A Hybrid Genetic Algorithm for Sustainable Wireless Coverage of Drone Networks

Shanshan Lu *, Xiao Zhang †
College of Computer Science
South-Central University for Nationalities
*360943967@qq.com
†xiao.zhang@my.cityu.edu.hk

Yu Zhou ‡
College of Computer Science
and Software Engineering
Shenzhen University
‡ zhouyu_1022@126.com

Shilong Sun §
School of Mechanical
Engineering and Automation
Harbin Institute of Technology, Shenzhen
§ shilosun-c@my.cityu.edu.hk

***Abstract*—Recent years have witnessed increasingly more uses of drone networks for providing wireless coverage to ground users. Each drone is constrained in its energy storage and wireless coverage, and it consumes most energy when flying to the top of the target area, leaving limited leftover energy for hovering at its deployed position and providing wireless coverage. The literature largely overlooks this sustainability issue of drones' energy consumption during deployment, and we aim to minimize the maximum energy consumption among all drones after their deployment. This min-max drone deployment problem solving requires drones to cooperate with each other in deployment distance and altitude to evenly use up their energy, which is shown to be NP-hard. Thus, we propose a hybrid genetic algorithm to solve the min-max drone deployment problem. In our proposal, the integer code scheme is used to encode the sequence of drones' deployment. The energy consumption determined by the horizontal and vertical flying distance is adopted as the fitness value. With the determined order of the drones sequence by coding process, we introduce a feasibility checking operator with binary search to archive the optimum. Experimental study shows that the algorithm has capability and superiority to find good solutions under different drones' characteristics distribution and outperforms solutions from existing competitors by extensive simulations.**

***Index Terms*—Genetic algorithm, Drone networks, Wireless coverage, Energy consumption**

I. Introduction

Drones have been gradually used in military and civilian fields ([1], [2], [3]). Specially, the drone networks have emerged as important applications for providing wireless coverage to ground users. Among these applications, UAVs serve as flying base stations to serve a target area (e.g., cell edge or disaster zone) out of the capacity or reach of territorial base stations. However, the continuing development of drone applications for providing wireless coverage is still a challenging problem.

The existing works of drone networks widely assumes drones are already in or around the target area to serve ground users, and overlooks the energy consumption issue during the deployment phase of drones to reach the target (e.g., [4], [5]). [4] uses a drone-aided flying base station to serve ground users and jointly optimize the transmit power and the drone trajectory to maximize the average throughput per ground user. [5] studies the fast drone swarm deployment for emergence scenario. [6] aims to decrease operation completion time by genetic algorithm. [7] studies the drone deployment problem to optimize the coverage, fault-tolerance, and redundancy simultaneously. In [8], the problem is to find the optimum number of drones and their optimum location while considering coverage, data rate, latency, and throughput. Genetic algorithm is adopted to find the optimized solution much faster by coding. Due to a drone's small wireless service coverage, it consumes most energy when flying over a long distance to the top of the target area, leaving limited leftover energy for the drone swarm's hovering and wireless coverage in service phase. It is important to minimize the maximum energy consumption before the actual service phase, yet this sustainable deployment issue is largely overlooked in the literature and the target problem is typically NP-hard.

Based on the aforementioned limitations, we formulate this drone network deployment problem to minimize the maximum energy consumption after all drones' deployment. This min-max drone deployment problem belongs to the field of combinatorial optimization, which is shown to be NP-hard as in [5]. This objective is to avoid irrational deployment results such that some users have long-lasting wireless services while others can only get wireless services for lasting shortly. We specifically defined as the deployment arrangement of drones. The difficulty of the problem is how to arrange the UAV, thus we propose an algorithm to encode the sequence of the UAV. Our key novelty and main contributions are summarized as follows.

- With the aim of prolonging the drone network's lifetime by minimizing the maximum energy consumption among all the UAVs after their deployments, we formally formulate this min-max drone deployment problem by seeking drones' mutual cooperation.
- Due to the hardness of min-max drone deployment problem, we present a hybrid genetic algorithm (HGA), which incorporates a feasibility checking operator and binary search to archive the optimum.
- We conduct extensive simulations to validate our proposed algorithm. It shows that the developed hybrid genetic algorithm proves its capability and superiority to archive optimum and outperforms solutions from two widely used competitors in all cases.

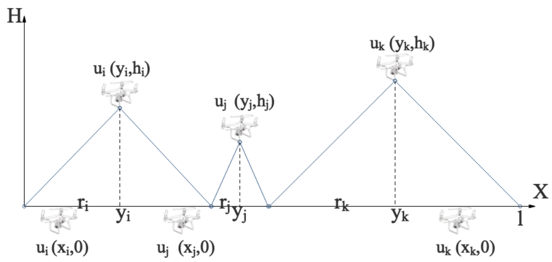


Fig. 1: System model for deploying drones to provide wireless coverage to the target interval $L = [0, l]$, where drone u_i with coverage radius r_i is deployed from x_i initially to $y_i \in [0, l]$ at operating altitude h_i

TABLE I: Basic and Morphology Features

Notation	Description
u_i	Index of $drone_i$
n	Number of drones
y_i	Final location of $drone_i$
E_i	The ratio of ev_i and eh_i
x_i	Initial location of $drone_i$
r_i	Coverage radius of $drone_i$
h_i	Operating altitude of $drone_i$
ev_i	Energy consumption of vertical flying
eh_i	Energy consumption of horizontal flying

The remainder of this paper is organized as follows. Section II gives the task model and assumptions, and describes the problem formulation. The details of algorithm, including the specification and implementation, are given in Section III. The experiment results and performance comparisons are provided in Section IV. Finally, this paper is concluded in Section V.

II. System Model and Problem Formulation

A. Model and Assumptions

We first consider the target as a long, narrow region which can be abstracted to a line segment L. Drones $\{u_1, u_2, \ldots, u_n\}$ are randomly distributed on L. An example scenario is given to illustrate the model in Fig.1.

The ratio of horizontal direction to vertical direction energy consumption per unit distance for each drone is $E_i = \frac{eh_i}{ev_i}$ where E_i is a proportionality constant, eh_i is horizontal direction energy consumption per unit distance and ev_i is vertical direction energy consumption per unit distance for u_i. Table.I gives all the notations and corresponding meanings.

B. Min-max drone deployment problem

Let L be a line segment on the x-axis. The coordinates of left and right endpoint of L is 0 and l respectively. Let $U = \{u_1, u_2, \ldots, u_n\}$ be a set of drones and each drone initially located in different locations $\{x_1, x_2, \ldots, x_n\}$ on the L. Without loss of generality, we assume $x_1 {\leq} x_2 {\leq} \ldots {\leq} x_n$. During deployment, drone u_i flies from the initial position$(x_i, 0)$ to the final position (y_i, h_i). The drone u_i has a coverage radius r_i. Then drone u_i hovering at the operating altitude h_i to provide wireless coverage. Drones consume power during flight, including energy consumption for vertical and horizontal flying. The unit energy consumption ratio of u_i in the vertical and horizontal directions is E_i and the vertical direction energy consumption for u_i is ev_i. Thus the energy consumption by a particular drone u_i moving to final position (y_i, h_i) is defined in Equation.1.

$$W_i = h_i \times ev_i + |y_i - x_i| \times eh_i \tag{1}$$

We define the maximum consumption among all drones till reaching the target position(y_i,h_i) as the optimization objective. The problem is formulated as follows.

Decision Variables : Operating location of drone u_i's: $(y_i's, h_i's)$.

Constraint: Each point p of L is covered by at least one drone:$p \in [y_i - r_i, y_i + r_i]$.

Objective: Minimizing the maximum energy consumption: f = $\min \max_{1 \leq i \leq n} W_i$ as shown in Equation (2).

$$\begin{aligned} & f = \min \max_{1 \leq i \leq n} W_i \\ & s.t. y_i - r_i \leq p \leq y_i + r_i \\ & 0 \leq p \leq l \\ & 1 \leq i \leq n \end{aligned} \tag{2}$$

III. Proposed Algorithm

Since problem (2) is NP-hard generally, there is no efficient algorithm to find the optimal solution. In this section, we propose a hybrid genetic algorithm to solve this challenging problem.

A. Solution Encoding, Crossover and Mutation

The solution is represented by a 2-tuple coding structure γ=U_n,I_n = $\{$(u_1,ind_1),...,(u_i,ind_i),...,(u_n,ind_n)$\}$. The u_i describes drones and ind_i denotes its order. We denote that there is a line segment of length *l* and drones(u_1,u_2,...,u_n) deployed on the line segment. The initial order I_n is formed of randomly generated numbers from [1, n] and there are no duplicate values in I_n. Fig.2 shows an example, we assume that sixteen drones are deployed on the line segment *L*. The solution randomly generate initial sequence I_n =(5,4,3,...,14,12,1), excluding U_n with coordinate I_n which is encoded as (u_1 =1,ind_1 =5),(u_2 =2,ind_2 =4),...,(u_{15} =15,$ind_1 5$ =12),(u_{16} =16,$ind_1 6$ =1).

γ																	
	Un	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
	In	5	4	3	6	15	7	10	16	2	8	9	13	11	14	12	1

Fig. 2: Example of 2-tuple coding structure and the corresponding encoding solution.

The $\tilde{N}^i$ of the solution sets are produced in the initialization step. We set I_a to the current solution for *i*th subproblem, and randomly select a solution I_b as the other parent from $\{\tilde{I}^t$— $I_a \in \tilde{N}^i\}$. Randomly select the fragment coordinates of the gene, swap the gene fragments of I_a and I_b. Noted that there are no duplicate numbers in I_a and I_b after the swap, thus check the un-exchanged fragments in I_a and I_b, replacing the repeated

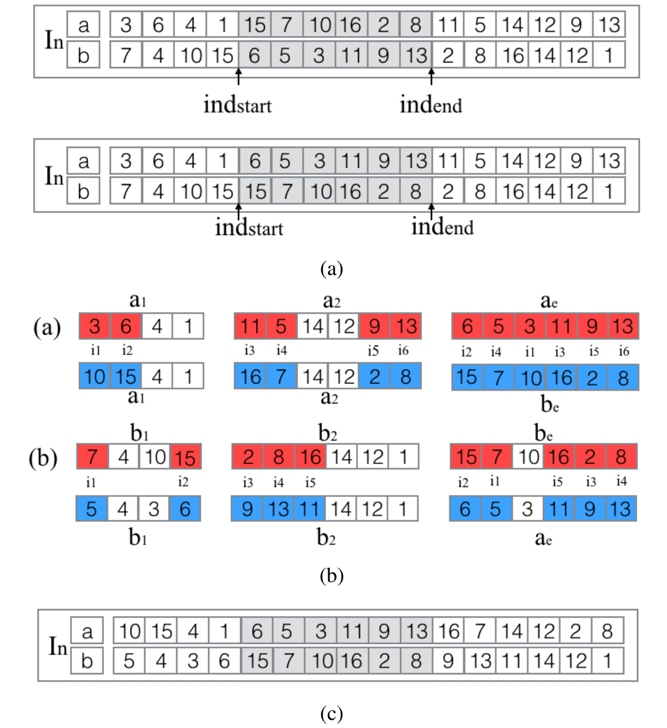


Fig. 3: Example of offspring reproduction: cross. Exchange process presents in (a), (b) illustrates duplicate values in the swapped sequence and (c) shows the final cross status.

values. Fig.3 gives a concrete example, the start and end points of the gene exchange are randomly selected, then exchange the corresponding fragments in I_a and I_b. Define exchange segment as b_e and a_e in I_a and I_b. There exist duplicate values in exchanged fragments a_e and the original fragments a_1, a_2. Define the coordinates *i*=$\{i_1$,i_2,...,$i_j\}$ of repeated values of a_1 and a_2, then replace the repeated values of a_1 and a_2 with the values corresponding to *i* in b_e. Then, new solutions can be generated by successive segment crossings on solutions I_a and I_b. We choose the better solution as I_y, then replace the solution I_a of corresponding i-th subproblem if improved.

We can use mutation operator, i.e., interchange as shown in Fig.4, to make the number of gene "ind_p" and "ind_q"($1 \leq$ p,q $\leq$ n) as mutation position. The mutation operator selects two nonidentical genes within a relatively small interval in random, in order to be further improved by fine-tuning the solution. For the replacement, we can use the newly generated solution I_m to replace I_i if adaptability improved.

B. Feasibility Checking

We first define the feasibility checking problem as follows: given any power consumption W > 0 and order requirement γ determine whether drones can be moved to reach a full coverage within deadline W. We next design a feasibility checking algorithm to determine whether such W is feasible to achieve via drone dispatching.

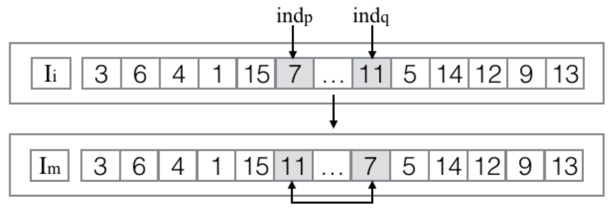


Fig. 4: Example of offspring reproduction: mutation

Consider any W $>$ 0, for u_i if $\frac{W}{ev_i} > h_i$, $\frac{W-\frac{W}{ev_i}}{eh_i}$ is the maximum horizontal distance to move on L $\in$[0,l]. We define pl_i as the leftmost point and pr_i as the rightmost point on L that can be covered by u_i within W. We call pl_i (resp., pr_i) the leftmost(resp., rightmost) *W-coverable* point of u_i. Then we have

$$\begin{aligned} pl_i &= x_i - r_i - \frac{W - \frac{W}{ev_i}}{eh_i} \\ pr_i &= x_i + r_i + \frac{W - \frac{W}{ev_i}}{eh_i} \end{aligned} \tag{3}$$

Algorithm 1 solves the feasibility checking problem. It first computes pl_i and pr_i for u_i in Equations 3, then deploy the drones one by one according to the order γ from the left endpoint of target interval [0,l]. Given our current covered interval[0,$\bar{l}$] where the boundary $\bar{l}< l$, iteration i starts with checking whether drone u_i can cover to $\bar{l}$ or not.

- if u_i can cover to $\bar{l}$, we will efficiently deploy u_i to y_i = min($\bar{l}$+r_i, pr_i-r_i) and update $\bar{l}$ = y_i + r_i.
- if u_i can't cover to $\bar{l}$, it will not be dispatched and $\bar{l}$ remains unchanged.

Noted that once u_i is deployed to the left of u_j, in which y_j<y_i, the Algorithm 1 in line 9 will not use this order requirement γ and end the loop. After a successful dispatching of drone u_i, the covered interval prolongs from [0, $\bar{l}$] to [0,y_i+r_i] in this interation. If W is feasible, our our algorithm will return the order requirement γ and their new locations y_i to fully cover target L within W.

C. Binary Search over Feasible Budget

With the help of Algorithm 1, we can verify whether a given budget *W* is feasible or not. The minimum budget among all feasible ones is actually the optimum of the problem. Here, we apply binary search to find the minimum deadline and solve problem. Before the search, we still need to determine the step and search scope.

For each single u_i, the minimum moving distance is altitude h_i. Thus, the lower bound of W (denoted as W_{min}) among all drones can be determined according to

$$W_{min} = \min_{1 \leq i \leq n} h_i \times ev_i \tag{4}$$

In general, W_{min} is not feasible because it is the minimum possible power consumption among all drones. We next determine the upper bound of W (denoted as W_{max}). For drone

Algorithm 1 Feasibility Checking

Require:
U = u_1,u_2,...,u_n
γ = ind_1,ind_2,...,ind_n
W : a given budget of energy consumption for all drones
Ensure:
y_i: final locations of u_i
Initialize pl_i and pr_i in Equation. (3), $\bar{l} = 0$
for i=1 to n **do**
  if $\bar{l} \notin [pl_i, pr_i]$ **then**
    $y_{ind_i} \leftarrow x_{ind_i}$
  else
    $y_{ind_i} \leftarrow \min(\bar{l} + r_{ind_i}, pr_{ind_i} - r_{ind_i})$
    $\bar{l} \leftarrow y_{ind_i}$+$r_{ind_i}$
    if y_{ind_i}<y_{ind_j} where ind_j<ind_i **then**
      Break;
    end if
  end if
end for
if $\bar{l}$ <l **then**
  return W is not feasible
else
  return W is feasible
end if

u_i, the maximum possible power consumption of u_i is to reach position (0,h_i) or (l,h_i) beyond the leftmost or rightmost location on the target interval $L = [0, l]$. Thus, W_{max} among all drones is given by

$$W_{max} = \max_{1 \le i \le n} (h_i \times ev_i + \max x_i \times eh_i, l - x_i \times eh_i) \quad (5)$$

In the binary search, we define the relative error as α which is a small constant value, and accordingly set the search accuracy as αW_{max}. The binary search starting with W_{max} stops once switching from infeasible budget W_1 to feasible W_2, such that the resultant W_2 is our searched optimum for the problem. Then, we can obtain the following Algorithm 2 combined with Algorithm 1 to solve the problem with predetermined drones order.

Generally, we use an integer sequence to code the drones' order after deployment. Then, we design a feasibility checking algorithm with binary search to obtain the optimal solution under the predefined drones' order, in which the optimal energy storage obtained is returned as fitness of our genetic algorithm. The hybrid genetic algorithm is given in Algorithm 3.

IV. Experimental Results and Analysis

In this section, experiments are conducted based on datasets of different distributions. The proposed algorithm is coded on Python 3.7.3, and the experiments are conducted on a computer with Intel(R) Core(TM) i5-5250U processor (1.60GHz) with 8GB of RAM. Take 80 drones and 5000 meters of coverage as an example. The experimental parameters are set

Algorithm 2 Binary Search over Feasible Deadlines

Require:
W = αW_{min},$2\alpha W_{min}$,...,$\lceil \frac{W_{max}}{\alpha W_{min}} \rceil \alpha W_{min}$ where W_{min} and W_{max} are given in 4 and 5
Ensure:
I(idx): idx is the index
low $\leftarrow$ 1 and high $\leftarrow W_{max}$
while low $\le$ high **do**
  mid $\leftarrow$ floor((low+high)/2)
  feasibility checking by Algorithm Algorithm 1 on I(mid)
  if I(mid) is feasible **then**
    high $\leftarrow$ mid
  else
    low $\leftarrow$ mid
  end if
  if low == high-1 **then**
    idx $\leftarrow$ high
    break
  end if
end while
return I(idx);

Algorithm 3 Offspring Generation for *i*th Subproblem

if rand() $<prob_i$ **then**
  $I_a \leftarrow I_i$ and select $I_b \in U_i$ in random
  if rand() $<probability\ of\ crossover_i$ **then**
    Generate new solutions I_y by crossover operator on I_a and I_b
  end if
  Computing the lowest possible consumption W_{I_y} and W_{I_a} with Algorithms 1 and Algorithms 2
  if W_{I_y} <W_{I_a} **then**
    Set I_a = I_y
  end if
  if rand() $<probability\ of\ mutation_i$ **then**
    Generate a new solution I_m by randomly interchange two non-identical genes on I_i
  end if
  Computing the lowest possible consumption W_{I_m} and W_{I_i} with Algorithms 1 and Algorithms 2
  if W_{I_m} <W_{I_i} **then**
    Set I_i = I_m
  end if
end if

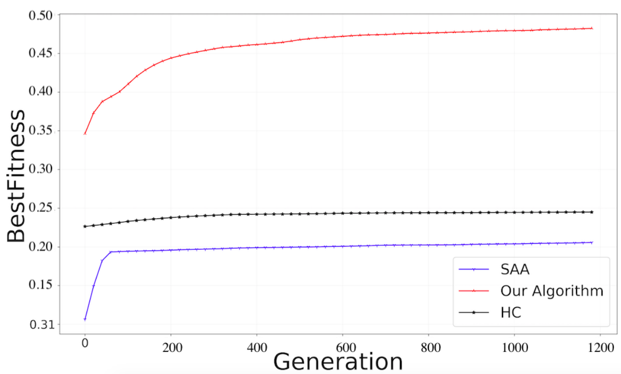
as follows. The initial position of the drone follows the specified distribution. Referring to the current common civil drone feature, the flight altitude range in [100,200], and the coverage radius range in [10,50]. The antibody population size is set to 100, the cross probability range in [0.4,0.7], the mutation probability range in [0.2,0.4], and the maximum operation generation number is set to 1500. The above parameters were obtained after multiple tests on different instances of different

TABLE II: Distribution Method and Required Parameters

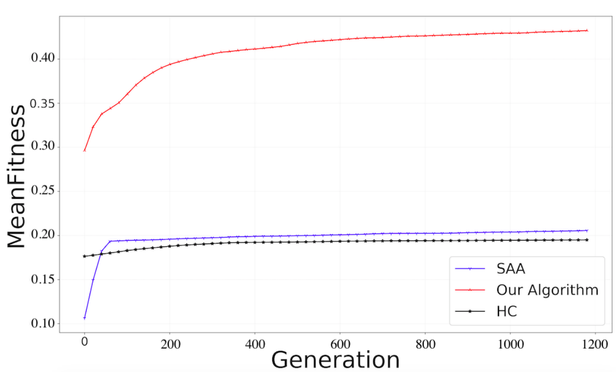
Distribution	Parameters
Exponential Distribution	λ=3
Beta Distribution	α=2,β=5
Gamma Distribution	α=3;β=2
Normal Distribution	μ=0;σ=2
Lognormal Distribution	μ=0;σ= $\frac{1}{2}$
Random Distribution	Ranges$\in$[1,n]
Triangle Distribution	Ranges$\in$[1,n], Mode= $\frac{n}{2}$

sizes. According to the problem model and optimization objective established in this paper, the proposed specific genetic algorithm is run 200 times randomly.

First, we compare the proposed algorithm by using seven differently distributed datasets, the selected distribution method and the required parameters are shown in Table II.



(a)



(b)

Fig. 5: In the case of random distribution, the results of the deployment scheme by three algorithms.(a) shows the comparing results of best fitness and (b) shows the mean fitness.

The initial position of drones depends on these datasets. In the case of using the proposed algorithm, the best fitness and the mean fitness of the population size of each generation with the proposed algorithm are recorded, and four of results are shown in Fig. 6. It can be known that before the optimization, the initial fitness values are all unexpected especially triangle distribution, the fitness value obtained from the triangle distribution dataset is the lowest. After optimization, the distribution scheme of drone changes; that is, the flight order after executing coding scheme is changed, so the energy consumption is reduced. It can be seen that in the initial stage of the adjustment, the algorithm proposed aims to minimize the maximum energy consumption of drones, determines the best solution for deployment, assign each drone to the suitable location, and gives the flight order. At the later stage of the algorithm, in order to continue to optimize the plan, the flight plan obtained from the previous operation is further optimized and modified. By comparing the changes in the fitness before and after the execution of the algorithm, it can be seen that the deployment scheme has been further optimized, so the encoding scheme and optimization process proposed in this paper are effective.

In order to further highlight the solution quality and advantages of the proposed algorithm, Simulated Annealing Algorithm(SAA) [9] and Hill Climbing Algorithm(HC) [10] are used as competitors in this paper. In the case of random distribution, the results are shown in Fig. 5, among three algorithms, the best fitness of our proposed algorithm, SAA and HC are 0,4862, 0.2315 and 0.1941 respectively. In terms of mean fitness, the results obtained by the proposed algorithm, SAA and HC are 0.4371, 0.2080 and 0.1986 respectively. This indicates that the hybrid genetic algorithm is effective and advantageous in terms of solution quality. After comparison, it can be found that although the convergence speed of the proposed algorithms is lower than SAA and HC, when the algorithms converge, the final results are much better than the algorithms compared. The above results show that SAA and HC can find the current optimal path segmentation in a given task points sequence, but the result is not necessarily the global optimal solution. In addition, the 50 groups of best fitness and mean fitness obtained by the proposed algorithm are recorded. The results are shown in Figure 7. From the curve settlement process of the optimal value, it can be seen that the random operation in the process will not greatly affect the convergence of the final result, and all experimental results will tend to be close. From the above analysis, the proposed algorithm has good stability. Compared with the SAA and HC, the proposed algorithm can provide a better energy-saving solutions for drone network deployment, thereby further verifying the effectiveness of the further optimization.

V. Conclusion and Future Work

In this paper, we study the min-max drone deployment problem to minimize the maximum energy consumption among all drones to archive full coverage over a target area. To efficiently solve this challenging problem, we propose a hybrid genetic algorithm, in which the integer code scheme is used to encode the sequence of drones' deployment. The energy consumption determined by the horizontal and vertical flying distance is adopted as the fitness value. With the determined order of the drones sequence by coding process, we introduce a feasibility checking operator with binary search to archive the optimum. Experimental study shows that the algorithm has capability and superiority to find good solutions under

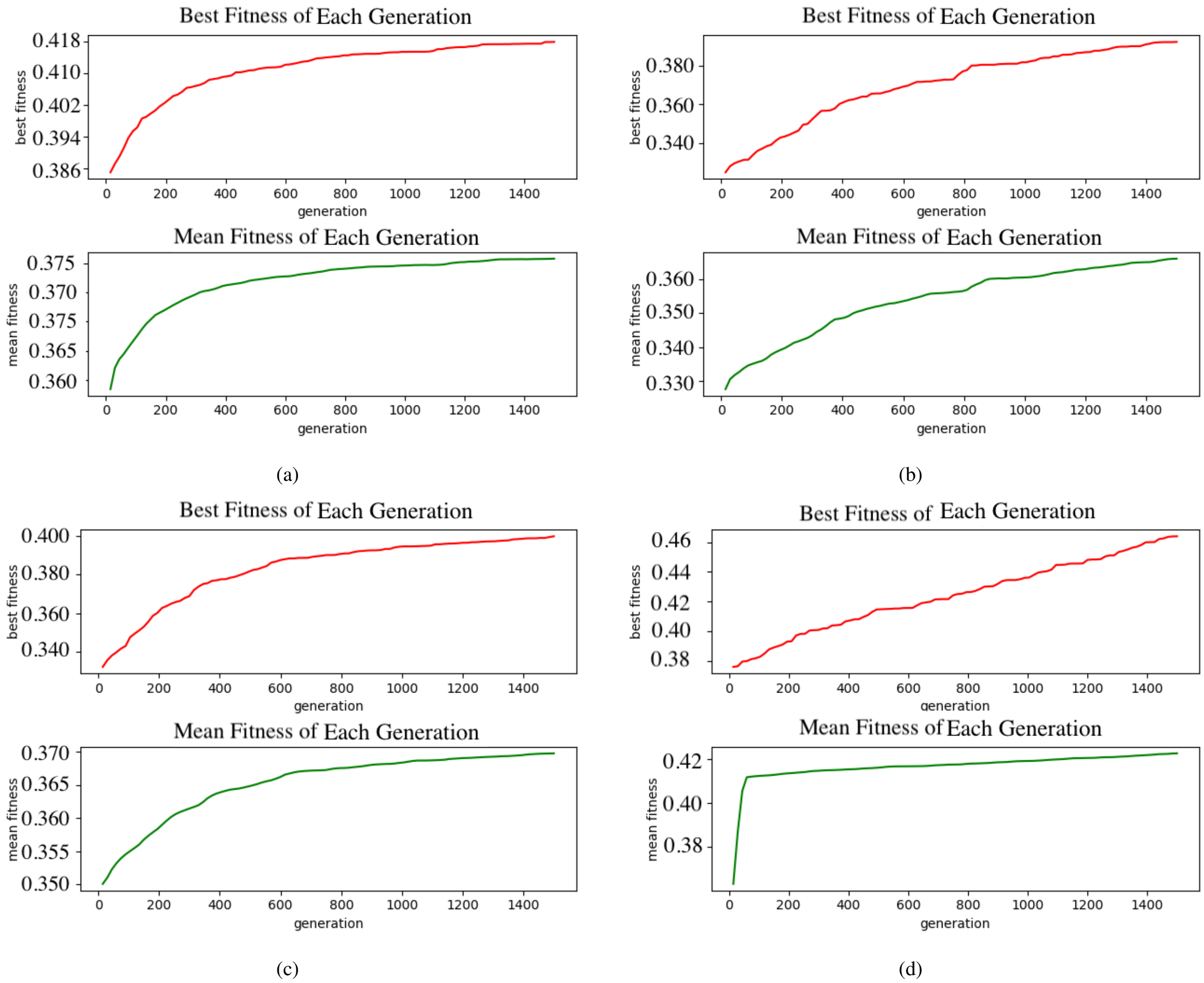


Fig. 6: The best fitness and the mean fitness of the population size of each generation with the proposed algorithm from different distribution.(a) shows the result for beta distribution, (b) for exponential distribution, (c) for gamma distribution, (d) for random distribution.

different drones' characteristics distribution and outperforms solutions from existing competitors by extensive simulations.

The research presented in this paper will form the foundation for future research: when the energy consumption and the number of drones are limited at the same time, the proposed method will be extended to multiple optimization goals. Therefore, the problem of sustainable wireless network coverage under multiple conditions and its corresponding solutions are all the subjects of planned future work.

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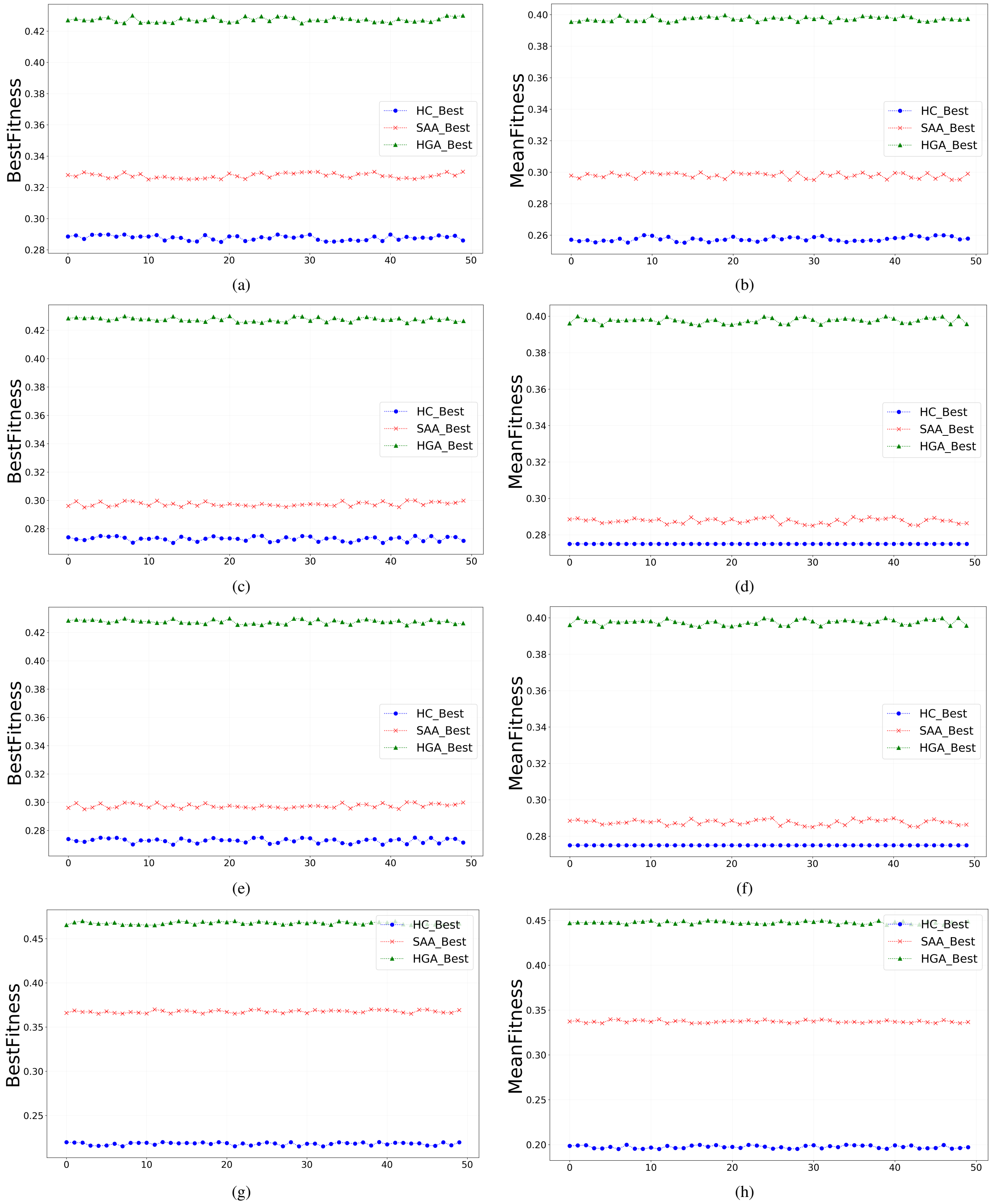

Fig. 7: The 50 groups of optimal fitness and mean fitness by the proposed algorithm, (a) and (b) shows 50 groups experimental results: best fitness and mean fitness with three algorithms for beta distribution, (c) and (d) shows the results for exponential distribution, (e) and (f) shows results for gamma distribution, (g) and (h) for random distribution.

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