Cost Function Minimization-Based Joint UAV Path Planning and Charging Station Deployment (Workshop)

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Abstract. The rapid development of automatic control, wireless communication and intelligent information processing promotes the prosperity of unmanned aerial vehicles (UAVs) technologies. In some applications, UAVs are required to fly from given source places to certain destinations for task execution, a reasonable path planning and charging stations (CSs) strategy can be designed to achieve the performance enhancement of task execution of the UAVs. In this paper, we consider joint UAV path planning and CS deployment problem. Stressing the importance of the total time of the UAVs to perform tasks and the cost of deploying and maintaining CSs, we formulate the joint path planning and CS deployment problem as a cost function minimization problem. Since the formulated optimization problem is an NP-hard problem which cannot be solved easily, we propose a heuristic algorithm which successively solves two subproblems, i.e, path planning subproblem and destination path selection subproblem by applying the A* algorithm, K-shortest path algorithm and genetic algorithm (GA), respectively. Simulation results validate the effectiveness of the proposed algorithm.

Keywords: UAV · Path planning · Charging station deployment · Cost function

1 Introduction

The rapid development of automatic control, wireless communication and intelligent information processing promotes the prosperity of unmanned aerial vehicles (UAVs) technologies. Being capable of flying under certain commands and executing specific tasks without a human pilot on board, UAVs have been commonly applied in public and military fields [1].

In some applications [2–5], UAVs are required to fly from given source places to certain destinations for task execution, a reasonable path planning strategy for the UAV should be designed. Furthermore, due to the limited battery capacity of the UAVs, long-distance continuous flying might be difficult. To tackle this problem, various charging stations (CSs) can be deployed, i.e., deploying multiple CSs in the flying area of the UAVs, can be an efficient and practical approach. By charging at the CSs, long distance flight for UAVs might be possible.

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In recent years, researchers have carried out studies on UAV path planning and CS deployment. The algorithm in [6] studied the path planning problem of UAVs and proposed an A* algorithm-based heuristic search method to obtain the shortest flight time. Aiming to minimize the flight time, the authors in [7] proposed a path planning method based on A* algorithm and Dubins path strategy. Considering the flight constraints of the UAVs during the planning process, the authors in [8] modeled the threat regions as points and proposed a K-shortest path algorithm-based strategy with the objective of minimizing the total flight time. To determine the paths with the shortest flight time, the authors in [9] discussed any-angle path planning algorithm that are variants of classical A* algorithm. Through propagating information along the edges of the flight grid, the shortest paths can be determined. In [10], the authors proposed a path planing algorithm which aims to minimize the flight time of UAVs.

The problem of CS deployment was considered when planing paths for UAVs [11, 12]. In [11], the authors studied the problem of determining a path for an energy-limited UAV to visit a set of sites, and presented an algorithm aiming to find the shortest time for UAVs and the optimal locations to place CSs. The authors in [12] consider deploying mobile CSs for the UAVs, and proposed a joint UAV path planning and CS deployment algorithm to obtain the optimal UAVs flight path and require the shortest time for the CSs reach the charging points.

In this paper, we study joint UAV path planning and CS deployment problem. Stressing the importance of the total time of the UAVs to perform tasks and the cost of deploying the CSs, we formulate the joint path planning and CS deployment problem as a cost function minimization problem. Since the formulated optimization problem is an NP-hard problem which cannot be solved easily, we propose a heuristic algorithm which successively solves two subproblems, i.e, path planning subproblem and destination path selection subproblem by applying the A* algorithm, K-shortest path algorithm and genetic algorithm (GA), respectively.

The rest of this paper is organized as follows. Section 2 describes the system model considered in this paper and the discrete processing of the UAV flight area. Section 3 presents the formulation of the cost function minimization problem. The solution to the optimization problem is described in Sect. 4. Section 5 presents the numerical results. The conclusion is drawn in Sect. 6.

2 System Model and Discrete Processing of the Flight Area

In this paper, we consider the scenario that multiple UAVs are required to perform tasks in a rectangular area. We denote X, Y respectively as the length and the width of the area, U_l as the lth UAV, $1 \leq l \leq L$, L is the total number of UAVs. Let $\mathrm{S} = \{\mathrm{S}_1, \mathrm{S}_2, \ldots, \mathrm{S}_L\}$ denote the set of task sources and $\mathrm{D} = \{\mathrm{D}_1, \mathrm{D}_2, \ldots, \mathrm{D}_L\}$ denote the set of task destinations of the UAVs, where S_l, D_l denote respectively the task source and destination of U_l.

Due to the limited endurance of the UAVs, they may not perform long-distance tasks, thus should be charged during the flight. We assume that CSs can be deployed in the flight area of UAVs, let $\mathrm{C} = \{\mathrm{C}_1, \mathrm{C}_2, \ldots, \mathrm{C}_M\}$ denote the set of CSs, where C_m denotes the mth CS, $1 \leq m \leq M$, M is the total number of CSs. We further assume that there are some threats in the flight area and the CSs can only be deployed in the area without obstacles. Figure 1 shows the system model considered in this paper. For simplicity, we conduct two-dimensional discrete processing over the flight region of the UAVs, more specifically, we model the flight area of the UAVs as a two-dimensional grid. Let Δ_x and Δ_y respectively be the distance between the adjacent grids in row and columns, let $N_x^{\max}$ and $N_y^{\max}$ be the maximum number of the grids in row and column, respectively, where $N_x^{\max} = [\frac{X}{\Delta_x}]$, $N_y^{\max} = [\frac{Y}{\Delta_y}]$. $\mathrm{N}_{i,j}$ denotes the node in the ith row and the jth column, $0 \le i \le N_x^{\max}$, $0 \le j \le N_y^{\max}$. Let $\mathrm{N}_l^{\mathrm{s}}$ denote the source grid of U_l and $\mathrm{N}_l^{\mathrm{d}}$ denotes the destination grid of U_l, we obtain $\mathrm{N}_l^s = \arg\min\{\,|\mathrm{S}_l - \mathrm{N}_{i,j}\,|^2\}$, $\mathrm{N}_l^d = \arg\min\{\,|\mathrm{d}_l - \mathrm{N}_{i,j}\,|^2\}$.

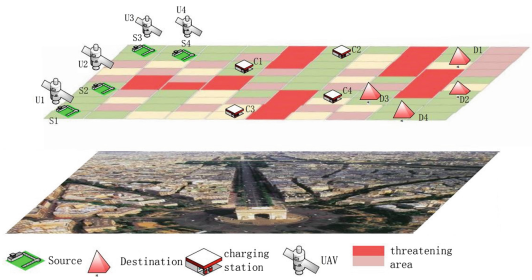

Fig. 1. System model

Let $y_{i,j,m}$ denote CS deployment variable, if C_m is deployed at $\mathrm{N}_{i,j}$, $y_{i,j,m} = 1$, otherwise, $y_{i,j,m} = 0$. We denote $x_{l,m}$ as the charging variable of the UAVs, if U_l charges at C_m, $x_{l,m} = 1$, otherwise, $x_{l,m} = 0$. The flight path of the UAVs might be subject to certain types of threats, i.e., atmospheric threats, terrain threats, etc., we denote $G_{i,j}$ as the threats indicator of $\mathrm{N}_{i,j}$, that is, if $\mathrm{N}_{i,j}$ is the threatening area, $G_{i,j} = 1$, otherwise, $G_{i,j} = 0$. Figure 2 shows the two-dimensional discretization of the flight area of the UAVs.

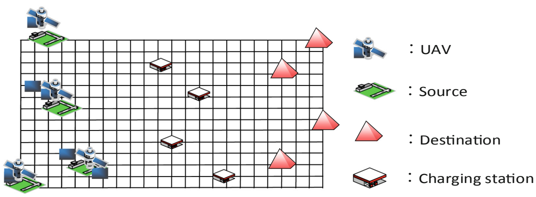

Fig. 2. System model

3 Optimization Problem Formulation

In this section, we examine the overall cost of the UAVs performing tasks and formulate the joint UAV path selection and CS deployment problem as a cost function minimization problem.

3.1 Objective Function

Stressing the importance of the total time required for the UAVs to perform missions and the cost of deploying the CSs, we define the cost function, denoted by Q as

$$Q = T + \lambda F \tag{1}$$

where T denotes the time required for the UAVs to perform the tasks, F denotes the cost of deploying the CSs, and λ denotes the weighting factor. T can be computed as

$$T = \sum_{l=1}^{L} T_l \tag{2}$$

where T_l denotes the time required for U_l to fly from $\mathrm{N}_l^{\mathrm{s}}$ to $\mathrm{N}_l^{\mathrm{d}}$, and can be calculated as

$$T_l = T_l^{\mathrm{t}} + T_l^{\mathrm{c}} \tag{3}$$

where T_l^{t} denotes the flight time required for U_l to reach the destination, and can be expressed as

$$T_l^{\mathrm{t}} = \sum_{i_1=0}^{N_x^{\max}} \sum_{j_1=0}^{N_y^{\max}} \sum_{i_2=0}^{N_x^{\max}} \sum_{j_2=0}^{N_y^{\max}} z_{l,i_1,j_1,i_2,j_2} T_{l,i_1,j_1,i_2,j_2} \tag{4}$$

where z_{l,i_1,j_1,i_2,j_2} denotes path planing variable. If U_l reaches N_{i_2,j_2} via N_{i_1,j_1}, then $z_{l,i_1,j_1,i_2,j_2} = 1$, otherwise, $z_{l,i_1,j_1,i_2,j_2} = 0$, T_{l,i_1,j_1,i_2,j_2} denotes the flight time required for U_l to fly from N_{i_1,j_1} to N_{i_2,j_2}, which can be computed as

$$T_{l,i_1,j_1,i_2,j_2} = \frac{D_{i_1,j_1,i_2,j_2}}{v_l} \tag{5}$$

where v_l denotes the flight speed of U_l, D_{i_1,j_1,i_2,j_2} denotes the flight distance between N_{i_1,j_1} and N_{i_2,j_2}, in the case no threatening area between N_{i_1,j_1} and N_{i_2,j_2}, D_{i_1,j_1,i_2,j_2} can be expressed as

$$D_{i_1,j_1,i_2,j_2} = \sqrt{(i_1 - i_2)^2 \Delta_x^2 + (j_1 - j_2)^2 \Delta_y^2}. \tag{6}$$

However, in the case that there exists threatening area between N_{i_1,j_1} and N_{i_2,j_2}, D_{i_1,j_1,i_2,j_2} should be calculated as discussed in later subsections.

T_l^{c} in (3) denotes the charging time of U_l during the flight from $\mathrm{N}_l^{\mathrm{s}}$ to $\mathrm{N}_l^{\mathrm{d}}$, and can be expressed as

$$T_l^{\mathrm{c}} = \sum_{i_2=0}^{N_x^{\max}} \sum_{j_2=0}^{N_y^{\max}} \sum_{m=1}^{M} T_{l,i_1,j_1,i_2,j_2}^{m} x_{l,m} y_{i_2,j_2,m} \tag{7}$$

where T^m_{l,i_1,j_1,i_2,j_2} denotes the charging time of U_l at C_m when flying from N_{i_1,j_1} to N_{i_2,j_2}, which can be computed as

$$T^m_{l,i_1,j_1,i_2,j_2} = \frac{W_{l,i_1,j_1,i_2,j_2}}{P_m} \tag{8}$$

where P_m denotes the charging power of C_m, W_{l,i_1,j_1,i_2,j_2} denotes the energy consumption of U_l when flying from N_{i_1,j_1} to N_{i_2,j_2}. The energy consumption of the UAV is related to the flight distance, and can be expressed as

$$W_{l,i_1,j_1,i_2,j_2} = \mathrm{W}_l D_{i_1,j_1,i_2,j_2} \tag{9}$$

where W_l denotes the unit energy consumption of U_l.

F in (1) can be expressed as

$$F = \sum_{i=0}^{N_x^{\max}} \sum_{j=0}^{N_y^{\max}} \sum_{m=1}^{M} F_{i,j,m} y_{i,j,m} \tag{10}$$

where $F_{i,j,m}$ denotes the cost of C_m at node $\mathrm{N}_{i,j}$, and is given by

$$F_{i,j,m} = F^{\mathrm{o}}_{i,j,m} + F^{\mathrm{c}}_{i,j,m} \tag{11}$$

where $F^{\mathrm{o}}_{i,j,m}$ denotes the cost for deploying C_m at node $\mathrm{N}_{i,j}$, $F^{\mathrm{c}}_{i,j,m}$ denotes the cost required for maintaining C_m at node $\mathrm{N}_{i,j}$. In this paper, we assume that both $F^{\mathrm{o}}_{i,j,m}$ and $F^{\mathrm{c}}_{i,j,m}$ are given constants.

3.2 Optimization Constraints

To achieve efficient path planning and CS deployment, the following constraints must be considered.

Charging Station Deployment Constraints. In this paper, we assume that at most one CS can be deployed at any node, i.e.,

$$\mathrm{C1}: \sum_{m=1}^{M} y_{i,j,m} \leq 1. \tag{12}$$

In addition, we assume that each CS can at most be deployed at one node, hence, the constraint can be expressed as

$$\mathrm{C2}: \sum_{i=0}^{N_x^{\max}} \sum_{j=0}^{N_y^{\max}} y_{i,j,m} \leq 1 \tag{13}$$

UAV Path Planing Constraints. Through flying from the sources to the destinations, the following path planning constraints must be considered.

$$\text{C3}: \sum_{i_2=0}^{N_x^{\max}} \sum_{j_2=0}^{N_y^{\max}} z_{l,i_1,j_1,i_2,j_2} = 1, \text{ if } \mathrm{N}_{i_1,j_1} = \mathrm{S}_l, \quad (i_2, j_2) \neq (i_1, j_1) \tag{14}$$

$$\text{C4}: \sum_{i_1=0}^{N_x^{\max}} \sum_{j_1=0}^{N_y^{\max}} z_{l,i_1,j_1,i_2,j_2} = 1, \text{ if } \mathrm{N}_{i_2,j_2} = \mathrm{D}_l \quad (i_2, j_2) \neq (i_1, j_1) \tag{15}$$

$$\text{C5}: \sum_{i_1=0}^{N_x^{\max}} \sum_{j_1=0}^{N_y^{\max}} z_{l,i_1,j_1,i_2,j_2} = \sum_{i_3=0}^{N_x^{\max}} \sum_{j_3=0}^{N_y^{\max}} z_{l,i_2,j_2,i_3,j_3}, \quad \text{if } \mathrm{N}_{i_2,j_2} \neq \{\mathrm{S}_l, \mathrm{D}_l\} \tag{16}$$

Maximum Flight Distance Constraint. The path between two adjacent nodes can be selected for the UAVs only if the distance between two points is less than the maximum flight distance of the UAVs, hence, we can express the maximum flight distance constraint as

$$\text{C6}: z_{l,i_1,j_1,i_2,j_2} = 0, \text{ if } D_{i_1,j_1,i_2,j_2} > D_l^{\max} \tag{17}$$

where $D_l^{\max}$ denotes the maximum flight distance of U_l.

Maximum Number of UAVs Constraint. We assume that limited by the charging power of the CSs, the constraint on the maximum number of UAVs must be considered, i.e.,

$$\text{C7}: \sum_{i_1=0}^{N_x^{\max}} \sum_{j_1=0}^{N_y^{\max}} \sum_{l=1}^{L} z_{l,i_1,j_1,i_2,j_2} y_{i_2,j_2,m} x_{l,m} \leq N_m \tag{18}$$

where N_m denotes the maximum number of UAVs allowed to charge at C_m.

Flight Area Constraint. As the UAVs cannot fly over the threaten areas, the constraint can be expressed as

$$\text{C8}: z_{l,i_1,j_1,i_2,j_2} = 0, \text{ if } G_{i_2,j_2} = 1 \tag{19}$$

Maximum Task Execution Time Constraint. Let $T_l^{\max}$ denote the maximum allowable time for U_l to reach the destination, the maximum task execution time constraint can be expressed as

$$\text{C9}: T_l \leq T_l^{\max} \tag{20}$$

3.3 Optimization Problem

Considering the objective function and optimization constraints, we formulate the joint UAV path planning and CS deployment problem as

$$\begin{aligned} \min_{x_{l,m}, y_{i,j,m}, z_{l,i_1,i_2,j_1,j_2}} \quad & Q \\ \text{s.t.} \quad & \text{C1} - \text{C9}. \end{aligned} \tag{21}$$

Through solving above optimization problem, we can obtain the joint path planning, CS deployment strategy.

4 Solution to the Optimization Problem

The optimization problem formulated in (21) is an NP-hard problem which cannot be solved easily using traditional convex optimization tools. In this section, we propose a heuristic algorithm which successively solves two subproblems, i.e, path planning subproblem and destination path selection subproblem by applying the A* algorithm, K-shortest path algorithm and genetic algorithm (GA), respectively.

4.1 Path Planning Subproblem

In this subsection, for simplicity, we assume that CS deployment strategy is given, i.e., $y_{i,j,m} = 1$, $0 \leq i \leq N_x^{\max}$, $0 \leq j \leq N_y^{\max}$, $1 \leq m \leq M$. As $F_{i,j,m}$ is a given constant, the path planing process of different UAVs is relatively independent, hence, the optimization problem formulated in (21) reduces to a set of path planning subproblems. For U_l, the path planning subproblem can be formulated as

$$\begin{aligned} \min_{x_{l,m}, z_{l,i_1,i_2,j_1,j_2}} \quad & T_l \\ \text{s.t.} \quad & \text{C3} - \text{C9 in (21)}. \end{aligned} \tag{22}$$

K-shortest Paths Algorithm-Based Path Planning Strategy. To solve the optimization problem in (22), we model the system model as a weighted graph $G = (V, E, W)$, where $V = \{\text{N}_l^s\} \cup \{\text{N}_l^d\} \cup \{\text{N}_{i,j}\}$, $1 \leq l \leq L$, $1 \leq m \leq M$, $0 \leq i \leq N_x^{\max}, 0 \leq j \leq N_y^{\max}$. Let V_i denote the ith vertex in V, $1 \leq i \leq |V|$, $|a|$ denotes the number of elements in set a, $E = \{E_{i,j}, 1 \leq i, j \leq N, i \neq j\}$ denotes the link set, where $E_{i,j}$ represents the link between V_i and V_j, and $W = \{W_{i,j}, 1 \leq i, j \leq I, i \neq j\}$ denotes the weight set of links, $W_{i,j}$ denotes the weight of $E_{i,j}$. Let V_i and V_j represent N_{i_1,j_1} and N_{i_2,j_2}, respectively, $W_{i,j}$ can be computed as

$$W_{i,j} = T_{l,i_1,j_1,i_2,j_2} + \sum_{m=1}^{M} T_{l,i_1,j_1,i_2,j_2}^{m} y_{i_2,j_2,m} \tag{23}$$

Given $W_{i,j}$, we apply the K-shortest paths algorithm to obtain the K candidate paths offering the minimum cost. Let P_l denote the set of the K candidate paths of U_l, p_l^k denote the kth candidate path of U_l, we may express P_l as $P_l = \left\{p_l^1, p_l^2, \ldots p_l^k, \ldots p_l^K\right\}$.

It should be noticed that to calculate $W_{i,j}$ based on (23), the distance between V_i and V_j, denoted by D_{l,i_1,j_1,i_2,j_2} should be calculated. However, since various types of threats might exist along the flight path between V_i and V_j, the flight distance may not exactly equal to the length of the directly connected link between the two positions. In next subsection, we apply A* algorithm to calculate the optimal D_{l,i_1,j_1,i_2,j_2}.

A* Algorithm-Based Flight Distance Determination. A* algorithm is commonly used to solve the problem of path planning in the scenario consisting of threat areas or obstacles. The basic idea of A* algorithm is that given start position and destination position, a cost function is defined, and a feasible path from start position to destination position is obtained through determining the intermediate nodes successively. To determine individual intermediate nodes, we select the one offering the smallest cost function.

Let s and d denote respectively the start position and destination position, the process of determining the optimal path between s and d based on A* algorithm can be summarized as follows:

(1) Initialization
Set $\Psi_1 = \{s\}$ and $\Psi_2 = \Phi$, where Φ denotes the empty set.
(2) Calculating cost function
Let x denote the reachable node of s, update Ψ_1 as $\Psi_1 = \Psi_1 \cup \{x\}$. Let $C(x)$ denote the cost of selecting x as the next-hop node, $C(x)$ can be calculated as

$$C(x) = ag(x) + bh(x) \tag{24}$$

where $g(x)$ denotes the cost required for routing from the start position s to x, $h(x)$ denotes the estimated cost due to flying from x to the destination position d, a and b are weighting parameters.
(3) Determining one hop reachable nodes of s
Select the reachable node of s which offers the smallest cost as the next-hop node, i.e., $x^* = \arg\min C(x)$.
(4) Update Ψ_1 and Ψ_2, and s
Remove x^* from Ψ_1, i.e., set $\Psi_1 = \Psi_1 \setminus \{x^*\}$ and add x^* to Ψ_2, i.e., $\Psi_2 = \Psi_2 \cup \{x^*\}$, set $s = x^*$.
(5) Algorithm termination condition
If $x^* = d$, the algorithm completes, otherwise, back to Step (2).

Applying the A* algorithm, we will be able to determine the optimal flight strategy between any two nodes V_i and V_j in G, and obtain the optimal flight distance denoted by D^*_{l,i_1,j_1,i_2,j_2}.

4.2 Destination Path Selection Subproblem

While each UAV may fly according to the obtained K candidate paths strategy, i.e., P_l, $1 \leq l \leq L$, considering the possible sharing on CSs and the various deployment cost of the CSs, it is highly possible that the overall cost might be reduced by selecting suitable candidate path for individual UAVs. More specifically, among K candidate paths, we may select one candidate path for each UAV so as the achieve the total cost minimization.

It can be demonstrated that given the K candidate paths set of all the UAVs, the problem of selecting one candidate path for each UAV can be formulated as an optimization problem. Let $T^*_{l,k}$ denote the cost of U_l when choosing the kth candidate path, $y_{i,j,m,l,k}$ denote the CS deployment strategy of U_l on the kth candidate path. That is, if C_m is deployed at $\mathrm{N}_{i,j}$, which is selected as the intermediate node of the kth candidate path of U_l, $y_{i,j,m,l,k} = 1$, otherwise, $y_{i,j,m,l,k} = 0$. Notice that given the candidate path selection strategy P_l, $y_{i,j,m,l,k}$ is a known constant.

Redefine the cost function Q as Q', we obtain

$$Q' = \sum_{l=1}^{L}\sum_{k=1}^{K}\alpha_{l,k}T_{l,k}* - \sum_{m=1}^{M}\sum_{l=1}^{L}\sum_{k=1}^{K}\sum_{i=0}^{N_x^{\max}}\sum_{j=0}^{N_y^{\max}}\frac{\alpha_{l,k}y_{i,j,m,l,k}F_{i,j,m}}{A_m} \quad (25)$$

where $\alpha_{l,k}$ is the destination path selection variable, i.e., $\alpha_{l,k} = 1$, if U_l chooses the kth candidate path, $\alpha_{l,k} = 0$, otherwise. A_m is the number of UAVs which share C_m, and can be expressed as

$$A_m = \sum_{l=1}^{L}\sum_{k=1}^{K}\sum_{i=0}^{N_x^{\max}}\sum_{j=0}^{N_y^{\max}}\alpha_{l,k}y_{i,j,m,l,k}. \quad (26)$$

The destination path selection problem can be formulated as

$$\min_{\alpha_{l,k}} Q' \\ \text{s.t.} \sum_{k=1}^{K}\alpha_{l,k} = 1. \quad (27)$$

where the constraint indicates that one UAV can only select one candidate path as its destination path.

The formulated optimization problem in (27) is an nonlinear integer optimization problem, which can be solved via the extensive search method for the scenario with small number of UAVs and relatively small path planning area of the UAVs. However, the computation complexity becomes prohibitive as the size of the problem increases. In this subsection, we model the optimization problem as a biological evolution process and propose a low-complexity GA-based destination path search strategy.

Defining the combination of the candidate paths selected for various UAVs as population, and choosing Q' in (25) as fitness function, we can solve the problem based on GA [13].

The steps for obtaining the GA-based destination path search strategy can be summarized as follows.

(1) Initialization
Set generation counter $t = 1$, denote population size by N and $p_{l,t,n}$ as the candidate path of UAV_l of the nth individual in the tth generation, i.e., $p_{l,t,n} = p_l^{k_l}$,

Table 1. Simulation parameters

Parameters	Value
The flight speed of UAVs (v_k)	10 km/h
The cost for deploying and maintaining CSs ($F_{i,j,m}$)	10,000.0
Number of iterations $T_{\max}$	100.0
Chromosome mutation probability (P_{mut})	0.2
Weighting factor (λ)	1.0/1.5
Number of candidate paths K	8
Number of UAVs n	4, 6
Number of threaten areas	10

$1 \leq k_l \leq K, 1 \leq n \leq N, 1 \leq t \leq T_{\max}$ where N and $T_{\max}$ denote respectively the maximum number of individuals and generations. Defining the population of the nth individual in the tth generation as

$$R_{t,n} = \left(p_{1,t,n,}, p_{2,t,n}, \cdots, p_{L,t,n}\right)^{\mathrm{T}}, \tag{28}$$

and denoting R_t as the population in the tth generation, we express the initial population as

$$R_1 = \left(R_{1,1}, R_{1,2}, \cdots, R_{1,N}\right)^{\mathrm{T}}. \tag{29}$$

(2) Fitness function evaluation
Substitute $R_{t,n}$ into the fitness function Q', the corresponding fitness value can be obtained.

(3) Gene selection
Through a fitness proportionated-based process [13], the fitness function assigns each fitness value a probability of selecting individuals. The probability of selecting $R_{t,n}$ can be defined as

$$P(R_{t,n}) = \frac{Q'(R_{t,n})}{\sum_{n=1}^{N} Q'(R_{t,n})}. \tag{30}$$

Selecting individuals with high $P(R_{t,n})$ from the population R_t, and conducting reproduction, we can obtain the reproduced population $R_t^{(1)}$.

(4) Crossover process
Randomly select two parent individuals R_{t,n_1}, R_{t,n_2} from $R_t^{(1)}$, $1 \leq n_1, n_2 \leq N$, crossover the two parent individuals to form two children individuals R'_{t,n_1}, R'_{t,n_2} of the next generation through applying crossover-based method.

(5) Mutation process
Based on Gaussian mutation process, mutating the two children individuals R'_{t,n_1}, R'_{t,n_2} with certain mutation rate P_{mut}, and collecting the resulting individuals $R_{t,n}$, we can obtain the next generation:

$$R'_t = (R'_{t,1}, R'_{t,2}, \ldots, R'_{t,N}). \tag{31}$$

(6) Termination condition
If $|Q'(R'_t) - Q'(R_t)| \leq Q_{\mathrm{th}}$, where Q_{th} denotes the threshold of Q', the algorithm terminates and the obtained R'_t offers the feasible destination path selection solution. If $t = T_{\max}$, the process terminates and the destination path selection algorithm fails, else set $R_{t+1} = R'_t$, $t = t + 1$, go to Step (3).

5 Simulation and Result Analysis

In this section, we examine the performance of the proposed joint path planning and CS deployment algorithm via simulation. In the simulation, we consider a square region with the size being 50 km × 50 km where a number of UAVs perform tasks from source position to destination position. We assume that threaten areas are randomly located in the region. Other parameters used in the simulation are summarized in Table 1. Simulation results are averaged over 100 independent processes involving different simulation parameters.

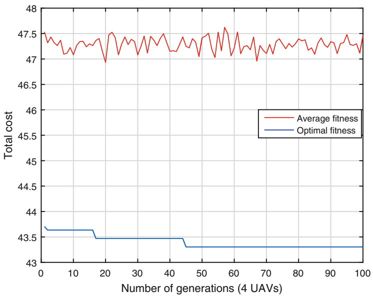

Fig. 3. Total cost versus number of generations (4 UAVs).

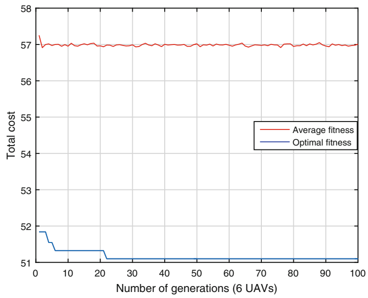

Fig. 4. Total cost versus number of generations (6 UAVs).

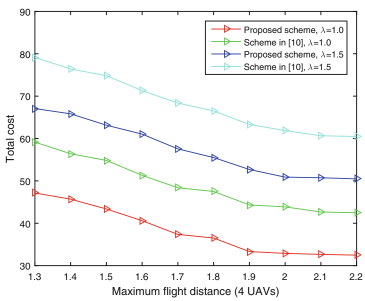

Fig. 5. Total cost versus maximum flight distance (4 UAVs).

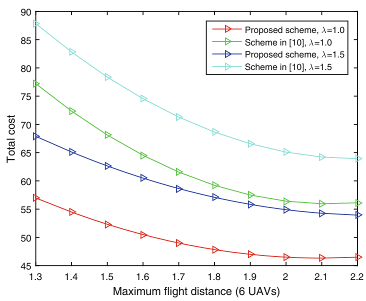

Fig. 6. Total cost versus maximum flight distance (6 UAVs)

In Figs. 3 and 4, we plot the total cost of UAVs versus the number of generations of GA. The number of UAVs is set as 4 and 6 in Figs. 3 and 4, respectively. It can be seen from the figure that the total cost converges to a constant, demonstrating the effectiveness of the applied GA.

Figures 5 and 6 show the total cost versus the maximum flight distance of the UAVs with different weighting factor. The number of UAVs is set as 4 and 6 in Figs. 5 and 6. For comparison, we plot the total cost of the UAVs obtained from our proposed scheme and the scheme proposed in [10]. We can see from the figures that the total cost decreases with the increase of the maximum flight distance of the UAVs. This is because as the maximum flight distance of the UAVs increases, the number of the CSs required to be deployed will decrease, which will result in the decrease of the total cost in turn. It can also be observed from the figures that, for both schemes, the total cost increases with the increase of weighting factor. Comparing the results obtained from our proposed scheme and the scheme proposed in [10], we can see that our proposed algorithm outperforms the scheme proposed in [10]. The reason is that our proposed scheme aims at minimizing the total cost, while the scheme proposed in [10] mainly considers the minimization of the flight time of UAVs and fails to consider the deploy time of the UAVs, thus may result in undesired total time.

6 Conclusions

In this paper, we jointly investigate UAV path planning and CS deployment algorithm. To stress the importance of the total time of the UAV to perform tasks and the cost of deploying and maintaining CSs, we formulate the joint optimization problem as a total cost minimization problem. Since the formulated optimization problem is an NP-hard problem, which cannot be solved easily, we transform the problem into two subproblems, i.e., path planning subproblem and destination path selection subproblem, and solve the two subproblems by applying the A* algorithm, K-shortest path algorithm and GA, respectively. The simulations demonstrate the effectiveness of the proposed algorithm.

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