SIDE: Semi-Distributed Mechanical Equilibrium based UAV Deployment

Shuxin Zhong, Yu-Xuan Qiu, Rukhsana Ruby, Lu Wang, Kaishun Wu
College of Computer Science and Software Engineering, Shenzhen University
Email: zshuxin_1113@163.com, qiuyuxuan1@email.szu.edu.cn, {ruby,wanglu,wu}@szu.edu.cn

***Abstract*—Recently, we have seen the unprecedented development in unmanned aerial vehicles (UAVs) from different aspects. Accordingly, an increasing number of applications have emerged based on UAVs. Among which, placing UAVs as Aerial Base Stations (ABSs) has received considerable interest in both the industrial and academic community. Existing solutions focus on the optimization of the UAV deployment problem for static user topology using the control information obtained from the Terrestrial Base Station (TBS), that makes hard for the controller to make real-time decisions. To break this stalemate, we propose a SemI-DistributEd system, named SIDE, for the UAV self-deployment. In SIDE, we introduce a mechanical equilibrium based approach, named EMech, via which the UAV positions are self-adapted according to users' attraction (e.g., user distance and traffic demand) within their transmission range. To facilitate the EMech, we propose a fine-grained area splitting strategy, termed KDivision, that partitions the service area in accordance with the user density. Finally, an area merging technique, namely RMerge, is exploited to approximately optimize the positions of the UAVs assisted by an Utility Function that strikes a balance amid the network performance and economic cost. We conduct field experiments to validate the feasibility of EMech. Extensive simulation results show that the proposed SIDE finds the optimal number of assigned UAVs, which not only reduces the cost of the system significantly, but also improves the achievable rate up to 74.6% compared to the existing solutions while consuming almost the same energy level.**

I. Introduction

Placing Unmanned Aerial Vehicles (UAVs) as Aerial Base Stations (ABSs), to enhance the coverage and throughput of wireless networks, has received increasing attention from both the industrial and academic community, particularly in critical scenarios like temporary hotspots and disaster situations [1]–[5]. For instance, in sport events or concerts, Terrestrial Base Stations (TBSs) might fail to provide the desired performance due to the flash crowd traffic, and it is not feasible to invest a huge level of currency for an infrastructure that will provide revenue for a relatively short period of time. A promising solution is to assist the cellular network via UAVs. UAVs have the merits of flexibility and economy, that make them especially suitable for temporarily increasing traffic demand. Moreover, UAVs have higher possibility of line-of-sight (LOS) links with users because of their flying characteristics, which provide better link quality for the communication.

With such promising features, the deployment of UAVs for the improvement of throughput in cellular networks has widely been studied. The works [6]–[8] offered several methods to position one UAV for maximizing coverage or throughput.

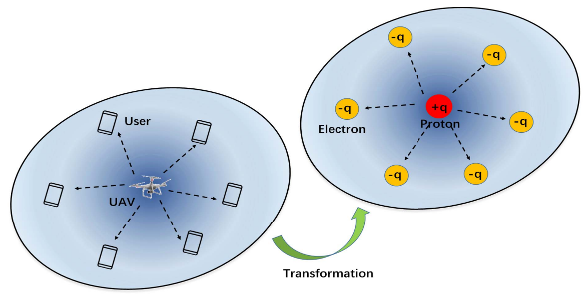

Fig. 1. The key insight of SIDE is to envision UAV deployment as a mechanical equilibrium problem.

Some researchers [9]–[13] attempted to study the multi-UAV deployment problem. Especially, Sharma et al. [10] utilized the priority dominance and entropy concept in order to allocate UAVs over a region. However, it mainly mapped the UAVs to sub-areas instead of determining their accurate positions. Mozaffari et al. [12] exploited the constrained K-means method which clustered the IoT devices in an iterative manner and put each UAV at the centroid of each cluster [14]. The limitation of this work is that the resultant minimum and maximum size of the clusters are highly uneven, which might lead to the wastage of resources in the system.

Despite that existing works have made significant progress on the UAV deployment problem to assist the cellular network, there are still two vital limitations. 1) Static user topology: Since static user deployment is a fundamental assumption of the previous works in [8], [9], [11], [14], it might lead to the over-provisioning of UAV resources. For example, in a sudden gathering or disaster scenario, if we apply the existing approaches to support the mobile users, an UAV remain underutilized when the highly mobile users move out of their coverage. 2) Centralized controller: Most works [10], [12], [14], [15] suppose that there is a centralized virtual controller that takes care of the entire decision making task. When the user topology changes gradually, the virtual controller requires re-clustering of the users. It might incur huge computational cost and difficulties for the controller to make real-time decisions. Therefore, utilizing the UAV resources efficiently to benefit the network performance, especially under a dynamic user topology, turns out to be a crucial problem.

To cope with the aforementioned limitations, in this paper, we introduce SIDE, a novel SemI-DistributEd system for the

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UAV self-deployment problem. Unlike the existing systems that deploy UAVs under the assumption of static user topology using the control information from the TBS, SIDE adopts a mechanical equilibrium based approach, termed EMech, which enables the deployed UAVs to find their positions in an autonomous manner. It is not only utilized for static user topology but also adaptive to the variation of dynamic user typologies. As illustrated in Fig. 1, the key insight is that if we envision a user as a stationary electron in physics and an UAV as a mobile proton, the virtual force between the UAV and the user should be proportional to the user demand and inversely proportional to the SINR. It is similar to the effect of the signed magnitudes and the distance between two charged particles in Coulomb's law [16]. Therefore, if we put an UAV randomly in a region, it is bound to move because of the net force from the users until it reaches the equilibrium state.

Though the basic idea sounds straightforward, it is non-trivial to realize SIDE due to the following two challenges.

1) Challenge 1: one important step in EMech is to find the initial position of an UAV. However, due to the mutual influence among different deployment positions, it is tough for multiple UAVs to find their initial positions within the whole demand area at the same time. To deal with this problem, we propose a *kd*-tree based splitting method, namely KDivision, to partition the demand area into sub-areas, which ensures the number of assigned UAVs in each sub-area based on its size. Thereupon, an UAV can find its initial position as a local optimal solution in each sub-area. In order to obtain a globally optimal solution for the original deployment problem, we further propose RMerge, to merge the resultant sub-areas back to the demand area. During RMerge, the operations, e.g., addition, removal and relocation of UAVs, are carried out to maximize the overall achievable rate.

2) Challenge 2: seldom work has paid attention to number of assignable UAVs and assumed that this number is fixed. However, in practice, the number of required UAVs is usually unknown in advance as it is related to the user distribution. To address this challenge, we propose an *Utility Function* assisted heuristic algorithm, which strikes a balance between network performance and economic cost. It is used as a criterion to judge whether an operation, such as addition or removal of UAVs, would lead to a better performance. In this way, the number of deployed UAV is adjustable to the user distribution.

Through theoretical and experimental analysis, we verify the feasibility of EMech comparing with the existing work in [12]. We further conduct extensive simulations to validate the performance of our proposed method. The results demonstrate that the average achievable rate outperforms other state-of-the-art solutions [9] and [12] by 37.1% and 32.2% in the evenly distributed user topology, and by 74.6% and 73.1% in the cluster based user topology. On the other hand, the total energy consumption is almost the same or much less. The results reveal that SIDE provides a more flexible and efficient semi-distributed self-deployment algorithm for the self-adaptive UAV deployment problem. Overall, the contributions of this work can be summarized as follows.

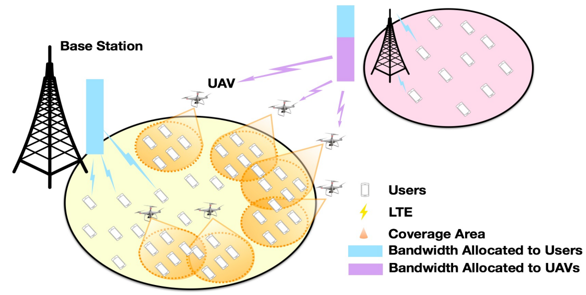


Fig. 2. A sample scenario of SIDE: UAV-assisted celluar network to alleviate the erratic supply-demand mismatch.

- We are the first one in the literature to transform the UAV deployment problem to a mechanical equilibrium problem. The proposed self-deployment algorithm EMech is not only suitable for a static user topology but also adaptive with the variation of dynamic user topology. From the resultant outcome of EMech, the position of an UAV is self-adapted based on the user attractions (e.g., SINR and traffic demand).
- We propose a fine-grained area splitting strategy, KDivision, and a novel merging technique, Rmerge, to obtain globally optimal UAV positions. We further formulate the UAV deployment problem as an optimization problem to strike a balance amid the total UAV deployment cost and network performance.
- Through a field-level experiment, we verify the feasibility of EMech. Extensive simulation results show that the proposed approach improves the overall rate of the system at most by 73.1% compared to the state-of-the-art solutions.

II. System Overview

Consider a scenario where flash crowds cause overloading at the TBS in LTE networks. If the number of users is constantly increasing, the demand will be more pressing. In this case, an ABS is an appealing solution to alleviate the erratic supply-demand mismatch in the hotspot area efficiently and economically. As shown in Fig. 2, an UAV is equipped with a cellular backhaul (LTE) that is connected to the TBS in its neighboring area, and then also builds an LTE network to the users within its transmission range. We suppose that the bandwidth resources are abundant in neighboring areas and non-overlapping bandwidth is allocated to each UAV. The users that are uncovered by any UAV obtain service from the nearby TBS directly. We assume that all the UAVs are equipped with sensing, communication, mobility and computational capability features. Computational ability for an UAV is required as it requires to support a distributed deployment algorithm. As the number of UAVs and their corresponding positions influence the performance of the entire network, in this paper, we introduce SIDE to find the number of required UAVs and their corresponding positions in order to benefit the network in the best possible manner.

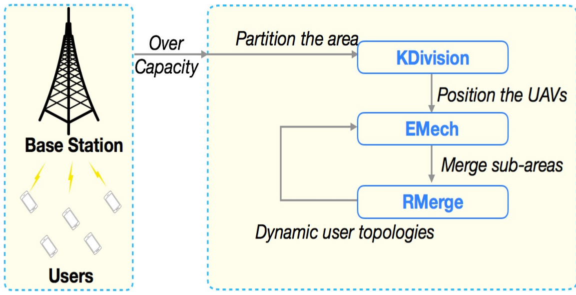


Fig. 3. The flowchart of SIDE.

SIDE is a semi-distributed mechanical equilibrium based system that enables the UAVs to organize themselves in an adaptive manner according to the attraction of the users, which consists of SINR and traffic demand. It is not only suitable for static user topology but also adaptive with the variation of dynamic user typologies. Fig. 3 illustrates the framework of SIDE. At the beginning, the TBS collects information about the number of users within its service area and their corresponding locations via GPS periodically. Once the entire user information is gathered, the TBS executes SIDE automatically.

SIDE formulates the deployment problem of the UAVs as an optimization problem. However, since the problem is NP-hard, it is challenging to find the optimal solution in reasonable time. Consequently, from the insights of the optimal solution, we design an incremental self-deployment algorithmic framework based on the concept of a designed *Utility Function*, which enables the UAVs to locate themselves autonomously and independently to assist the cellular network in a hotspot area. The algorithmic framework consists of the following components.

- **KDivision:** Instead of dividing the hotspot area into fix-sized blocks, the TBS adopts a fine-grained area splitting strategy termed KDivision. It partitions the demand area into several sub-areas with heterogeneous-size such that the number of users in each sub-area satisfies the capacity constraint of the designated UAV.
- **EMech:** Rather than putting an UAV at the centroid of a user cluster, we exploit a distributed mechanical equilibrium based algorithm for an UAV to find its position autonomously. The initial position of an UAV is above the region that has a maximum number of users. Then, it moves due to the net attraction from the users in that sub-area until reaching the equilibrium state. In this way, the position of an UAV is not only determined by the locations of the users, but also influenced by fluctuating link quality and traffic demand.
- **RMerge:** As KDivision splits the high demand area into several heterogeneous sub-areas, the position of an UAV is only determined by the users within each sub-area. Consequently, RMerge is employed to combine the solutions of all sub-areas to a complete fine-tuned one of the original deployment problem. As the steps of this technique, the operations, e.g., addition, removal and relocation of UAVs, are taken out based on the outcome of the *Utility Function* while targeting on the maximization of the network performance and the minimization of economic cost.
- Once the initial deployment positions are determined, the UAVs periodically collect information about the users within their transmission range, such as SINR and user traffic demand, and then calculate the net attraction of each user. When the equilibrium state is broken, the corresponding UAV decides its movement via EMech repeatedly until it finds another equilibrium point again.

III. Problem Formulation

Suppose there is a set of M ground users, which is denoted by $G = \{g_1, g_2, ..., g_M\}$, and are distributed randomly within the boundary of high demand area. The coordinate of user g_j is represented as (x_{g_j}, y_{g_j}). In this scenario, a set $\mathcal{K} = \{u_1, u_2, ..., u_K\}$ of K UAVs are deployed to assist the overloaded TBS by providing communication service for congested ground users effectively. Each UAV can handle up to X users at one time. We use $(x_{u_i}, y_{u_i}, h_{u_i})$ to denote the location of UAV u_i. The researchers in [17] have already calculated the optimal altitude of an UAV for the maximum coverage in urban environments, and we suppose that the altitude for each UAV in this paper is optimal and fixed. Therefore, we denote the coordinate of UAV u_i $(x_{u_i}, y_{u_i}, h_{u_i})$ as (x_{u_i}, y_{u_i}) throughout the rest of the paper [18].

The transmission range of each UAV is assumed to be ideal, which means that the coverage area has a circular shape without any irregularity. According to [19], user g_j is said to be served by UAV u_i if the distance between them is shorter or equal to the maximum transmission range R_{max}. I_{u_i} is denoted as the set of users covered by UAV u_i.

According to Shannon's capacity formula, the achievable rate of user g_j at location (x_{g_j}, y_{g_j}) associated with UAV u_i can be expressed as

$$R_{u_i}(x_{g_j}, y_{g_j}) = W_{u_i} log_2(1 + \frac{P_{u_i}/\overline{L}_{u_i}(x_{g_j}, y_{g_j})}{N_0}), \quad (1)$$

where W_{u_i} and P_{u_i} denote the transmission bandwidth and transmission power of UAV u_i, respectively. $\overline{L}_{u_i}(x_{g_j}, y_{g_j})$ represents the average path loss between UAV u_i and user g_j which is calculated according to the air-to-ground channel model in [17] and N_0 is the noise power. Moreover, $W_{u_i} = \frac{B_{u_i}}{|I_{u_i}|}$, where B_{u_i} is the assigned bandwidth to UAV u_i. Consequently, it is easy to derive the rate of UAV u_i as $R_{u_i} = \sum_{j=1}^{|I_{u_i}|} R_{u_i}(x_{g_j}, y_{g_j})$.

In this setting, we denote the sum of achievable rate of all the user-UAV and user-TBS pairs referred as Global Rate, which is $R_w(\mathcal{K}) = \sum_{i=1}^{K} R_{u_i} + \sum_{i=1}^{G-\sum_{j=1}^{K}|I_{u_i}|} R_{TBS}(x_{g_j}, y_{g_j})$, where R_{TBS} is calculated according to the Hata Model [20]. Furthermore, contrary to the Global Rate, the more the UAVs we deploy, the more expense we require to endure. To capture the cost of our deployment problem, we define a Cost Function $Cost(K) = \zeta \times K$, which is a function of K and the per UAV cost ζ.

Based on the Global Rate and the Cost Function, we define a *Utility Function* to explore the performance maximization and cost minimization aspects of the UAV deployment problem, which can be stated as $Assign(\mathcal{K}) = R_w(\mathcal{K}) - Cost(K)$. In this paper, our goal is to find the optimal number of UAVs in set $\mathcal{K}$ for the purpose of deployment and their positions so that the *Utility Function* is maximized.

The problem described herein is NP-hard, which can be proved by a reduction procedure. We set $Cost(K) = 0$, $G = \sum_{j=1}^{K} I_{u_i}$, $B_{u_i} = 1$, $P_{u_i} = N_0$, $\overline{L}_{u_i}(x_{g_j}, y_{g_j}) = d_{ij}^{\alpha}$. Consequently, we can rewrite the aforementioned problem as an optimization problem, which is as follows.

$$
\begin{aligned}
&\max \sum_{i=1}^{K} \sum_{j=1}^{|I_{u_i}|} \log_2\left(1 + \frac{1}{d_{ij}^{\alpha}}\right)^{\frac{1}{|I_{u_i}|}} \\
\texttt{s.t.} \quad &\sum_{i=1}^{K} |I_{u_i}| = M \\
&|I_{u_i}| \in Z^{+} \\
&d_{ij} \in R^{+} \\
&\alpha \in [2, 4],
\end{aligned}
\tag{2}
$$

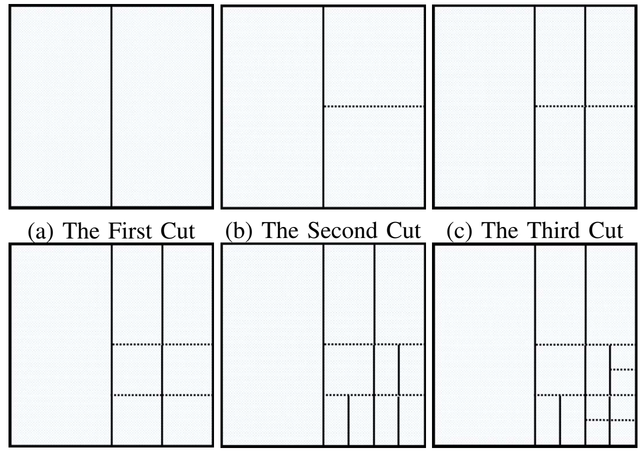
which is proved to be an mixed integer non-linear programming (MINLP) problem, and hence NP-hard. Especially for this problem, it is challenging to find the optimal solution due to the mutual dependency among $(x_{u_1}, y_{u_1}), \ldots, (x_{u_K}, y_{u_K})$. Therefore, we propose an *Utility Function* assisted heuristic solution for the UAV deployment problem in the next section.

IV. Mechanical Equilibrium based UAV Deployment

The formulated problem in the previous section is intractable as it is an NP-hard problem. Consequently, we devise an *Utility Function* assisted heuristic solution in this section. We first partition the demand area into several heterogeneous-sized sub-areas using the proposed method KDivision such that the number of users in each sub-area satisfies the capacity of an UAV. Then, we proposed a mechanical equilibrium based solution, named EMech, that enables the deployed UAVs to find their positions in an autonomous manner within their sub-areas. Afterwards, a novel area merging technique, RMerge, is designed to combine the local optimal solutions to obtain an optimal global one that can benefit the network in terms of both the overall rate and the deployment cost.

*A. Dividing Demand Area - **KDivision***

In previous works [9], [10], the authors introduced the *zone guider lines* concept that divides the traditional hexagonal cell into a set of small independent regular areas, and map the UAVs to the desired areas. Due to the random user distribution, the resultant number of users in each small area is uneven, so that this dividing method might degrade the utilization of UAV resources. It is therefore attractive to consider a fine-grained



(a) The First Cut (b) The Second Cut (c) The Third Cut

(d) The Fourth Cut (e) The Fifth Cut (f) The Sixth Cut

Fig. 4. A sample illustrations of the KDivision method.

area division strategy that the number of users in each sub-area satisfies the capacity constraint of an UAV to exploit the resources of the UAVs in an optimal manner.

Inspired by the way of constructing a *kd*-tree that always divides the space from the longest dimension, we exploit the KDivision method to partition the demand area which always splits the parent area into two sub-areas along the longest edge. For example, as shown in Fig. 4, suppose that the number of users in a given area has already exceeded the capacity constraint of the designated UAV, we partition the parent area into two sub-areas in a vertical manner. Then, if the number of users in one of the sub-areas still exceeds the UAV capacity, we will divide it into two parts in a horizontal manner. This partitioning processes is recursively repeated on each sub-area until the number of users in each sub-area fulfills the capacity constraint of the designated UAVs. In a nutshell, as we can see in Fig. 4, odd cuts are made via solid lines, whereas the even cuts are made via dotted lines. Through this strategy, we find that each sub-area contains roughly the same number of users, which means if the users in one sub-area is denser than that of other sub-areas, the area of this sub-area would be smaller. This interesting property provides the possibility of improving the utilization of an UAV in the deployment problem in which users are distributed in a non-uniform manner.

*B. Finding the Optimal Location of an UAV - **EMech***

Mozaffari et. al. [12] exploited a constrained K-means clustering approach to optimally cluster the IoT devices and they also proved that the optimal location of an UAV corresponds to the centroid of the demand area. However, deploying UAVs at the center of formed clusters has its own limitations, which are listed as follows.

- First, it only considers the distance between a user and an UAV, which might be impractical since the attenuation of a signal is not simply determined by the distance but also

influenced by the multi-path propagation, referred to as shadowing from obstacles particularly in urban scenarios.
- Second, the user topology changes gradually, and the virtual controller needs to re-cluster the users once the user topology changes. It might incur huge computational overhead and difficulties for the controller to make real-time decisions.

As a result, applying the existing approaches in practice might affect network performance negatively. Consequently, it is necessary to develop a distributed algorithm by which the UAVs can relocate themselves autonomously as required when the location of users and their availability change dynamically.

This algorithm is motivated by the **Mechanical Equilibrium** concept in which a particle is in static equilibrium if the net force on that particle is zero. As we all know, the force between two particles is proportional to their magnitude and inversely proportional to their distance. While deploying an UAV to provide communication provision for the ground users, we observe a similar phenomenon. The users, that suffer worse link quality or have higher traffic demand, have tendency to attract the UAV to become closer for reducing the attenuation of signal. We envision a user as a stationary electron in Physics and an UAV as a mobile proton. The force between the user and the UAV is proportional to traffic demand and inversely proportional to the SINR, which is similar to the effect of the signed magnitudes and distance on the physical force [16]. The equilibrium position of the UAV is closer to those users that suffer fluctuating link quality or have pressing traffic in order to achieve higher network performance. Therefore, if we put an UAV in an area randomly, the UAV would adjust its position autonomously from the initial location until it reaches the equilibrium state according to the net force from the users.

In order to achieve the desired objective, we introduce the concept of attraction of UAV u_i from user g_j to define the movement of the UAVs during the deployment process. It is calculated as

$$F_{g_j->u_i} = k_a \frac{r_{g_j} r_{u_i}}{SINR^2_{g_j->u_i}}, \tag{3}$$

where r_{g_j} denotes the traffic demand of user g_j, k_a is the attraction coefficient and the default value of r_{u_i} is 1. Different from the Coulombs law [16], this attraction is dependent on the SINR and traffic demand. The attraction satisfies the following conditions:

- Inverse Relation: The attraction is inversely proportional to the SINR, which means the attraction from the users that suffer worse link quality is greater than that have better channel quality.
- Positive Correlation: The attraction is proportional to the traffic demand, which means that the attraction from the users that have more pressing traffic demand is greater than that with relatively small traffic requirements.

We design an algorithm that begins with the specification of traffic demand (r_{g_j}) and the initial location (x_{g_j}, y_{g_j}) of the users. An UAV can sense the users within its transmission range and obtain their instantaneous locations (x_{g_j}, y_{g_j}) via GPS. Moreover, when the active users send service request messages to an UAV, it can acquire their traffic demand (r_{g_j}) and can calculate the instantaneous SINR ($SINR_{g_j->u_i}$) through the measurement of the signal quality.

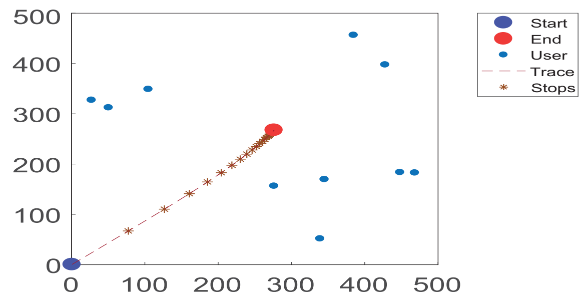


Fig. 5. A sample trace of finding the positions of an UAV.

First, we suppose that an UAV is added and its initial location is in a region that has a maximum number of users. Then, according to the virtual attraction imposed on the UAV from the users at the current location, the UAV decides its next movement in an autonomous manner. After moving to a new position, the net attraction to the UAV from the users changes in accordance with the distance and availability of the users, which drives the UAV to move again. This process is repeated until an equilibrium state is reached where a particle has zero velocity. In this paper, we assume that when the movement of an UAV is less than a certain predefined threshold, the static equilibrium for that UAV is achieved.

In the final step of the algorithm, we apply the outcome of the *Utility Function* to judge whether we should put an UAV in this area. If the value of the *Utility Function* is larger, we add the corresponding UAV to the area, otherwise not.

In order to illustrate the equilibrium point finding mechanism (i.e., EMech) of an UAV, we plot Figure 5 that shows a sample trajectory of an UAV in the process of finding its optimal position from its initial point. In this figure, 10 users are non-uniformly distributed and they are marked by black dots. Each UAV chooses its initial position randomly that is denoted by a blue dot. The movement of the UAV is decided by the net force from the users and the temporary stops are indicated by the stars. The process is repeated until it reaches the equilibrium state and the final position is specified by a red dot.

It can be easily proved that our proposed solution is equivalent to the traditional K-means based methods [12], [14]. If we only take the distance of the users to the UAV into account, the outcome of our solution approach would be as same as that of the K-means based methods. As shown by the relation in (3), the force can be written as $F_{g_j->u_i} \propto \frac{1}{SINR^2_{g_j->u_i}}$. Since $SINR_{g_j->u_i} \propto \frac{1}{d_{ij}}$, we have $F_{g_j->u_i} \propto d^2_{ij}$. Consequently, we need to prove that the force equilibrium point is the centroid. Let a list of planar points $A_1 = (x_1, y_1), A_2 = (x_2, y_2), \ldots, A_n = (x_n, y_n)$.

Hence, in the k-means method, we need to find a point $P=(x,y)$ which satisfies $\min\sum_{i=1}^{n}(x-x_i)^2+(y-y^2)$. We can rewrite the minimization problem further as $\min n(x-\frac{x_1+x_2+\ldots+x_n}{n})^2+n(y-\frac{y_1+y_2+\ldots+y_n}{n})^2+K$. The optimal outcome of this minimization problem is the centroid, i.e., $x=\frac{x_1+x_2+\ldots+x_n}{n}, y=\frac{y_1+y_2+\ldots+y_n}{n}$. In our solution, the force equilibrium point $P'=(x',y')$ satisfies the following two equations.

$$\begin{cases}(x_1-x')+(x_2-x')+\ldots+(x_n-x') & =0.\\(y_1-y')+(y_2-y')+\ldots+(y_n-y') & =0.\end{cases}$$

Hence, we also have $x'=\frac{x_1+x_2+\ldots+x_n}{n}, y'=\frac{y_1+y_2+\ldots+y_n}{n}$, which implies that $P=P'$. Thus, the proof is completed.

Therefore, our proposed method EMech is suitable for a more complex scenario as it not only considers the distance but also the attenuation of a signal and user demand. More importantly, EMech is a distributed algorithm by which an UAV can adjust its location in an autonomous manner according to the SINR and the demand of the users even in a mobile network. The detailed procedure to deploy an UAV in a certain area is summarized in Algorithm 1.

*C. Utility Function assisted Merging Technique - **RMerge***

Poineer work [9], [10] proposed the area splitting scheme in order to simplify the problem of mapping high-demand sub-areas with UAVs. As the splitting strategy partitions the whole area into several sub-areas, the position of an assigned UAV is only determined by users within the corresponding sub-area, which is a local optimum solution. However, the globally optimal location of an UAV might also be affected by the users in the edges of neighboring sub-areas. In order to optimize the solution, we obey an inverse version of the KDivision method, termed RMerge, which is devised to combine local solutions to obtain a global solution of the original deployment problem. For each pair of two blocks, it falls under each of three conditions: *1) neither block A nor block B has any UAV 2) either block A or block B has at least one UAV 3) both block A and B have at least one UAV*. In these cases, the operations, e.g., addition, removal and relocation of UAVs, are carried out to maximize the network performance.

When two blocks are merged to a new one, actions are likely to be taken out in the bounding area to optimize the solution. For example, If the coverage area of an UAV is out of one block, this UAV might adjust its location due to the users in the edge of the other block. For convenience, we introduce *Border Area* which is formed by moving the boundary line of two blocks towards both sides by a distance of R_{max}.

1) Neither Block A nor Block B has any UAV: It is the simplest condition in the RMerge method. This problem can be transformed to find the location of an UAV within *Border Area* after combining two blocks into a new one. EMech (i.e., Algorithm. 1) can be adopted to solve this problem.

2) Either Block A or Block B has at least one UAV : We first need to check whether the addition of a new UAV u_{new} leads to better performance, as illustrated in Fig. 6(b).

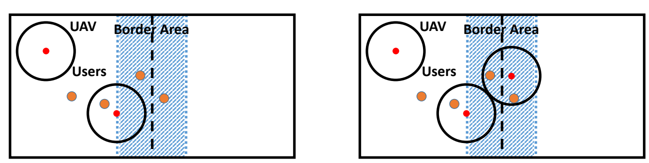
Algorithm 1: The deatiled steps for the initial placement of an UAV - **EMech**.

Input: A sub-area A_c that is generated by the KDivision method, and the set of user locations within sub-area A_c is L.

Output: The sub-area A_c' after deploying an UAV.

Calculate the Utility Function when no UAV is added:
$R_1=R_w(\emptyset)-Cost(0)=\sum_{i=1}^{|I_{A_c}|}R_{TBS}(x_{g_i},y_{g_i})$.
Suppose UAV u is added, and choose the initial location $l\in L$ which has the maximum number of users within the R_{max} range.
$ForceMove(A_c,\{u\})$.
/* after ForceMove, UAV u is at the new location l' */
$R_2=R_w(u)-Cost(1)$.
if $(R_2>R_1)$ **then**
  Add UAV u to sub-area A_c and return the resultant sub-area A_c'.
else
  No UAV is added and return the original sub-area A_c.

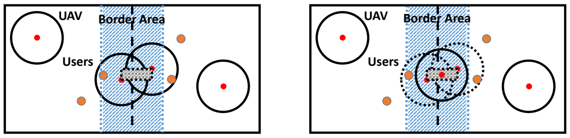
Procedure ForceMove(A_c,U)
while *true* **do**
  $Forceflag\leftarrow 0$
  foreach $u_i\in U$ **do**
    /* maybe more than one UAV in sub-area A_c. */
    $F\leftarrow CombinedForce(I_{A_c}-\sum_{j=0,j\neq i}^{j=|U|}I_{u_j})$.
    $Forceflag\leftarrow Forceflag+F$.
    u_i moves d units which is calculated according to the combined force F.
  Find the radius and height of each UAV $u_i\in U$ that satisfies the following constraints:
    1) radius $r_{u_i}\leq R_{max}$
    2) $|I_{u_i}|\leq X$
  if $Forceflag\leq\epsilon$ **then**
    break.



(a) Initial State (b) Addition of a New UAV

Fig. 6. A sample illustration of the merging process.

We can take the help of Algorithm. 1 to find the position of UAV u_{new} in the *Border Area*. If the performance is enhanced, the corresponding UAV set will be updated, otherwise u_{new} will not be added. Then, the UAVs in the *Border Area* are influenced by the users at the edge of the other sub-areas, and hence re-adjust their positions in the new combined block in an autonomous manner.



(a) Two Close UAVs (b) The Removal of One of the Two UAVs

Fig. 7. Another sample illustration of the merging process.

TABLE I
PARAMETER CONFIGURATIONS

Parameter	Value	Description
A	10000*10000	Simulation Area
M	1200-2000	Number of Users
X	200	Maximum Number of Users Handled by one UAV
R_{max}	2000 m [17]	Maximum Radio Range of an UAV
h_{min}	2100 m [17]	Minimum Altitude of an UAV
N_0	-173dBm/Hz	Noise
α	4	Path Loss Exponent
C	9.6 [17]	Environment dependent Constant
D	0.28 [17]	Environment dependent Constant
η	100 [17]	An Additional Attenuation Factor due to the NLOS Signal
f_c	2GHz	Carrier Frequency
W_{BS}	100 MHz	BS Bandwidth
P_{BS}	43 dBm	BS Transmit Power
W_{UAV}	20 MHz	UAV Bandwidth
P_{UAV}	23 dBm	UAV Transmit Power

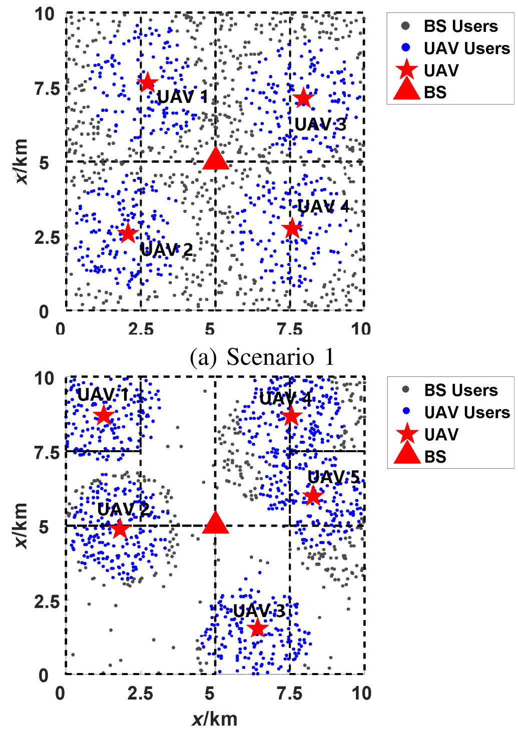
3) Both Block A and Block B have at least one UAV: This case is more complicated, and more actions, e.g., addition and removal, need to be considered. There are three possible sub-cases of this case, which are described as follows. First, if there are two UAVs extremely close within the *Border Area*, i.e., the distance between them is less than R_{max}, as illustrated in Fig. 7(a), we might consider whether we can remove one of them for saving economic cost. The initial position of the other UAV is within the shadowed rectangular area shown in Fig. 7(a). This action is accepted if and only if the resultant value of the *Utility Function* increases by this. Second, new UAVs are considered to be assigned within the *Border Area*, which is similar to the first case. Thirdly, the positions of the UAVs adjust according to the change of user availability in the new block, which is explained in the second case.

V. Performance Evaluation

In this section, we conduct field experiments to validate the feasibility of EMech and simulations to verify the performance of SIDE by comparing it with other two works [9], [12] in terms of *overall rate, the number of covered users, total energy consumption* and *the value of the Utility Function*.

A. Evaluation Setup

We first conduct a field-level experiment to verify the feasibility of EMech. As shown in Fig.13, our testbed consists of three Android devices and an access point (AP). The positions of three devices form an isosceles right triangle. We compare the position of the AP calculated via EMech with that by the method in [12].



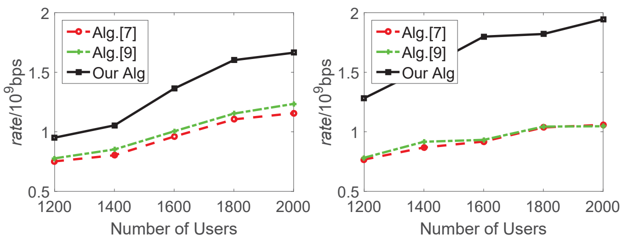
(b) Scenario 2

Fig. 8. The locations of UAVs in different scenarios: a) evenly distributed topology b) cluster based topology.

Then, extensive simulations are conducted to validate the performance of SIDE. The demand area is of 10000×10000 m^2, and different number of users ranging from 1200 to 2000 are non-uniformly distributed in this area. As shown in Fig. 8, user topology is categorized into evenly distributed (Scenario 1) and cluster based (Scenario 2) scenarios. We assume that SIDE operates in urban environments, and thus we choose the values of the environment dependent attenuation constrants C, D and η [17] accordingly. Moreover, when it comes to the value of economic cost ζ of an UAV, it depends on the intention of the operator. If the service operator wants to maximize the overall throughput, the value of ζ can be set to a lower value. On the other hand, if the service operator wants to reduce the infrastructure related deployment cost, a higher value of ζ is beneficial. In the simulation, we set the value of ζ to 3×10^7. The detailed simulation parameters are given in Table I. All our approaches are implemented using Python language and all the simulations are conducted on an Ubuntu 16.04.1 Linux System with Intel(R) Xeon(R) CPUE5-2620 v3 (2.40 GHz) and 32 GB main memory. In the following, each data point is the average of 10000 random runs.

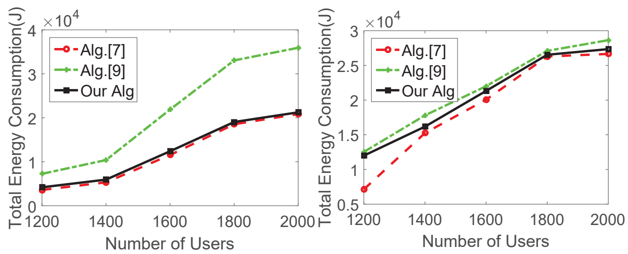
B. Experimental Results

In Fig. 13, we show the positions of the AP obtained by EMech and the method in [12] by red and black dots, respectively. In this setup, we let a person stand nearby device 1. We observe that if we put the AP at the centroid of the users



(a) Scenario 1 (b) Scenario 2

Fig. 9. The achievable rate with the varying number of users.



(a) Scenario 1 (b) Scenario 2

Fig. 11. Total energy consumption with the varying number of users.

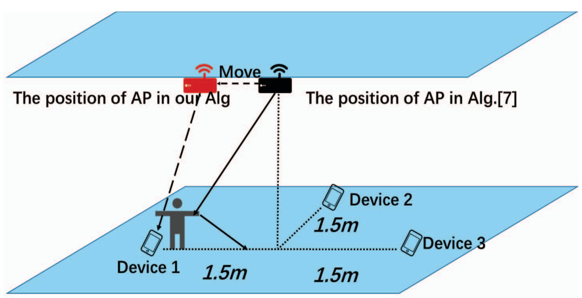
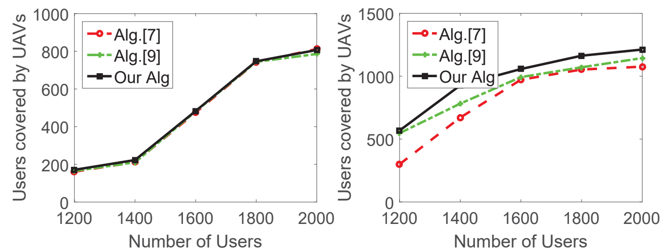
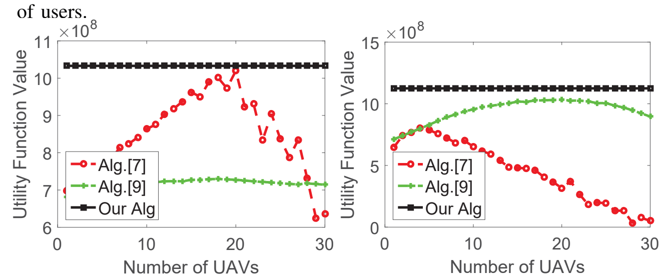


Fig. 13. A sample experiment scenario for validating the feasibility of EMech.



(a) Scenario 1 (b) Scenario 2

Fig. 10. The number of covered users by the UAVs with the varying number of users.



(a) Scenario 1 (b) Scenario 2

Fig. 12. The value of the *Utility Function* with the varying number of users.

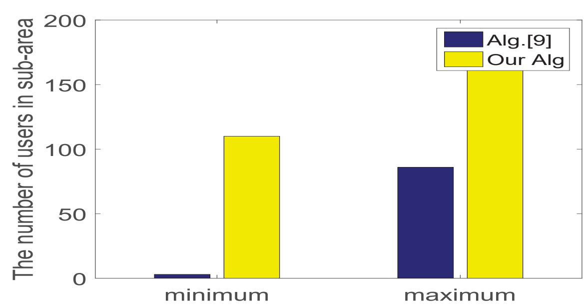


Fig. 14. A sample example of maximum and minimum number of users in each sub-area.

as proposed in [12], the standby person blocks the signals, and hence the received signal power of device 1 results in -47 dBm. However, if we move the AP to the position calculated by EMech, the received power of device 1 increases to -38 dBm. Although the received power of device 2 and device 3 both decrease to -34 dBm from -30 dBm, the overall performance is enhanced by our EMech technique.

C. Performance Comparison

1) Performance of KDivision: For $M = 1200$ in the system, Fig. 14 shows that the maximum and minimum number of users in a sample sub-area is 86 and 3 by the splitting strategy in [9], respectively, and 190 and 110 via the KDivision method, respectively. We observe that the number of users in each sub-area achieved by the KDivision method is approximated by the capacity of the designated UAV, particularly in Scenario 2. On the other hand, the authors in [9] partitioned the demand area into a set of small fixed-sized areas without considering user distributions. However, via the KDivision method, the size of each sub-area is flexible and is determined in accordance with the user densities in order to make sure that the resultant number of users in all sub-areas are roughly the same.

2) The Locations of UAVs: As an illustrative example, Fig. 8 shows the locations of the TBS and UAVs as well as the coverage partitions obtained after applying SIDE. The TBS is presented by the red triangle and the positions of the UAVs are denoted by five-pointed stars. Indicated by black dots, the users are served by the TBS directly while those governed by the UAVs are marked by blue color. In Fig.8(a), the positions of the UAVs are $(2.719, 7.639)$, $(2.065, 2.57)$, $(7.565, 2.731)$ and $(7.955, 7.127)$. On the other hand, in Fig. 8(b), the coordinates of the five UAVs are $(1.281, 8.869)$, $(1.802, 4.871)$, $(6.422, 1.552)$, $(7.556, 8.681)$ and $(8.284, 5.993)$. We observe that the UAVs tend to cover those users who are far away from the TBS as those users might suffer worse link quality in both the scenarios, which could achieve more distinguishable performance.

3) Effect of Global Rate $R_w(K)$: SIDE outperforms the algorithm in [12] and [9] by 37.7% *and* 31.1% *in Scenario* 1*, respectively, and by* 79.7% *and* 77.8% *in Scenario* 2*, respectively.* In Fig. 9, the increment of global rate with the increasing number of users is a natrual trend. Basically, the approach proposed in [12] first clustered the IoT devices and then deployed the UAVs at the center of the formed clusters, which is the main reason of such serious performance degradation. Via this approach, the resultant number of users covered by each UAV is so uneven that the UAV resources are not properly utilized. Besides, it only considers the distance between a user and an UAV, which may not be realistic since the attenuation of a signal is not simply determined by the distance but also influenced by multi-path propagation, referred to as shadowing from obstacles.

4) Effect of the total number of users covered by the UAVs: SIDE outperforms the algorithm in [12] and [9] by 9.8% and 17.5% in Scenario 2, respectively. Fig. 10(a) shows that the difference of covered users in Scenario 1 is not so obvious compared with other two approaches due to the evenly distributed user topology. Whereas, in Fig.10(b), we observe that more users are covered by the UAVs in SIDE. The reason is that the authors in [12] proposed a constrained K-means algorithm to cluster the IoT devices while ignoring the constraint on the cluster size, which leads to the highly uneven number of users among the resultant clusters. On the other hand, in [9], while partitioning the demand area, they are concerned about the physical size of each sub-area rather than the number of users in that sub-area. Moreover, they assume that each sub-area acts independently and each high demand sub-area can be mapped to one UAV. Therefore, since the number of users covered by the UAVs is uneven in both approaches, the UAV capacity is not fully utilized. In contrast, via SIDE, each sub-area contains roughly the same number of users and the RMerge technique is exploited to break the boundary of the sub-areas to cover more users.

5) Effect of the number of users covered by each UAV: In Fig. 15, we show that the number of users covered by each UAV via our method is more even compared to that calculated by [12] and [9]. Therefore, the exploitation of UAV resources achieved by SIDE is much higher than other two approaches. The algorithm in [9] divides the traditional hexagonal cell into a set of small regular independent areas, and the UAVs are mapped to these areas. On the other hand, the algorithm in [12] clusters the IoT devices and an UAV is placed at the centroid of each cluster. Consequently, the number of users covered by each UAV depends on the number of users in each area or the cluster size, which results in the uneven number of users covered by each UAV. As a result, the UAV resources are not fully utilized by this approach.

6) Effect of Energy Consumption: The total energy consumption achieved by SIDE has close performance to that of [12] which aims to minimize the energy consumption. In order to compare the power consumption via SIDE with the work in [12], we calculate the consumed power of the UAVs using Eq. 4 of [12] for making sure that the rate of the farthest user covered by each UAV satisfies the threshold. Although the algorithm in [12] has lower energy consumption, they have worse overall performance as shown in the previous results. This method incurs the lowest energy consumption since it minimizes the distance between the users and an UAV in order to reduce the attenuation of signal. Whereas, to exploit environmental diversity of real scenarios, our scheme consider the overall SINR and traffic demand of the users, and consequently achieves slightly higher energy consumption compared to that in [12].

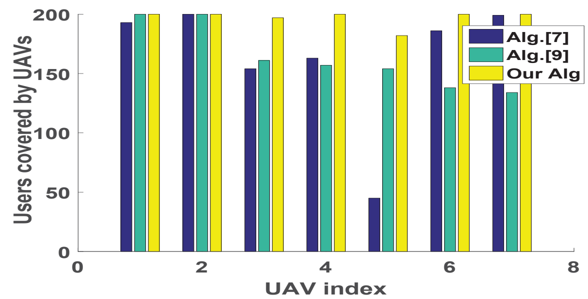


Fig. 15. The number of users covered by each UAV (Scenario 2).

7) Effect of the Utility Function: The number of assigned UAVs K achieved by SIDE strikes a balance between the maximization of performance and the minimization of overall cost. Fig. 12 depicts the changing value of the *Utility Function* with the increasing value of K when the number of users is 1200. We observe that the value of the *Utility Function* increases first as the number of assigned UAVs increases. However, after reaching the highest point, we see a sharp decreasing trend due to the imbalance between the performance and the economic cost. Therefore, we introduce the concept of *Utility Function* to strike a balance amid the UAV deployment cost and network performance to find the optimal number of deployed UAVs K instead of deploying a fixed number of UAVs.

VI. Related Work

Numerous approaches have been proposed to solve the deployment of UAVs in difference scenarios. We primarily categorize the UAV placement works in terms of the number of UAVs: i) *single UAV* and ii) *multiple UAVs*

Single UAV: Dhekne et al. [6] is the first one to adopt the ray tracing technology for finding the possible positions of one UAV. Mozzafari et al. [7] studied the optimal altitude for one UAV in order to maximize the coverage. The works in [8], [21] proposed a theoretical method to position one UAV over a wireless ad hoc network as a relay to enhance the performance. Lyn et al. [22] maximized the minimum throughput of all mobile terminals by jointly optimizing the trajectory of the UAVs, bandwidth allocation and user partitioning.

Multiple UAVs: There are mainly two kinds of methods for the deployment problem of multiple UAVs: i) *partition* and ii) *cluster*. For the first one, Sharma et al. [9]–[11] proposed a partitioning scheme that divides the traditional hexagonal cell into a set of independent standard areas, and map UAVs to the desired areas. They introduces several methods to map the UAVs, such as the method based on the priority dominance and entropy concept and the neural-based cost function approach. They not only consider the overall throughput of the system, but also the delay and coverage. However, the limitation is that UAVs are just assigned to specific demand areas without paying much attention to their accurate positions. For the second one, the work [12], [13] introduced an K-means based algorithm to cluster the users and then put each UAV at the centroid of each cluster. The limitation is that they ignored the constraint on cluster size, which leads to the highly uneven number of users among the resultant clusters. Since the number of users covered by the UAVs is uneven, the UAV capacity is not fully utilized via this approach.

VII. Conclusion

We proposed a semi-distributed system, named SIDE, for the self-deployment of UAVs to offload data traffic of a cellular network in emergency situations. The key insight of SIDE is to envision the UAV deployment problem as a mechanical equilibrium problem, termed EMech, which enables the UAVs to self-adapt their positions according to user attraction (e.g., SINR and traffic demend) within their transmission range. It is suitable not only for the static user topology but also for the variation of dynamic user topology. In order to facilitate EMech, we proposed a fine-grained area splitting scheme, KDivision, which partitions the demand area into sub-areas in accordance with the user density while considering the full utilization of UAV resources. Moreover, a novel area merging technique, RMerge, was exploited to combine the resultant sub-solutions for obtaining a complete solution that strikes a balance between the throughput maximization and cost minimization aspects of the problem. Numerical results showed that our splitting scheme KDivision can partition the high demand area in a more flexible manner and more users can be covered by the deployed UAVs. Furthermore, we showed that the proposed approach significantly improves the network throughput while saving the infrastructure cost and consuming almost the same energy level compared to the state-of-the-art solutions. We hope that this paper will lead to a new practical way to address the hotspot issue.

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