Power-Aware Path Planning for Vehicle-Assisted Heterogeneous UAVs in Mobile Crowd Sensing

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***Abstract*—With the development of microelectronics in recent years, the performance of unmanned aerial vehicles (UAVs) has been improving continuously. Modern rotary-wing UAVs possess high maneuverability and agility, making them widely applied in mobile crowd sensing (MCS). In order to solve the shortcoming of limited battery capacity and expand the mission area of UAVs, the ground vehicle is introduced as a platform for transportation, launch, recycle, and recharging UAVs. However, existing studies only consider the case of vehicle-assisted homogeneous UAVs. In reality, due to different sensing requirements and UAV hardware, vehicles may need to assist heterogeneous UAVs with different sensors, flight speeds, and battery capacities. In this paper, we formalize and study the vehicle-assisted heterogeneous UAVs path planning problem, and decompose it into three sub-problems, namely detection point allocation, UAV path planning, and vehicle route planning. In order to solve the above problems, we proposes an efficient power-aware path planning algorithm for vehicle-assisted multi-heterogeneous-UAV (VHUPA). In VHUPA, we first design the genetic algorithm to find the allocation scheme of the detection points, then plan flight paths of UAVs at each parking spot according to the allocation scheme, and finally optimize the route of the ground vehicle according to the power consumption of UAVs to minimize the waiting time for charging. Performance evaluation demonstrates that time cost of the VHUPA solution is reduced by more than 21% compared with the existing algorithm.**

***Index Terms*—unmanned aerial vehicle, vehicle-assisted UAV, power-aware, path planning, mobile crowd sensing**

I. Introduction

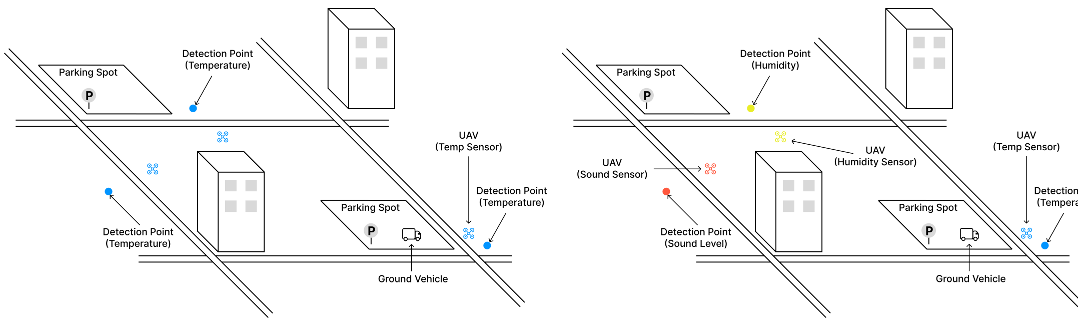
With the increase in sensor-rich mobile devices over the past few years, MCS has developed rapidly as a sensing method that relies on personal smart devices [1]. Human involvement is one of the most important characteristics of MCS. Human mobility offers unprecedented opportunities for both sensing coverage and data transmission. Meanwhile, MCS is obviously more cost-effective than traditional sensing systems. Therefore, MCS has been applied in many fields especially in modern cities, such as air quality detecting and traffic monitoring [2]. Besides, due to the economy, flexibility, and convenience of UAVs, they have been widely applied in many fields, such as military, agriculture, smart city, etc. With the increasing popularity of UAVs, UAVs have been considered to bring new possibilities for MCS in the future [3], [4]. UAVs integrating computing, control, communication, and sensing modules can collect data in areas that traditional MCS cannot penetrate, such as crisis areas and remote areas without ground equipment.

Despite the mentioned benefits of UAVs, their hovering time is greatly limited by their battery capacity, which makes them unable to provide services over a wide range. To optimize this issue, the ground vehicle is introduced as a platform for transportation, launch, recycle, and recharging UAVs. Specifically, the vehicle transport UAVs close to the mission point and launches them to collect data. After completing sensing, UAVs fly back to the vehicle and are recycled by the vehicle. Compared to MCS with UAVs, MCS with vehicle-assisted UAVs can further expand the mission range and reduce the mission costs [5], [6].

In vehicle-assisted UAVs system, the path planning algorithm is a key issue, which affects the time cost, fuel cost, and mission range of the system. There are many studies on vehicle-assisted UAVs for package delivering [7]–[11]. In these studies, vehicles can also perform delivering, which is not applicable to the sensing problem studied in this paper. In sensing problem, the ground vehicle is mainly used to transport and charge UAVs.

There are some works that have investigated the path planing of the vehicle-assisted homogeneous UAVs in sensing problem [5], [6], [12], [13], as shown in Fig. 1(a). However, The reality is that a vehicle-assisted UAVs system may consist of different types of UAVs, as MCS missions require different sensors [14], [15], as shown in the Fig. 1(b). In addition, it is difficult to guarantee that the UAVs on the vehicle will perform exactly the same. Depreciation and production batches may lead to different performance of UAVs. Besides, the heterogeneity in UAVs exploits various characteristics of different types of UAVs with different hardware, flight speed and sensing capabilities, which means have more robust than homogeneous UAVs [16], [17]. In [18], an experiment was conducted to compare the performance of homogeneous UAVs with heterogeneous UAVs, and concluded that in a heterogeneous system, both slow and fast UAV swarm agents performed better than homogeneous UAVs. Heterogeneous UAVs mean have different sensors, flight speeds, and battery capacities. There may also be multiple types of detection points. Therefore, the existing path planning algorithms that only consider homogeneous UAVs cannot be applied.

When involving heterogeneous UAVs and detection points, path planning of the vehicle and UAVs becomes more complex, which cannot be solved using a single existing optimization method. To solve the problem, we formalize the



(a) Homogeneous detection points and UAVs

(b) Heterogeneous detection points and UAVs

Figure 1. Different MCS mission scenarios

path planning and task assignment problem, and then propose an efficient power-aware path planning algorithm for vehicle-assisted multi-heterogeneous-UAV (VHUPA). In VHUPA, we consider that UAVs can carry different types of sensors, and detection points have different sensing requirements. In addition, we take into account the difference in battery and flight speed of UAVs. After completing a mission, UAVs can be charged on the ground vehicle. And we plan the route of the ground vehicle according to the remaining power of UAVs. In general, our goal is to globally optimize the driving route of the vehicle and the flying paths of UAVs to minimize the task completion time.

II. Related Work

For MCS with vehicle-assisted UAV, there have been many studies concerned with path planning for the vehicle and the UAV to minimize time cost or rewards. Luo et al. [12] introduced a UAV-vehicle cooperated routing problem, which is similar to the one studied in this paper, and proposed two heuristic algorithms. Savuran and Karakaya [19] designed a path optimization algorithm that allows the vehicle and UAVs to operate simultaneously.

For vehicle-assisted multi-UAV path planing, Hu et al. [20] introduced a novel vehicle-assisted multidrone routing and scheduling problem, and contributed an efficient algorithm(VURA) to solve it. Experiments show that VURA is superior to other algorithms in efficiency and effectiveness. In [13], Hu et al. designed a novel algorithm (VAMU) based on VURA, which allows UAVs to be launched in one place and recycled in another. It can further improve the efficiency of both the vehicle and UAVs. Xi, Jie, et al. [5] proposed a vehicle-assisted multi-UAV path planning algorithm that considers power consumption. It is the first to take the power consumption and charging time of UAVs into consideration, and optimizes the vehicle route, with the purpose of reducing the charging time in the parking spot. Deng, Xudong, et al. [10] designed a new vehicle-assisted UAV delivery solution that allows UAVs to serve multiple customers and takes energy consumption into account, and presented a hybrid heuristic algorithm based on an improved K-means algorithm and ant colony optimization.

However, the above-mentioned works only considered homogeneous UAVs, which is not consistent with the reality. In reality, there are likely to be many types of information that need to be sensed, or there may be UAVs with different capabilities on the vehicle. Therefore, this motivates us to consider a more general scenario: using heterogeneous UAVs with different sensors, flight speeds, and battery capacities to perform sensing tasks in the MCS system.

III. System Model and Problem Formulation

In our scenario, there is a ground vehicle carrying multiple heterogeneous UAVs. A set of detection points with multiple different sensing requirements is distributed in the target area. Our mission is to meet every sensing requirements of all detection points. Heterogeneous UAVs are equipped with different types of sensors, corresponding to different sensing requirements. Each detection point may contain single or multiple types of sensing requirements. Therefore, each detection point may need to be visited by one or several different UAVs. UAVs can consecutively visit multiple detection points in single flight (i.e., perform sensing tasks). But their endurance is greatly limited by their battery capacity. The vehicle acts as a charging station, and UAVs can return back to the vehicle to recharge before the battery runs out.

As shown in Fig. 2, with the transportation of the ground vehicle, the mission scope of UAVs is expanded. The ground vehicle sequentially transports UAVs to the pre-selected parking spots. Once the ground vehicle arrives at a parking spot, UAVs are launched and fly to nearby detection points to perform sensing tasks. After the UAV completes the sensing task, it returns to the ground vehicle for recharging. After all nearby detection points have been visited and all UAVs have returned, the ground vehicle carrying UAVs sets off for the next pre-selected parking spot, until every sensing requirement of all detection points is met.

The problem modeling is as follows: Let $S = \{s_1, s_2, \ldots, s_{N_s}\}$ represent the set of different sensor types. In order to plan the path of UAVs and the vehicle, we construct an undirected graph $G = \{V, E\}$ to represent the road network, where V is the set of vertex and E is the set of edge. And V is composed of $V_d = \{d_1, d_2, \ldots, d_{N_d}\}$ and $V_p =$

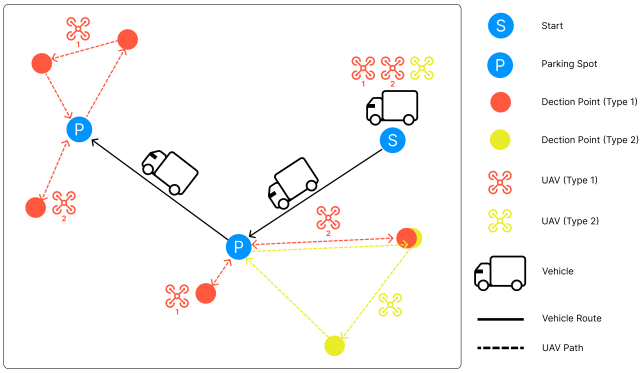


Figure 2. System model

$\{p_1, p_2, \ldots, p_{N_p}\}$, which represent the detection points set and the candidate parking spots set, respectively. The detection point is donated by $d_i = (x_i, y_i, R_i)(1 \leq i \leq N_d)$, where x_i, y_i and $R_i = \{s_{k_1}, s_{k_2}, \ldots, s_{k_{N_{R_i}}} | s_{k_j} \in S\}$ represent the coordinate and sensing requirements of d_i, respectively. The parking spot $p_i = (x_i, y_i)(1 \leq i \leq N_p)$, which x_i and y_i represent the coordinate of p_i. UAVs carried by the ground vehicle are denoted as $U = \{u_1, u_2, \ldots, u_{N_u}\}$. And $u_i = (sp_i, r_i)(1 \leq i \leq N_u)$, where sp_i represents the flight speed of u_i, and $r_i = \{s_{k_1}, s_{k_2}, \ldots, s_{k_{N_{r_i}}} | s_{k_j} \in S\}$ represents the sensor list of u_i. Besides, we use the constants SP and C to represent the speed of the ground vehicle and the power consumption rate of UAVs, respectively.

The total time t is the sum of the total movement time and the staying time at each parking spot. And the staying time at the parking spot is the maximum flight time of each UAV at this point. The main optimization goal of this paper is to optimize the sensing task assignment and the path planning of the ground vehicle heterogeneous UAVs such that the total time t is minimized.

There are three key issues. The first one is how to assign detection points to parking spots, which is a many-to-many assignment problem. A detection point is assigned to a parking spot means that when the ground vehicle parks at the parking spot, UAVs will visit the detection point. Furthermore, each sensor requirement of a detection point can be assigned separately, that is, assigned to different parking spots. We use a_{d_i,k_j} and A_{d_i} to denote the allocated parking spot for the requirement s_{k_j} of the detection point d_i and the allocation scheme of detection point d_i, respectively. We denote the allocation scheme for d_i by A_{d_i} $A_{d_i} = \{a_{d_i,k_1}, a_{d_i,k_2}, \ldots, a_{d_i,k_{N_{R_i}}} | a_{d_i,k_j} \in V_p, 1 \leq j \leq N_{R_i}\}$

The second is how to plan the flight path of each UAV at each parking spot. After the ground vehicle arrived at the parking spot p_i, UAVs will be released and fly to each detection point $(\{d_j | p_i \in A_{d_j}\})$ for sensing according to the flight route. The flight path needs to cover all the detection points assigned to the parking, and take as little time as possible. Donate the task time (i.e., the parking time of the vehicle) at p_i as t_{p_i}, then we have

$$t_{p_i} = \max_{1 \leq j \leq N_u} t_{p_i,u_j}$$

where the flight time of u_j at p_i is t_{p_i,u_j}, and N_u represents the number of UAVs.

The last one is how to plan the route of the ground vehicle. This is similar to the Traveling Salesman Problem (TSP), but more factors need to be considered, such as the charging time of UAVs. If the charging time of UAVs is longer than the driving time of the ground vehicle, the ground vehicle needs to wait for charging at the parking spot. The total movement time of the ground vehicle, denoted as t_u, is the sum of the travel time and the time to wait for charging. Therefore, we have the total time t of task:

$$t = t_u + \sum_{1 \leq j \leq N_p} t_{p_i}$$

where N_p is the number of parking spots.

IV. Algorithm Design

A. Detection Point Allocation

To reduce flight distance of UAVs, detection points should be assigned to the closest possible parking spot. However, this does not mean that selecting the nearest parking spot is the best solution. The ideal would be for all types of UAVs to work the same amount of time. Obviously selecting the closest parking spot will make the allocation uneven, some parking spots have too many detection points of a certain type, others too few, resulting in UAVs of this type be idle or too busy. We design a algorithm to find a better assignment than selecting the closest parking spot in polynomial time. It has been proven that genetic algorithms is able to find optimal and near optimal solutions in generalised assignment problem [21]. The performance also compares favourably to all other existing heuristic algorithms. So we modified genetic algorithm to solve the assignment problem of detection points. Chromosomes representing allocation schemes are defined as $C = \{A_{d_1}, A_{d_2}, \ldots, A_{d_{N_d}}\}$. We first add the allocation scheme of selecting the nearest parking spot as a reference chromosome to the chromosome pool, which ensures that the final scheme must be better than or equal to selecting the nearest parking spot. We used the method in Section IV-B to calculate the task time consumed by the allocation scheme in the chromosome, and use the task time as the fitness of the chromosome, chromosomes with higher fitness will be eliminated. In order to ensure that the allocation scheme is feasible, if the calculated power consumption required by the UAV is greater than the battery capacity of the UAV during the evaluation, the fitness will be set to infinity.

Next, we perform several rounds of iterations of genetic algorithm, including selection, crossover, and mutation. The selection operator removes chromosomes with higher fitness from the chromosome pool. The crossover operator randomly select two chromosomes to take a piece of gene and combine them into a new chromosome. The mutation operator randomly changes the genes of a chromosome. After several rounds of iterations, the chromosome with the lowest fitness in the chromosome pool is taken as an approximate solution.

The pseudocode of the algorithm is shown in the Algorithm 1.

Algorithm 1: Detection Point Allocation

input : The detection points set V_d and the candidate parking spots set V_p
output: The allocation scheme $\{A_{d_1}, A_{d_2}, \ldots, A_{d_{N_d}}\}$

$S_{chromosome} \leftarrow \{\}$;
$S_{chromosome} \xleftarrow{+}$ The chromosome of selecting the nearest parking spot;
$S_{chromosome} \xleftarrow{+}$ Randomly generated chromosomes;
for $i \leftarrow 1$ **to** $N_{iterations}$ **do**
  Randomly select a pair of chromosomes in $S_{chromosome}$, and eliminate the one with higher fitness;
  Randomly select a pair of chromosomes in $S_{chromosome}$, and take the gene fragments of the two to generate a new chromosome to $S_{chromosome}$;
  Select a chromosome in $S_{chromosome}$, and randomly exchange its 2 genes;
return $\texttt{best}(S_{chromosome})$;

B. UAV Path Planning

When evaluating the allocation scheme, the path of the UAVs needs to be planned. After the ground vehicle reaches the parking spot p_i, UAVs will be released, and the UAVs will visit all detection points allocated to p_i. Xi, Jie, et al. [5] has proposed an algorithm for homogeneous UAVs path planning, and achieved better performance than basic algorithms in the experiment. However, it does not apply to heterogeneous UAVs. Therefore, We choose it as the basic algorithm and make some improvements to make it capable of handling heterogeneous UAVs. The algorithm in [5] is denoted as $f(p, U, V_d)$. The input is the parking spot p, the list of homogeneous UAVs U and the distribution of detection points V_d, and the output are flight path of UAVs at the parking spot p. We decompose the requirements of the detection points so that $f(p, U, V_d)$ can be applied to heterogeneous UAVs, as shown in Algorithm 2. Specifically, we decompose each detection point with multiple requirements into multiple detection points with a single requirement. Then the detection points with the same requirement are grouped, denoted by V_r. And UAVs with corresponding sensors U_r are used for path planning.

C. Vehicle Route Planning

After the flight path of UAVs are determined, we get the power consumption of UAVs to perform data collection tasks at each parking spot. The power consumption at parking spot p_i is the flight time of the UAV at p_i multiplied by the power consumption speed C. In addition, we deduce the power charged of UAVs in the ground vehicle based on the distance between the parking spots. We adopt the following heuristic algorithm to plan the driving route of the ground vehicle according to power consumption and power charged. We ensure that UAVs reach each parking spot with more power. Besides, we reduce the coupling degree between the path planning of the ground vehicle and the charging time of UAVs at parking spots through the heuristic strategy, hence both of them can be optimized independently. The steps to construct the route of the ground vehicle are as follows:

Algorithm 2: Heterogeneous UAV Path Planning

input : The parking spot p, heterogeneous UAV list U, the set of heterogeneous detection points V
output: The path for every UAVs

$S_{routes} \leftarrow \{\}$;
$V_{decomposed} \leftarrow \{\}$;
$S_{requirment} \leftarrow \{\}$;
foreach v *in* V **do**
  $x, y \leftarrow$ Coordinate of v;
  $R \leftarrow$ Sensing requirements of v;
  foreach r *in* R **do**
    $v_{new} \leftarrow \{x, y, \{r\}\}$;
    $V_{decomposed} \xleftarrow{+} v_{new}$;
    if r *not in* $S_{requirment}$ **then**
      $S_{requirment} \xleftarrow{+} r$;
foreach *sensor requirement* r *in* $S_{requirment}$ **do**
  $V_r \leftarrow \{v \mid v \in V_{decomposed}$ & sensing requirements of $v = \{r\}\}$;
  $U_r \leftarrow \{u \mid u \in U$ & sensing type of $u = r\}$;
  $S_r \leftarrow \texttt{f}(p, U_r, V_r)$;
  $S_{routes} \xleftarrow{+} S_r$;
return S_{routes};

(1) Construct Initial Candidate Solution

We propose a greedy algorithm to construct the initial route R_v with the shortest driving time between the parking spots. It ensures the minimum driving time first and then optimize the driving route. The pseudo-code is shown in Algorithm 3.

(2) Optimize the Candidate Solution

We design this vehicle route optimization algorithm inspired by the Floyd-Warshall algorithm [22], which is a simple and widely used algorithm to compute shortest paths. The steps of optimizing the candidate solution are as follows:

1) Set i to 1.
2) Find the predecessor parking spot p_x of $(R_v)_i$. p_x has a set of candidate parking spots S, which includes all the next parking spots except $(R_v)_i$ that should be reached by the ground vehicle.
3) Traverse S, and swap the traversed candidate parking spot and $(R_v)_i$ to generate new routes.

Algorithm 3: Initialize Candidate Solution

input : The selected parking spots set f and the starting point p

output: The driving route of the ground vehicle R_v

$R_v \leftarrow \{p\}$;

$n \leftarrow \mathtt{sizeof}(f)$;

for $i \leftarrow 1$ **to** n **do**

  Find the closest parking spot f_j to $\mathtt{top}(R_v)$;

  $R_v \xleftarrow{+} f_j$;

  $f \xleftarrow{-} f_j$;

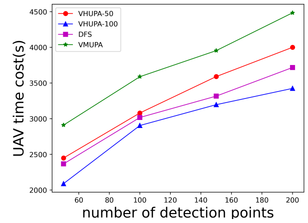
return R_v;

4) Calculate the time cost of the new routes generated by step 3. Choose the route with the shortest time cost and update the sequence R_v of the new route at the same time.
5) Set i to i + 1 and repeat the above steps until the time cost of the new route no longer changes.

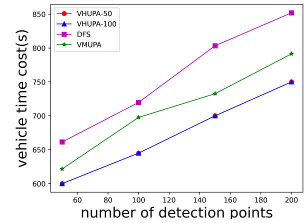
V. Experiments

In this section, we evaluate the proposed algorithm through some simulation experiments. We use the simulator implemented in [6]. Since we are the first to consider vehicle-assisted heterogeneous UAVs, there are no similar algorithms for comparison. Therefore, in order to evaluate the performance of VHUPA, we designed two base algorithms for comparison. The first one is VMUPA [5], which is a power-aware path planning algorithm for vehicle-assisted homogeneous UAVs. We made some modifications to it to support heterogeneous UAVs. In the modified version, we assign all sensor requirements of all detection points to the nearest parking spot, and solve the route independently for each type of UAVs. The second is the DFS algorithm, which uses DFS to enumerate allocation schemes or routes, then evaluates in the same way as VHUPA, and finally selects the optimal solution. Note that DFS does not enumerate all the solutions, but only greedily select several options for enumeration, otherwise the time complexity is too high.

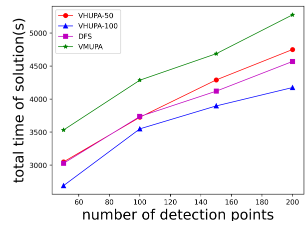
In our experiments, a number of detection points and parking spots are randomly generated in the 10000 unit * 10000 unit area, of which 1 unit represents 1 m. There are 5 different sensor types, and each detection point may require one or more of them. (e.g., $R_1 = \{s_1, s_3, s_5\}$ means detection point d_1 requires data from sensors s_1, s_3, s_5) A ground vehicle with several heterogeneous UAVs is used to visit detection points in the target region. The speed of the vehicle and UAVs are set to be 20 unit/s and within the interval [30, 60] unit/s, respectively. We paid special attention to two performance metrics. The first is the time cost t of the solution, which is the sum of the ground vehicle time cost t_u and UAV flight time cost. The second is the time consumed by the algorithm, which can be used to evaluate the time complexity of the algorithm.



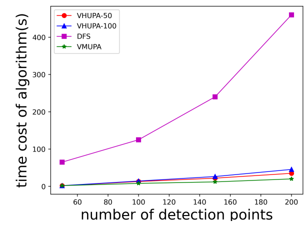
(a) UAV time cost



(b) Vehicle time cost



(c) Total time of solution



(d) Algorithm time cost

Figure 3. Time cost under different number of detection points

In the first experiment we investigated the impact of the number of detection points on different algorithms, as shown in Fig. 3. The performance of VHUPA are related to the number of iterations of the genetic algorithm. As mentioned in the second experiment below, better result quality can be achieved when the number is set to 100, and better algorithm efficiency can be achieved when the number is set to 50. Therefore, in the first experiment, the number of iterations is set to 50 and 100, which are denoted as VHUPA-50 and VHUPA-100, respectively. It can be seen that the time cost is positively correlated with the number of detection points. The total solution time of the VHUPA algorithm is shorter than that of VMUPA. With the increase of detection points, the advantages of VHUPA become more and more obvious. When the number of detection points is low, the total solution time of DFS is basically the same as that of VHUPA, and when the number of detection points is large, the result of DFS becomes worse. Because DFS adopts a greedy strategy for partial enumeration, when the number of detection points is large, the coverage of enumeration becomes lower, resulting in worse results. Fig. 3(c) shows the total time consumed by the entire system. When the number of detection points exceeds 100, the running time of DFS exceeds 100s. The time consumption of DFS increases exponentially. It is foreseeable that when the number of detection points continues to grow, DFS will no longer be feasible because the algorithm takes too long. VHUPA and VMUPA still maintain a short algorithm running time when the number of detection points is large, and the overall running time of VHUPA is lower than that of VMUPA. When the number of detection points is 200, the time cost of the VHUPA is reduced by more than 21% compared with VMUPA.

VHUPA uses two genetic algorithms, and the number of

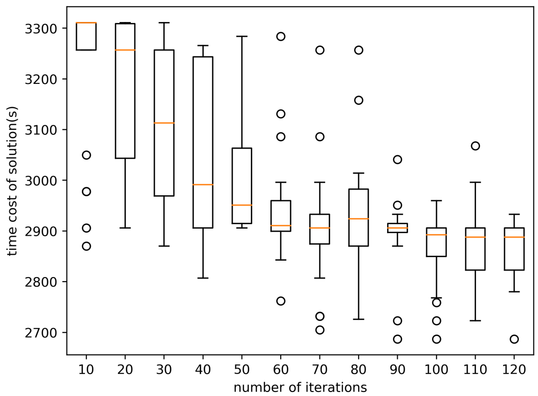


Figure 4. Time cost under different number of iterations

iterations of the genetic algorithm has impact on the results. A second experiment is designed to investigate the effect of the number of iterations on VHUPA. Take the number of detection points as 100, take the number of iterations as 10 to 120, and take 30 results for each group. The time cost distribution of the solution by VHUPA is shown in Fig. 4. It can be seen that when the number of iterations is 10, VHUPA can only obtain the worst result. When the number of iterations is between 20 and 50, the distribution of the results is relatively scattered. When the number of iterations is greater than 50, the distribution of the results tends to be stable and close to the optimal solution. When the number of iterations is greater than 100, the distribution does not change further. Therefore, when the number of iterations is between 50 and 100, a balance between result quality and algorithm efficiency can be achieved.

VI. Conclusion

In this paper, we propose an efficient and power-aware path planning algorithm for vehicle-assisted heterogeneous-multi-UAV. To the best of our knowledge, we are the first to take the heterogeneous UAVs and detection points into consideration. We formalize this problem and prove that it is NP-hard. And we design the VHUPA algorithm that can solve the problem. In VHUPA, we first use genetic algorithm to select a detection point allocation scheme, allocate the detection points to parking spots, then calculate the UAV path at each parking spot, and finally plan vehicle route according to the power consumption of UAV at each parking spot. The simulation results have shown that VHUPA significantly outperforms DFS and VMUPA in terms of efficiency and result quality. In most cases, the time cost of the VHUPA solution is reduced by more than 21% compared with VMUPA.

Acknowledgments

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