Deployment of High Altitude Platforms Network: A Game Theoretic Approach

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***Abstract*—The High Altitude Platforms (HAPs) have been considered as a promising technique for providing wireless communication and other services. They operate at an altitude from 17km to 22km, which exploit both advantages of satellites and terrestrial wireless communication networks. It is possible to deploy HAPs network rapidly and adjust them dynamically to cover specific regions requiring communication services. In this paper, the problem of deploying HAPs network to provide wireless communication for terrestrial users is investigated. The aim of deployment is to providing communication services to ground users as many as possible with quality of service (QoS) guaranteed. To find an optimal solution, we model the problem as a potential game. And a restricted spatial adaptive play (RSAP) learning algorithm is introduced for the game. Using this algorithm, the HAPs can be deployed to cover the user areas in a self-organized manner with high QoS achieved. Finally, the simulation results also demonstrate that the HAPs network can achieve the optimal deployment.**

***Index Terms* —Wireless communication, High altitude platform, Quality of service, Potential game, Learning algorithm**

I. INTRODUCTION

The high altitude platform system is considered as a promising wireless communication system which is expected to co-work with terrain and satellite communication systems in a complementary and integrated fashion [1].

High Altitude Platforms are usually based on quasi-stationary aerial platforms (or airship, balloon, UAV, and etc.) operating in the stratosphere, at an altitude of 17km to 22km [2]. They have the potential to provide various kinds of communications services and other applications cost effectively (e.g., broadband, mobile communication, or environment monitoring). Many countries proposed their own research projects on HAPs system, i.e. CAPANINA, HALO, SkyNet, etc.[3]. The International Telecommunication Union (ITU) has recognized the HAP from 1997 as a separate category of radio stations: The High Altitude Platform Station (HAPS) and attributed the 2, 31/28 and 47/48 GHz frequency ranges for its operation.

Comparing with terrestrial communication infrastructure and satellite communication system, HAPs have the advantage of easy and rapid deployment, high cost-effective, wide range covering, low transmission delay and flexible operation [4]. Since the HAPs can be easy to launch and fast to deploy, they are suitable for constituting networks over certain ground area to provide communications or surveillance services. A single HAP station can supply a much larger coverage area than a terrestrial base station with comparative high communication capacity. And the channel attenuation is much less than the terrestrial channel. HAPs network are designed to provide wireless communication service. Since the HAPs are operating at the high altitude space, they can be deployed flexibly without the restrictions by the Geographical conditions.

Previous work focuses more attentions on studying the capability of the HAP station on providing wireless communication service. A setting of multiple HAPs communication networks is proposed in [5] and the capacity of networks is presented. In [6] the performance of multiple HAPs scenario is analyzed in the terms of CINR and capacity.

However, there is little literature involving how to deploy the HAPs networks effectively according certain mission requirement. It is generally expected that the deployment of the HAPs should cover the ground user as many as possible with required quality of service. A method based on K-mean clustering for placement of multiple HAPs is presented in [7]. Given the number of ground nodes and area coverage, the ground users are clustered to determine the HAPs location. In [8], a deployment optimization model of airships is developed for HAPs based genetic algorithm, whose solution has high time complexity. Both above methods are centralized controlling scheme, which need central controller calculate the optimal configuration and coordinate the movement of HAPs. In addition the QoS for users and interferences between HAPs are not taken into consideration. These factors are important for practical application.

In this paper, we investigate the deployment problem of HAPs network providing wireless communication for terrestrial users. The HAPs' coverage and interference model are taken into consideration. In our system, QoS for ground users are determined by the transmitting data rate between HAPs and users. The objective of the HAP network deployment is formulated to maximize the total transmitting rate of HAPs network, meanwhile, and to guarantee the user minimum service requirement. It is expected that the deployment could be implemented in a self-organized way. The HAPs cooperate to accomplish the aim of providing optimal wireless services. Consequently, a game-theoretic analysis is called for the deployment problem. The HAPs are modeled as rational and self-organized players which seek optimal configuration to maximum their utilities of the HAPs. We introduced restricted spatial adaptive play (RSAP) learning algorithm to solve the

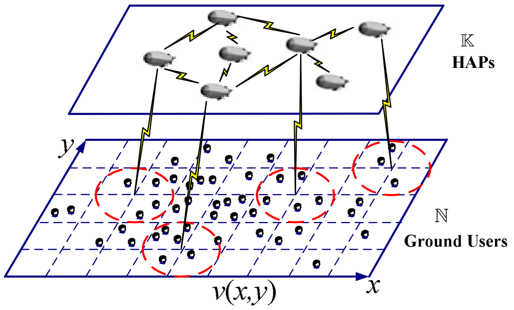


Fig. 1. HAPs network communication system

deployment game. The learning algorithm guarantees that the HAPs explore the distribution of user and converge to the optimal positions with high probability. The simulation results show the effectiveness of our scheme.

The rest of the paper is organized as follows. Section II introduces the HAPs network deployment problem, and the problem is modeled as a potential game. Then in section III, the learning algorithm is proposed to achieve optimal configuration for the deployment game. The simulation results show the effectiveness of the algorithms in section IV. At the last section, we provide the concluding remarks.

II. Deployment Problem Formation

Consider a communication system in which High Altitude Platform deliver wireless communication (or other wireless services) to ground users (show in fig.1). High Altitude Platforms act as wireless base stations. And they link with each other to construct backbone networks. The ground users could access to the network for mobile communication and other wireless services.

A. Problem formation

Let $\mathbb{K}=\{1,\dots,k,\dots,K\}$ be a set of HAPs, the service providers. Each HAP k operated at the altitude h. There are a number of ground users requiring communication services. Let $\mathbb{N}=\{1,\dots,i,\dots,N\}$ be the set of users and $\mathbb{S}^u=\{s_1^u,\dots,s_i^u,\dots, s_N^u\}$ be the users distribution on the ground, where s_i^u denotes the position of user i. The HAPs deployment problem is aim to seek a tuple of optimal locations $\mathbb{S}^h=\{s_1^h,\dots,s_k^h,\dots,s_K^h\}$ (s_k^h denotes the position of HAP k at high altitude space) for HAPs $\mathbb{K}$. The optimal deployment should fulfill users' service requests as many as possible with certain quality level guaranteed.

The HAP could deliver communication services within its coverage region from the high altitude space. The QoS that HAP provides for users depends on the HAP's transmitting power shadowed on the footprint area (as fig. 2). For a HAP-to-ground communication link, the receiving signal power on the ground is related to the path loss of the channel, which can be considered as free space propagation model [9]. Let p_t be the transmitting power of the HAP, and p_r be the receiving power of the user on the ground. There is

$$p_r(s_i^u,s_k^h)=\frac{\delta}{\left\|s_i^u-s_k^h\right\|_2^{\alpha}}p_t,\quad i=\{1,\dots,N\}, \tag{1}$$

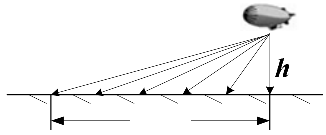


Fig. 2. HAPs coverage model

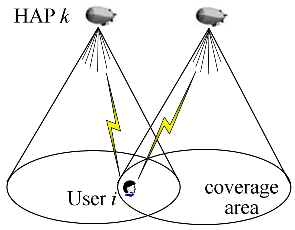


Fig. 3. Interference model

where $\left\|s_i^u-s_k^h\right\|_2$ is the distance between user i and HAP k, and α is the signal fading factor. For the common HAPs communication links, α is 2~4 [3]. δ denotes the loss factor specified by the given transmitting radio wave and environment.

The receiving power of user is also affected by the antenna. If the effect of beam shapes for directed antenna is taken into consideration, p_t will change with transmitting angle. In this paper, we do not consider the beam shape and gain of antenna for the radio signal transmitting, and assume that p_t is constant for any angle of the antenna(such as omni antenna).

When users receive communication services, the transmitting data rates should be maintained at certain level to guarantee the QoS. For a particular traffic type along with the required bit error rate are not discussed here. The maximum theoretical transmitting data rate from HAP to a ground user is given as follow[5],[1]

$$r_{ik}=B\log_2(1+CINR_{ik}), \tag{2}$$

where r_{ik} is the maximum transmitting data rate from HAP k to user i, the $CINR_{ik}$ is the carrier-to-interference-plus-noise ratio (CINR) of the channel between HAP k and the user i. B denotes the communication bandwidth.

It is very common that a user may fall in multi-HAPs' service coverage areas as shown in fig.3. However, user will only set up a link with the HAP which can provide best QoS and other HAPs' signal power will interfere with the link. We have the $CINR_{ik}$ expression [5] as

$$CINR_{ik}=\frac{g_{ik}p_{r,ik}}{N_T+\sum_{l\in\mathbb{K}\setminus k}g_{il}p_{r,il}}, \tag{3}$$

where the N_T denotes the thermal noise power observed by the user, which is constant for certain bandwidth. $p_{r,ik}$ is the user i's receiving power from the HAP k that offers communication services, and $p_{r,il}$ denotes the interference signal power from other HAPs that have not offered the communication services to user i. g_{ik} and g_{il} are the gain factor for the users' receiver. They are constant for a given scenario.

If there is no inference from other HAPs, From (3), we can see that the data rate only depends on the receiving signal power. The receiving CINR is determined by HAP's transmitting power and the distance between it and user. Given a maximum transmitting power, the HAP could only delivered service

[1] The Shannon equation is only perfectly accurate for a Gaussian noise source. Interference will only be approximately Gaussian.

within a limited range (denoted as S_r) according to minimum data rate demand.

The goal of a HAP is to maximize the total data rate to fulfill ground users' demands. Given M_k users within HAP k's service range, the total data rates from HAP k is

$$\begin{aligned} R_k &= \sum_{i=1}^{M_k} r_{ik} = \sum_{i=1}^{M_k} B\log_2(1+CINR_{ik}) \\ &= \sum_{i=1}^{M_k} B\log_2(1+\frac{g_{ik}P_{r,ik}}{N_T+\sum_{l\in\mathbb{K}\setminus k} g_{il}P_{r,il}}) \end{aligned} \quad (4)$$

For the HAPs network, the sum data rate of all HAPs, namely the throughput of the network, is given as follow

$$\Phi = \sum_{k\in\mathbb{K}} R_k \quad . \quad (5)$$

Given a number of Users $\mathbb{N}$ and their positions $\mathbb{S}^h$, the goal of HAPs network is to solve the following optimization problem,

$$\begin{aligned} \max \quad & \Phi = \sum_{k\in\mathbb{K}} R_k(s_1^h,\ldots,s_k^h,\ldots,s_K^h), \\ \text{subject to} \quad & s_k^h \in \mathbb{S}^h, \\ & r_i \ge r_{\min}. \end{aligned} \quad (6)$$

In the constrains, $\mathbb{S}^h$ denotes the HAP k's available positions space. Here s_k^h is assumed discrete and finite. $r_{\min}$ is the minimum data rates between HAP and user. The data rate for a user should exceed the minimum data rate to ensure the quality of certain communication service.

The sum data rate provide by HAPs network is determined by the locations of HAPs and users and the HAP's transmitting power. In this paper we assume that the HAP's transmitting power is unchangeable. The total data rate of HAPs network is only the function of HAPs' positions $\mathbb{S}^h = \{s_1^h,\ldots,s_k^h,\ldots,s_K^h\}$ and users' distribution $\mathbb{S}^u = \{s_1^u,\ldots,s_i^u,\ldots,s_N^u\}$.

As the HAPs have limited communication scopes S_r, they can detect the presents of the users within their coverage region. In fact, the sensing range is much larger than the service range, since the receiving power level cannot fulfill the minimum data rate for the wireless communication. We assume the HAPs could only sense the users' positions within their maximum communication scopes S_r. under this situation, the deployment is much complicated.

B. Game theoretic model

The proposed HAPs deployment problem is to find the optimal position of the multi-HAPs. We will show that the optimization problem can be model as a game and there exist Nash Equilibrium that is the optimal or suboptimal solution for the optimization problem.

Since individual HAPs do not collaborate among themselves, evenly they may impair the benefit of each other. This communication scenario can be modeled as a non-cooperative game [10]. The HAPs are non-cooperative players and their available positions are their action sets. Given certain users distribution on the ground, the areas that the HAPs could cover represent the set of admissible strategies of this HAP.

In non-cooperative game, the selfish players are trying to maximize their own utilities. In the deployment game, the HAP will benefit themselves from provide more services to ground users. Let u_k denotes the utility of player HAP k. Then, A Nash equilibrium of this game [10] is a tuple of actions $\{s^{*h}_k\}_{k=1}^K$, such that for any $k\in\mathbb{K}$

$$u_k(s^{*h}_1,\cdots,s^{*h}_k,\cdots,s^{*h}_K) \ge u_k(s^{*h}_1,\cdots,s^h_k,\cdots,s^{*h}_K), \quad \forall s_k^h \in \mathbb{S}^h \,. \quad (7)$$

In other words, a Nash Equilibrium of this game is a locally optimal strategy for each player that no player has an incentive to unilaterally move.

Intuitively we can assign the data rate R_k as HAP k's utility function, since the rewards that service subscribers pay to providers can be evaluated by the accessing data rate. Here we define the utility of each HAPs U_k which satisfies

$$U_k(s_k^h,s_{-k}^h) = \Phi(s_k^h,s_{-k}^h) - \Phi(s^{0h}_k,s_{-k}^h), \quad (8)$$

where s^{0h}_k denote the HAP k provide no services to any user. The player's utility function $U_k(s_k^h,s_{-k}^h)$ denotes the contribution of the global payoff, the total data rates, under strategy $\{s_k^h,s_{-k}^h\}$.

This utility function implies the single HAP's contribution to the global profit. By allocating HAP this utility function, the global object function will possess the monotonicity relative to single HAP's payoff. Whereas taking data rate of HAP as utility function does not show this property. Based on above definition we have following proposition.

Proposition: The HAPs deployment game is a potential game [11] and has a pure strategy (deterministic) Nash equilibrium.

This proposition comes from the fact that we can define the potential function

$$\rho(s_1^h,\cdots,s_k^h,\cdots,s_K^h) = \Phi(s_1^h,\cdots,s_k^h,\cdots,s_K^h), \quad (9)$$

which satisfies

$$U_k(s_k'^h,s_{-k}^h) - U_k(s_k^h,s_{-k}^h) = \rho(s_k'^h,s_{-k}^h) - \rho(s_k^h,s_{-k}^h)\,. \quad (10)$$

where s_{-k}^h the actions of HAPs except k. Hence, we can start from an arbitrary deterministic action vector, and at each step once one player increases it's utility ρ is increased identically. Since ρ can accept a finite amount of values, it will eventually reach a local maximum. At this point, no player can achieve any improvement, and we reach a Nash Equilibrium (NE).

Finding the optimal deployment of the HAPs is to maximizing the ground objective function, which leads to a pure NE maximizing the potential function. The NE can be reached in a distributed method. In the sequence, we propose a learning algorithm to achieve the NE, which give us a satisfied solution for the HAPs deployment problem.

III. Solution to Deployment Game

In the above section, we have developed the mathematic basis for the setting in the deployment of HAP network. The deploying optimization problem has been modeled as a potential game. This section focuses on solutions to the deployment game.

When the users' positions are known, it is much easier to determine the best location for HAPs by searching or genetic algorithm. However, the centralized algorithms are invalid in practices, because the users' distribution is often unknown and even changing in the deployment process.

Generally, a heuristic algorithm could be applied for this game, such as greedy algorithm. While this kind of method often converge to local optimal. We introduced the RSAP learning algorithms for the deployment game. The learning algorithms allow the HAPs working in a self-organized manner. The HAPs determine their deploying policy by their own utility without central controller. The algorithms will lead to game converging to NE, where HAPs achieve optimal deployment for given users.

A. RSAP Learning Algorithm

Some games may result in Nash Equilibria that are suboptimal from the point of view of all players. So the learning dynamics has been introduced to game theory. The learning algorithm works in the form of repeated game. It could find the optimal solutions of the maximizing the group's objective function.

In a general game, the players are permitted to take any actions in theirs strategies sets. In the process of deployment game, a HAP can only move to a position within a fixed radius around its current position at each time slot. That means the player can only adopt restricted actions which is depended on its current action state in the game.

For this restricted-action potential game, the restricted spatial adaptive play (RSAP) [12] learning algorithm are introduced. It allows each player choose an actions from a limited action set determined by its previous action. The algorithm guarantees the iteration process probabilistic converging to a pure Nash Equilibrium that maximizes the potential function.

Let $s_k^h(t-1)$ be the action at time t–1. The set of actions available for player k at time t will be denoted as $\mathbb{S}_k^R(s_k^h(t-1)) \subset \mathbb{S}^h$. It is a function of player k's action at time t–1. The learning algorithm are described as follow.

Algorithm II: RSAP Learning Algorithm

Step 1: chosen one player HAP $k \in \mathbb{K}$ randomly, (with equal probability for each player) and permitted to select a new action. All other players maintain their states, i.e. $s_{-k}^h(t) = s_{-k}^h(t-1)$.

Step 2: the active player HAP k randomly selects a trial position $\hat{s}_k^h$ from its state-dependent action set $\mathbb{S}_k^R(s_k^h(t-1))$ with the following probabilities:

$$\begin{cases} \Pr[\hat{s}_k^h = s_k^h] = (1/z_k), \\ \qquad\qquad \text{for any } s_k^h \in \mathbb{S}_k^R(s_k^h(t-1)) \setminus s_k^h(t-1); \\ \Pr[\hat{s}_k^h = s_k^h(t-1)] = 1-((\left|\mathbb{S}_k^R(s_k^h(t-1)\right|-1)/z_k), \end{cases} \quad (12)$$

where z_k denotes the maximum number of actions in any restricted action set for player k, i.e., $z_k = \max_{s_k^h \in \mathbb{S}_k^R} \left|\mathbb{S}_k^R(s_k^h)\right|$.

Step 3: After player k chooses a trial action $\hat{s}_k^h$, k updated its action state at time t with the following probabilities:

$$\begin{cases} \Pr[s_k^h(t) = \hat{s}_k^h] = \dfrac{\exp\left\{\beta U_k(\hat{s}_k^h, s_{-k}^h(t-1))\right\}}{D} \\ \Pr[s_k^h(t) = s_k^h(t-1)] = \dfrac{\exp\{\beta U_k(s_k^h(t-1))\}}{D} \end{cases}, \quad (13)$$

where

$$D = \exp\{\beta U_k(\hat{s}_k^h, s_{-k}^h(t-1))\} + \exp\{\beta U_k(s_k^h(t-1))\}, \quad (14)$$

and $\beta \geq 0$ is an exploration parameter.

Step 4: Repeat the process from step 1.

This algorithm induces a markov process which has a unique stationary distribution [12]. The stationary distribution μ is in the joint actions set that maximize the potential function [13]. That means the stationary distribution is the NE of game. There are

$$\mu(\vec{s}^h) = \frac{\exp\{\beta\rho(\vec{s}^h)\}}{\sum_{\vec{s}^{h*}\in A}\exp\{\beta\rho(\vec{s}^{h*})\}} \quad \text{for any } \vec{s}^h \in \vec{\mathbb{S}}^h \text{ [12]}, \quad (15)$$

where $\vec{s}^h$ denotes the action profile, and $\vec{\mathbb{S}}^h$ is the action profile space. As $\beta \uparrow \infty$ and sufficiently large times t >0, the game converges to the optimal distribution where the action profiles maximize the potential function.

In this deployment game, all the players can evaluate his utility using only local information without the global users distribution. All the learning process can be carried out by the players themselves without any supervision. For sufficiently large t and β, the optimal solution to the deployment of the HAPs over specific mission space could be obtained through the learning algorithm.

IV. Simulation Results

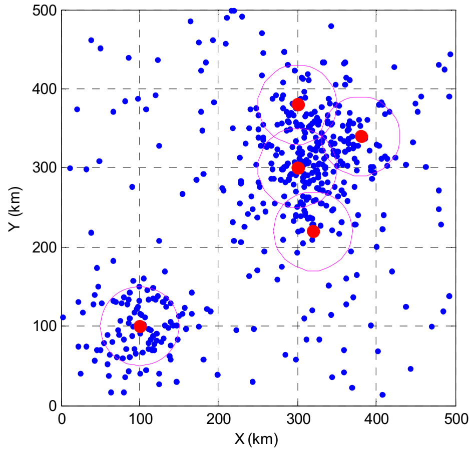
In the following simulation, the scenario is set within 500km×500km area. Within the area, 500 users are located in four partitions. Users' distribution meets Gaussian distribution within two partitions, which simulate the urban population distribution. The other two partitions are uniform distribution, which correspond with the rural population distribution.

The HAP's is assumed at an altitude of 20km. For the communication channel, there are α=2 and δ=0.01. The HAP's transmitting power P_t is 1W. We assume the communication bandwidth B=1MHz, and the thermal noise N_T =5×10^{-13}W. For each user, the minimum transiting rate $r_{\min}$ to maintain communication service is set as 200kHz.

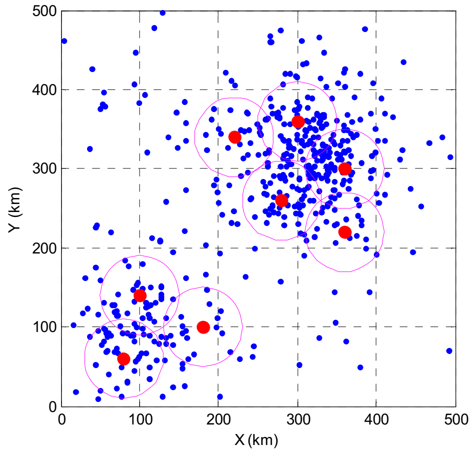
All HAPs initially start at location (0, 0, h). As mention before, we assume the HAPs' location is discrete and finite. In the simulation, the HAPs moves 1km at each time step in four directions along the axes. For the learning algorithm, the β is 0.002.

Fig. 4 shows the deployment results from the view of overlooking. There are 5 and 8 HAPs being deployed over the area. Cause the constraint of minimum service data rate, the coverage region radius is about 50km. From the figure we can see that the HAPs tend to cover more users in their footprint areas. Despite starting from origin (0,0,20km), the HAPs have scattered to converge to user-dense-region. Beside they avoid falling into the local extreme which near the starting points.

Fig. 5 shows the global maximum data rate changing with the iteration steps. The global maximum data rate also denotes the potential function of the deployment game. As the iteration number goes up, the HAPs could achieve good performance. Since the learning algorithm using probability decision method, we can see that there is still fluctuation around the optimal configuration.



(a) 5 HAPs



(b) 8 HAPs

Fig. 4. The deployment of different numbers of HAPs

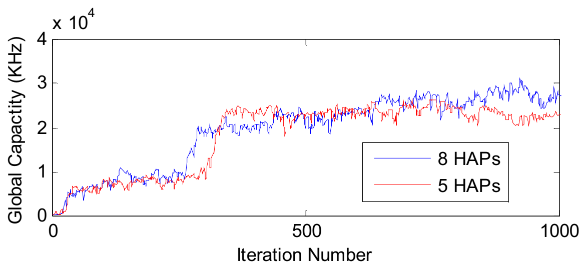


Fig. 5. Global maximum data rate of HAPs network

Generally the simulation results show that the HAPs could achieve a global optimal deployment. The HAPs could catch the distribution of users and perform a good distribution.

V. Conclusion

In this paper, the deployment problem of HAP networks is explored. Ensuring high QoS is set as the target of networking. The HAPs network deployment problem is formulated as optimizations problem of total throughput of HAPs network. We model the deployment problem as potential game to develop distributed deploying methods. The RSAP learning algorithm is introduced to lead the game to Nash equilibrium, which offers the optimal solution to the HAPs deployment problem. The learning algorithm allows HAPs being deployed in a self-organized manner without any priori information, while the cost is slow convergence to global optimal solutions. Finally the simulations show the effectiveness of our methods.

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