Deployment of High Altitude Platforms in Heterogeneous Wireless Sensor Network via MRF-MAP and Potential Games

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***Abstract*—With the development of wireless sensor network (WSN), the design and maintenance of WSN are still challenge in a large number of sensor nodes which are constrained in energy and bandwidth. Thus, a new solution is high altitude platforms (HAPs) that can be employed as the relay nodes of WSN in order to reduce the energy consumption of sensor nodes because of multi-hop relay transmission and to enlarge the coverage range of WSN. In this paper, a novel heterogeneous WSN system consisting of HAP layer, WSN layer and mission layer is proposed. In the system, we model a deployment model of HAPs based on markov random field with maximum a posteriori probability (MAP) framework, thus obtaining the energy function of HAPs. Then, a potential game approach is introduced to analyze the energy function, which proves to be able to achieve a pure Nash equilibrium. In addition, a modified distributed learning algorithm called sequential spatial adaptive play is presented to solve the proposed potential game. Finally, simulation results illustrate that the proposed method can achieve Nash equilibrium and the optimal deployment of HAPs.**

***Index Terms*—High altitude platform, Heterogeneous wireless sensor network, Deployment model, Markov random field, Potential games**

I. INTRODUCTION

With the evolution of numerous low-cost, low-power sensors with limited capacity, wireless sensor networks (WSN) are increasingly concerning recently [1]. Nevertheless, it is greatly challenging to design the deployment of heterogeneous WSN with limited energy and bandwidth. Meanwhile, the energy consumption of sensor nodes with multi-hop relay transmission is large in practical scenarios constrained by obstructions on the ground. High altitude platforms (HAPs), as an emerging technique for recent wireless communication network, is approximately at an altitude 20 km, used as relay nodes of WSN such that the energy consumption of sensors can be obviously decreased. Integrating the advantages both satellite networks and the terrestrial networks, HAPs may be unmanned or manned aircrafts and may be also aeroplane or airships to offer wireless services, which have widespread use in the fields of communication relay, remote sensing, disaster management, intelligent transportation system, and social network [2].

Existing researches on HAPs mainly focus on the channel modeling, the array optimization, and the system capacity. However, the deployment of HAPs is seldom studied [3] [4]. In [3], a *K*-mean clustering method is proposed for the deployment of HAPs, which usually obtains a local optimal solution. In [4], a coverage model of HAPs is developed for HAPs based on a deterministic annealing algorithm, which has high computational and time complexity. Meanwhile, HAP-WSN system is given in [5], however, it fails to consider optimizing the deployment of HAPs because of the assumption that there exists one HAP utilized as the sink of WSN. Considering the measures about coverage, energy consumption and connectivity of nodes, the study on the deployment of nodes in heterogeneous WSN has become a rising issues [6].

In our work, markov random field with maximum a posteriori probability (MRF-MAP) framework is utilized to formulate the deployment model, which has been studied in [7] [8]. In [7], MRF is applied to design the power control and the resource allocation protocol in WSN. In [8], a two-layer MRF is presented to consider densities of nodes and two nodes wireless communications in WSN. On the other hand, potential games are also introduced to optimize the deployment of HAPs, including cooperative control [9], power control [10], respectively.

A heterogeneous WSN composed of mission layer, WSN layer and HAP layer is proposed in this paper, where all nodes in mission layer are divided according to a Voronoi partition approach and sensor nodes can be connected in the coverage range of HAPs. In this system, considering the energy consumption, coverage and connectivity of HAPs, an optimal deployment model is built by using MRF-MAP framework, obtaining the energy function of HAPs. Furthermore, the energy function of HAPs is analyzed based on potential games, and proves to achieve a pure Nash equilibrium. Then, a modified learning algorithm named sequential spatial adaptive play is proposed to optimize the potential game. Finally, the preliminary simulations are utilized to illustrate the presented optimization model.

The remaining part of this paper is provided as follows. Section II offers a heterogeneous wireless sensor network. The model of deployment of HAPs based on MRF-MAP is presented in Section III. Section IV offers potential games for the deployment of HAPs. Simulation results are introduced in Section V. The conclusion is in the final section.

II. HETEROGENEOUS WIRELESS SENSOR NETWORK

In Fig. 1, a novel heterogeneous WSN system in the paper is composed of mission layer, WSN layer, and HAP layer. The detailed introduction of the heterogeneous WSN is offered as follows.

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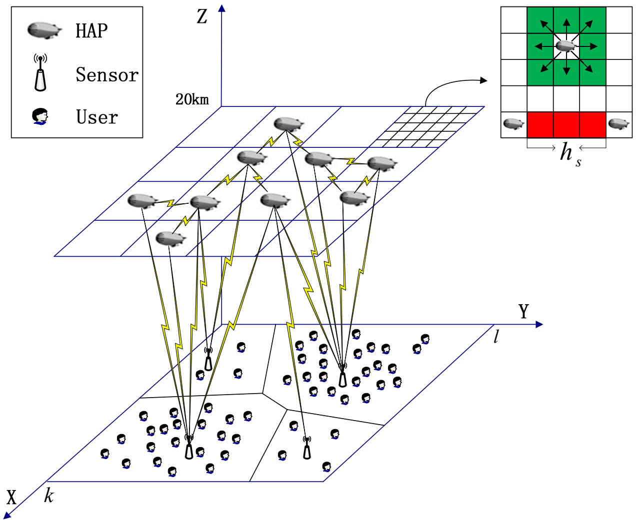


Fig. 1. A heterogeneous WSN system

A. Mission Layer

Mission layer in the heterogeneous system is composed of users in the area of $k \times l$ area, in which there are one background spot and K_0 hot spots. We assume that the density of users in one hot spot obeys Gaussian distribution because of the declining tendency of users from the center of the metropolis to suburbs [4]. In addition, the density of users in the background spot is considered as a uniform distribution. Let $Q(r)$ define the density of users in the mission layer, i.e.,

$$Q(r) = \sum_{k=1}^{K_0} w_k \rho_k(r) + U_0(r), \tag{1}$$

where w_k is the parameter of the density of users in the kth hot spot, $U_0(r)$ is the density of users in the background spot, and $\rho_k(r)$ is denoted as the density of users in the kth hot, which is defined as

$$\rho_k(r) = \frac{U_k}{\sqrt{2\pi}\sigma_k} \exp\left[-\frac{(r-u_k)^2}{2\sigma_k^{\ 2}} \right], \tag{2}$$

where U_k is the number of users for the kth hot spot, r is the measure between users and the center of the kth hot spot, u_k is the mean of positions of users in the kth hot spot, and σ_k is the standard deviation of positions of users in the kth hot spot.

B. WSN Layer

In WSN layer, we assume that there are m fixed sensors, whose positions are denoted as $S = \{s_1, s_2, \cdots s_m\}$. The set of users is divided by all the sensors using a Voronoi partition method. The Voronoi region of the sensor i is expressed as L_i that is the region of users which are closer to that sensor rather than other sensors, which is defined as

$$L_i = \{\ q \in Q \ \mid \ \|q - s_i\| \le \|q - s_j\|, \ \forall j \ne i\ \}, \tag{3}$$

where $\|q - s_i\|$ is the Euclidean distance between user q and sensor i. The set of regions $L(S) = \{L_1, L_2, \cdots L_m\}$ is called the Voronoi diagram for the sensors $S = \{s_1, s_2, \cdots s_m\}$. Thus, a given sensor s_i can communicate with the users belonging to the set L_i.

C. HAP Layer

In HAP layer, let the set of HAPs be $P = \{1, 2, \cdots n\}$ and $H = \{h_1, h_2 \cdots h_n\}$ be positions of HAPs. Let Λ_i define the set of HAPs in the safe communication of the ith HAP,

$$\Lambda_i = \{ j \ \mid \ \|h_i - h_j\| \ge h_s, \ \forall j \ne i\ \}, \tag{4}$$

where h_s is the minimum safe range for two HAPs, and the restricted action set of the ith HAP is defined as

$$R_i = \{\ p \ \mid \ \|h_i - p\| \le R_{hp}, \ \ \forall i\ \}, \tag{5}$$

where R_{hp} is the maximum moving range between the next action position and the current position of HAPs. In Fig. 1, the restricted action range is simplified into the green area, and the red region is expressed as the minimum safe range. Thus, the effective action set of the ith HAP is defined as

$$R_i^e = \Lambda_i \cap R_i \tag{6}$$

On the other hand, let N_i be the set of indexes of the neighbors of the ith HAP, which is represented by

$$N_i = \{\ j \ \mid \ \|h_i - h_j\| \le R_{hh}, \ \ \forall j \ne i\ \}, \tag{7}$$

where R_{hh} is the maximum connectivity range between two HAPs, and Ω_i is the set of sensors in the coverage range the ith HAP, i.e..

$$\Omega_i = \{ j \ \mid \ \|h_i - s_j\| \le R_{hs}, \ \forall i\ \}, \tag{8}$$

where R_{hs} is the maximum coverage range between HAPs and sensors.

III. Model Of Deployment of HAPs based on Markov Random Field

A. Problem Formulation

In the heterogeneous WSN system, we consider the objective to optimize the positions of HAPs such that HAPs can achieve the minimum energy consumption, the maximum coverage of sensor nodes and complete connections among HAPs, which is, typically, formulated as a multi-objectives non-convex optimization problem known as a NP-Hard. Due to the exponential complexity of this problem, some deterministic methods maybe lead to a local optimal solution as well as an enormous running time in large deployment area. In our work, MRF-MAP is proposed to formulate the above problem to a single-objective energy function that can be minimized to obtain the optimal deployment of HAPs, where energy consumption, coverage and connectivity are considered.

B. Deployment Model Based on MRF-MAP

In MRF-MAP framework, the set of the positions of the sensors S and the set of the positions of HAPs H represent the observed data and configured data, respectively. Our deployment goal is to seek the optimal configure H, given the observation S, which requires the maximum posterior probability $P(H \mid S)$ as below,

$$H^* = \arg\max_H P(H \mid S) . \tag{9}$$

The maximum posterior probability $P(H \mid S)$ can be assumed to obey the Gibbs distribution [8], that is

$$P(H \mid S) = Z^{-1} \exp(-U(H \mid S)/T) , \tag{10}$$

where Z is a normalizing constant, $U(H \mid S)$ is the posterior energy function and T is the system temperature, respectively. Based on the Bayesian rule, we obtain

$$P(H \mid S) \propto P(S \mid H)P(H) , \tag{11}$$

where $P(S \mid H)$ is the likelihood energy term, $P(H)$ is the prior energy term.

In addition, the Gibbs distribution is considered in the Bayesian rule, which leads to

$$P(S \mid H)P(H) \propto \exp(-(U(S \mid H) + U(H)/T) . \tag{12}$$

Thus, maximizing the posterior probability $P(H \mid S)$ would be equal to minimize the sum of the prior $U(H)$ and the likelihood $U(S \mid H)$ energy term, which is given

$$H^* = \arg\min_H U_s(H) , \tag{13}$$

$$U_s(H) = U(S \mid H) + U(H) . \tag{14}$$

An MRF model is considered as a conditional probability model, in which the probability of a HAP position depends on the position within a given neighborhood. The positions in neighbors are grouped into the cliques, which depend on the composition of the system. The energy function $U_s(H)$ can be estimated as a sum of local potentials including the prior potential $V(h_{N_i})$ and the likelihood potential $V(s_i \mid h_i)$ in the cliques. The prior energy is the sum of all clique potentials, denoted as

$$U(H) = \sum_{i \in P} V(h_{N_i}) , \tag{15}$$

where $V(h_{N_i})$ is formulated as

$$V(h_{N_i}) = \begin{cases} \sum_{j \in N_i} (A_i \left\| h_i - h_j \right\|^{\alpha}) & N_i \neq \varnothing \\ M_0 + \sum_{j \in N_i} (A_i \left\| h_i - h_j \right\|^{\alpha}) & N_i = \varnothing \end{cases} . \tag{16}$$

where A_i and α represent the connectivity coefficient parameter and the connectivity exponential parameter among HAPs, respectively. From Eq. (16), it is noticeable that when the ith HAP cannot connect the other HAPs, which means that N_i equals empty set, the prior potential $V(h_{N_i})$ becomes large by adding a constant M_0, which can be used to guarantee the connectivity among HAPs. Furthermore, the likelihood energy term $U(S \mid H)$ is denoted as the sum of all likelihood potentials under the observed data S, that is

$$U(S \mid H) = \sum_{i \in P} V(s_j \mid h_{N_i}) , \tag{17}$$

where $V(s_j \mid h_{N_i})$ is expressed as

$$V(s_j \mid h_{N_i}) = \sum_{j \in \Omega_i} \frac{B_i (h_i - s_j)^{\beta} + \sum_{k \in L_j} C_i (s_j - u_k)^{\gamma}}{W_j \mid L_j \mid^{\lambda}} . \tag{18}$$

where B_i and β represent the energy coefficient parameter and the energy exponential parameter between HAPs and sensors, respectively. C_i and γ represent the energy coefficient parameter and the energy exponential parameter between sensors and users, respectively. W_j and λ represent the number of users coefficient parameter and the number of users exponential parameter in Voronoi area, respectively. $\mid L_j \mid$ represents the number of users in Voronoi area of the ith sensor. For Eq. (18), it is noticed that the molecule of Eq. (18) means the energy consumptions that include the energy consumption between the ith HAP and its neighborhood sensors and the energy consumption between sensors and users in its Voronoi region, which can measure the energy consumption level of HAPs. The denominator of Eq. (18) reflects the number of users in the Voronoi area of the sensors, which can guarantee the maximum coverage to obtain the on-demand deployment goal.

Considered the energy, connectivity and coverage of HAPs, the optimal deployment of HAPs in the heterogeneous WSN system can be obtained by using the MRF-MAP framework to minimize the energy function, as expressed in Eq. (19),

$$\begin{aligned} H^* &= \arg\min_H U_s(H) \\ &= \arg\min_H \{\sum_{i \in P} V(h_{N_i}) + \sum_{i \in P} V(s_j \mid h_{N_i})\} \end{aligned} . \tag{19}$$

We next present a potential game approach to analyze the energy function, which is solved by using a sequential spatial adaptive play algorithm.

IV. Potential Game for Deployment of HAPs

In this section, the basic concepts of potential game are firstly given. Then, the energy function is analyzed with potential game, which proves to be able to get a pure Nash equilibrium. Finally, a sequential spatial adaptive play algorithm is presented to solve the proposed potential game.

A. Basic Concepts of Game Theory

A game model in normal strategic form is denoted as $\Gamma(P, A, F)$. It mainly includes the following three components:

1) $P = \{1, 2, \cdots n\}$ is defined as the set of HAPs, where n is the number of HAPs in game theory .

2) $A = A_1 \times \cdots \times A_n$ is defined as the set of all possible strategies of HAPs. $a_i \in A_i$ expresses the strategy of the ith HAP, and $a_{-i} \in A_{-i}$ represents the strategies of the other $n-1$ HAPs, where

$$a_{-i} = (a_1, \cdots a_{i-1}, a_{i+1}, \cdots a_n) , \tag{20}$$

and

$$A_{-i} = A_1 \times \cdots A_{i-1} \times A_{i+1} \times \cdots A_n . \tag{21}$$

Thus, the collection of strategies is denoted as $a = (a_i, a_{-i}) \in A$.

3) $F_i : A \to \mathrm{R}$ is defined as the utility value of the i-th HAP. The utility value models the preferences of any one HAP for given strategy. $F = \{F_1, \cdots F_i, \cdots F_n\} : A \to \mathrm{R}^n$ represents the vector of all utility values.

In the game theory, a stable solution as Nash equilibrium (NE) can be obtained for the given game where each HAP has no incentive to increase the utility value by unilaterally changing its strategy from all possible strategies.

Definition 4.1: A strategy profile $a^* = (a^*_i, a^*_{-i})$ is a NE, as long as, $\forall i \in P$ and $\forall a_i \in A$,

$$F_i(a^*_i, a^*_{-i}) \geq F_i(a_i, a^*_{-i}). \quad (22)$$

Generally, a game may own either unique, multiple or no NE. Potential games can be considered as a class of games, owning at least one NE in given strategies. Meanwhile, the convergence to NE is guaranteed by using learning algorithms for potential games.

Definition 4.2: An strategy profile $\Gamma(P, A, F)$ is a potential game as long as there is an potential value $\phi: A \to \mathrm{R}$ such that, $\forall i \in P$, $\forall a_{-i} \in A_{-i}$ and $\forall a_i^{'}, a_i^{"} \in A_i$,

$$F_i(a^{"}_i, a_{-i}) - F_i(a^{'}_i, a_{-i}) = \phi(a^{"}_i, a_{-i}) - \phi(a^{'}_i, a_{-i}). \quad (23)$$

In general, an ordinal potential game that can replace the equality in (23) with inequalities that has the equal extent change as the utility value for each HAP, which can be obtained the same result.

In potential games, an improvement on the utility of the i HAP will result in an improvement of the potential function, when the other HAPs take no action. Nash equilibrium of potential games can be obtained and offered proof in the following lemma [11].

Lemma 4.1: Every potential game has at least one NE, that is the strategy profile a that maximizes the potential value $\phi(a)$.

B. Analysis of Nash Equilibrium

In MRF-MAP framework, the energy function can be rewritten as

$$U_s(H) = \sum_{i \in P} U_i(h_{N_i}), \quad (24)$$

$$U_i(h_{N_i}) = V(h_{N_i}) + V(s_j \mid h_{N_i}), \quad (25)$$

where $U_i(h_{N_i})$ is the local energy function of the i-th HAP.

Let us define the potential value for the deployment model of HAPs as

$$\phi = -U_s(H) = -\sum_{i \in P} U_i(h_{N_i}). \quad (26)$$

Therefore, the following theorem is provided.

Theorem 4.1: The game $\Gamma(P, A, F)$ where the utility of the i-th HAP is given by

$$F_i = -U_i(h_{N_i}) = -[V(h_{N_i}) + V(s_j \mid h_{N_i})], \quad (27)$$

becomes a potential game for the potential value (26), which can obtain a NE.

Proof: The potential game can be denoted as

$$\begin{aligned}\phi(a_i, a_{-i}) &= -\sum_{i \in P} U_i(h_{N_i}) \\ &= -U_i(h_{N_i}) - \sum_{i^{'} \in A_{-i}} U_{i^{'}}(h_{N_{i^{'}}}), \\ &= F(a_i, a_{-i}) + U(a_{-i})\end{aligned} \quad (28)$$

where $U(a_{-i}) = -\sum_{i^{'} \in A_{-i}} U_{i^{'}}(h_{N_{i^{'}}})$ can be obtained by strategy a_{-i}. Thus, for $\forall i \in P$, $\forall a_{-i} \in A_{-i}$ and $\forall a_i^1, a_i^2 \in A_i$, the variation in the potential value $\phi(a_i, a_{-i})$ by switching from strategy a_i^1 to strategy a_i^2 for the i-th HAP , assumed that other HAPs play a_{-i}, is

$$\begin{aligned}\phi(a^2_i, a_{-i}) - \phi(a^1_i, a_{-i}) &= F_i(a^2_i, a_{-i}) + U(a_{-i}) \\ &\quad - F_i(a^1_i, a_{-i}) - U(a_{-i}) \\ &= F_i(a^2_i, a_{-i}) - F_i(a^1_i, a_{-i})\end{aligned}. \quad (29)$$

Thus, we have the game $\Gamma(P, A, F)$ is the potential game. Based on Lemma 4.1, we can get that the game has at least one NE.

The deployment of HAPs is now defined as a potential game, which can guarantee that HAPs strategies converge to a Nash equilibrium by using learning algorithms. Next, we propose a distributed learning algorithm named sequential spatial adaptive play algorithm for our solution.

C. Distributed Learning algorithm

In this subsection, spatial adaptive play, as a learning algorithm, is described in the following, which can obtain an approximately optimal solution in potential games [12]. For the k-th time, one HAP i is randomly selected by using same probability for each HAP to take its action, and the selected HAP is offered opportunity to change its strategy $a_i(k)$. All other HAPs must repeat its strategies such that $a_{-i}(k) = a_{-i}(k-1)$. The updating HAP i can take the strategy according to the probability distribution, where the component $p_i^{a_i}(k)$ of its strategy is defined by

$$p_i^{a_i}(k) = \frac{\exp\{\mu F_i(a_i, a_{-i}(k-1))}{\sum_{a_i^j \in A_i} \exp\{\mu F_i(a_i^j, a_{-i}(k-1))}, \quad (30)$$

where the parameter $\mu > 0$. The value of μ determines the correlation between HAPs. For large μ, the adjacent HAPs nodes in HAP i are highly correlated, otherwise approximately independent. In other words, the updating HAP takes action to optimize its utility according to the other HAPs remaining at the previous interation.

Considering that the spatial adaptive play has a low convergence speed, we propose a modified distributed algorithm called sequential spatial adaptive play (SSAP) to accelerate the optimal solution for the deployment of HAPs, which is given in the following steps. At each time $k > 0$, the algorithm chooses sequentially every HAP to take its action, and every chosen HAP is given to update its strategy $a_i(k)$ based on the expression (30).

Theorem 4.2: Under potential game $\Gamma(P, A, F)$ with potential value $\phi(a)$, the optimal deployment of HAPs generated by SSAP has a unique stationary distribution $\Pi(a)$,

$$\Pi(a) = \frac{\exp\{\mu\phi(a)\}}{\sum_{a^j \in A} \exp\{\mu\phi(a^j)\}} \text{ for any } a^j \in A, \quad (31)$$

and

$$\lim_{u \to \infty} \lim_{k \to \infty} \Pr\{\, a(k) \text{ is an optimal deployment }\} = 1. \quad (32)$$

Proof: SSAP can lead to an irreducible Markov process, obtaining a unique stationary distribution. As in Theorem 6.2 proposed in [12], the unique distribution can be (31) by proving the balanced equation

$$\Pi(a)\Pr(a\to b)=\Pi(b)\Pr(b\to a)\ \ \forall a,b\in A\,. \tag{33}$$

The above equation requires the difference between a and b in exact one position such that $a_i\neq b_i$ and $a_{-i}=b_{-i}$. Thus we have

$$\Pr(a\to b)=\frac{\exp\{\mu F(b)\}}{\exp\{\mu F(a)\}+\exp\{\mu F(b)\}}\,. \tag{34}$$

In addition, since $F(b)-F(a)=\phi(b)-\phi(a)$, we have,

$$\begin{aligned}\frac{\Pr(a\to b)}{\Pr(b\to a)}&=\exp\{\mu F(b)-\mu F(a)\}\\&=\exp\{\mu\phi(b)-\mu\phi(a)\}=\frac{\Pi(b)}{\Pi(a)}\end{aligned}\,. \tag{35}$$

Thus, we prove the balanced equation. $\Pi(a)$ has a high probability to the optimal deployment of HAPs that maximizes a potential value when $\mu\to\infty$ and $k\to\infty$.

For our SSAP algorithm, the computational complexity relies on the scale of the grid of the action space, the number of HAPs, and the number of iteration, which proves to find a pure NE solution in the potential game with polynomial time complexity.

A pseudo code of distributed deployment algorithm based on sequential spatial adaptive play is summarized as follows.

Algorithm 1: Distributed deployment algorithm based on sequential spatial adaptive play

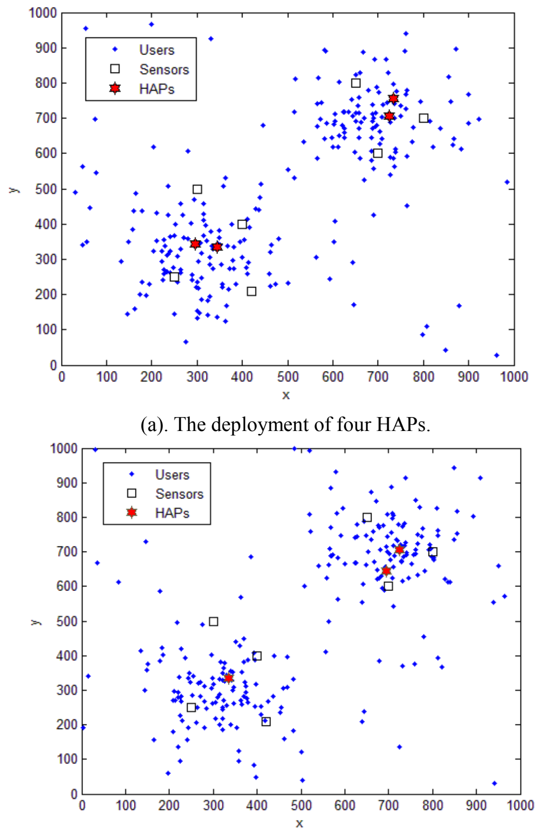
Input : $n,\ \mu_{\max},k_{\max},\ \varepsilon>1$
Output : $a_i^{opt}, i=1\cdots n$
Initialize : $a_i,\ \mu,\ k;$
while $\mu\le\mu_{\max}\ \&\&\ k\le k_{\max}$
    for i=1 to n
        for $a^j{}_i\in R_i^e$
            compute $F_i(a^j{}_i)$ according to *Theorem* 4.1
        end for
        for $a^j{}_i\in R_i^e$
            compute $P(a_i=a^j{}_i)\leftarrow\dfrac{\exp\{\mu F_i(a^j{}_i)\}}{\sum_{a^j{}_i\in R_i^e}\exp\{\mu F_i(a^j{}_i)\}}$
        end for
        update a_i
    end for
    $u\leftarrow\varepsilon u$
    $k\leftarrow k+1$
end while
$a_i^{opt}=a_i,\ i=1\cdots n$

V. SIMULATION RESULTS

In the section, we demonstrate the effectiveness of the presented approach by using numerical and simulation examples. In the simulation, a mission space of area of 1000km×1000km is considered, which consists of 50 uniformly distributed users, 2 Gaussian distributed users —100 users with its center of space position at (700km,700km) and of variance 80km and 100 users with its center of space position at (300km,300km) and of variance 80 km. On the other hand, there are 7 sensors that locate (250km, 250km), (400km, 400km), (300km, 500km), (420km, 210km), (700km, 600km), (800km, 700km) and (650km, 800km), respectively. The other parameters of simulation are given in TABLE 1.

TABLE 1 The other simulation parameters

$R_{hh}=300\text{km}$, $R_{hs}=300\text{km}$
$\alpha=\beta=\gamma=2$, $\lambda=2.7$
$A_i=B_i=C_i=2$, $W_j=10$, $M_0=1000000$
$k=200$, $u_{\max}=1000000$, $\varepsilon=1.95$



(a). The deployment of four HAPs.

(b). The deployment of three HAPs.

Fig. 2. The deployment of different numbers of HAPs

Fig. 2 illustrates the deployment results of HAPs. From Fig. 2(a), we can see that the final deployment of four HAPs are approximately these of coordinates that are (295km, 345km, 20km), (725km, 705km, 20km), (735km, 755km, 20km), and (345km, 335km, 20km), respectively. The near optimal deployment of HAPs in Fig. 2(a) satisfies Theorem 4.2. Fig. 2(b) shows the similar results.

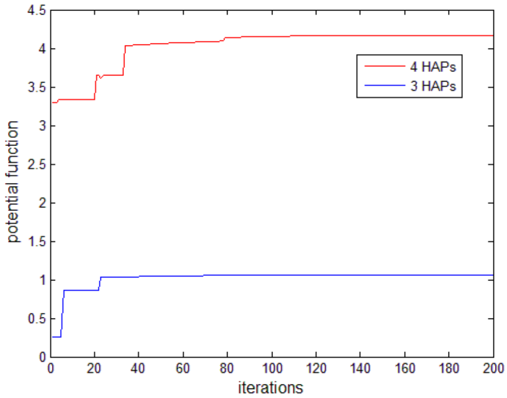
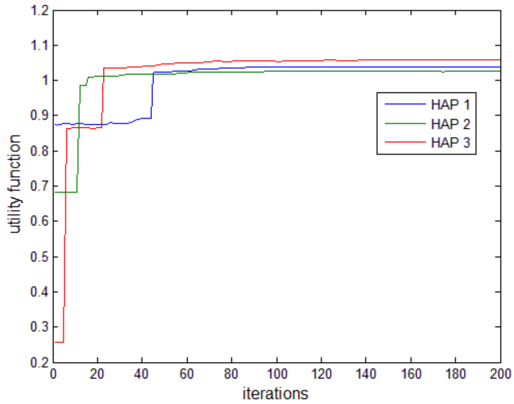
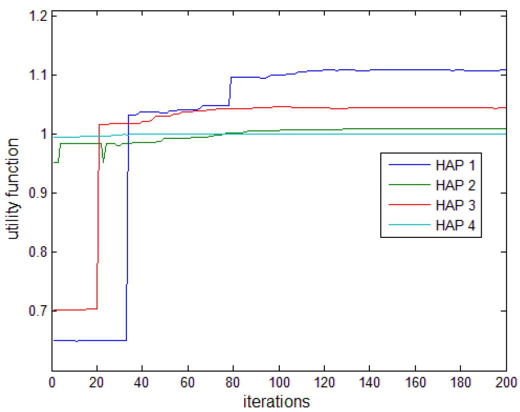


Fig. 3. The evolution of potential value of different numbers of HAPs



(a). The evolution of utility value of three HAPs.



(b). The evolution of utility value of four HAPs.

Fig. 4. The evolution of utility value of different numbers of HAPs

Fig. 3 illustrates the evolution of potential value of different numbers of HAPs. From Fig. 3, it is noticed that the potential value becomes convergence at about 80 steps for four HAPs. On the other hand, the convergence for three HAPs can be achieved at about 60 steps.

Fig. 4 illustrates the evolution of utility value of different numbers of HAPs. From Fig. 4(a), we see that Nash equilibrium can be achieved at most approximate 45 steps. The individual utilities in Fig. 4(b) can achieve convergence to Nash equilibrium at about 80 steps. Thus, from the above experiments, we can further verify that Theorem 4.1 is satisfied.

VI. CONCLUSION

In this paper, an optimal deployment model of HAPs based on MRF-MAP framework is formulated as an energy function of HAPs. Then, potential games are introduced to analyze the energy function, which proves to achieve a pure Nash equilibrium. Further, a sequential spatial adaptive play algorithm is presented to solve the proposed potential game. Finally, the preliminary simulation results show that Nash equilibrium of individual and the energy function of HAPs and the optimal deployment of HAPs can be achieved by the proposed approach, which will be used as fundamental work for social network.

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