linear Programming (MILP) model that integrates route optimization with charging facility deployment. The model comprehensively accounts for key factors such as charging modes, battery health, maintenance cycles, and cost control, with the objective of minimizing total system cost.

To tackle the computational difficulty of solving large-scale instances, a hybrid optimization framework is further developed by combining a two-stage genetic algorithm with a commercial solver. Experimental results on both benchmark datasets and real-world forest scenarios demonstrate that the proposed approach outperforms traditional methods in solution quality and computational efficiency, and can effectively support the scheduling and deployment strategies of practical forest wildfire prevention systems.

Contents

Chapter 1

Introduction

1.1 Study background

With global warming and the frequent occurrence of extreme weather, the frequency of forest fires and the extent of their damage have been increasing. As an important part of the Earth's ecosystem, the protection and management of forests has become one of the core tasks of ecological environmental protection. The traditional manual patrol approach suffers from high labor costs, slow response times, and limited coverage, making it inadequate for the demands of modern, efficient, and intelligent forest resource management [19]. In response, Unmanned Aerial Vehicle (UAV) offer a compelling alternative to traditional patrol methods for forest monitoring.

The application of UAVs in the forest environment mainly includes tasks such as fire monitoring, illegal logging detection and biodiversity surveys. However, due to the physical constraints of UAVs in terms of flight time, battery capacity, communication range, etc., they still face many challenges during their actual deployment. Especially in large forest scenarios, how to effectively plan the patrol paths of multiple UAVs, coordinate their task assignments, and reasonably set up midway charging stations to meet the energy replenishment and coverage requirements has become a core issue that restricts its widespread applications.

1.2 Problem formulation

This study focuses on the "Multi-UAVs Wildfire Detection and Charging Station Siting Problem", with the core objective of minimizing the overall operational costs, including the cost of charging station construction, UAV usage, and patrol time, while ensuring adequate patrol coverage of the forest area. The forest area is discretized into a uniform hexagonal grid to facilitate coverage modeling. To simplify coverage evaluation, we assume that when a UAV visits a grid, all of its neighboring cells are also considered covered, thereby defining adjacency in the graph structure.

Meanwhile, considering the limited range of the UAV, we introduce a charging mechanism in the model and further distinguish between two modes: fast charging and slow charging. It is found that both fast charging with higher voltage and overcharging have a large negative impact on battery life[25]. Therefore, in order to prolong the UAV lifetime, we limit the maximum charging amount in the model when fast charging is employed, while slow charging, although longer, can charge the battery to full capacity. This setting is not only more realistic,

but also introduces a new modeling complexity: the charging strategy will directly affect the UAV's path planning and charging station layout.
At the model level, we construct a Mixed Integer Linear Programming (MILP) model to jointly model decision variables such as UAV patrol paths, charging behavior, and charging station siting, and introduce key constraints such as sub-patrol path connectivity, charging constraints, and constraints on the dynamic change of energy, so as to ensure that the solution is physical feasibility and scheduling rationality.
Although the MILP model has strong modeling capabilities and optimality guarantees for theoretical solutions, in the actual solution process, due to the huge size of the NP-Hard attributes and variables of the problem, the direct use of commercial solvers (e.g., Gurobi, CPLEX) on medium and large-scale instances often faces the problems of long solution time[21]. For this reason, we designed a hybrid solution framework that integrates heuristic search and exact optimization methods in a hybrid solution approach. The framework takes the Genetic Algorithm (GA) as the global search backbone, and utilizes its advantages of strong search diversity and good convergence in complex solution space to generate a set of feasible solutions that satisfy the constraints; when a solution has a better cost performance, a commercial solver is introduced to perform a local refinement on the solution to further improve the quality and feasibility of the solution.

1.3 Main Contribution

For the challenges of complex path planning, energy constraints, diverse charging behaviors, and difficult charging station siting in multi-UAV collaborative wildfire monitoring missions, this paper carries out system modeling and algorithm design work, and the research work has the following major contributions:

1. We propose a mixed-integer linear programming model that, for the first time, comprehensively considers multiple real-world factors, such as UAV power limitations, maximum mission time, charging mode, charging time, and station deployment, in the context of using multiple UAVs for wildfire detection. The model effectively simulates the complex decision-making environments encountered in real-world forest inspection tasks.

2. To address the high computational cost of the model, we propose a hybrid approach that combines a genetic algorithm with a commercial solver, achieving a balance between accuracy and efficiency.

3. We designed several randomly generated test instances and conducted a real-world case study in China to systematically evaluate the performance of the proposed models and algorithms in terms of solution performance, cost convergence, and other metrics.

1.4 Thesis structure

The structure of this paper is organized as follows: Chapter 2 reviews and summarizes the related researches on multi-drone path planning, charging station siting, multi-objective optimization and hybrid algorithms. Chapter 3 describes in detail the assumptions underlying the problem modeling and the structure of the MILP model, and proposes a solution method that hybridizes the GA and the commercial solver and describes the details of the core algorithms.

Chapter 4 demonstrates the experimental setup and the analysis of the results. Chapter 5 summarizes the whole paper and proposes future research directions. To facilitate reproducibility and further research, all source code and experimental data have been made publicly available at: `https://git.liacs.nl/optimization/mastertheses.git`.

Chapter 2

Literature Review

The purpose of this chapter is to sort out two major research areas closely related to this study: first, the research on vehicle route planning (VRP) around unmanned aerial vehicles (UAVs); and second, the development of forest fire monitoring and patrolling systems, covering the evolutionary trend from traditional manual methods to modern intelligent technologies. By reviewing the above studies, a theoretical foundation is laid for the hybrid modeling and algorithmic approach proposed in this study.

2.1 Research on UAV routing problem

2.1.1 UAV routing problem

The UAV route planning problem can often be abstracted as a variant of the vehicle path problem (VRP), where the goal is to find a set of optimal paths such that multiple mission points can be efficiently visited while satisfying practical conditions such as energy constraints, time windows, and task assignments [28].

Much of the research has focused on using drones to solve the problem of last-mile delivery. Liu et al. [16] investigate the option of using multiple drones to perform in-delivery resupply for multiple trucks in a distribution so that packages arriving late at the warehouse arrive on time. Ren et al. [24] proposed a heuristic algorithm for solving multiple variants of the UAV-assisted vehicle path problem (VRPD). The study considers the case of UAVs taking off and landing at different nodes, supports multiple trucks and UAVs for collaborative distribution, and optimizes the transportation cost or completion time.

Other common research scenarios include the use of UAVs for surveillance or charging, etc. In the paper from Amorosi et al. [1], they explored the routing problem of using UAVs for surveillance using multiple UAVs and a mothership scenario, proposing a MINLP formulation and solving it using both a commercial solver and mathematical methods. Zhou et al.[32] investigated the use of UAVs as mobile charging stations for charging IoT sensors, developed a charging model with a hybrid charging strategy, and solved it using a greedy algorithm.

2.1.2 Energy constrained UAV routing problem

With the widespread use of electric drones, researchers are beginning to expand on Energy-constrained VRP. For example, Tamke et al.[27] focuses on VRP with drone speed selection, also considers speed-dependent energy consumption and drone-charging process. Shen et al.[26] explored drone allocation and battery management strategies in a multi-warehouse UAV delivery system, proposing heuristic algorithms to optimize drone scheduling assuming a fixed charging time. They found that battery replacement is superior to plug-and-play charging, and the shared scheduling strategy for UAVs is more advantageous in terms of throughput enhancement and cost reduction. In the paper from Cokyasar et al.[8], they investigated the use of automated battery replacement devices to extend the range of drones in a drone delivery network and constructed a mixed integer nonlinear model to solve it. The use of drones to improve the safety of transportation of high-value items was investigated by Zandieh et al[31]. They used drones to monitor safety in ground vehicle routes while using charging stations to change batteries for the drones. They proposed an iterative local search algorithm to optimize the problem. Unlike the traditional VRP using graphs, in Liu's study, a spatially-continuous MIP formulation describes the UAV on-demand food delivery model and proposes an online scheduling algorithm to solve the problem, which is proved to be effective in a simulation case[17]. For the application of spraying UAVs in environmental pollution or epidemic response, Manshadian et al. proposed a mixed-integer linear programming model for coordinating ground vehicles and UAVs to work together, in which the UAVs can recover their power by changing batteries in the vehicles. To solve large-scale instances, they designed a hybrid heuristic algorithm incorporating simulated annealing and forbidden search, and verified the effectiveness of the model and algorithm with real data[18]. Nguyen er al.[22] introduce a parallel drone scheduling vehicle routing problem(PDSVRP), which uses multiple drones that change batteries at warehouses to assist vehicles in providing services.

2.1.3 Location-Routing problem with recharging station

Considering the joint optimization of location and path planning for charging facilities is a hot research topic in recent years. Vichitkunakorn et al. [29] studied the stock-taking drone routing problem (STDRP), where a fleet of drones is routing through a warehouse for stock-taking purposes as well as deciding on the location of charging stations on the warehouse floor, and proposed a heuristic algorithm based on Adaptive Large Neighborhood Search (ALNS) for solving it. Chen et al.[6] constructed a charging station locating and capacity optimization model for the range-constrained problem of UAV delivery, integrating task assignment, path planning and charging scheduling to minimize the investment cost and task time, and combining the algorithms of Variable Neighborhood Search (VNS) and Mixed-Integer Linear Programming to efficiently find high-quality solutions in large-scale instances.

2.2 Research on wildfire surveillance

2.2.1 Traditional wildfire inspections

The traditional wildfire prevention system mainly relies on manual inspection, watchtower monitoring and ground communication means, in the vast, high mountains, remote and other terrain there are monitoring blind zones and response lag, but also has very high labor costs and security risks, difficult to meet the needs of modern forest fire prevention [19]. Satellites are also commonly used for forest fire detection. In a study by Rashkovetsky et al. [23], a supervised deep learning approach, trained on satellite images, can achieve a 96% detection rate for forest fires that have already occurred. In wildfire detection using ground-based sensors, weather monitoring sensors, gas sensors, and optical sensors are currently used for detection, but also face challenges including energy consumption, latency, and detection accuracy [5].

2.2.2 Application of UAVs in wildfire detections

In recent years, UAVs have been widely used in wildfire monitoring due to their high mobility, low cost and multi-sensor integration capability. Studies have shown that UAVs can realize wildfire detection at the initial stage of fire by carrying infrared thermal imaging equipment or optical equipment through deep learning technology, with excellent response time and detection accuracy [3]. In the research by Osama et al, [4], a UAV-based wildfire detection system was proposed and demonstrated better performance for early wildfire detection using UAVs compared to traditional IoT devices.

2.2.3 VRP models for wildfire detections

Fewer current studies jointly model energy constraints, multi-UAVs collaboration, and charging station deployment with mission coverage requirements. Rodrigo et al. [9] explored the construction of a forest fire monitoring method including watchtowers, monitoring balloons with UAVs in mountainous areas, and the use of UAVs to expand the coverage of watchtowers, but did not consider issues such as the charging process of UAVs. For the UAV path planning and scheduling problem in forest fire monitoring, Sadati [33] constructs a MILP model and proposes a metaheuristic method to improve the solution efficiency by introducing Benders decomposition. The model performs well on CoVRP and EVRP datasets, and the value of UAV application in wildfire monitoring is verified by a case study in Belgrade Forest, Istanbul. In the research from Momeni et al. [20], they propose a multi-objective mixed-integer planning model for coordinated patrolling between UAVs and ground vehicles for difficult-to-access areas in forest fire monitoring. The solution efficiency is improved by the Benders decomposition algorithm, and the effectiveness of the method is verified in large-scale datasets. Li et al. [15] developed a mixed-integer linear programming model for the path optimization problem in forest firefighting with the objective of minimizing the total fire point loss, and proposed a parallel genetic algorithm combined with variable neighborhood search (PGA-VNS), which outperforms a variety of benchmark algorithms in multiple scale instances. Bailon-Ruiz et al. [2] propose a wildfire monitoring system based on fixed-wing UAV formation, which uses a variable neighborhood search algorithm to plan UAV trajectories for efficient observation of dynamically spreading fires. The model integrates terrain, wind, fire propagation and UAV characteristics, and the effectiveness of the system in tracking fire changes is verified by simulated reality tests. In the paper from Cheng at al. [7], they establish a collaborative truck-UAV-motorcycle site-path robust optimization model for the mountain wildfire emergency transportation problem to minimize the material distribution time, and use a boxed uncertainty set to deal with the demand uncertainty. An improved adaptive large neighborhood search (IALNS) algorithm is proposed, which combines multiple deletion and collaborative strategies to effectively enhance the solution efficiency. Ozkan et al. [12] proposed a UAV path planning method based on minimizing fire probability for the problem of early detection of forest fires far from residential areas. Their model combines heuristic scheduling rules with simulation optimization algorithms while considering the uncertainty and dynamics in real environments, and its effectiveness in real scenarios is demonstrated through experiments. Xu et al. [30] proposed a UAV patrol path planning method based on forest fire risk maps, using the ring self-organizing mapping

(RSOM) algorithm to generate routes based on risk levels and combining with Gaussian hybrid clustering to divide the area, and designing a multi-UAVs collaborative patrolling strategy, so as to solve the problem of the limited range of a single aircraft in the monitoring of fires in large forest areas.

2.3 Research gaps

To analyze the characteristics and shortcomings of the existing studies, we compared the current researches from multiple dimensions. The main comparisons include: the way of environment modeling, whether to support multi-UAVs collaboration, whether to consider energy limitation, charging behavior, charging time, and the way of charging station setup.

Authors	Multi-UAVs	Dynamics	Energy Constraint	Charging Method	Charging Time	Charging Station Deployment
Rodrigo et al. (2024)	yes	no	yes	change battery	no	no
Sadati (2025)	yes	no	yes	change battery	no	no
Momeni et al. (2022)	yes	no	yes	change battery	no	no
Li et al. (2024)	yes	no	yes	not considered	no	no
Bailon-Ruiz et al. (2022)	yes	wildfire state	no	not considered	no	no
Cheng et al. (2024)	no	no	no	not considered	no	no
Ozkan et al. (2022)	no	no	no	not considered	no	no
Xu et al. (2022)	yes	no	no	not considered	no	no
Our research	**yes**	**no**	**yes**	**on-site charging**	**yes**	**yes**

In summary, the current research on multi-UAVs wildfire patrol path planning and charging strategies still has many shortcomings. Most of the literature only considers the basic energy constraints and battery replacement methods, and less involves the modeling of on-site charging behavior as well as charging time, not to mention the lack of systematic research on the optimization of charging station deployment. In contrast, the model proposed in this paper provides more comprehensive modeling in terms of multi-UAVs support, energy constraints, on-site charging behaviors and charging station setups, which helps to fill the key gaps in the current research and provides theoretical support for a wildfire monitoring system that is closer to practical application scenarios.

Chapter 3

Problem Statement and Method

3.1 Problem description

This model addresses the joint problem of UAV path planning and charging station placement in forest patrol tasks. The primary goal is to determine the optimal number of UAVs, their patrol routes, and suitable locations for charging stations to ensure full-area monitoring while minimizing operational costs.

For modeling and practical deployment, we divide the forest area into hexagonal grids with equal side lengths. In order to simulate the detection effect of UAVs, it is assumed that when a UAV arrives at a grid, that grid and all of its six neighboring grids are considered to have been successfully detected, thus achieving coverage of the area.

Considering the power consumption of UAVs during flight, a certain number of charging stations must be constructed in the region to ensure that UAVs can be recharged to replenish energy during mission execution. Unlike the traditional method of using replacement batteries, we allow the UAV to be charged at the charging station at the advance charging rate. Considering the effects of higher charging speeds, deep discharging, and overcharging on the battery life [25], we limit the minimum charge level when the UAV is operating, and set the charging speed to two levels: fast charging can only charge up to 80% of the battery's maximum capacity, and slow charging allows the battery to be fully charged, but takes longer. The charging process is considered to be a linear increase.

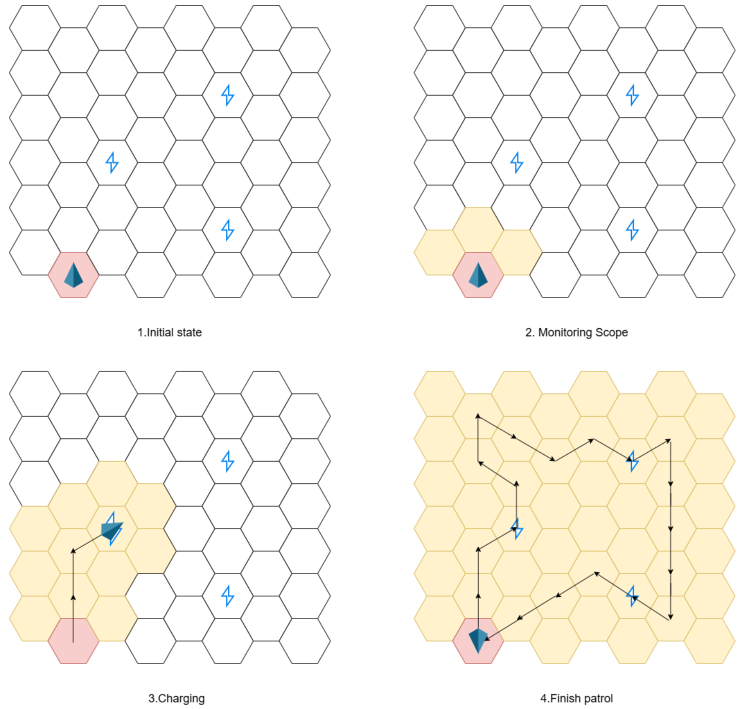

Figure 3.1.1: Grid structure

Figure 4.1.1 illustrates the map structure consisting of a hexagonal grid. In each patrol mission, the UAV starts from the node representing the warehouse, patrols the forest area according to the pre-planned path, can replenish its power at the set charging station node on the way, and finally returns to the warehouse node to complete the mission. In Figure 4.1.1.1, we show the initial scenario using one UAV with three automatic charging stations set up in the area. The area that can be monitored by the drone in the starting state is shown in Figure 4.1.1.2. Figure 4.1.1.3 shows the monitoring of the region when the drone arrives at the charging stations for charging after a period of operation. When the UAV completes a patrol, its operation route and coverage state are shown in Figure 4.1.1.4.

3.2 Model formulation

We propose a mixed-integer linear programming model. The optimization objective of the model is to find the least costly solution by combining the expense of setting up the charging station, the expense of the drone with the time cost of patrolling. The parameters and variables used are shown in Table 3.2.1.

Sets:	
V	set of all nodes without warehouse.
V_0	$V_0 = V \cup 0$ set of nodes includes warehouse 0.
S	current charging station.
Parameters:	
K	maximum number of drones.
Q	maximum battery level.
δ_{ij}	node i is the neighbor of node j.
d	distance between two nodes.
t	time to move between two conjoint nodes.
e	power consumption between two nodes.
v_f	charging speed for fast charging.
v_s	charging speed for slow charging.
C_s	charging station setup costs.
C_d	drone costs.
C_t	time costs per hour.
C_m	maintenance intervals for equipment.
Decision Variables:	
x_{ij}^k	whether drone k move from node i to j.
r_i^k	whether drone k using fast charge at node i.
f_i	whether node i is charging node or not.
d_k	whether drone k is used.
τ_i^k	the time that the drone k reaches the node i.
t_{max}^k	the total time spent on one patrol for drone k.
ω_i^k	charge of drone k at node i.
y_i^k	battery level for drone k at node i.

Table 3.2.1: Variables and parameters used in the model

$$\text{Minimize} \quad C_s \sum_{i \in V} f_i + C_d \sum_{k \in K} d_k + C_m C_t \sum_{k \in K} t^k_{max} \tag{3.1}$$

$$\sum_{i \in V} \sum_{l \in V} \sum_{k \in K} \delta_{ij} \cdot x^k_{li} \geq 1, \quad \forall j \in V \tag{3.2}$$

$$f_i = 1, \quad \forall i \in S \tag{3.3}$$

$$x^k_{ij} \leq d_k, \quad i, j \in V_0, k \in K \tag{3.4}$$

$$\sum_{j \in V} x^k_{ij} = \sum_{j \in V} x^k_{ji}, \quad \forall i \in V, k \in K \tag{3.5}$$

$$\sum_{i \in V} x^k_{0i} \leq d_k, \quad \forall k \in K \tag{3.6}$$

$$\sum_{i \in V} x^k_{i0} \leq d_k, \quad \forall k \in K \tag{3.7}$$

$$y^k_i \geq 0.2 \cdot Q, \quad \forall i \in V, k \in K \tag{3.8}$$

$$y^k_i \leq Q \cdot (1 - 0.2 r^k_i), \quad \forall i \in V, k \in K \tag{3.9}$$

$$\omega^k_i \leq Q \cdot f_i, \quad \forall k \in K, i \in V_0 \tag{3.10}$$

$$y^k_j - \omega^k_j \leq y^k_i - e x^k_{ij}, \quad i \in V_0, j \in V, k \in K \tag{3.11}$$

$$\tau^k_i + t x^k_{ij} + \omega^k_i \cdot (\frac{r^k_i}{v_f} + \frac{1 - r^k_i}{v_s}) - M(1 - x^k_{ij}) \leq \tau^k_j, \quad \forall i \in V_0, j \in V, i \neq j, k \in K \tag{3.12}$$

$$t^k_{max} \geq \tau^k_i, \quad \forall i \in V, k \in K \tag{3.13}$$

$$x^k_{ij} \in \{0, 1\}, \quad i, j \in V_0, k \in K \tag{3.14}$$

$$r^k_i \in \{0, 1\}, \quad i \in V_0, k \in K \tag{3.15}$$

$$f_i \in \{0, 1\}, \quad i \in V_0 \tag{3.16}$$

$$d_k \in \{0, 1\}, \quad k \in K \tag{3.17}$$

$$\tau^k_i, \omega^k_i, y^k_i \in \mathbb{R}_{\geq 0}, \quad i \in V_0, k \in K \tag{3.18}$$

Objective function 3.1 minimizes the total cost of building charging stations, purchasing drones, and patrolling routes. Since the UAV performs multiple missions during a single maintenance cycle. We set the UAV to perform one patrol per day and therefore multiply the maintenance cycle by the path cost of a single mission as the total path cost. The constraint 3.2 is the drone coverage constraint. The constraint 3.3 indicates whether there are already charging stations in the forest. The constraint 3.4 restricts activation to only purchased drones.The constraint 3.5 ensures the continuity of the drone's route. The constraints 3.6 - 3.7 constrain the drone from and back to the warehouse. The constraint 3.8 - 3.9 are on battery health where 3.8 ensure the battery level is higher than 20% and 3.9 limits maximum battery level for fast and slow charging. Constrain 3.10 constraint drones can only charged at charging station. Constraint 3.11 indicates the change in power level of the drones. Constraint 3.12 is sub-tours eliminating constrains considering movement and charging times. The constraint 3.13 is used to ensure that t^k_{max} records the running time for drone k to complete a patrol. Finally, the constraints 3.14 - 3.18 denote the domains of definition of the variables.

3.3 Hybrid method

Although the Mixed Integer Linear Programming (MILP) model can accurately describe the constraints and optimization objectives of the forest patrol and charging station site problem, as the size of the problem increases (e.g., the number of nodes and the number of available UAVs increase), solving the complete model using commercial solvers (e.g., Gurobi, CPLEX) will face high computational resources consumption and slow convergence problems[13]. To solve this problem, we propose a hybrid optimization method that combines a Genetic Algorithm (GA)[14] with a commercial MILP solver, aiming to balance global exploration and local refinement.

Genetic algorithm is an optimization method that simulates the process of natural selection and genetic variation, and its basic process includes:

- population initialization: generate a set of initial feasible solutions that satisfy the constraints.
- Adaptation Evaluation: calculate the adaptation degree of each individual based on the objective function.
- Selection: select quality individuals into the next generation based on fitness.
- crossover and mutation: perform crossover and mutation on the offspring to explore the new solution space;
- evolutionary iteration: repeat the above process until the termination condition is satisfied.

However, for the complex variable space of our model, running the genetic algorithm directly on the full variable space will cause inter-variable interference, resulting in slow convergence and poor solution quality. Therefore, we designed a two-stage genetic algorithm to improve the search stability and solution space coverage by staged crossover and optimization of the variable subspace. Its structure is as follows:

1. Initialization set: First, in order to enhance the population quality and early convergence speed of GA, we design an initial solution generation method based on graph partitioning and greedy optimization. The specific steps are as follows:
   - Initial path construction: for each subgraph, solve a path that starts from the depot and completely covers all grids within the subgraph before returning to the depot. The path can be obtained by solving the TSP with a commercial solver.
   - Path Refinement Optimization: After obtaining a complete path, sequentially try to delete noncritical nodes in the path, and observe whether the coverage requirement can still be satisfied for all grids and their neighboring grids in the graph. If the coverage is still satisfied the constraint 3.2, the deletion operation is retained until the path cannot be further compressed.
   - Charging station deployment: On the refined path, the battery consumption of the UAV is simulated step by step based on the power usage per grid movement. According to the constraint 3.8 and constraint 3.9, if the remaining battery falls below 20% of the full capacity before the next move, a charging station is deployed

at the current grid and a fast-charging operation is triggered to recharge the battery up to 80%. These charging decisions are recorded in the solution as binary station placement variables. The resulting path ensures energy feasibility for each UAV to complete its task and return safely to the depot.

- Initial solution set construction: Repeat the above process from 1 to K times to construct feasible paths using 1 to K UAVs and charging station deployment scenarios, and ultimately obtain a diversified initial solution set with reasonable structure and constraints satisfied, which serves as the initial population of GA.

2. Two-stage genetic algorithm Search: We use a two-stage genetic algorithm for localized search. The crossover and mutation is performed on the multi-UAVs path or the charging station location in the current solution in each of the two phases, and the two phases are repeated to gradually optimize the solution.

   - Fix the path variables, and only crossover the charging station deployment related variables to optimize the charging station deployment scheme.
   - Fix the charging station layout and perform genetic operations only on the multi-UAVs detection paths to optimize the path structure.

3. Global refinement: To overcome the defect that out two-stage genetic algorithms may fall into local optimization in complex constraint spaces, in this paper, after completing the complete two-phase search cycle each time, the commercial solver is automatically invoked to perform fine solving for the feasible solutions with higher quality in the current population.

   - Select the feasible solution with better objective value from the current solution set as the initial solution to be passed into the commercial solver, and construct the corresponding problem for refining the solution.
   - If the objective value is better after refinement, replace the original individual with the new solution and update the population.
   - If the refinement fails or there is no improvement, the maximum solution time for the next call to the solver is extended to improve its solving capability.

4. Iteration and Termination: Repeat the above two steps until the solver give the optimized solution or the set upper algebraic limit or convergence criterion is satisfied, and finally outputs the current optimal solution set.

Algorithm 1 Hybrid GA and MILP Solver for Wildfire Patrol and Charging Station Planning

```
Input: Graph G = (V, E), depot node, UAV and energy constraints, max UAV count K
Output: Optimal or near-optimal patrol paths and charging station layout
for k = 1 to K do
    Partition G into k subgraphs
    for each subgraph do
        Solve TSP path covering all grids from depot and returning to depot
        while there exists a deletable noncritical node do
            Try deleting the node
            if coverage constraints (Eq. 3.2) still satisfied then
                Keep deletion
            else
                Revert deletion
            end if
        end while
        Deploy charging stations on the refined path according to UAV energy constraints
    end for
    Add constructed k-UAVs solution to initial population P_0
end for
while termination criteria not met do
    while termination criteria not met do
        Fix paths, apply crossover and mutation on charging station variables only
        Fix charging stations, apply crossover and mutation on path variables only
    end while
    Select best feasible individual(s) from current population
    Pass as initial solution(s) to MILP solver for refinement
    if refined solution improves objective then
        Replace original individual and update population
    else
        Increase MILP solver runtime limit for next call
    end if
end while
Return the best solution found
```

Chapter 4

Computational Experiments

4.1 Experiment setting

4.1.1 Benchmarking instances

To validate the effectiveness of the proposed model and algorithm, we designed two types of experimental datasets: basic test instances and real forest data.
The base test instance uses a randomly generated hexagonal grid to model the forest region. The edge length of the grid is the unit distance, each node represents a node in the UAV movement path, and the edges indicate the reachable paths. The connectivity between the grids is guaranteed, and the adjacency relationship is considered for simulating the coverage of the UAV. The specific test instance data is shown in table 4.1.1, which includes the instance name, the number of grids to be monitored(N) and the maximum number of drones available(K).

Instance	N	K	Instance	N	K
a1	18	1	b7	36	2
a2	20	1	b8	42	2
a3	30	1	b9	48	2
a4	36	1	c1	12	3
a5	42	1	c2	16	3
a6	48	1	c3	18	3
b1	12	2	c4	20	3
b2	16	2	c5	24	3
b3	18	2	c6	30	3
b4	20	2	c7	36	3
b5	24	2	c8	42	3
b6	30	2	c9	48	3

Table 4.1.1: Instances

The real data as shown in figure 4.1.1 comes from a forest in the northern region of China. By processing the map data, we transformed the field forest area into an equilateral hexagonal grid map and labeled the location of the starting point (warehouse). Finally, we obtain a forest graph structure with 92 valid nodes, which has some practical feasibility.

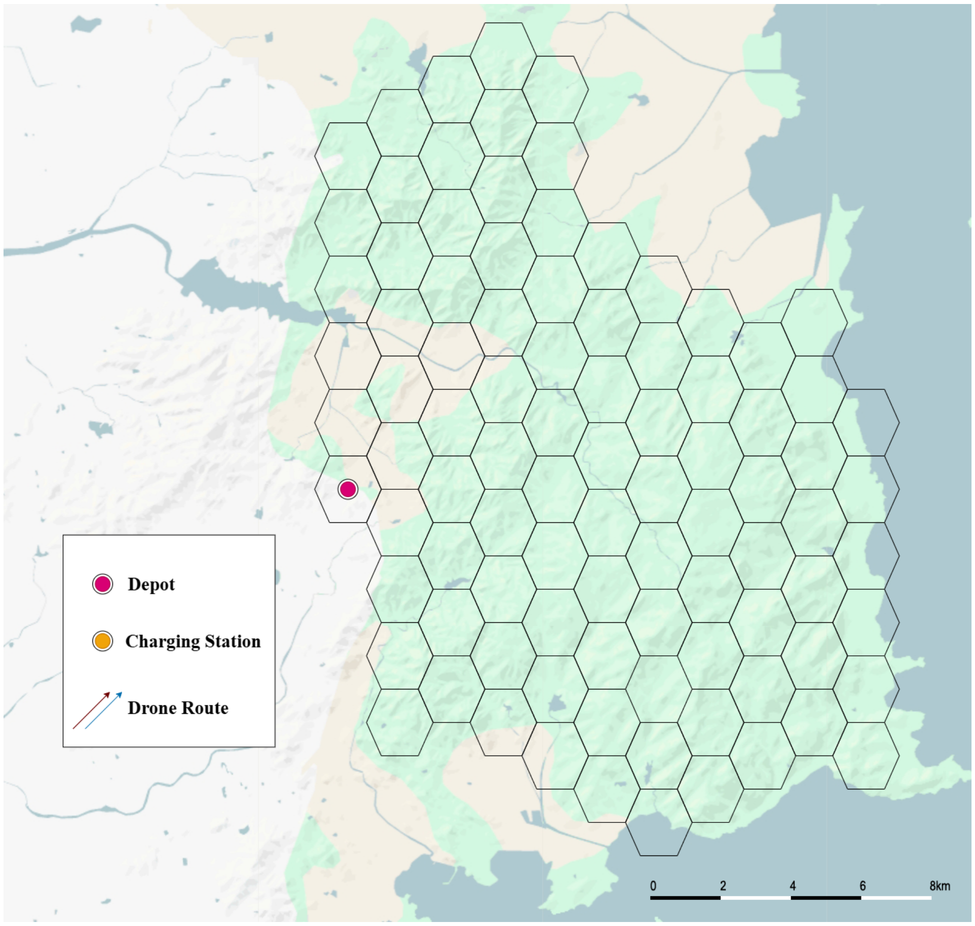

Figure 4.1.1: Real World Data

4.1.2 UAV parameter setting

The key parameters in the experiments are shown in Table 4.1.2.The selected UAV and charging station parameters were taken from the technical specifications of Heisha Tech[11] and DJI[10]. The model of the charging station used is Heisha Tech V200 and the model of the UAV is DJI FlyCart 30.

Paremeters	Value
UAV cost	1000$
Charge station cost	3000$
Time cost	3.6$/h
Maintenance Cycle	365 Days
Maximum SOC in fast charge	80%
Minimum SOC	20%
UVA battery energy	2000Wh
Fast charge power	180W
Slow charge power	45W
UAV speed	20m/s
Power usage between node	20Wh

Table 4.1.2: Parameters setting

4.1.3 Hyperparameter Tuning

To improve the performance of the hybrid algorithm and ensure high quality solutions in a reasonable time, we tuned the hyperparameter of one of the genetic algorithms. The goal of tuning is to balance the solution quality and computational efficiency, mainly focusing on five hyperparameter: population size, number of offspring, crossover probability, termination period, and maximum number of iterations.
We used grid search to test the combination of the above parameters on base test instance b6 and averaged the results based on multiple random initial seeds to ensure the stability of the results. Table ?? shows the search range with the final selected parameter combinations.

Hyperparameter	**Search Space**	**Result**
pop_size	100, 200, 300, 400, 500, 600, 800, 1000	300
n_offsprings	30, 50, 70, 100, 150, 200	150
crossover_prob	0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95	0.9
termination_period	10, 15, 20, 25, 30	20
n_max_gen	100, 200, 300, 400, 500, 600	300

Table 4.1.3: Hybrid method hyperparameter tuning

Among all candidate combinations, the final selected parameter configuration is: pop_size=300, n_offsprings=150, crossover_prob=0.9, termination.period=20, termination.n_max_gen= 300.This combination shows stable search capability with fast convergence on the test instances, and high quality solutions are obtained in reasonable time on most runs.

4.1.4 Benchmarking environment

All experiments were running on the ALICE compute resources provided by Leiden University. Here are the hardware and software configurations:

- CPU: Intel Xeon Gold 6126 2.6GHz 12-Core
- Memory per cpu: 4GB
- Programming language: Python 3.12.3
- Solver: gurobi 12.0.0
- GA: implement from pymoo 0.6.1.5

4.2 MIP performance

Table 4.2 shows the performance of Gurobi on the base test instance. The column "Drone Route Length" reports the monitoring path length of each UAV. When multiple UAVs are used, values are separated by a "|" symbol. From the results:

- For small-sized instances, Gurobi is able to find the optimal solution in a very short period of time, and the optimal solution has exactly the same upper and lower bounds.

- As the number of nodes and the number of UAV increase, the size of the problem grows rapidly and the number of variables and constraints grows exponentially. For example, instance c9 contains more than 7500 variables and 20,000 constraints.
- In medium- to large-sized instances, Gurobi has not yet found an optimal solution within the specified time limit of 7200 seconds, and the optimality gap is generally more than 75%, which demonstrates the high computational complexity of the problem.
- Certain medium-sized instances were able to find the optimal solution, but took longer, reaching hundreds of seconds or even nearly time limit.

This result shows that although the MIP model can obtain an accurate solution on small instances, its efficiency is limited when dealing with large-scale instances, especially in the case of an increasing number of UAVs, where the solution space expands rapidly, resulting in search difficulties.

Instance	UB	LB	Gap (%)	Time (s)	Station Count	Drone Count	Drone Route Length
a1	3920.0	3920.0	0.0	50.93	0	1	8
a2	3920.0	3920.0	0.0	3.98	0	1	8
a3	12030.0	7285.0	39.44	7200.00	1	1	22
a4	14585.0	2460.0	83.13	7200.00	1	1	29
a5	19410.0	2456.0	87.20	7200.00	2	1	34
a6	22695.0	2095.0	90.77	7200.00	2	1	43
b1	2460.0	2460.0	0.0	1.59	0	1	4
b2	3190.0	3190.0	0.0	1.93	0	1	6
b3	3920.0	3920.0	0.0	6.55	0	1	8
b4	3920.0	3920.0	0.0	40.46	0	1	8
b5	7475.0	7475.0	0.0	5975.50	0	2	8 | 7
b6	7475.0	3460.0	0.15	7200.00	0	2	8 | 7
b7	14585.0	2095.0	85.63	7200.00	1	1	29
b8	18870.0	2101.0	88.87	7200.00	1	2	33 | 5
b9	24155.0	2095.0	91.32	7200.00	2	1	47
c1	2460.0	2460.0	0.0	1.04	0	1	4
c2	3190.0	3190.0	0.0	26.88	0	1	6
c3	3920.0	3920.0	0.0	105.05	0	1	8
c4	3920.0	3920.0	0.0	203.24	0	1	8
c5	7475.0	4920.0	34.18	7200.00	0	2	8 | 7
c6	7475.0	2475.0	66.89	7200.00	0	2	8 | 7
c7	14585.0	2101.0	88.87	7200.00	1	1	29
c8	18140.0	1735.0	90.43	7200.00	1	2	33 | 3
c9	22695.0	2095.0	90.76	7200.00	2	1	43

Table 4.2.1: Gurobi experiment result

4.3 Hybrid method performance

4.3.1 Performance on base test instance

To evaluate the effectiveness of the proposed hybrid algorithm, we use Gurobi, Hybrid method, and two-stage genetic algorithm without refinement process to solve on base test instance respectively. Table 4.3.1 shows the results of the three methods in terms of solution quality and solution time.

In terms of solution quality, Gurobi, as an exact solver, succeeds in obtaining optimal solutions in most small-scale instances. However, as the problem size increases, Gurobi exhausts the set maximum runtime (7200 seconds) in several instances (e.g., a3, a4, a5, etc.) without obtaining a feasible solution or with suboptimal solution quality. In contrast, the hybrid method finds feasible solutions in a short time in all instances and reaches or approaches Gurobi's optimal results in most of the cases, and even outperforms Gurobi in some instances (e.g., b8, b9, and c8), with the optimal solutions outperforming Gurobi by 9.6%, 6.0%, and 2.0%, respectively. This indicates that the hybrid algorithm has stronger robustness and solution space search capability while maintaining good convergence.

Further observation of the difference between the Init cost and Min cost shows that the hybrid algorithm significantly reduces the objective function value during the optimization process, with an average reduction of more than 30%, which verifies the synergy between the two-stage genetic search mechanism and the global refinement strategy. The results obtained using the two-stage GA are generally higher than those of the hybrid algorithm and Gurobi, indicating that the unrefined genetic algorithm is prone to fall into local optimality on this problem.

In terms of solution efficiency, Gurobi takes a significant amount of time in most medium to large instances, reaching the upper limit of 7,200 seconds in several instances, while the hybrid algorithm is able to obtain a high-quality solution within a few minutes in the majority of cases, demonstrating good computational efficiency. For example, in the a6 instance, the hybrid algorithm obtained a solution comparable to Gurobi in only 160 seconds, which is a significant improvement in efficiency.

In summary, the proposed hybrid algorithm outperforms the traditional GA in terms of solution quality and solving efficiency in this model, and is able to match or even exceed Gurobi's performance in most instances, which verifies the applicability and practicality of the method in complex wildfire detection tasks.

	Gurobi		Hybrid method								GA	
Instance	Cost	Time(s)	Init cost	Min cost	Init cost gap(%)	Min cost gap(%)	Station Count	Drone Count	Drone Running Time	Time(s)	Cost	Time(s)
a1	**3920.0**	50.93	12760.0	**3920.0**	69.27	0.0	0	1	8	13.18	**3920.0**	7.47
a2	**3920.0**	3.98	12760.0	**3920.0**	74.95	0.0	0	1	8	13.25	**3920.0**	8.40
a3	12030.0	7200.00	14585.0	**12030.0**	17.52	0.0	1	1	22	66.06	13490.0	16.87
a4	**14585.0**	7200.00	21455.0	15680.0	35.08	6.9	1	1	32	74.82	21455.0	28.04
a5	**19410.0**	7200.00	24885.0	21235.0	14.67	8.5	2	1	39	85.58	21600.0	58.52
a6	**22695.0**	7200.00	34455.0	23790.0	30.95	4.6	2	1	46	160.02	28535.0	94.65
b1	**2460.0**	1.59	3140.0	**2460.0**	21.65	0.0	0	1	4	1.91	2825.0	1.64
b2	**3190.0**	1.93	4055.0	**3190.0**	21.33	0.0	0	1	6	2.86	**3190.0**	1.72
b3	**3920.0**	6.55	9020.0	**3920.0**	56.54	0.0	0	1	8	8.89	5285.0	5.23
b4	**3920.0**	40.46	8570.0	**3920.0**	54.25	0.0	0	1	8	32.29	6380.0	17.42
b5	**7475.0**	5975.50	10845.0	**7475.0**	31.08	0.0	0	2	8 | 7	71.23	7840.0	31.81
b6	**7475.0**	7200.00	11030.0	**7475.0**	32.23	0.0	0	2	8 | 7	55.87	**7475.0**	44.64
b7	**14585.0**	7200.00	25020.0	**14585.0**	41.70	0.0	1	1	29	101.63	24155.0	86.57
b8	18870.0	7200.00	26295.0	**17045.0**	35.18	-9.6	1	2	25 | 7	160.48	24885.0	91.47
b9	24155.0	7200.00	31630.0	**22695.0**	28.24	-6.0	2	1	43	152.23	28805.0	106.70
c1	**2460.0**	1.04	3700.0	**2460.0**	33.5	0.0	0	1	4	2.10	2825.0	1.05
c2	**3190.0**	26.88	5040.0	**3190.0**	36.71	0.0	0	1	6	18.29	**3190.0**	11.51
c3	**3920.0**	105.05	8110.0	**3920.0**	51.66	0.0	0	1	8	29.19	5285.0	15.90
c4	**3920.0**	203.24	9450.0	**3920.0**	58.51	0.0	0	1	8	34.57	6380.0	16.34
c5	**7475.0**	7200.00	11030.0	**7475.0**	32.23	0.0	0	2	8 | 7	83.22	7840.0	52.45
c6	**7475.0**	7200.00	10665.0	**7475.0**	29.91	0.0	0	2	8 | 7	103.84	7475.0	54.22
c7	**14585.0**	7200.00	26490.0	**14585.0**	44.95	0.0	1	1	29	126.67	24155.0	104.53
c8	18140.0	7200.00	30770.0	**17775.0**	42.25	-2.0	1	2	3 | 32	170.07	24885.0	108.62
c9	**22695.0**	7200.00	35065.0	**22695.0**	35.28	0.0	2	1	42	249.01	28805.0	163.07

Table 4.3.1: Result on generated dataset

4.3.2 Performance on real world data

On the real forest inspection dataset shown in figure 4.1.1, we further validate the practical adaptability and optimization performance of the proposed hybrid optimization method. The experimental results are shown in table 4.3.2 and the obtained UAV routes with charging station locations are shown in figure 4.3.1.

Result:	
Init cost	81155.0
Min cost	28520.0
Gap	64.85%
Time	272.47s

Table 4.3.2: Result summary on real world data

From the results, it can be seen that the hybrid method effectively reduces the total cost of the problem in a shorter period of time, from 23,159 for the initial solution to 11,242 for the final solution, with an optimization of 51.46%. This fully demonstrates that the hybrid algorithm has good convergence ability and solution efficiency in the complex, multi-constraint, multi-objective real forest inspection task.

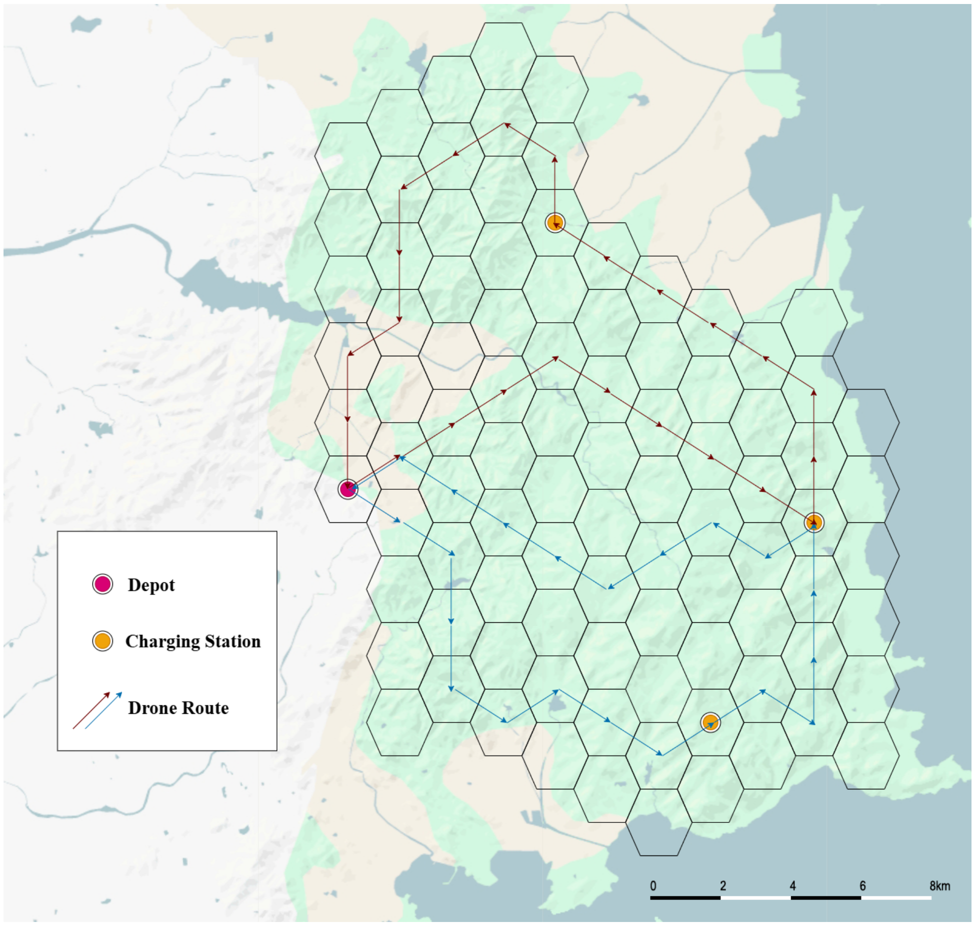

Figure 4.3.1: Real world result

4.4 Impact of UAV parameters

To further investigate the sensitivity of the model to key parameters, we designed a set of comparative experiments to analyze the effects on the total system cost, the number of charging stations, the number of UAVs and the mission path structure by varying the key parameters such as the charging station construction cost, the UAV acquisition cost, the number of UAVs with the maximum range nodes, and the maximum maintenance cycle, respectively.

Station Cost	Drone Cost	Maximum Operating Node	Maintenance Cycle	Cost	Station Count	Drone Count	Drone Route Length
3000	1000	10	365	19045	2	1	33
1000	1000	10	365	15045	2	1	33
5000	1000	10	365	23045	2	1	33
10000	1000	10	365	33045	2	1	33
3000	100	10	365	18145	2	1	33
3000	500	10	365	18545	2	1	33
3000	1000	7	365	22045	3	1	33
1000	100	10	365	14245	2	2	28	5
3000	1000	20	365	10395	0	2	11	11
3000	1000	10	180	12940	2	1	33
3000	1000	10	720	30760	2	1	33

We find that the increase in charging station costs, drone costs and maintenance interval leads to a linear cost increase. With a constant configuration, only the total cost is affected without changing the overall scheduling structure. Say It is shown that the model is difficult to further compress the fixed costs of charging stations and drones, exhibiting a stronger dependence on infrastructure.

UAV range has a significant impact on the optimization results. When the maximum number of operable nodes is increased from 10 to 20, the system completely removes the charging station deployment and uses 2 UAVs to complete the paths separately, significantly reducing the total cost. Whereas, when the range is reduced, additional charging stations must be deployed to meet mission feasibility as the remaining infrastructure costs remain the same.

Meanwhile, in the combination scenario of low UAV cost and low site cost, the system tends to enable multiple UAVs to share the task, resulting in path splitting, demonstrating the ability of the scheduling mechanism to adapt to the cost structure.

In summary, the system optimization results are most sensitive to range capability, followed by the infrastructure price. For practical deployments, improving UAV range or reducing the infrastructure cost within a reasonable range will have the most significant effect on overall system cost control.

4.5 Discussion

This chapter evaluates the effectiveness of the proposed multi-UAVs wildfire inspection and charging station siting planning model and its solution method through a series of experiments. First, in the constructed basic test instances, we validate the model's solution capability at different scales. Subsequently, the proposed hybrid optimization algorithm is further tested on real maps. Compared to solving with gurobi and genetic algorithm, it performs better in terms of runtime speed while the solution quality remains stable. In addition, combining the UAV operation parameters with the actual charging strategy settings, the experiment also verifies the feasibility and flexibility of the model in real deployment.

Chapter 5

Conclusions

This study focuses on the path planning and charging station siting problem for multi-UAVs collaborating in wildfire monitoring missions, and proposes a multi-objective mixed-integer planning model that considers energy constraints, charging behaviors (including fast and slow charging), charging time, and charging station deployment. To cope with the difficulty of solving this problem under large-scale instances, this paper designs a hybrid solving framework based on the collaborative solution of genetic algorithm (GA) and commercial optimizer, which takes into account both the solution quality and the solving efficiency.

Through testing on generated and real geographic data, we verify that the proposed model can effectively plan the cooperative patrol paths of multiple UAVs, accomplish the wildfire monitoring task under the premise of satisfying the energy constraints and battery health, and realize the reasonable arrangement of charging resources. Compared with the existing studies that focus only on the path planning itself, ignoring the practical issues such as charging time and station deployment, the work in this paper has obvious advantages in terms of modeling depth and real-world adaptability.

This research has theoretical and practical significance. In the theoretical aspect, this paper constructs a realistic optimization model, which provides a modeling idea and solution method for the multi-UAVs routing problem. In practice, the research results can be widely used in wildfire protection, agricultural monitoring, border security and other practical scenarios that require large-scale patrol. The related models and algorithms are of high reference value for researchers, engineering practitioners and even forest management departments, which can help them design more efficient and sustainable UAV scheduling schemes, and improve the efficiency of resource use and system intelligence.

Future research can be expanded in the following directions: first, the dynamic response model of wildfire is introduced to make UAV scheduling closer to real emergency response needs. The second is to add communication constraints and cooperative mechanisms to enhance the UAV's mission coordination capability in complex environments. Third, uncertainty and robust optimization are considered to improve the stability and anti-disturbance of the model in real deployment. Fourth, we promote the integration of the model with the actual system, combine remote sensing images, terrain data and flight control platform to carry out joint testing of hardware and software, and verify the application effect of the model in reality.

Overall, this paper explores the modeling depth, realistic constraint considerations, algorithm design, and application effects, providing a foundation for the construction of an intelligent UAV wildfire monitoring system.

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