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Energy-Efficient Deployment of Airships for High Altitude Platforms: A Deterministic Annealing Approach

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***Abstract*—Nowadays, a promising solution to the demand for high capacity wireless services is provided by the high altitude platforms (HAPs), which can exploit the advantages of both satellites and terrestrial networks. However, due to the limited energy of the communication nodes on HAPs, energy-efficient deployment of airships for HAPs becomes increasingly important. In this paper, a heterogeneous network system comprising mission layer, HAP layer and satellite layer is presented. In the system, the mission space is partitioned according to the assumption of one-hop relay which guarantees that all the users are effectively covered by airships in HAP layer. Then, we model an expected energy consumption function of airships, which is minimized using deterministic annealing algorithm. Furthermore, the optimal solution to this approach is analyzed and proved. Simulation results demonstrate that the proposed method can get the goal of the minimum energy consumption and achieve a near optimal deployment of airships.**

***Index Terms*—High altitude platform, Heterogeneous network system, Energy consumption, Deployment model, Deterministic annealing algorithm**

I. INTRODUCTION

As the demand grows for communication services, wireless solutions are becoming increasingly important, which may solve the 'last mile' problem. The satellite networks that can provide wireless communication services to mobile and fixed users have a large-area coverage compared with the terrestrial networks, but suffer from the problem of expensive cost and high delay [1]. A new technique for effective space communication systems is high altitude platforms (HAPs) in the stratosphere at an altitude between 17 and 22 km, which may be aeroplanes or airships and may be manned or unmanned aircrafts [2], [3]. HAPs can exploit the advantages of both terrestrial networks and satellite networks to provide high-capacity services, which have been widely applied in the fields of environment monitoring, intelligent transportation systems, disaster recue and military surveillance.

Recently, research about HAPs mainly considers the array optimization, the channel model, and the system capacity [4], [5], [6]. However, there are few works on the deployment of HAPs [7], [8]. In [7], an approach based on *K*-means clustering is proposed for placement of multiple HAPs without considering the satellite networks. In [8], a deployment optimization model of airships is developed for HAPs based genetic algorithm, whose solution has high time complexity. In addition, the energy consumption and network lifetime for HAPs have never been considered, both of which are a rising issues in wireless communication system due to the limited energy resource.

The energy-efficient deployment approaches to wireless network are investigated [9], [10], [11]. The total energy function is typically minimized by gradient-descent algorithms, usually leading to local optima. To this end, Deterministic annealing, a global optimal method for clustering, classification, regression and related problems [12], is utilized to minimize the expected energy consumption of airships for HAPs to obtain an optimal deployment.

In this paper, a heterogeneous network system consisting of mission layer, HAP layer and satellite layer is established, which provides users on the ground with full connection by other airships or a satellite, and users in every grid are partitioned into three parts in terms of the assumption of one-hop relay. In addition, an energy consumption model of airships for HAPs that is defined as the function of the distance between two nodes is constructed. Then, the deterministic annealing modified to obtain the optimal location of airships is employed to solve the expected energy consumption, and the optimal solution is analyzed and proved. Finally, some experiments are conducted to demonstrate the effectiveness of the proposed model and solution method.

The remainder of this paper is organized as follows. The heterogeneous network system (HNS) is proposed in Section II. Section III presents the energy model of the deployment of airships based on deterministic annealing. In Section IV, the analysis of the optimal solution is given. Deterministic annealing scheme is introduced in Section V. Simulation results and analyses are given in Section VI. The final section is conclusion.

II. HETEROGENEOUS NETWORK SYSTEM

A heterogeneous network system considered in this paper consists of three layers, i.e., mission layer, HAP layer and satellite layer, as shown in Fig. 1, and it can make airships in the stratosphere connect all the users on the ground by other airships or a satellite. The detailed introduction of HNS is given as follows.

A. Mission Layer

We model the mission space made up of users in the region of $a \times b$ area, where the distribution of users is assumed to obey Gaussian distribution in hot spots due to the decreasing trend of users from the urban to the rural areas. Besides, we assume that

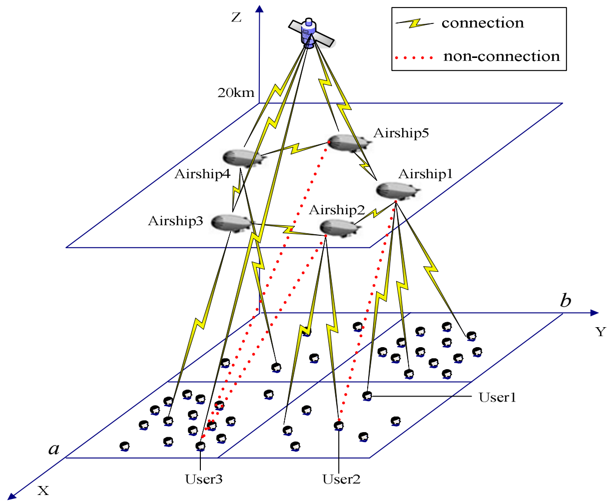


Fig. 1. A heterogeneous network system

there are N_0 hot spots and one background spot in the mission space. Let $\rho(r)$ denote the distribution of users for hot spot k, that is

$$\rho(r)=\frac{U_k}{\sqrt{2\pi}\sigma_k}\exp\left[-\frac{(r-u_k)^2}{2\sigma_k^{\ 2}}\right], \tag{1}$$

where u_k is the center of hot spot k, σ_k is the standard deviation of the hot spot k, r is the distance between the center of hot spot k and users, U_k is the number of users for hot spot k. Let $p(r)$ denote the distribution of users for the mission space, we have

$$\begin{aligned} p(r)&=\sum_{k=1}^{N_0} w_k\rho(r)+U_0(r) \\ &=\sum_{k=1}^{N_0}\frac{w_kU_k}{\sqrt{2\pi}\sigma_k}\exp\left[-\frac{(r-u_k)^2}{2\sigma_k^{\ 2}}\right]+U_0(r) \end{aligned}, \tag{2}$$

where w_k is the weight of the distribution of users for the hot spot k, and $U_0(r)$ is the distribution of users obeying uniform distribution for the background spot.

To determine the local sparse level of users in the mission space, we utilize a grid structure in the mission layer. As shown in Fig. 1, the region of $a\times b$ area is evenly divided into $k_0\times l_0$ square grids, and let $\varphi(N_{kl})$ denote the probability density of users in the $(k,\ l)$ square area, that is

$$\varphi(N_{kl})=\frac{\sum_{r\in N_{kl}} p(r)}{\sum_{k,l}\sum_{r\in N_{kl}} p(r)}, \tag{3}$$

where N_{kl} is the set of the users in the $(k,\ l)$ square area.

B. HAP Layer

Although the height range of stratospheric is typically between 10 and 50 km, and the altitude of 20km is considered as the optimal height for HAP Layer for the slow wind speed and stable environment. Suppose that there are M airships and the location of the i-th airship is $h_i=(m_i\ n_i\ 20)$, and the communication range between airships and users in the ground is limited. Let Q_i denote the set of airships in communication range of the ith airship, that is

$$Q_i=\{\ j\ |\ \|h_i-h_j\|\le R_{hh},\ \ \forall j\neq i\ \}, \tag{4}$$

where R_{hh} is the maximum communication distance between two airships, and $\|h_i-h_j\|$ is the Euclidean distance between h_i and h_j. Ω_i is defined as the set of users in communication range the i-th airship and users, that is

$$\Omega_i=\{\ q\ |\ \|h_i-u_{mn}^{(q)}\|\le R_{hs},\ \forall m,n\ \}, \tag{5}$$

where $u_{mn}^{(q)}$ is the position of the q-th user in the $(m\ n)$ square grid, and R_{hs} is the maximum communication distance between the airship and users.

C. Satellite Layer

In satellite layer, it is assumed that there is only one satellite at the space position, defined as $s=(s_x,\ s_y,\ s_z)$, which can connect to all users and airships due to the large range that the satellite covers.

D. Heterogeneous Network

In HNS, one-hop relay is assumed, that is to say, when one user is not covered by one airship, the satellite or one of other airships can be utilized as a relay to connect the user and the airship. Thus, all the users in grids have effective access to airships. For example, shown in Fig. 1, User1 can be directly covered by Airship1, while User2 is outside the maximum communication distance of Airship1 that can be covered by Airship2 relying. On the other hand, although Airship2 and Airship5 can be utilized as the relay of Airship2, the connection between Airship1 and User3 is not guaranteed, thus the satellite can be used as the relay.

In order to measure the assumption of one-hop relay, users in every square grid are partitioned into three parts: users that are covered by the airship, ones that are covered by other airships relaying and others that are covered by utilizing the satellite as relay. Let M_{ikl} denote the set of users that are directly covered by the airship i in the $(k,\ l)$ square grid, that is

$$M_{ikl}=\{\ q\ |\ q\in\Omega_i\ \ and\ \ q\in N_{kl}\ \}, \tag{6}$$

and V_{ikl} denote the set of users that are covered by other airships in the $(k,\ l)$ square grid when the airship i cannot directly cover them, which is expressed by

$$\begin{aligned} V_{ikl}=\{\ q\ |\ q\notin\Omega_i\ \ and\ \ q\in N_{kl}\ \ and \\ \exists\, L_i\subseteq Q_i,\forall j\in L_i,\ such\ that\ q\in\Omega_j\ \} \end{aligned}, \tag{7}$$

and S_{ikl} denotes the set of users that are only covered by the satellite in $(k,\ l)$ square grid when the airship i cannot either directly cover them or secondhand cover them , that is

$$S_{ikl}=\{\ q\ |\ q\notin\Omega_i\ \ and\ \ q\notin V_{ikl}\ \ and\ \ q\in N_{kl}\ \}. \tag{8}$$

From Eq. (6-8), it can be inferred that M_{ikl} , V_{ikl} and S_{ikl} satisfy the constraints expressed by Eqs. (9) and (10)

$$M_{ikl}\cap V_{ikl}\cap S_{ikl}=\varnothing, \tag{9}$$

$$M_{ikl}\cup V_{ikl}\cup S_{ikl}=N_{kl}. \tag{10}$$

Thus, M_{ikl} , V_{ikl} and S_{ikl} are one hard partition of users in the $(k,\ l)$ square grid. Users in the other grids are divided in the same way.

III. Energy Model Using Deterministic Annealing Approach

In HNS, given the distribution of users and the satellite, we focus on the problem of how to optimize the deployment of airships so that the airships in HAP layer can consume the minimum energy. Based on the one-hop relay assumption, we firstly define the total energy consumption function, which includes three types of energy consumption between airships and users corresponding to the three sets of the users that are M_{ikl} , V_{ikl} and S_{ikl} , respectively. For optimizing the minimum total energy consumption may lead to the local solution, we utilize the deterministic annealing approach to optimize the energy function, in which the expected energy consumption is minimized by introducing association probability. Moreover, the entropy is utilized as a measure of constrain of association probability. Thus the problem of the energy optimization is formulated as a constrained optimization model, which can be solved by Lagrangian approach.

A. Basic Energy Consumption Model

In order to obtain the optimal deployment of airships, we apply an energy model in HNS, in which the energy consumption of one airship is a function of the communication distance between the airship and users in the grid. First, we define that the energy consumption of airship i that can directly cover users in the square area $(k,\ l)$ is $E_{ikl}{}^{1}$, which is given by

$$E_{ikl}{}^{1} = \sum_{q \in M_{ikl}} A_i \left\| h_i - u_{kl}{}^{(q)} \right\|^{\alpha} , \qquad (11)$$

where A_i and α are the energy consumption parameters of airship i . In addition, $E_{ikl}{}^{2}$ is the average energy consumption of airship i that can cover users in the $(k,\ l)$ square area by other airships relaying, that is

$$E_{ikl}{}^{2} = \sum_{q \in V_{ikl}} \mathop{\mathbf{E}}_{j \in L_i} \left[B_i \left\| h_i - h_j \right\|^{\beta} + A_j \left\| h_j - u_{kl}{}^{(q)} \right\|^{\alpha} \right], \qquad (12)$$

where B_i and β are the energy consumption parameters of airship i . Finally, $E_{ikl}{}^{3}$ is the energy consumption of airship i that can cover users in the square grid $(k,\ l)$ by the satellite relaying, which is expressed by

$$E_{ikl}{}^{3} = \sum_{q \in S_{ikl}} (C_i^1 \left\| h_i - s \right\|^{\gamma} + C^2 \left\| s - u_{kl}{}^{(q)} \right\|^{\eta}) , \qquad (13)$$

where C_i^1 and γ are the energy consumption parameters of airship i to communicate with the satellite, C^2 and η are the energy consumption parameters of the satellite to cover users in the square area $(k,\ l)$. From Eqs. (11)-(13), we can obtain that the total energy consumption of airship i covering users in the $(k,\ l)$ square area is E_{ikl} , which is given by

$$E_{ikl} = E_{ikl}{}^{1} + E_{ikl}{}^{2} + E_{ikl}{}^{3} . \qquad (14)$$

Thus, the minimum total energy consumption of all the airships for HAP layer to cover users in the whole square area, is formulated as

$$\min_{\{h_i\}} \ E = \sum_{k=1}^{k_0} \sum_{l=1}^{l_0} \sum_{i=1}^{M} \varphi(N_{kl}) E_{ikl} . \qquad (15)$$

Because M_{ikl} , V_{ikl} and S_{ikl} are one hard partition of users in the $(k,\ l)$ square grid, the direct optimization of the total energy consumption will be a non-convex problem, which may lead to a local minimum using gradient-descent based methods. In other words, the optimal number of airships cannot be obtained by minimizing the total energy consumption. Thus, a way to circumvent the difficulty is to optimize the energy function by searching over the space of random, in such a way an optimal solution can be obtained. Next, we introduce a deterministic annealing approach to achieve the global optimal solution.

B. Deterministic Annealing For Energy Consumption

To obtain the global optimal solution, the deterministic annealing method introduces randomization within the design phase over probabilistic assignment $P(h_i \mid N_{kl})$ that is the association probability of the square grid $(k,\ l)$ relating with airship i . First of all, let D denote the expected energy consumption as shown in Eq. (16)

$$D = \sum_{k=1}^{k_0} \sum_{l=1}^{l_0} \varphi(N_{kl}) \sum_{i=1}^{M} P(h_i \mid N_{kl}) E_{ikl} . \qquad (16)$$

Then, the optimization of the expected energy consumption is to minimize D , which is expressed as

$$\min_{\{h_i,\, P(h_i|N_{kl})\}} \ D = \sum_{k=1}^{k_0} \sum_{l=1}^{l_0} \varphi(N_{kl}) \sum_{i=1}^{M} P(h_i \mid N_{kl}) E_{ikl} . \qquad (17)$$

Because the probabilistic assignment $P(h_i \mid N_{kl})$ for the optimization objective cannot be well controlled, the direct minimum expected energy consumption D may lead to local minima as well. Thus, the Shannon entropy that can be viewed as a measure of the level of the randomness of the probabilistic assignment $P(h_i \mid N_{kl})$ is introduced as the constraint

$$H = -\sum_{k=1}^{k_0} \sum_{l=1}^{l_0} \varphi(N_{kl}) \sum_{i=1}^{M} P(h_i \mid N_{kl}) \log P(h_i \mid N_{kl}) . \qquad (18)$$

We seek the optimal parameters $\{h_i, P(h_i \mid N_{kl})\}$ at a given level of randomness as the one which minimizes the expected energy consumption while maintaining H at a prescribed level $\widehat{H}$. The constrained optimization problem is thus formulated as

$$\begin{aligned} &\min_{\{h_i,\, P(h_i|N_{kl})\}} \ D = \sum_{k=1}^{k_0} \sum_{l=1}^{l_0} \varphi(N_{kl}) \sum_{i=1}^{M} P(h_i \mid N_{kl}) E_{ikl} \\ &\text{subject to} \qquad\qquad\qquad\qquad\qquad . \qquad (19) \\ &\qquad H = \widehat{H} \end{aligned}$$

The deterministic annealing algorithm involves solving a sequence of optimization for decreasing values of $\widehat{H}$. The constrained optimization problem, naturally, can be reformulated as the minimization of the unconstrained Lagrangian, which is given by

$$\min_{\{h_i,\, P(h_i|N_{kl})\}} \ F = D - TH , \qquad (20)$$

where T is the temperature of the system. Obviously, for the larger values of T, the entropy is mainly optimized. As the values of T decrease, the optimization is carried out at each temperature to seek the optimal parameters $\{h_i, P(h_i \mid N_{kl})\}$ that minimize F. As $T \to 0$, minimizing the Lagrangian F is to minimize D. Finally, this approach can achieve the global optimal solution.

IV. Analysis of Deterministic Annealing Scheme

In deterministic annealing algorithm, our goal is to seek the optimal parameter set $\{h_i, P(h_i \mid N_{kl})\}$ which minimizes the Lagrangian F. Since estimating the optimal parameters is a formidable task, an alternative approach for solving parameters $\{h_i, P(h_i \mid N_{kl})\}$ is considered. In other words, we use the following two-step processes:

$$P^*(h_i \mid N_{kl}) = \arg\min_{P(h_i \mid N_{kl})} \; F(h_i^*, P(h_i \mid N_{kl})), \tag{21}$$

$$h_i^* = \arg\min_{h_i} \; F(h_i, P^*(h_i \mid N_{kl})). \tag{22}$$

From Eq. (21) and Eq. (22), it is noted that we firstly can obtain the optimal association probability $P^*(h_i \mid N_{kl})$. Then, the result $P^*(h_i \mid N_{kl})$ is substituted into F to yield F^*, and the optimal position h_i^* can be obtained by minimizing F^*.

A. Optimal Association Probability

In the first step, we optimize the association probability $P(h_i \mid N_{kl})$, which satisfies the following constraint

$$\sum_{i=1}^{M} P(h_i \mid N_{kl}) = 1. \tag{23}$$

Lemma 1: The association probability $P(h_i \mid N_{kl})$ that satisfies Eq. (23) and minimizes F is the Gibbs distribution, which is given by

$$P^*(h_i \mid N_{kl}) = \frac{\exp(-\frac{E_{ikl}}{T})}{Z_{kl}}, \tag{24}$$

where Z_{kl} is the normalizing factor, that is

$$Z_{kl} = \sum_{i=1}^{M} \exp(-\frac{E_{ikl}}{T}). \tag{25}$$

Proof: In deterministic annealing algorithm, we seek the minimum F with respect to $P(h_i \mid N_{kl})$ subject to (23). Based on Lagrangian technique, we can obtain the following expression,

$$F = D - TH - \lambda[\sum_{i=1}^{M} P(h_i \mid N_{kl}) - 1]. \tag{26}$$

Performing the differentiation on Eq. (26)

$$\frac{\partial F}{\partial P(h_i \mid N_{kl})} = \sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl})(E_{ikl} + T\log P(h_i \mid N_{kl}) + 1 - \frac{\lambda}{\varphi_0}), \tag{27}$$

where

$$\varphi_0 = \sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}). \tag{28}$$

Let $\frac{\partial F}{\partial P(h_i \mid N_{kl})} = 0$, we can obtain

$$P(h_i \mid N_{kl}) = \exp(\frac{\lambda}{\varphi_0 T} - 1 - \frac{E_{ikl}}{T}). \tag{29}$$

Substituting Eq. (29) into Eq. (24-25) leads to

$$\exp(\frac{\lambda}{\varphi_0 T} - 1) = \frac{1}{\sum_{i=1}^{M} \exp(-\frac{E_{ikl}}{T})}. \tag{30}$$

Substituting the above into Eq. (29), we can obtain the results (24) and (25).

The minimum of F is obtained by substituting Eq. (24) back into Eq. (20), we have

$$\begin{aligned} F^* &= \min_{P(h_i \mid N_{kl})} F \\ &= \sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl})[\sum_{i=1}^{M} P(h_i \mid N_{kl}) E_{ikl} \\ &\quad + T\sum_{i=1}^{M} P(h_i \mid N_{kl})(-\frac{E_{ikl}}{T} - \log Z_{kl})] \\ &= -T\sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) \sum_{i=1}^{M} P(h_i \mid N_{kl}) \log Z_{kl} \end{aligned}. \tag{31}$$

According to Eq. (23), we can obtain

$$\begin{aligned} F^* &= \min_{P(h_i \mid N_{kl})} F \\ &= -T\sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) \log Z_{kl} \end{aligned}. \tag{32}$$

B. Optimal Position of Airships

In the second step, the deterministic annealing algorithm is to optimize Lagrangian F^* in order to obtain the optimal position h_i^* of airship i. Because F^* is a nonlinear function, the gradient descent algorithm is employed to optimize F^*.

Lemma 2: The gradient of Eq. (32) that minimizes F^* and satisfies Eq. (11-14) and Lemma 1 is given by

$$\frac{\partial F^*}{\partial h_i} = \sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) P^*(h_i \mid N_{kl})(\frac{\partial E_{ikl}{}^1}{\partial h_i} + \frac{\partial E_{ikl}{}^2}{\partial h_i} + \frac{\partial E_{ikl}{}^3}{\partial h_i}), \tag{33}$$

where

$$\frac{\partial E_{ikl}{}^1}{\partial h_i} = \sum_{q \in M_{ikl}} \alpha A_i \left\| h_i - u_{kl}{}^{(q)} \right\|^{\alpha-2} (h_i - u_{kl}{}^{(q)}), \tag{34}$$

$$\frac{\partial E_{ikl}{}^2}{\partial m_i} = \sum_{q \in V_{ikl}} \mathop{\mathrm{E}}_{j \in L_i} \left[\beta B_i \left\| h_i - h_j \right\|^{\beta-2} (h_i - h_j) \right], \tag{35}$$

$$\frac{\partial E_{ikl}{}^3}{\partial m_i} = \sum_{q \in S_{ikl}} \gamma C_i^1 \left\| h_i - s \right\|^{\gamma-2} (h_i - s), \tag{36}$$

Proof: Based on Lemma 1, we start by considering the following derivative:

$$\begin{aligned} \frac{\partial F^*}{\partial h_i} &= -T\sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) \frac{1}{Z_{kl}} \frac{\partial Z_{kl}}{\partial h_i} \\ &= -T\sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) \frac{1}{Z_{kl}} \exp(-\frac{E_{ikl}}{T})(-\frac{1}{T}) \frac{\partial E_{ikl}}{\partial h_i} \\ &= \sum_{k=1}^{k_0}\sum_{l=1}^{l_0} \varphi(N_{kl}) P^*(h_i \mid N_{kl}) \frac{\partial E_{ikl}}{\partial h_i} \end{aligned}. \tag{37}$$

The results Eq. (34-36) can be obtained by performing the differentiation on Eq. (11-13).

In term of Lemma 2, the iterative gradient descent formula is given by

$$h_i^{(k+1)} = h_i^{(k)} - \lambda \frac{\partial F^*}{\partial h_i}, \qquad (38)$$

where λ is the iterative step length. The optimal airship position can be obtained by

$$h_i^* = \lim_{k \to \infty} h_i^{(k)} \qquad (39)$$

V. Deterministic Annealing Scheme

In this section, the deterministic annealing scheme is implemented in detail, which consists of minimizing F with respect to the parameters $\{h_i, P(h_i \mid N_{kl})\}$, initiating at high value of temperature T and seeking the minimum while decreasing T. The core iteration includes the following two steps:

1) Fix the airship location h_i and utilize Lemma 1 to obtain the association probability $P^*(h_i \mid N_{kl})$;

2) Fix the association probability $P^*(h_i \mid N_{kl})$ and compute the airship location h_i according to Lemma 2.

In the simulation, the locations of airships are randomly deployed and temperature T is exponentially reduced, then, the optimal parameters can be obtained by iterating the above two steps. A pseudo code of the energy-efficient deployment scheme based on deterministic annealing is given as follows.

TABLE A: Energy-efficient deployment protocol of airships based on deterministic annealing

Input: M, T, $T_{\min}$, ζ, λ, $\varepsilon < 1$
Output: $h_i^{opt}, i = 1 \cdots M$
Initialize: $h_i = 100 \cdot \text{rand},\ i = 1 \cdots M$
while $T > T_{\min}$
  for i=1 to M
    compute $P^*(h_i \mid N_{kl})$ according to *Lemma* 1
  end for
  compute F^* according to Eq. (32)
  for $i = 1$ to M
    $k \leftarrow 1$
    while $\left| h_i^{(k+1)} - h_i^{(k)} \right| > \zeta$
      compute $\frac{\partial F^*}{\partial h_i}$ according to *Lemma* 2
      $h_i^{(k+1)} = h_i^{(k)} - \lambda \frac{\partial F^*}{\partial h_i}$
      $k \leftarrow k + 1$
    end while
  end for
  $T \leftarrow \varepsilon T$
end while
$h_i^{opt} = h_i \quad i = 1 \cdots M$

VI. Simulation Results and Analysis

This section provides numerical and simulation examples to demonstrate the effectiveness of the proposed approach. In the experiment, we have considered a mission space of area of 100km×100km and divide it into 2×2 square grids uniformly, which is composed of two Gaussian distributed and one uniform distributed users. The satellite locates at the point (50km, 50km, 36000km). The simulation parameters are listed in TABLE B.

TABLE B The experimental parameters

u_1=(30 30 20), $\sigma_1 = 5$ $U_1 = 100$
u_2=(70 70 20), $\sigma_2 = 5$ $U_2 = 100$
$w_1 = 0.5$, $w_2 = 0.5$
$R_{hh} = 60$, $R_{hs} = 60$
$\alpha = \beta = \gamma = \eta = 2$
$A_i = B_i = 2$, $C_i^1 = C^2 = 0.1$
$T = 1000000$, $T_{\min} = 1000$, $\zeta = 0.1$, $\lambda = 1$, $\varepsilon = 0.95$

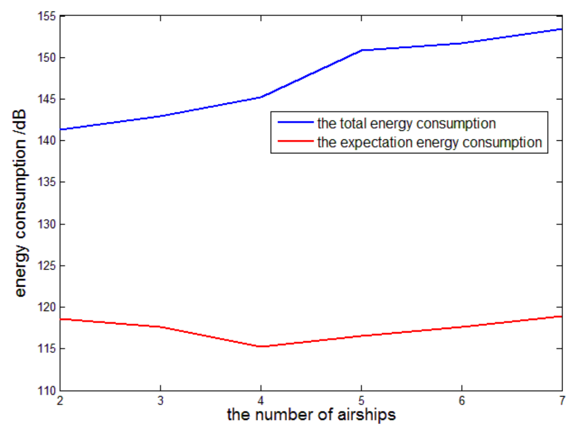


Fig. 2. The relationship between the energy consumption and the number of airships.

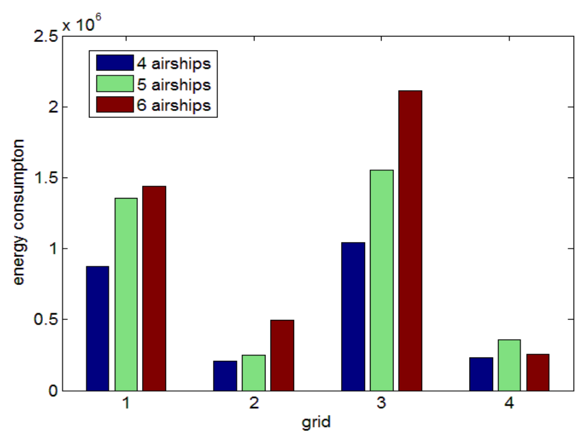
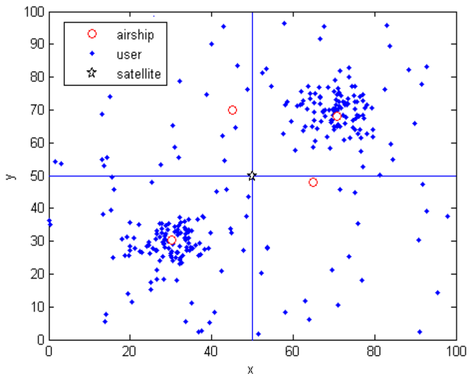


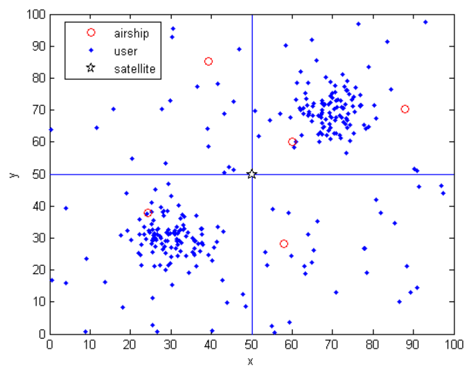
Fig. 3. The energy consumption of users in four grids

The relationship between the number of airships and the energy consumption of airships is shown in Fig. 2. It is noted that the total energy consumption of airships will increase with the number of airships, and the expectation energy consumption of airships is obviously lower than the total energy consumption, which can obtain the minimum result for 4 airships.

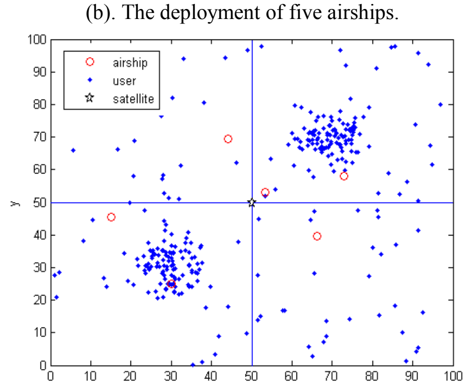
Fig. 3 shows the energy consumptions of users in four grids for different numbers of airships. The number of users in the first and third grids is much more than that in the second and fourth grids. Reasonably, the energy consumptions of users in former grids are larger than latter grids.



(a). The deployment of four airships.



(b). The deployment of five airships.



(c). The deployment of six airships.

Fig. 4. The deployment of different numbers of airships

Fig. 4 shows the energy-efficient deployment of different numbers of airships under the given distribution of users and satellite. We can see from Fig. 4(a) that the positions of four airships are approximately (70km, 68km, 20km), (46km, 70km, 20km), (65km, 48km, 20km), and (31km, 30km, 20km), respectively. The result provides a near optimal deployment of airships. Fig. 4(b-c) shows the similar results.

VII. CONCLUSION

In this paper, a mission-HAPs-satellite system differing from the traditional heterogeneous systems is proposed, which provides users in the mission space with full connection by airships and a satellite. Moreover, we model an energy consumption function of airships in HAPs layer, and solve it by using a modified deterministic annealing algorithm to optimize the expectation energy consumption model. The simulation results demonstrate that the energy-efficient deployment of airships based on deterministic annealing approach can obtain the minimum energy consumptions for different number of airships and achieve a near optimal deployment of airships in HAPs. In particular, this proposed method can also be applied to large wireless networks [13], [14].

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