Aerial Base Station Placement: A Gentle Introduction
Pham Q. Viet and Daniel Romero

Abstract—The deployment of Aerial Base Stations (ABSs) mounted on board Unmanned Aerial Vehicles (UAVs) is emerging as a promising technology to provide connectivity in areas where terrestrial infrastructure is insufficient or absent. This may occur for example in remote areas, large events, emergency situations, or areas affected by a natural disaster such as a wildfire or a tsunami. To successfully materialize this goal, it is required that ABSs are placed at locations in 3D space that ensure a high Quality of Service (QoS) to the ground terminals. This paper provides a tutorial introduction to this ABS placement problem where the fundamental challenges and trade-offs are first investigated by means of a toy application example. Next, the different approaches in the literature to address the aforementioned challenges in both 2D or 3D space will be introduced and a discussion on adaptive placement will be provided. The paper is concluded by discussing future research directions.

I. INTRODUCTION

The rapid development of the technology of unmanned aerial vehicles (UAVs) has spawned a myriad of use cases in wireless communications. One of the most prominent application scenarios involves mounting base stations on board UAVs to provide connectivity in areas where it is insufficient or absent. For example, such Aerial Base Stations (ABSs) can be deployed to provide connectivity to ground terminals (GTs) in remote areas with no cellular infrastructure or in mass events, such as concerts or festivals, where the terrestrial infrastructure is overwhelmed by an unusually large traffic demand. Another use case involves restoring coverage after the ground base stations are damaged because of e.g. a terrorist attack or a natural disaster, such as a flood or a large fire.

Thanks to their high mobility and swift deployment capabilities, ABSs are especially useful in these and, in general, other emergency situations, such as traffic accidents or wildfires.

The fundamental research problem that arises in this context is to determine where a collection of ABSs need to be placed in order to serve the GTs effectively. This problem is referred to as ABS placement and has been receiving exponentially growing attention in the last two years. There are three main challenges that complicate this problem. First, the suitability of a location to deploy an ABS depends mainly on the quality of the channel to the targeted GTs, but this channel is unknown. Second, due to the nature of the propagation of radio waves, the positions between two suitable positions need not be suitable. In other words, typical performance metrics are non-convex functions of the positions of the ABSs, which results in non-convex NP-hard placement problems. Finally, placement algorithms need to adapt to dynamic environments characterized by moving GTs and changes in operational conditions such as the number of available ABSs.

This article provides a tutorial introduction to ABS placement. After building up intuition through a toy application example, the main existing approaches will be described. Finally, a brief discussion of future directions is presented.

II. UNDERSTANDING THE PROBLEM

This section investigates the fundamental challenges and trade-offs involved in the problem of ABS placement. To this end, the main elements of this problem are condensed into a simple toy example of ABS placement in a single dimension.

Suppose that, due to a traffic accident or a bridge collapse, 10 vehicles lie static on a remote straight road segment of 1000m without cellular communication connectivity. An ABS is sent to
that region to provide connectivity to these GTs. The problem is to determine the best location for the ABS in terms of a given quality of service (QoS) metric, such as the sum rate.

Fig. 1 depicts the sum rate vs. the horizontal position of the ABS placed above the road for different heights assuming additive white Gaussian noise (AWGN) channels between the ABS and GTs with free space propagation and isotropic antennas. The first observation is that the sum rate is a rather irregular function of the horizontal position of the ABS with multiple local maxima. This effect is especially manifest for low heights (e.g. 20 m) since the distances between the ABS and each GT are markedly different. However, when the ABS is placed at a sufficiently large height (e.g. at 120 m), these distances resemble each other to a greater extent and therefore the sum rate function becomes flatter.

The second observation is that the sum rate tends to be larger when the ABS is placed on top of a cluster of GTs that lie near each other, as we can observe on the right side of Fig. 1. As discussed in the next section, when multiple ABSs need to be deployed, this idea suggests approaches where the GTs are grouped into clusters and each ABS is placed above the centroid of each cluster.

Fig. 1 also shows the min rate as a function of the horizontal position of the ABS for multiple heights. These curves reveal that, although e.g. for a height of 20 m the position that yields the largest sum rate would result in an average rate of around 350 Mbps/10 GTs = 35 Mbps per GT, some GTs only receive around 2 Mbps. This suggests that the sum rate is not a satisfactory QoS metric when it comes to promoting fairness across GTs, as it may be necessary in certain applications where a minimum rate needs to be guaranteed. In these cases, it may be preferable to adopt the min rate as QoS metric. As per Fig. 1, the min rate is a much better behaved function than the sum rate and features a single local maximum. Furthermore, the min rate is seen to be quasi-concave, which simplifies considerably its maximization. Besides, it can be shown that the min rate to the left (respectively right) of its maximum equals the rate of the right-most (left-most) GT. This means that the maximum is attained where both of these rates coincide. In this case, the optimal horizontal position of the ABS is the middle point between the left-most and right-most GTs. More generally, the min rate is maximized when the distance between the ABS and the farthest GT is minimized.

To investigate how to set the ABS altitude, Fig. 2 depicts the aforementioned QoS metrics vs. the height, where the horizontal position of the ABS is the one that maximizes the sum rate in Fig. 1 when the height is 20 m. It is observed that the sum and min rates are decreasing functions of the height and, therefore, maximized when the height of the ABS equals 0, i.e. the ABS is on the ground. To
understand why this is the case, one can resort to the Pythagorean theorem, which states that the distance between the ABS and a GT equals the square root of the square of the height of the ABS plus the square of the difference between the horizontal positions of the ABS and GT. The distance is therefore an increasing function of the height. Thus, when the height increases, the distance increases, the channel gain decreases and, therefore, the capacity decreases. This seemingly counter-intuitive fact is due to the assumption of free-space propagation. In practice, a low ABS altitude means that the link between the ABS and a GT will likely be obstructed by an object such as a vehicle or a tree. As the height increases, the probability of line of sight (LoS) increases. This gives rise to a trade-off in setting the altitude of the ABSs: increasing the altitude increases the probability of LoS but also the distance between the ABS and GTs. This implies that there exists an optimal altitude, as further discussed later.

After having investigated the fundamental phenomena occurring in ABS placement by means of this toy example, the rest of this article will delve into approaches for placing multiple ABSs in different kinds of channels.

III. Placement at a Fixed Altitude

As indicated in the previous section, assuming that propagation takes place in free space regardless of the ABS altitude implies that the optimal altitude is 0. There are two main ways of dealing with such an artifact: One is not to assume free space propagation, as explored in the next section. The other is to fix the altitude to a sufficiently large value in such a way that the free-space assumption approximately holds.

In this context, a large number of schemes have been proposed to set the 2D position of multiple ABSs in a horizontal plane with a given height.

A. Clustering-based Placement

As discussed in the previous section, the sum rate tends to be high when the ABS is above a cluster of closely-located GTs. This suggests approaches for multiple-ABS placement where the GTs are grouped into clusters and an ABS is deployed above each one. Each ABS therefore serves the GTs in its cluster.

![Fig. 3: An application of K-means in ABS placement to group 100 GTs into 7 clusters seen from above. Colored markers denote GTs. Black dots represents centroids where ABSs are placed.](image)

Given that the channel capacity is a decreasing function of the distance, it makes sense that the clustering procedure is performed in such a way that the GTs lie as close as possible to the assigned ABS. Fig. 3 illustrates an example of placement in 2D where this clustering task is solved using the well-known K-means algorithm. This algorithm groups the GTs into clusters and produces a centroid for each cluster. An ABS needs to be deployed above each cluster at the prescribed altitude.

B. Circle-based Placement

With K-means, the number of ABSs is given and the (sum of the squared) distances from the ABSs to the GTs minimized. Thus, this algorithm cannot guarantee a maximum distance between a GT and the nearest ABS. In practice, this means that a fraction of the GTs may be too far from their corresponding ABS to attain a certain minimum rate. However, as indicated earlier, a minimum GT rate needs to be guaranteed in certain applications. This calls for approaches that seek the minimum number of ABSs required to ensure that all GTs receive at least a given rate. Since in free-space conditions guaranteeing a minimum rate amounts to ensuring a maximum distance, this gives rise to a formulation that is complementary to clustering-based placement: instead of minimizing the distances between GTs and their nearest ABSs for
a given number of ABSs, the problem is now to minimize the number of ABSs given a maximum distance between GTs and the nearest ABS.

Since the rate decreases radially with distance, the set of points that receive the minimum rate from a given ABS forms a sphere centered at the ABS. The coverage area on the ground is therefore the intersection between a horizontal plane and this sphere, which defines a circle on the ground whose center is the projection of the ABS on the ground. The ABS placement problem becomes in this way a geometric problem, named the geometric disc cover problem, where one needs to minimize the number of circles of a certain radius necessary to cover a set of points, in this case the GT locations. Since this problem is NP-hard, a number of heuristics have been proposed in the literature. For example, in [3], the ABSs are placed sequentially following an inward spiral around the uncovered GTs. Specifically, at each step, the convex hull of the locations of the uncovered GTs is obtained and an ABS is placed on the boundary to maximize the number of GTs inside its coverage circle. Afterwards, the newly covered GTs are marked as covered and the process repeated.

Another heuristic is proposed in [4] based on a sparse-recovery optimization approach. The idea is to assign a virtual ABS to each GT and then optimize over the locations of these virtual ABSs such that (i) they lie at most within the given maximum distance from the assigned GT and (ii) the number of different locations of the virtual ABSs is minimized. Once the optimization is completed, an actual ABS is deployed for each distinct location of the virtual ABSs. Thus, by enforcing that many of the virtual ABS locations coincide, one effectively minimizes the number of actual ABSs. The main limitation of this scheme is that the complexity of the optimization algorithm scales with the sixth power of the number of GTs and, therefore, it is only suitable for a small number of GTs.

Besides the assumption of free-space propagation, which may not be realistic in certain scenarios, one of the main limitations of circle-based approaches is that they disregard interference between nearby ABSs.

C. Virtual Force-based Placement

As stated earlier, the ABSs need to be as close as possible to their served GTs. However, in case that the ABSs share spectral resources, this may give rise to a large inter-ABS interference. For this reason, the distance between ABSs should be kept sufficiently high. One approach for balancing these two goals, namely attaining a low distance between ABSs and GTs but a large distance between ABSs, is by means of virtual forces [5]. Particularly, one can consider an attractive force for each (ABS,GT) pair and a repulsive force between each (ABS,ABS) pair. Specifically, for each (ABS,GT) pair, the attractive force acts on the ABS in the direction towards the GT, whereas for each (ABS,ABS) pair, the repulsive force acts on both ABSs in the direction away from each other. Each ABS computes the sum of the virtual forces that act on it and moves in its direction. In this way, the ABSs tend to spread across space and, at the same time, move to hotspots with a high number of GTs.

The strengths of the approach based on virtual forces in [5] are low complexity and adaptability to changes in the operational environment.

IV. 3D ABS PLACEMENT

Relative to the schemes in the previous section, it is clear that an improved QoS can be attained if the ABS altitude is also optimized. As concluded earlier from the toy example, this requires lifting the free-space propagation assumption. Each of the ensuing subsections outlines a different possibility towards this end.

A. Channel-agnostic Placement

Instead of adopting any assumptions on the channel, one can think of relying on measurements. A simple possibility is that each GT measures the channel to each ABS and associates with the one whose channel is strongest. In this way, a large number of GTs will be associated with those ABSs at locations with favorable propagation conditions. This information can be used to determine at which locations one needs to deploy a larger number of ABSs.

The main strength of such an approach is that ABSs need not know the locations of or distances to the GTs. A detailed knowledge of the channel
is not required either: it suffices to know which is the strongest one, which can be known by the GTs based on the received signal strength (RSS) of beacon signals transmitted by the ABSs. Therefore, this scheme features a low communication overhead between ABSs and GTs.

An example of channel-agnostic placement can be found in [6]. The scheme therein introduces several classes of virtual forces to set the 3D positions of the ABSs. Some of these forces are repulsive and aim at spreading the ABSs across space. Others are attractive and bring together ABSs that have a different number of associated GTs. The altitude is set by another virtual force that aims at decreasing the coverage area of overloaded ABSs by increasing their height. The obvious drawback of such an approach is that the channel to the rest of GTs will generally worsen.

The main limitation of channel-agnostic placement is that it cannot know whether a spatial arrangement of ABSs is satisfactory beforehand, i.e., before the ABSs actually occupy those locations, which is clearly inconvenient if one wishes to find a close-to-optimal placement. Besides, there may be locations with very favorable propagation conditions that are never discovered by the system because no ABS ever visits them. Moreover, by relying solely on the number of associated GTs with each ABS, it is expected that the resulting placement arrangements yield lower performance than if more detailed information were used, such as channel state information or location information.

B. Altitude Optimization via Empirical Models

As indicated earlier, channel-agnostic schemes cannot determine how favorable a candidate ABS location is unless an ABS actually visits that location and the channels to the GTs are measured. A natural approach to alleviate this limitation is to rely on a model that provides the channel quality given the locations of the ABSs and GTs. However, as discussed previously, such a model should not assume free-space propagation.

The most widely used model is the one in [1], which captures the phenomenon described earlier that the probability of LoS increases with elevation. Specifically, this empirical model classifies links between a GT and an ABS into one out of two categories, depending on the magnitude of the excess path loss relative to the free-space path loss, namely LoS (or near-LoS) and non-LoS. The path loss is then modeled as a Gaussian distribution whose parameters depend on the elevation of the link, the link category, and characteristic parameters of the environment (e.g. urban or rural). The values of these characteristic parameters could be found by fitting a set of measurements. In [1], reference values are provided by fitting simulated data in four scenarios that adhere to the guidelines of the International Telecommunication Union (ITU-R).

The model also provides the probability of LoS as a function of the elevation of the link. Similarly, the parameters of this function are also fitted to the data. Knowing the probability of each category as well as the distribution of the path loss under each of them allows the computation of the mean path loss.

A large number of works rely on this empirical model. The typical approach involves formulating an optimization problem that aims at optimizing a certain QoS metric subject to communication constraints where the optimization variables are the locations of the ABSs. The positions are related to the necessary communication metrics, such as capacity, by approximating the path loss between a GT and an ABS as the mean path loss given by the aforementioned model. The difficulty is that, given the form of the model, the resulting optimization programs are non-convex. This has motivated global optimization approaches such as the one in [7], which relies on particle swarm optimization. Here, the problem is to minimize the number of ABSs to ensure a minimum average spectral efficiency. Similarly, genetic algorithms are applied in [8], [9]. Another example is [10], which provides an ad hoc algorithm where the height is optimized using a game-theoretic approach. The objective is to maximize the sum rate under different constraints such as the requirement of minimum spectral efficiency of each associated GT.

C. Placement Using Terrain Maps

The approaches considered in the previous section rely on empirical models of the mean of the path loss across a class of scenarios, e.g. generic
Fig. 4: Example of ABS placement in an urban environment. Markers on the ground denote GTs whereas orange circles stand for ABS positions. Black dots in the air represent a fly grid; cf. section on radio maps.

urban environments. However, the actual value of the path loss may greatly differ from its mean value, which suggests that schemes based on such empirical models may yield highly sub-optimal placements in a specific environment. One possible approach to accommodate information about the path loss in a specific propagation environment is to rely on terrain maps or 3D city models; see Fig. 4. Techniques such as ray tracing can be then used to predict the actual path loss between the GTs and positions that no ABS has necessarily ever visited. A related approach is pursued in [11], where a 3D city map is used to construct a set of cones in such a way that if a GT is in the cone associated with an ABS location and vice versa, then they can communicate with LoS. An optimization problem is then formulated and the solution approximated with a greedy algorithm. Another possibility could be to attempt a 3D extension of [12], where a deep reinforcement learning technique is applied to maximize the number of covered GTs using path loss predictions based on a 3D city map.

Clearly, the fact that 3D models or terrain maps enable predictions of the channel from the GTs to each spatial location without visiting it with an ABS constitutes an important advantage over the channel-agnostic approach alluded to previously. This is vitally important to decrease the time required by placement algorithms.

Unfortunately, terrain maps or 3D models are seldom available and, even when they are, their resolution is typically insufficient for predicting the channel in conventional bands. To see this, note that a typical resolution for a terrain map is 20 m [11]. This is much larger than the scale of channel variations, usually in the order of the wavelength, which typically ranges from a few millimeters to a few centimeters. Besides, approaches based on this kind of maps cannot accommodate the case where a user is inside a building.

D. Placement Using Radio Maps

Terrain maps and 3D models provide the positions and shapes of obstacles in the propagation environment. Therefore, they provide the path loss in an indirect fashion. This observation suggests that it can be beneficial to directly map path loss. Specifically, one can utilize radio maps that provide the shadowing attenuation between all possible ABS locations and the GTs. As an important advantage relative to city maps, radio maps provide channel information about the environment even when GTs lie inside buildings.

Radio maps are typically based on the so-called radio tomographic model, which prescribes that the attenuation between two points equals the line integral of a function of the spatial location termed spatial loss field (SLF), which quantifies how much a radio signal attenuates at each location. By gathering measurements at a collection of pairs of points, one can estimate the SLF and then use it to predict attenuation between any pair of points.

To be able to manipulate this line integral, the SLF needs to be approximated by a piecewise constant function, meaning that only its values at a set of voxels are stored. To obtain the line integral, one needs to determine which voxels the line segment between the ABS and a GT traverses and take a linear combination of the values of the SLF at those voxels. An illustration in 2D is shown in Fig. 5.

Radio maps have been used for 3D ABS placement in [13]. In this work, the set of all possible ABS locations is discretized into a grid and the path loss from each GT to each grid point is obtained by means of a radio map. The placement problem is then formulated as finding the smallest number of ABSs required to serve all GTs. One of the main strengths is that the resulting optimization
VoxelCentroid

Fig. 5: In the tomographic model, the attenuation between two points is a function of the line integral of the SLF.

Fig. 6: Comparison of a representative subset of placement algorithms.

The problem is convex and its solution entails just linear complexity. Besides, this scheme can take into account no-fly zones or airspace occupied by buildings, unlike the vast majority of placement algorithms in the literature. The limitation of this kind of schemes is that the construction of a high-resolution radio map could be challenging if a fine discretization of the 3D space is required.

To close this section, a representative subset of the algorithms discussed so far are compared in Fig. 6, namely the algorithms by Huang et al. [4], Galkin et al. [2], Lyu et al. [3], Hammouti et al. [10], and Romero et al. [13]. The simulation takes place in an urban environment such as the one in Fig. 4. It can be seen that using radio maps yields a clear advantage over schemes which adopt other assumptions about the channel.

V. ADAPTIVE PLACEMENT

The approaches introduced so far cannot naturally cope with changes in the positions of the ABSs and GTs over time. This motivates schemes where the ABSs can adapt their positions to changes either in the GT locations or in the working conditions. For example, if an ABS becomes inoperative, e.g. because it runs out of battery, the remaining ABSs need to adapt their positions accordingly.

One simple approach inspired by [14] could rely on simple ad-hoc adaptive algorithms. For the sake of illustration, consider a 1D setup with a single ABS that has a right and a left sector, each one with an antenna that points in either direction. Each GT connects to the sector from which it receives the highest power. The ABS can then move right if more GTs are connected to the right sector and vice versa. This idea could also be extended to placement in 2D by using at least 3 sectors. One of the main strengths of such an approach would be that no knowledge of the channel or GT positions would be necessary. However, applying such an idea to multiple ABSs and studying the convergence properties remains an open problem.

These difficulties can be sidestepped by resorting to the framework of stochastic optimization. Specifically, adaptive placement for multiple ABSs in 2D space is studied in [15]. There, multiple ABSs adapt their locations by moving in the direction of a gradient estimate of a suitably designed utility function. The movement of the users leads to a change in this function but these changes can be naturally tracked by the stochastic optimization algorithm. The main strength of such an approach is that ABSs need not communicate with each other or with any central controller: the scheme is decentralized and non-cooperative. The downside is that the location of the GTs and a channel model are required.

Finally, more sophisticated approaches could be developed based on reinforcement learning, e.g. along the lines of [9]. The main challenge with such approaches is to avoid the need for retraining every time the operational conditions, such as the environment or number of ABSs, change.

VI. CONCLUSIONS AND OPEN PROBLEMS

This article provided a tutorial introduction to ABS placement in UAV-assisted networks. First, a toy example shed light on the fundamental phenomena occurring in this problem. It was observed
that common QoS metrics may have multiple local optima and that the optimal altitude under the free-space propagation assumption is 0. Next, different approaches for 2D and 3D placement were presented according to how they deal with the channel and adaptive implementations briefly discussed.

Although ABS placement has been subject to extensive research efforts, a number of open problems still remain. First, most algorithms are non-adaptive. This implies that small changes in the operational conditions or GT locations may result in large changes in the ABS locations or even the number of ABSs. This calls for adaptive alternatives which can furthermore account for the physical constraints on the movement of the UAVs. Likewise, little attention has been paid on the fact that the operational time of ABSs is finite due to the limited capacity of their batteries or energy sources. To alleviate this limitation, schemes for fixed-wing UAVs would be desired.

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