This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

Location Optimization and User Association for Unmanned Aerial Vehicles Assisted Mobile Networks

Yang Sun, Tianyu Wang, *Member, IEEE*, and Shaowei Wang, *Senior Member, IEEE*

***Abstract*—To meet the rapid growth of diverse traffic demand in mobile networks, unmanned aerial vehicles (UAVs) are proposed to support terrestrial networks by carrying base stations towards demand when needed. However, how to deploy the UAVs effectively and efficiently is a challenging task. In this paper, we investigate this problem from the load balancing perspective. Our goal is to make the traffic loads of UAVs almost equal so that the networks can be stable and robust to unexpected events. In the pre-processing stage, we introduce a clustering method to divide users into several categories so as to initialize the positions of UAVs in the maximal local density areas. Then, we propose a user association strategy to make the UAVs serve almost equal traffic demand, where our optimization task is to minimize the maximum traffic demand of subregions with constraints on the capacity and the shape of subregions. Third, we propose a local search procedure to relocate UAVs based on backtracking line search to refine the load balance among the system. By alternately invoking user association and location algorithms, we can obtain (near) optimum UAV positions. Finally, we adjust the altitude of each UAV to decrease power consumption of the system. Numerical results indicate that our proposal can serve more users compared with the SINR-based strategy. Moreover, the traffic capacity among UAVs and the areas of subregions of UAVs are more balanced.**

***Index Terms*—Optimization, unmanned aerial vehicle (UAV), user association, workload balancing.**

I. Introduction

As smart phones become an important part of our daily lives, users expect excellent quality of experience everywhere and anytime, which is expected to be achieved in the 5G mobile communications by various network architectures, such as heterogeneous networks [2], cloud radio access networks [3]. These methods can enhance the mobile network capacity by densely deploying terrestrial access points, locations of which are designed rigidly according to the long-term traffic demand of the specified region. Consequently, such kind of networks can not effectively deal with events that yield unexpected traffic demand, such as rallies, congested traffic, sporting events and natural disasters. It is obvious that additional supports are needed in emergencies to achieve effective connectivity in mobile networks.

Unmanned aerial vehicles (UAVs), mounting base stations (BSs) towards demand to support terrestrial mobile networks, are proposed to address these problems [4]. The UAVs can improve network performance wherever and whenever due to the feature of arbitrary flight. Flexibility is the main advantage of UAVs. Besides, UAVs can help mobile networks trapped in unexpected traffic achieve flexible and agile management so as to prevent over-engineering. As the rapid development of microelectronics, UAVs can provide good maneuver performance with inexpensive acquisition and maintenance costs, which can effectively reduce the capital expenditure and the operating expense of mobile networks.

The main applications of UAVs can be categorized as ubiquitous coverage, relaying and information transmission/data acquisition [5]. For the ubiquitous coverage applications, UAVs are deployed to assist the terrestrial communication infrastructure to provide seamless coverage whenever needed in the serving area. For example, UAVs can help recover essential communication services to disaster areas where terrestrial communication infrastructure is damaged [6, 7]. Besides, UAVs can offload traffic from terrestrial BSs in hot spots, which is one of the key scenarios in the 5G era. The second application of UAVs is relaying, where UAVs act as intermediate nodes to provide connectivity between users who are far away from each other without reliable communication links. Last but not least, UAVs can transmit information and collect data. Sensors with limited battery can benefit from UAVs. Instead of transmitting data to distant BSs with high power consumption, UAVs can be used to fly toward clusters of sensors and carry out low power communication, so as to prolong the lifetime of sensors. In summary, UAVs can improve the performance of current mobile networks significantly if deployed properly.

BS planning is an important issue in the traditional ground mobile networks [8, 9], so as in the UAV-assisted mobile networks. Intuitively, they share some similarities. First, both ground mobile networks and UAV-assisted networks need to

Manuscript received November 27, 2018; revised April 1, 2019, June 18, 2019 and July 15, 2019; accepted July 29, 2019. Part of this work has been presented at the IEEE ICC 2018 [1], Kansas City, USA, May 20-24, 2018. This work was supported in part by the National Natural Science Foundation of China under Grants 61671233 and 61801208, in part by the Jiangsu Science Foundation under Grant BK20170650, in part by the Postdoctoral Science Foundation of China under Grants BX201700118 and 2017M621712, in part by the Jiangsu Postdoctoral Science Foundation under Grant 1701118B, and in part by the Open Research Fund of National Mobile Communications Research Laboratory under Grant 2019D02. The review of this paper was coordinated by Prof. G. Mao. (*Yang Sun and Tianyu Wang are co-first authors.*) (*Corresponding author: Shaowei Wang.*)

Y. Sun and S. Wang are with the School of Electronic Science and Engineering, Nanjing University, Nanjing 210023, China (e-mail: MG1623068@smail.nju.edu.cn; wangsw@nju.edu.cn).

T. Wang is with the School of Electronic Science and Engineering, Nanjing University, Nanjing 210023, China, and also with the National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China (e-mail: tianyu.alex.wang@nju.edu.cn).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

take power coverage issue and rate requirements of users into consideration. Thus, user distribution is one of the main factors for both of them. However, there are also some significant differences. Confined to natural terrain and city construction in urban areas, location selection of terrestrial BSs can only be chosen from limited candidate sites, which is usually constrained in practical environment [10]. As a result, the BS planning problems in terrestrial mobile networks are generally intractable because the formulated optimization task is usually NP-hard due to the discrete sites of terrestrial BSs. In contrast with terrestrial BSs, UAVs can be located almost anywhere since the site selection of UAVs is unrestricted by geographical environment and air field is unimpeded. Therefore, the formulated optimization task could be a continuous optimization problem, leading to methods different from traditional BS planning ones.

When the locations of UAVs are determined, service area partition among UAVs becomes another important issue since it has a significant impact on the quality of user experience due to the following reasons [11]. First, the service partition determines the service area of each UAV, which impacts the channel gain between the users and the UAVs. If the area of the region is too large, the edge user will suffer severe pathloss. Second, service area partition also determines the number of users that each UAV serves. When the number of users increases, the amount of bandwidth for each user decreases since the total bandwidth is limited. In this case, users in the subregion that UAVs have high traffic load will achieve low throughput, which leads to unbearable delays.

In this paper, we jointly design UAV location and user association strategies from the viewpoint of load balance. The rationale behind our proposed scheme is as follows: The number of users served by UAVs is maximized if the traffic load of each UAV is near equal. Besides, a workload balancing system is stable and robust to handle unknown events such as flash crowd traffic. At the initialization stage, we introduce a clustering algorithm to place UAVs in the position of the maximum local density so that UAVs can serve users as many as possible. Then, we develop a user association strategy to minimize the maximum traffic demand among the UAVs, followed by a local search procedure to relocate the UAVs. Finally, we adjust the altitude of each UAV to decrease power consumption of the system. The main contributions of this work are summarized as follows:

- We investigate the UAV location and user association problem from the viewpoint of load balance, which can make the network stable and robust to handle unknown events. As far as we have knows, this is the first article to study the UAV deployment problem from the perspective of load balancing.
- We introduce an efficient clustering method to place UAVs in the maximal local density areas. The number of UAVs can be adjusted flexibly according to the distribution of users so that our proposed scheme can be employed in different scenarios.
- We study the user association problem from a load balancing perspective, where we can minimize the maximum traffic demand among UAVs. We develop a local search algorithm to relocate UAVs to refine the load balance among the system. Simulation results verify that our proposal scheme is effective and practical in wireless mobile networks.

The rest of this paper is organized as follows. Related work is presented in Section II. In Section III, system model is given, as well as problem formulation. In Section IV, our proposed algorithms are presented in detail. In Section V, numerical results are shown. Conclusions and future works are discussed in Section VI.

II. Related Work

A proactive deployment framework of UAVs is proposed to relieve traffic congestion caused by flash crowd traffic in [12], where three scenes including the gathering traffic, the parade and the stadium are taken into consideration. A prediction operation control and integration/disintegration scheme is employed to boost the capacity of UAVs. In [13], a centralized algorithm for deploying UAVs is proposed to maximize the throughput of a software-defined disaster area UAV communication network. In [14] a pattern formation system is introduced to track time-varying nature of user density and a sequential Markov-greedy-decision strategy is proposed to minimize the UAV-recall-frequency. In [15], a cooperative UAV clustering scheme is proposed to offload traffic demand from traditional ground mobile base stations to cooperative UAV clusters. Clustering method is widely used in UAV deployment problem. A clustering algorithm is proposed in [16] to select several UAVs acting as cluster heads to collect the data from the sensors in wireless sensor networks. In [17], a modularity-based clustering method relying on modified Louvain method is proposed to minimize the total transmit power of all users for UAVs-aided mobile communications.

On the other hand, workload balancing has become a hot topic of discussion in mobile networks [18, 19]. In [20], a facility location problem is investigated to minimize the maximum workload imposed on facilities. The demand nodes are assumed to be continuous distribution and the cost of serving a demand node is supposed to be the function of the distance to the facility that services it. Simultaneous facility placement is also considered in this work. In [21], considering a territory with obstacles, a region partition strategy is proposed to minimize the overall workload while simultaneously determining their workload. A novel resource allocation scheme is designed in [22], which designs the coverage area of mobile network in a balanced way and allocates resource remained among access points in a balanced way to reduce the pressure on backhauls between the access points and the centralized baseband processing pool.

III. Network Model

Consider a convex region R, as shown in the Fig. 1. We consider there are n UAVs serving K users. The set of UAVs is denoted by $\mathcal{N} = \{1, 2, \ldots, n\}$ and the set of users is denoted by $\mathcal{K} = \{1, 2, \ldots, K\}$ respectively. In this paper, the users are abstractions of traffic demand nodes, which can represent mobile phones, tablets and so on. The traffic requirement of

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

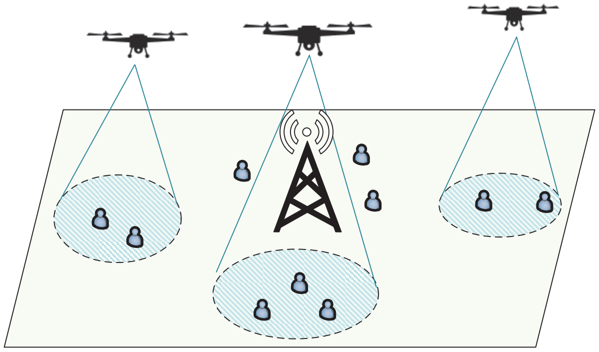

Fig. 1. System model.

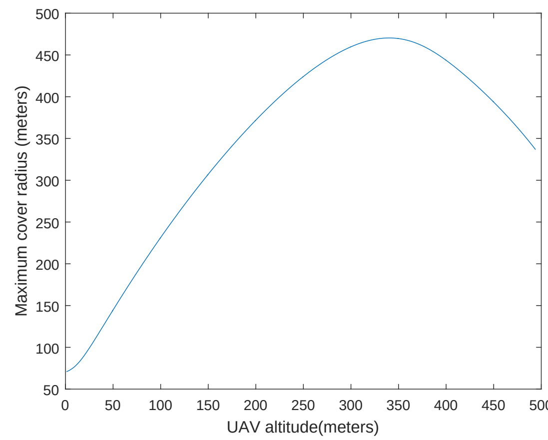

Fig. 2. Coverage radius vs. UAV altitude curve for dense urban environments.

user k is r^k_{min}, which can be different for users. The positions of UAVs are denoted as $\mathcal{P} = \{p_1, p_2, ..., p_n\}$. The maximum number of users that a UAV can serve is denoted as M_u.

For UAVs, the air-to-ground channel (ATG) model is different with the ground channel model [23]. Typically, ATG should take probabilistic line-of-sight (LoS) links and non-link-of-sight (NLoS) links into consideration. The probability of LoS links relies on the positions of UAVs and users, geographical environments, the density of buildings and so on, which can be calculated as [24]:

$$P(LoS, \theta) = \frac{1}{1 + a\exp(-b(\theta - a))}, \tag{1}$$

where a, and b are constants related to the environments and θ represents the elevation angle between the users and the UAVs. θ can be expressed as $\theta = \frac{180}{\pi} \times sin^{-1}(\frac{h}{r})$, where h is the altitude of UAVs and r is the horizontal distance between the users and the UAVs. Besides, the probability of NLoS is $P(NLoS, \theta) = 1 - P(LoS, \theta)$.

The average path loss model of ATG that adopted in this paper is

$$\begin{aligned} PL(h, r) = \quad & 20\log d + 20\log f + 20\log \tfrac{4\pi}{c} \\ & + P(LoS, \theta)\eta_{LoS} + P(NLoS, \theta)\eta_{NLoS}, \end{aligned} \tag{2}$$

where c is the light speed and f represents the carrier frequency. Variable d represents the distance between a user and a UAV, which equals to $\sqrt{h^2 + r^2}$. Respectively, η_{LoS} and η_{NLoS} represent the excessive pathloss of LoS and NLoS links related to environments.

Then, we presuppose the altitude of UAVs. First, a constant ρ is introduced to represent the maximum pathloss corresponding to QoS requirement of users. Users are assumed to be served by the UAVs if $PL(h, r) \leq \rho$. The coverage radius of a UAV is the maximum range within which the pathloss of users served by the UAV is less than ρ. Mathematically, the coverage radius can be obtained by

$$R_{max} = \{r | PL(h, r) = \rho\}. \tag{3}$$

Since neither h nor r can be written as explicit function of each other, Eq.3 is implicit. To get the optimal height that yields the best coverage, we need to search for the value of h which satisfies the equation, $\partial R_{max}/\partial h = 0$. that is to say, we need to get the point at which the radius-altitude curve in Eq.3 changes its direction. Fig. 2 shows the variation of R with respect of h as per (1) for the dense urban environment. From this figure, we can obtain the point at which the radius-altitude curve changes its direction.

Denote $z_{k,i}$ as the assignment index indicating whether user j is served by UAV i or not:

$$z_{k,i} = \begin{cases} 1 & \text{user } k \text{ is served by UAV } i, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

The key issue in our strategy is to design a rational arrangement of user association and UAV location strategy to achieve equilibrium, which means the traffic demand of UAVs should be the same as much as possible.

Our objective function is to minimize the maximum traffic demand of UAVs. The variable P represents the $3D$ position of UAVs. Given a set of UAVs $\mathcal{N}$, the user association problem is mathematically formulated as follows:

$$\begin{aligned} \underset{P,z}{\text{minimize}} \quad & t \\ s.t. \quad C_1: \quad & t \geq \sum_{k \in \mathcal{K}} z_{k,i} r_{min}, \forall i \in \mathcal{N}, \\ C_2: \quad & \sum_{k \in \mathcal{K}} z_{k,i} r_{min} \geq \varsigma, \forall i \in \mathcal{N}, \\ C_3: \quad & u_{k,i} z_{k,i} \leq R_{max}, \forall k \in \mathcal{K}, i \in \mathcal{N}. \\ C_4: \quad & \sum_{i \in \mathcal{N}} z_{k,i} = 1; \forall k \in \mathcal{K}. \\ C_5: \quad & z_{k,i} \in \{0, 1\}, \forall k \in \mathcal{K}, i \in \mathcal{N}. \end{aligned} \tag{5}$$

The variable t represents the maximum traffic demand of UAVs, as shown in C_1. C_2 ensures that the number of users served by UAV i should be larger than a constant ς, which avoids the cases that a UAV serves too many users to exceed its capability, or the number of service users is so small that it cannot give a full play of a UAV. ς is related to the number of UAVs and users, which guarantees that a UAV serves enough users so as to earn back its operating cost. The variable $u_{k,i}$ represents the horizonal distance between the user k and UAV i. C_3 indicates that UAV i cannot serve the user with a distance of more than R_{max}. C_4 ensures that each user should be assigned to a UAV. Note that both continuous variable $\bar{P}$

and binary variable $\bar{z}$ are involved in Eq. (5), which makes the problem generally NP-hard and difficult to work out the optimum solution.

IV. Our Proposed Algorithms

We try to design the UAV location strategy and user association strategy in an almost balanced way. Our proposed strategy is summarized as follows:

- Estimate the number of UAVs n. The number of UAVs is determined based on both the coverage constraint and the capacity constraint. A clustering algorithm is introduced to determine the initial locations of UAVs.
- Design the user association strategy with the initial UAV positions P. Constraints on the requirement demand of users and the capacity of UAVs are considered.
- Relocate UAV with the method of the backtracking line search algorithm. The subregions and the positions of UAVs are updated in an iterative manner until obtaining the local optimum.
- Adjust the altitude of each UAV. The UAVs with shorter maximum coverage radius can fly lower so as to save the transmission power.

A. Initialization

To start the optimization, we need to determine the number of UAVs that can satisfy all the users. The number of UAVs should take into account both coverage and capacity requirement. It is reasonable to assume the maximum coverage radius of UAVs and the capacity of UAVs are the same since they are from the same series and have similar performance. Considering the capacity requirement, the number of UAVs required can be calculated as $\lceil n_{cap} = K/M_u \rceil$. Then, we consider the coverage constraint. The theoretical coverage of UAVs is a circle. However, with circular coverage areas, there are gaps and/or overlaps among the circles and as a result a full coverage requires a larger number of UAVs than the result obtained with this equation. It is reasonable to assume the coverage areas as a square with a side length of$\sqrt{2}R_{max}$. The area of the region R is denoted as A, then the number of UAVs required can be calculated as $\lceil n_{cov} = A/2{R_{max}}^2 \rceil$. Thus, The final initial number of UAVs is $n = max\{n_{cap}, n_{cov}\}$. One or two UAVs can be added to cope with unknown traffic changes.

Then, we determine the initial horizontal location of UAVs. We try to place the initial positions of UAVs in the maximal local density areas. To achieve this goal, we introduce an effective clustering algorithm, *isodata* method [25].

This method is particularly suitable for our problem since it takes the users positions as input and clusters based on distance. Users are grouped together if they are closest to the same center of a cluster. Conventional clustering algorithms, such as k-means, set the number of clusters artificially, which in essence add human assumptions to the original data sets and ignore the natural structure of the data. Fortunately, *ISODATA* algorithm can dynamically adjust the number of cluster centers in the clustering process according to the actual situation of the samples contained in each class. If the degree of dispersion of the samples in a class is large (measured by variance), and the sample size is large, then it will be split. If two classes are relatively close (measured by the distance from the cluster center), the method will merge them.

The clustering algorithm is shown in Table I. At the initialization time, we should set some parameters. Denote L as the maximal iteration and E as the excepted cluster number respectively. Let H denote the minimal cluster size. Besides, $Sigma$ represents the allowed standard deviation of each cluster and d_{min} represents the minimal distance between two cluster centers.

First, select E_c samples randomly from the data set as the initial cluster centers and denote the clusters as $C_1, C_2, ..., C_{E_c}$. Then, for each user in the data set, assign it to the class corresponding to the cluster center that is closest to it.

$$C_i = \{x \in R| ||x - c_i|| \leq ||x - c_j|| \quad \forall j \neq i\}. \tag{6}$$

Second, determine whether the number of users in the above class $|C_i|$ is less than H. If $|C_i| < H$, discard the cluster i and reduce the number of the clusters E. The new cluster centers are

$$c_i = \frac{1}{\sum\limits_{x \in S_j} x}. \tag{7}$$

Third, we start split or merge mechanisms. If the number of the clusters is not greater than $1/2E$, we do the split operation. If the number of iterations is an even number or the number of the clusters is no less than twice the number we desired, we do the merge operation. Finally, if it is the last iteration, we end the process.

We explain the split and merge operations in detail. In a split operation, calculate the standard deviation of each cluster in distance vector σ_i and pick up the maximum variance denoted as σ_{max}. If $\sigma_{max} > Sigma$ and the number of users in this cluster is no less than $2H$, spilt the cluster into two cluster and $E = E + 1$. Two new cluster centers are calculated by

$$c_i^+ = c_i + \sigma_{max}, c_i^- = c_i - \sigma_{max}. \tag{8}$$

In a merge operation, calculate the distance between all the cluster centers, denoted as matrix D, where $D(i, i) = 0$. If $D(i, j) < d_{min}$, merge the two cluster centers c_i, c_j to get the new cluster center:

$$c_{new} = \frac{1}{|C_i| + |C_j|}(|C_i|c_i + |C_j|c_j). \tag{9}$$

The number of clusters is reduced to $E = E - 1$.

We use the user distribution as data set of *isodata* method and the excepted cluster number is set to be n. After the clustering operation, the number of the classes of the output and the cluster centers are used as the number and initial positions of UAVs respectively.

B. User association

The key issue in our strategy is to design the user association strategy in a balanced way. Our objective function is to minimize the maximum traffic demand among UAVs. Note that most of the cases that the territorial communication network needs UAVs for support occur when the users are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

TABLE I
ALGORITHM FOR CLUSTER

Algorithm 1

1: *Initialization:* set the parameters L, E, d_{min}, H and $Sigma$;
2: Select E_c samples randomly as the initial cluster center;
3: **repeat**
4: $l = l + 1$;
5: map users into clusters by Eq. (6);
6: **for** $i = 1 : E_c$
6: **if** $|C_i| \leq H$
7: $E_c = E - 1$;
8: map users into clusters by Eq. (6);
9: **end if**
9: **end for**
10: update cluster center according to Eq. (7);
11: **if** $E_c < E/2$
12: do split operation;
13: return to step 4;
14: **end if**
15: **If** $E_c > 2E \quad || \quad l \ mod \ 2 == 0$
16: do merge operation;
17: **end if**
18: **until** $l = L$;
19: **return** S.

densely distributed. Thus, this assumption is more reasonable and practical that we consider the user distribution as a continuous distribution. The density of users across the region is statistically formulated as $f(x)$, where x represents two-dimensional coordinates.

It is a thorny problem that how to determine the position and service region effectively. It is intuitive when we design the service area of each UAV, users within the area will be naturally served by related UAVs. So, we try to solve the user association problem by designing the service region of each UAV. By transforming this problem into a region partition problem, we can make the network more balanced macroscopically since both the area of service region and capacity of each UAV are optimized. Besides, we can determine the locations of UAVs more accurately.

Thus, we try to transform the user association problem into a region partition problem. First, to avoid a large difference in the shape of the subregion of UAVs, we introduce a penalty function $u_i(\cdot)$ to prevent the objective function from obtaining its optimality when users and UAVs are too far away. The penalty function $u_i(\cdot)$ is defined as the Euclidean distance between the UAV i and the users, that is, $u_i(\cdot) = \|x - p_i\|$. The overall penalty of UAV i can be calculated as $\iint_{R_i} f(x)u_i(x)dA$.

Then, the region partition problem, transformed by Eq. (5), can be expressed as follows [20]:

$$\begin{aligned} \min_{\bar{R}} \quad & t + \phi \sum_{i=1}^{n} \iint_{R_i} f(x)u_i(x)dA \\ s.t. \quad C_1: \quad & t \geq (1-\phi) \iint_{R_i} f(x)dA, \forall i, \\ C_2: \quad & \iint_{R_i} dA \geq \zeta, \forall i, \\ C_3: \quad & R_i \cap R_j = 0, \forall i \neq j, \\ C_4: \quad & \cup_i R_i = R, \\ C_5: \quad & x \notin R_i, \forall i : u_i(x) \geq R_{max}. \end{aligned} \tag{10}$$

Here, the variable ϕ is denoted as a penalty factor related to the penalty phase. As shown in C_1, the variable t denotes the maximum traffic demand among UAVs with the penalty function. The objective function is to minimize the maximum traffic capacity among UAVs with penalty function increasing to add barriers to optimality when service areas of UAVs cannot be connected as we expect. C_2 indicates that the service area of each UAV should be no less than a constant denoted as η. The total area of region R is normalized to constant one to simplify the discussion, which means η should set to be $1/n$ to obtain the optimal value. C_5 ensures that the distance between the users and the UAVs is no more than R_{max}. We add two constraints to make the region partition problem more reasonable and easier to solve. C_3 ensures that all the service areas of UAVs should not overlap with each other and C_4 makes sure that there should be no coverage holes.

To solve this problem efficiently, we try to reduce Eq. (10) into a low-dimensional convex optimization problem. First, we transform Eq. (10) into an infinite-dimensional integer programming problem. Let $I_i(x)$ be a {0,1}-valued index indicating whether the user x is served by UAV i or not. Then, Eq. (10) can be transformed as follows:

$$\begin{aligned} \min_{I_1(\cdot),\ldots,I_n(\cdot)} \quad & t + \phi \sum_{i=1}^{n} \iint_{R_i} f(x)I_i(x)u_i(x)dA \\ s.t. \quad C_1: \quad & t \geq (1-\phi) \iint_{R_i} f(x)I_i(x)dA, \forall i, \\ C_2: \quad & \iint_{R_i} I_i(x)dA \geq \zeta, \forall i, \\ C_3: \quad & \sum_{i=1}^{n} I_i(x) = 1, \forall i, \\ C_4: \quad & I_i(x) \in \{0,1\}, \forall i, x, \\ C_5: \quad & I_i(x) = 0, \forall i : u_i(x) \geq R_{max}. \end{aligned} \tag{11}$$

Since the variable I_i is an integer constraint, Eq. (11) is difficult to be solved. An intuitive idea is to relax the integer variable into a continuous variable. Thus, the linear relaxation of the problem (11) is:

$$\begin{aligned} \min_{I_1(\cdot),\ldots,I_n(\cdot)} \quad & t + \phi \sum_{i=1}^{n} \iint_{R_i} f(x)I_i(x)u_i(x)dA \\ s.t. \quad & C_1 \sim C_3, C_5 \text{ in } (11), \\ & I_i(x) \geq 0, \forall i, x. \end{aligned} \tag{12}$$

Then, we discretize Eq. (11) to get an approximate formulation. The region is discretized into N grid cells G_j with the area δ. f_j represents the average values of $f(x)$ and u_{ij} represents the Euclidean distance from UAV i to the center of G_j. Let z_{ij} be the fraction of G_j served by UAV i. The discretization of Eq. (11) can be expressed as:

$$\begin{aligned} \min_{Z} \quad & t + \phi\delta \sum_{i=1}^{n} \sum_{j=1}^{N} f_i Z_{ij} u_{ij} \\ s.t. \quad C_1: \quad & t \geq (1-\phi)\delta \sum_{j=1}^{N} f_i Z_{ij}, \forall i, \\ C_2: \quad & \delta \sum_{j=1}^{N} Z_{ij} \geq \zeta, \forall i, \\ C_3: \quad & \sum_{i=1}^{n} Z_{ij} = 1, \forall j, \\ C_4: \quad & Z_{ij} = 0, \forall i, j : u_{ij} \geq R_{max}, \\ C_5: \quad & Z_{ij} \geq 0, \forall i, j. \end{aligned} \tag{13}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

The dual problem of Eq. (13) is:

$$\begin{aligned} \min_{a,b,d,q} \quad & \sum_{i=1}^{n} \zeta b_i - \sum_{j=1}^{N} d_j \\ s.t. \quad C_1: \quad & a_i \geq 0, \forall i, \\ C_2: \quad & \sum_{i=1}^{n} a_i = 1, \\ C_3: \quad & b_i \geq 0, \forall i, \\ C_4: \quad & \delta\phi f_i u_{ij} + (1-\phi)\delta a_i f_j - \delta b_i + d_j + q_{ij} \geq 0, \forall i, j, \\ C_5: \quad & q_{ij} \geq 0, \forall i, j: u_{ij} \geq R_{max}. \end{aligned} \tag{14}$$

where $a \in R^n, b \in R^n, d \in R^N$ represent the Lagrange multiplier vectors. Let $\sigma_j = -d_j/\delta, \lambda_i = b_i$ and $\alpha_i = b_i$, Eq. (14) can be simplified to:

$$\begin{aligned} \min_{\lambda,\gamma,\sigma(\cdot),q} \quad & \sum_{i=1}^{n} \zeta \gamma_i + \delta \sum_{j=1}^{N} \sigma_j \\ s.t. \quad C_1: \quad & \lambda_i \geq 0, \forall i, \\ C_2: \quad & \sum_{i=1}^{n} \lambda_i = 1, \\ C_3: \quad & \gamma_i \geq 0, \forall i, \\ C_4: \quad & \sigma_j \leq \phi f_i u_{ij} + (1-\phi)\lambda_i f_j - \gamma_i + q_{ij}, \forall i, j, \\ C_5: \quad & q_{ij} \geq 0, \forall i, j: u_{ij} \geq R_{max}, \end{aligned} \tag{15}$$

which is a discretization of the following problem:

$$\begin{aligned} \min_{\lambda,\gamma,\sigma(\cdot)} \quad & \sum_{i=1}^{n} \zeta \gamma_i + \iint_R \sigma(x) dA \\ s.t. \quad & C_1 \sim C_3 \text{ in (15)}, \\ & \sigma(x) \leq \phi f(x) u_i(x) + (1-\phi)\lambda_i f(x) - \gamma_i, \\ & \qquad \forall x \in R, \forall i: u_i(x) \leq R_{max}. \end{aligned} \tag{16}$$

Eq. (16) is easy to be proved to be a convex problem, which can be efficiently solved by convex optimization techniques. In this paper, CVX, a powerful toolkit [26], is adopted to solve Eq. (16).

After solving Eq. (16), we consider the optimal dual variables $\lambda^\star$, $\alpha^\star$ and $\sigma^\star$. As before, $\{I_1^\star(\cdot), ..., I_n^\star(\cdot)\}$ is denoted as the optimal solution of the problem (11). Again, let $\sigma_i(x) = \phi f(x) u_i(x) + (1-\phi)\lambda_i f(x) - \gamma_i$. Note that for any $x \in C$, there must be some index i that maximizes $\sigma_i(x)$. If the index i is unique, it is obviously that $I_i^\star(x) = 1$ and $I_j^\star(x) = 0$ for other $j \neq i$,by complementary slackness. It is proved in [20] that the optimal solution to problem (10) still valid in spite of relaxation.

Therefore, we can find the optimal boundaries between subregions can be described as

$$\partial R_i^\star \cap \partial R_j^\star \subseteq \{x | x \in R, \sigma_i(x) = \sigma_j(x)\}. \tag{17}$$

Users that within the service area of the UAV will be served by the targeted UAV.

C. UAV relocation

After the user association strategy, the traffic demands among UAVs have been balanced as much as possible. Since the positions of UAVs have not been considered from a workload perspective, then we try to relocate UAVs to refine the load balance among the system.

TABLE II
ALGORITHM FOR OUR PROPOSAL

Algorithm 2

1: *Input:* A convex region R, the number of UAVs n;
2: Let P be the position of UAVs based on the clustering method.
3: Calculate λ, γ that satisfies the problem (16);
4: Recover the subregions $\{R_1, ..., R_n\}$ from λ, γ by (17);
5: Calculate $g \in R^{2n}$ by (19);
6: **while** $\|g\| \geq \varepsilon$ **do**
7: Let P denote the best placement obtained by the backtracking line search algorithm;
8: Calculate λ, γ that satisfies the problem (16);
9: Recover the subregions $\{R_1, ..., R_n\}$ from λ, γ by (17);
10: Calculate $g \in R^{2n}$ by (19);
11: **end**
12: **return** P and $\{R_1, ..., R_n\}$.

Denote $P = \{p_1, ..., p_n\}$ as the current positions of UAVs and $R = \{R_1, ..., R_n\}$ as the optimal solution to Eq. (10) at P. We define the objective function $F(P)$ by [20]

$$\begin{aligned} F(P) &= \iint_R \sigma^\star(x) dA \\ &= \sum_{i=1}^{n} \iint_{R_i} (\phi f(x) u_i(x) + (1-\phi)\lambda_i^\star f(x) - \gamma_i^\star) dA \\ &= \sum_{i=1}^{n} \iint_{R_i} \phi f(x) u_i(x) dA - \sum_{i=1}^{n} \gamma_i^\star \iint_{R_i} dA + \\ & \quad (1-\phi) \sum_{i=1}^{n} \lambda_i^\star \iint_{R_i} f(x) dA \end{aligned} \tag{18}$$

where $\sigma^\star(x), \lambda^\star$ and $\gamma^\star$ are optimal solution to Eq. (13). Let $p_i = (p_{i,1}, p_{i,2})$ and $x = (x_1, x_2)$, and $\frac{\partial F}{\partial p_i^k}$ can be calculated as

$$\begin{aligned} \frac{\partial F}{\partial p_i^k} &\approx \iint_{R_i} (\frac{\partial}{\partial p_i^k} \phi f(x) u_i(x)) dA \\ &= \phi \iint_{R_i} (f(x) \frac{x_k - p_{i,k}}{\|x - p_i\|}) dA \end{aligned} \tag{19}$$

To relocate the positions of UAVs, a local search is performed on the horizontal coordinates of UAVs. First, the gradient $\nabla F(P)$ is calculated approximately based on Eq. (19). Then, the next iteration of UAV placement P is chosen with the method of the backtracking line search after determining the direction $-\nabla F(P)$.

To sum up, our proposed strategies can be presented in Table II. Given the region R and the number of UAVs, we first deploy the positions of UAVs based on the clustering method, denote as P. Then we design the subregion of UAVs according to optimization results of Eq. (16). Third, the next placement P is chosen based on the backtracking line search after determining the direction $-\nabla F(P)$. The service areas and the locations of UAVs are updated iteratively until achieving optimum.

D. Altitude adjustment

After obtaining the final horizonal positions of UAVs, we can adjust the altitude of each UAV to reduce power consumption without degrading the user experience [27].

Obviously, the users at the border of the subregion of UAVs will suffer the highest pathloss compared with other covered users. Recall that when the pathloss threshold is set to ρ, the maximum coverage radius rises first and then decreases as the altitude of the UAV increases.

Note that we preset the initial altitude of the UAV as the inflection point of the curve, which means that the UAV can provide the maximum coverage radius to meet the requirement of path loss. At this time, if we shorten the service radius of UAV according to the actual service area of UAV, we can reduce the altitude on the premise of meeting the path loss, so as to reduce power consumption.

Therefore, after obtaining the final horizontal positions of UAVs, if the distance between cell edge users and the horizontal projection of UAV i is less than the maximized coverage radius, $max\{u_i(x), x \in R_i\} < R_{max}$, we can reduce the altitude of UAV. For each UAV i, denote the actual coverage radius as $r_a = max\{u_i(x), x \in R_i\}$, and the maximal pathloss is kept ρ, the altitude of UAV $h^\star$ can be calculated by :

$$PL(h^\star, r_a) = \rho. \tag{20}$$

V. Numerical Results

First, we introduce four evaluation indexes to measure the performance of our strategies. Denote κ as the percentage of users without service and τ as the average value of traffic capacity. Then, we introduce a balancing index to measure the balance of the network, which can be calculated as follows:

$$\psi = \frac{MSE}{M}, \tag{21}$$

where MSE represents the mean square error, and M represents the mean value. Denote ψ_t as the balancing index of traffic capacity among UAVs and ψ_a as the balancing index of the area of subregions.

Consider a rectangle region with a size of $2km$ by $2km$ and 500 users are assumed to distributed randomly in this area. Each UAV can serve 30 users at most. After normalization, the maximum traffic capacity of each UAV is 0.06. The traffic demand of users r_{min}^k is set to 0.003. The service region is an urban environment and the parameters of the ATG channels are $a = 9.61, b = 0.16, \eta_{LoS} = 1$ and $\eta_{NLoS} = 20$, which are calculated based on [24]. The carrier frequency is $f_c = 2GHz$. At the initialization, we set the maximum pathloss to $\rho = 95dB$, so the optimal altitude of the UAVs is calculated to be $h = 340m$ and the maximum cover radius is set to $R = 470m$. Consider a capacity margin for emergency situations, the initial number of UAVs that estimated is 20. For the clustering method, we set $E = 20, L = 100, H = 5, Sigma = 100, d_{min} = 10$ to get the initial UAV positions.

For comparison, we investigate the signal-to-interference-plus-noise ratio (SINR) based scheme with uniformly generated points. The SINR-based scheme is a traditional strategy where user k is assigned to a UAV that can provide maximum SINR [28]. Simulation results produced by our proposal and the SINR-based scheme are shown in the Fig. 3 and Fig. 4, respectively, where the positions of UAVs are marked as purple dots and the users are marked with different colors to represent the density. Blue dots means the user density is low while the red dots means the user density is high. Note that the black lines in the figures do not show the the actual boundary for connection of the users and the UAVs.

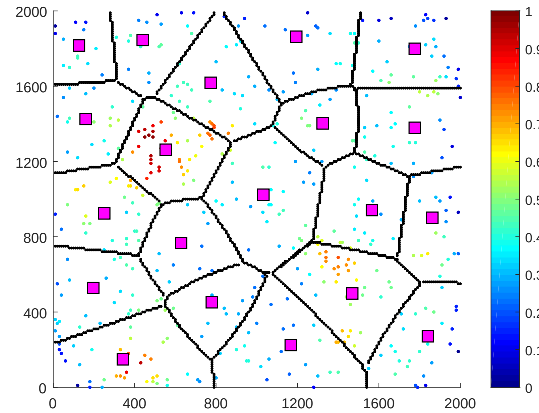

Fig. 3. Subregions designed by our strategies.

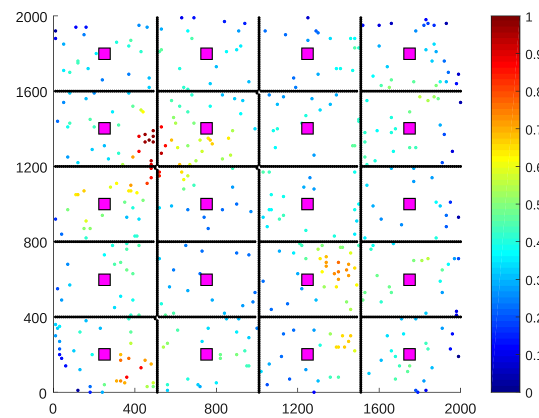

Fig. 4. Subregions designed by SINR-based scheme with uniformly distributed points.

As can be seen from Fig. 3, the locations of UAVs for our proposal are center in the maximal local density areas. Table III shows the traffic capacity of each UAV. Note that the maximum traffic load of UAVs in the SINR-based scheme is 0.0795, which is far greater than 0.0651 in our proposal. As we can see from Table IV, the balancing index of traffic load of UAVs is 0.0023 in our proposal and 0.0014 in the the SINR-based scheme respectively. Although the SINR-based scheme is more balancing than our proposal, our proposal can serve more users and the average capacity of UAVs is higher. Simulation shows our proposal can effectively improve the network throughput.

Then, we investigate the effectiveness of each part of our proposal. First, we evaluate the performance of the clustering method. For comparison purpose, we investigate the scheme of uniformed distribution points as initial positions. As is shown in Table V, there are 3.71% users without service for clustering method and 6.94% users without service for uniformly distributed points. Exclude users who cannot be

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

TABLE III
CAPACITY OF EACH UAV

Index	1	2	3	4	5	6	7	8	9	10
Our proposal	0.0651	0.0613	0.0480	0.0466	0.0549	0.0381	0.0651	0.0367	0.0513	0.0406
SINR-based scheme	0.0473	0.0632	0.0596	0.0422	0.0624	0.0391	0.0795	0.0438	0.0355	0.0457
Index	11	12	13	14	15	16	17	18	19	20
Our proposal	0.0453	0.0617	0.0651	0.0651	0.0343	0.0333	0.0651	0.0432	0.0516	0.0275
Our proposal	0.0367	0.0434	0.0448	0.0721	0.0450	0.0552	0.0502	0.0389	0.0449	0.0507

TABLE IV
PERFORMANCE OF OUR PROPOSAL

	Our proposed strategy	SINR-based scheme
κ	2.8%	4.0%
τ	0.0486	0.0480
ψ_t	0.0023	0.0014
ψ_a	117.9039	0

TABLE V
PERFORMANCE OF THE CLUSTERING METHOD

	Clustering method	Uniformly generated points
κ	3.71%	6.94%
τ	0.0481	0.0465
ψ_t	0.0012	0.0023
ψ_a	66.6739	4.4411

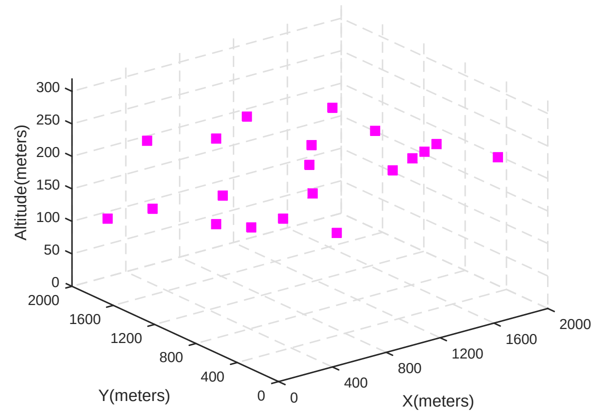

Fig. 5. 3D locations of UAVs after the altitude adjustment strategy.

served, the balancing index of traffic load among UAVs is 0.0014 for the clustering method and 0.0023 for the uniformed generated points respectively. Although we can not guarantee that the clustering algorithm has the best effect, it can provide us with an appropriate and effective initial locations of UAVs to implement the following algorithm.

Second, we study the performance of the region partition strategy and UAV relocation strategy. We take the SINR-based scheme with the clustering method for comparison. As is shown in Table VI, the percentage of users cannot be served decreases to 5.1% and the average value of traffic capacity of UAVs is 0.0475, both of which show improvement of service performance of UAVs. Moreover, the balancing index of traffic capacity among UAVs drops to 0.0013 and the balancing index of the areas among UAVs falls to 52.6324. We can conclude that our location strategy can make the traffic demand of subregions as balanced as possible so as to serve more users. Besides, our location algorithm requires about 70 iterations to converge to the local optimum. In other words, the complexity of the proposed algorithm is not high so it is practical for applications.

Third, we evaluate the performance of UAV altitude adjustment strategy. Fig. 5 shows the 3D locations of UAVs of Fig. 3 after the altitude adjustment strategy. Table VII shows the altitude of each UAV. As we can see, there are 12 UAVs hovering below 200 meters. UAVs that serve small subregions fly lower to save power consumption.

TABLE VI
PERFORMANCE OF OUR LOCATION STRATEGY

	Our location strategy	SINR-based scheme
κ	5.1%	7.53%
τ	0.0475	0.0462
ψ_t	0.0013	0.0016
ψ_a	52.6324	87.8242

Then, we investigate the total throughput of UAVs with different number of UAVs. As illustrated in Fig. 6, the total throughput increases with the increase of the number of UAVs, which is intuitive since UAVs can serve more users with the increase in number. The SINR-based scheme performs poor since it does not consider the distribution of user density and ignores the capacity balance among UAVs. Fig. 7 shows the total throughput with different number of users. As more users are randomly distributed in this area, UAVs can serve more users within its service region. When the number of users increases to 600, the traffic loads of UAVs are close to the maximum for both schemes, so the gap between two schemes is reduced.

Finally, we compare our algorithm with the optimal result under small-scale settings. Consider a rectangle region with a size of $500m$ by $500m$ and 50 users are assumed to be distributed randomly in this area. The initial estimated number of UAVs is 2. In order to obtain the optimal result, we divide the rectangular area into 100*100 meshes, where the UAVs can be placed in the center of area. We produce the optimal result by the exhaustive search, which takes more than 20 hours. Table VIII shows the load distribution of UAVs. Although the percentage of users out of service in our strategy is 1.8% more than the optimal result, the gap between them is slight, both of which are much better the SINR-based scheme. Considering the computational complexity of our algorithm is far less than

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVT.2019.2933560, IEEE Transactions on Vehicular Technology

TABLE VII
PERFORMANCE OF THE ALTITUDE ADJUSTMENT METHOD

Index	1	2	3	4	5	6	7	8	9	10
Altitude of UAV	112	185	205	189	153	261	168	211	210	210
Index	11	12	13	14	15	16	17	18	19	20
Altitude of UAV	188	303	159	222	195	161	152	162	235	110

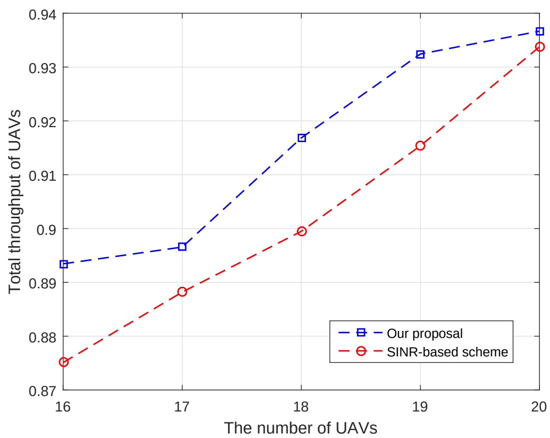

Fig. 6. Total throughput of UAVs as a function of the number of UAVs.

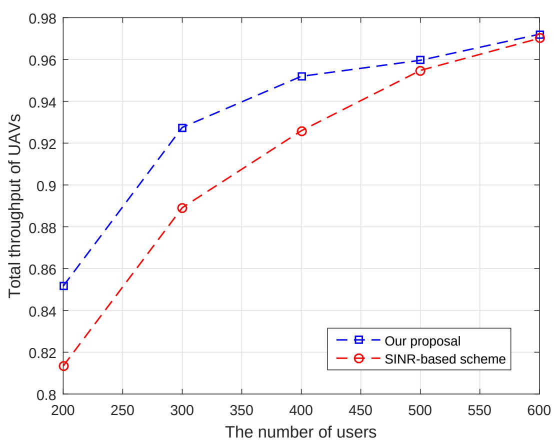

Fig. 7. Total throughput of UAVs as a function of the number of users.

the exhaustive search, it is more practical for applications.

Based on the simulation results shown in Fig. 3-7 and Table III - VIII, we can conclude that our proposed strategy can make the traffic demand among UAVs in a balanced way effectively.

TABLE VIII
LOAD DISTRIBUTION OF UAVS

	κ	τ
Optimal result	0	0.5
Our proposed strategy	1.8%	0.491
SINR-based scheme	11.3%	0.444

VI. CONCLUSIONS

In this paper, we investigated the UAV location and user association problem from a load balancing perspective. Our strategy can be divided into four steps. First, we introduced a clustering method to place UAVs in the maximal local density areas as initial positions. Then, we studied the region partition strategy, which tried to minimize the maximum traffic demand among UAVs so that the traffic capacity among UAVs can be balanced as much as possible. Third, we proposed a UAV location algorithm with the method of the backtracking line search algorithm to refine the load balance among the system. Finally, after determining the horizonal locations of UAVs, we adjust the altitude of each UAV to save power consumption. Simulation results show our proposal can serve more users and make the traffic load among UAVs more balanced compared with SINR-based scheme. The following problems are interesting for future work: First, the altitude and the horizontal position of each UAV should be optimized simultaneously; second, dynamic UAV location optimization is worth digging into; third, the heterogeneous traffic demand case is also an important problem since joint optimization of the UAV position and user association is more complex than the terrestrial mobile networks.

REFERENCES

[1] Y. Sun, T. Wang, and S. Wang, "Location optimization for unmanned aerial vehicles assisted mobile networks," in *Proc. IEEE ICC'18*, May. 2018.

[2] J. An, K. Yang, J. Wu, N. Ye, S. Guo, and Z. Liao, "Achieving sustainable ultra-dense heterogeneous networks for 5G," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 84–90, Dec. 2017.

[3] K. Miyanabe, K. Suto, Z. M. Fadlullah, H. Nishiyama, N. Kato, H. Ujikawa, and K. i. Suzuki, "A cloud radio access network with power over fiber toward 5G networks: QoE-guaranteed design and operation," *IEEE Wireless Commun.*, vol. 22, no. 4, pp. 58–64, Aug. 2015.

[4] Y. Li and L. Cai, "UAV-assisted dynamic coverage in a heterogeneous cellular system," *IEEE Network*, vol. 31, no. 4, pp. 56–61, Jul. 2017.

[5] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Commun. Surv. Tut.*, vol. 18, no. 4, pp. 2624–2661, Fourth Quarter 2016.

[6] S. Park, C. S. Shin, D. Jeong, and H. Lee, "DroneNetX: Network reconstruction through connectivity probing and relay deployment by multiple UAVs in ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 11 192–11 207, Nov. 2018.

[7] Y. Lin, T. Wang, and S. Wang, "UAV-assisted emergency communications: An extended multi-armed bandit perspective," *IEEE Commun. Lett.*, vol. 23, no. 5, pp. 938–941, May 2019.

[8] W. Zhao, S. Wang, C. Wang, and X. Wu, "Approximation algorithms for cell planning in heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1561–1572, Feb. 2017.

[9] S. Wang, W. Zhao, and C. Wang, "Budgeted cell planning for cellular networks with small cells," *IEEE Trans. Veh. Technol.*, vol. 64, no. 10, pp. 4797–4806, Oct. 2015.

[10] C. Ran, S. Wang, and C. Wang, "Cellular networks planning: A workload balancing perspective," *Comput. Netw.*, vol. 84, pp. 64 – 75, Jun. 2015.

[11] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Optimal transport theory for cell association in UAV-enabled cellular networks," *IEEE Commun. Lett.*, vol. 21, no. 9, pp. 2053–2056, Sept. 2017.

[12] P. Yang, X. Cao, C. Yin, Z. Xiao, X. Xi, and D. Wu, "Proactive drone-cell deployment: Overload relief for a cellular network under flash crowd traffic," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 10, pp. 2877–2892, Oct. 2017.

[13] S. Rahman, G. Kim, Y. Cho, and A. Khan, "Positioning of UAVs for throughput maximization in software-defined disaster area uav communication networks," *J. Commun. Netw.*, vol. 20, no. 5, pp. 452–463, Oct. 2018.

[14] J. Lu, S. Wan, X. Chen, Z. Chen, P. Fan, and K. B. Letaief, "Beyond empirical models: Pattern formation driven placement of UAV base stations," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 3641–3655, Jun. 2018.

[15] H. Wu, X. Tao, N. Zhang, and X. Shen, "Cooperative UAV cluster-assisted terrestrial cellular networks for ubiquitous coverage," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 9, pp. 2045–2058, Sept. 2018.

[16] C. Tazibt, M. Bekhti, T. Djamah, N. Achir, and K. Boussetta, "Wireless sensor network clustering for UAV-based data gathering," in *Proc. Wireless Days'17*, Mar. 2017, pp. 245–247.

[17] J. Yu, R. Zhang, Y. Gao, and L. Yang, "Modularity-based dynamic clustering for energy efficient UAVs-aided communications," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 728–731, Oct. 2018.

[18] Q. Shen, Z. Ma, and S. Wang, "Deploying C-RAN in cellular radio networks: An efficient way to meet future traffic demands," *IEEE Trans. Veh. Tech.*, vol. 67, no. 8, pp. 7887–7891, Aug. 2018.

[19] S. Wang and C. Ran, "Rethinking cellular network planning and optimization," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 118–125, Apr. 2016.

[20] J. G. Carlsson and R. Devulapalli, "Dividing a territory among several facilities," *Informs J. Comput.*, vol. 25, no. 4, pp. 730–742, Fall 2013.

[21] J. G. Carlsson, F. Jia, and Y. Li, "An approximation algorithm for the continuous k-medians problem in a convex polygon," *Informs J. Comput.*, vol. 26, no. 2, pp. 280–289, Spring 2014.

[22] C. Ran, S. Wang, and C. Wang, "Balancing backhaul load in heterogeneous cloud radio access networks," *IEEE Wireless Commun.*, vol. 22, no. 3, pp. 42–48, Jun. 2015.

[23] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *Proc. IEEE GLOBECOM'14*, Dec. 2014, pp. 2898–2904.

[24] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Commun. Lett.*, vol. 3, no. 6, pp. 569–572, Dec. 2014.

[25] G. H. Ball and J. Hall, "A novel method of data analysis and pattern classification," *Tech. Rep. AD-699616, Stanford Res. Inst*, 1965.

[26] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[27] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu, "3D placement of an unmanned aerial vehicle base station (uav-bs) for energy-efficient maximal coverage," *IEEE Wireless Commun. Lett.*, vol. 5, no. 4, May 2017.

[28] J. G. Andrews, F. Baccelli, and R. K. Ganti, "A tractable approach to coverage and rate in cellular networks," *IEEE Trans. Commun.*, vol. 59, no. 11, pp. 3122–3134, Nov. 2011.

Yang Sun received her BS and MS degrees from Nanjing University, Nanjing, China, in 2016 and 2019, respectively. Her research interests include load balancing in wireless mobile networks.

Tianyu Wang (S'11-M'16) received his BS, MS and PhD degrees from Peking University, China. He is currently an associate researcher of the School of Electronic Science and Engineering, Nanjing University, China. He has published more than 40 IEEE journal and conference papers, and received the Best Paper Award from the IEEE ICC15, IEEE GLOBECOM14, and ICST ChinaCom12. His current research interest includes network slicing, load balancing and machine learning in wireless networks.

Shaowei Wang (S'06-M'07-SM'13) received his BS, MS and PhD degrees from Wuhan University, China. He is currently a full professor of the School of Electronic Science and Engineering, Nanjing University, Nanjing, China. His research interests mainly include telecommunication systems, operations research and machine learning. He is on the editorial board of IEEE Communications Magazine, IEEE Transactions on Wireless Communications, and Springer Journal of Wireless Networks. He serves/served on the technical or executive committee of reputable conferences including IEEE INFOCOM, IEEE ICC, IEEE GLOBECOM, IEEE WCNC.