An Aerial Base Station Assignment Algorithm for 5G Networks

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Abstract. *Due to network capacity and coverage demands of existing 5G and Beyond 5G networks, Aerial Base Stations (ABS) based on Unmanned Aerial Vehicles (UAV) have been highlighted as a key strategy to expand terrestrial networks and assist mobile users. Nevertheless, ABS based on UAV (UAV-BS) are resource-constrained compared to terrestrial base stations, implying that resource management procedures are required to ensure efficient UAV-BS operation. In this respect, this work proposes a clustering-based user assignment solution for users to UAV-based ABS, employing a reallocation approach to avoid connection denial and evaluate the average number of allocated users and throughput.*

1. Introduction

Aerial Base Stations (ABS) using Unmanned Aerial Vehicles (UAVs) are an important solution for increasing the capacity and coverage of 5G and Beyond 5G networks. They help meet the growing need for mobile data and applications, especially during events like sports games and concerts. ABS can also provide communication during disasters or emergencies. Additionally, ABS can create line-of-sight (LOS) connections, improving the Quality of Service (QoS) for users on the ground [Kimura and Ogura 2021]. This helps solve the problem of limited coverage from traditional base stations. However, deploying UAV-based ABS comes with challenges. These UAVs have fewer resources than regular base stations, meaning they cover smaller areas and have shorter battery life. Therefore, more UAVs are needed to serve the same area, which requires careful energy management. Moreover, the flexibility and mobility of UAVs make it challenging to assign users to them. This assignment must change continuously based on user movements, demand, and environmental factors [Cheng et al. 2019]. Multiple approaches have been studied for user-to-UAV-based ABS (Aerial Base Station) assignments. For instance, in [Ozturk et al. 2020], the authors rank available UAVs based on their received Signal to Interference plus Noise Ratio (SINR) to select the best one. The work in [Mirzaeinia et al. 2020] focuses on UAV placement by considering user positions and required traffic through a weighted K-means clustering method. Additionally, [Kalantari et al. 2017] proposes a particle swarm optimization algorithm for user association and bandwidth allocation, while [Silva and Cardoso 2023] presents a UAV allocation strategy to improve connectivity for dynamically distributed users. However, these studies often overlook scenarios where users rejected by one UAV-BS can be redirected to others. Clustering techniques have also been employed in terrestrial BS environments, such as in [Zaw et al. 2017], which formulates a joint user clustering and power allocation strategy for Non-Orthogonal Multiple Access (NOMA) in 5G systems, and [Bouras et al. 2021], which introduces a Machine Learning (ML)-based resource allocation mechanism. In contrast to terrestrial networks that consider priority levels and available resources, user association in UAV-ABS environments is complicated by factors like UAV movement and limited energy. This paper proposes a clustering-based solution for user-to-UAV ABS assignments, incorporating a reallocation approach to avoid connection denials. Our results show that our method successfully allocated 99.5% of users, compared to 90.0% for the baseline, while also achieving an average throughput of 4.68 Gbps versus 3.77 Gbps for the baseline.

2. Key Concepts

2.1. Non-Terrestrial Network (NTN)

Base stations are classified as Terrestrial Networks (TN), while aerial networks composed of satellites, UAVs, drones, etc., are called Non-Terrestrial Networks (NTN). They compose a 3-dimensional (3D) Network, providing connectivity and wireless services globally. Fig. 1 shows an overview of a 3D Network with three main aerial network layers: Low Altitude Platform (LAP), High Altitude Platform (HAP), and Low Earth Orbit (LEO). LAP includes drones, surveillance aircraft, and atmospheric balloons. On the other hand, HAP refers to high-altitude airplanes, and the LEO layer is commonly used for low-orbit satellites [Iqbal et al. 2023]. UAVs are often associated with the concept of MEC (Multi-Access Edge Computing), which is the ability to perform computation and storage close to the network's edge [Ei et al. 2022]. With MEC, UAVs in 5G networks can perform computational tasks locally at the network's edge, resulting in faster and more efficient response times. Besides computational resources, UAVs can provide radio resources to terrestrial User Equipments (UEs). Acting as flying base stations, they increase the connection quality between a network remote node and a given terrestrial cellular base station [Amponis et al. 2022].

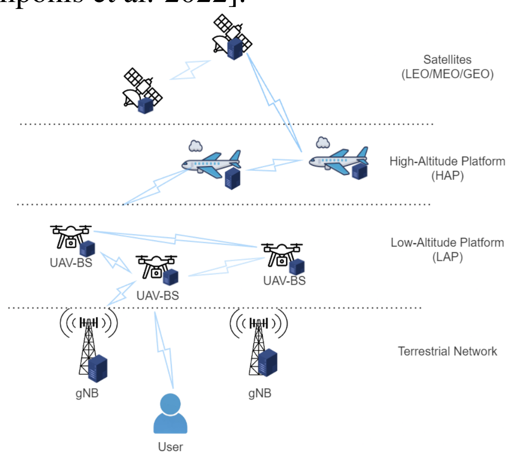

Figure 1. A 3-Dimensional-Network with a 3-layer NTN

2.2. K-Means

The clustering technique initially associates users with the nearest base station. Clustering is the process of grouping similar data into disjoint clusters. Among various clustering models, K-Means is a well-known clustering approach in which a number of clusters is predefined, and centroid points are randomly selected. Then, an iterative process begins associating each data point with its nearest centroid based on the Euclidean distance of all data elements. Upon completion of this step, the mean values for each cluster are evaluated, and a new centroid is determined. This process repeats until convergence is achieved [Unnati R. Raval 2016]. The motivation for using K-Means to assign proposed aerial base stations lies in the algorithm's efficiency in managing large data sets. This capability is essential in a scenario with a significant number of UEs in 5G mobile networks [Mirzaeinia et al. 2020]. By pre-defining the number of clusters corresponding to UAVs, K-Means allows for a quick and straightforward initialization, making it suitable for real-time applications where fast decision-making is required.

3. System Model

We consider a multi-UAV-based network comprising q UEs and n UAV-based ABS, denoted as UAV, placed in a given geographical area. At each time slot, UE i, with $i = (1, 2, ..., q)$, requests radio resources from UAV for downlink communication with data rate DR_i and its localization on the ground is given by a 2-dimensional coordinate (x_i, y_i). The UAV j, with $j = (1, 2, ..., n)$, manages R_j resource blocks, and it may assign R_i resource blocks (RBs) out of R_j RBs to the UE i according to the user's demand. The UAV j position is also given by (X_j, Y_j, Z_j) coordinates, which is fixed within the time slot (resource allocation). The system considers LoS communications and the free-space propagation model between UAVs and UEs.Thus, the path loss $P_{i,j}$ in dB of a UAV j communicating with a UE i by using a carrier frequency f in Hz is given by Eq. 1, where d is the Euclidian distance in meters between UAV j and UE i [Ozturk et al. 2020]. Also, g_t and g_r are transmission and reception gains, respectively.

$$P_{i,j} = 20 * log(d) + 20 * log(f) - 147.55 - g_t - g_r \tag{1}$$

Considering the UE i assigned to the UAV j requiring a data rate DR_i for communication, the minimal number of RBs to be allocated to the UE i by the UAV j to meet this demand is gotten by Eq. 2, where DR_{RB} is the data rate achieved using one RB, computed by Eq. 3, with B_{RB} denoting the RB bandwidth in Hz.

$$R_{i,j} = \left\lceil \frac{DR_i}{DR_{RB}} \right\rceil \leq R_j \tag{2}$$

$$DR_{RB} = B_{RB} * log_2(1 + SINR) \tag{3}$$

The Algorithm 1 shows how the proposed solution performs the UE-UAV assignment. UAVs correspond to centroids and UE to elements in the clustering context. Each UE requests resources from its cluster centroid (UAV). If it is rejected, the UE requests resources from the nearest UAV with available resources. The algorithm takes the following input parameters: the number of UAVs (n_uav), the number of UEs (n_ue), the carrier frequency (f), the RB bandwidth (B_{RB}), the available RBs for each UAV (R_j), the $SINR$ ($sinr$), and the user data rate requirement (DR_i). The K-means model is applied to group users into clusters according to the UE's location, see Fig. 2. Next, the path loss

Algorithm 1 Coverage and Resource Based User Allocation

input : n_uav, n_ue, h_uav, $sinr$, $range\_dr$, f, B_{RB}, R_j

Create UAV-BS user list using K-Means algorithm
  Calculate path loss $P_{i,j}$ in Eq. 1
  Organize UE list by path loss value
  Calculate the number of preferred R_i in Eq. 2
  while *All UEs are not allocated or rejected by all UAV* **do**
    for *UE i in UAV j Uplink list* **do**
      if $R_j >= R_i$ **then**
        $R_j = R_j - R_i$
        Update UAV resource available list
        $break$
      end
      else
        Find nearest UAV j to UE i
        if *New UAV $R_j >= R_i$* **then**
          New UAV R_j =New UAV $R_j - R_i$
          Update UAV resource available list
          $break$
        end
        continue
      end
      if *UE Rejected by all nearest UAV* **then**
        $break$
      end
    end
end

$P_{i,j}$ is calculated following Eq. 1. The $P_{i,j}$ determines the order in which the cluster UAV responds to resource allocation requests, from the UE with the lowest to the highest $P_{i,j}$.

The algorithm assumes that the UE is aware of the distance and resources available in the nearest UAV, creating the distance and UAV available resource lists. Given the UE data rate requirement, the number of RBs R_i required to fulfill its application is computed by Eq. 2. Therefore, following the order, UE requests R_i RBs from the UAV (e.g., UAV j). If there are enough resources, the UE is assigned to the UAV, and the quantity of available resources is determined. R_j is updated. Otherwise, a new UAV is selected based on the UE's position, considering centroid-based distance and available resources. If the new UAV has enough RBs, then R_i RBs are allocated to the UE, and the UAV resource availability is updated. The algorithm continues the assignment attempt in resource unavailability, considering other UAVs.

Our solution (Algorithm 1) assigns users to UAVs based on their proximity and radio resource availability, besides the path loss, adopting a redirection approach when a UAV does not accept a UE due to insufficient resources. For comparison, we consider a coverage-based user allocation scheme described in Algorithm 2. It also adopts the K-Means algorithm to associate UEs with UAVs. Similarly, each UE i is expected to request R_i RBs from its UAV j, where the allocation is performed when there are enough available RBs (R_j). Otherwise, the UE is rejected by the UAV, and it should refrain from making further requests. To analyze the proposed algorithm that assigns users to UAV-based UABs in 5G networks based on the distance and availability of resources, we adopt Python and K-Means libraries. Simulation parameters are presented in Table 1. We considered fixed UAV heights and UAVs positioned in the air following a grid format, as shown in Fig. 2, which denotes the UAVs and users' 3D locations as triangles and circles, respectively. The UEs and UAVs are randomly distributed in the grid area, and the SINR

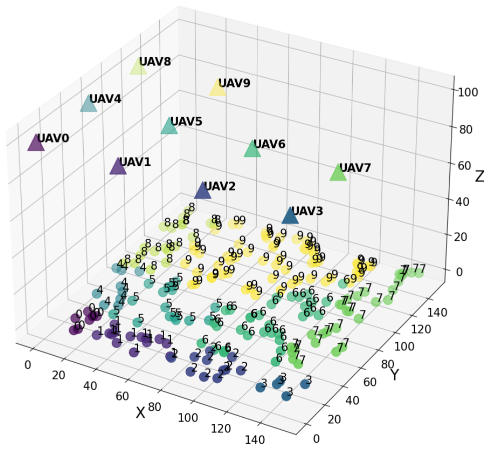

Figure 2. Network Scenario

perceived by the UEs and their data rate requirements are uniformly distributed within the intervals $[10, 25]dB$ and $[1Kbps, 10Mbps]$, respectively. Using fixed UAV positions and uniform user distribution simplifies initial analyses by reducing complexity and allowing us to focus on fundamental algorithmic performance without the added variability of dynamic mobility patterns. These assumptions facilitate an easier understanding of core mechanisms but acknowledge their limitations in representing real-world scenarios where UAVs and users exhibit more complex behaviors.

This approach provides a foundation for further refinement and extension to incorporate dynamic factors like mobility and non-uniform user distribution. In addition, we assume a flat propagation channel, where the frequency response is constant over the bandwidth of interest, an RB with 180 KHz wide in frequency, and a time slot duration of 0.5 milliseconds (msec), similar to [Kooshki et al. 2023]. We compare the proposed solution to the Algorithm 2 regarding the number of accepted and rejected users and the number of redirected users successfully allocated and aggregated throughput. The first two metrics assess the solutions' efficiency in handling user requests, indicating the capability to maximize the admission of user requests, ensuring their service quality requirements. The third metric evaluates the schemes' ability to manage and reallocate users not served immediately, reducing the service request denials. The last one measures the total throughput achieved by all attended users.

Table 1. Simulation Parameters

Parameter	Value
Channel Bandwidth	100 MHz
SINR	10 dB - 25dB
Number of Users	200
Number of UAVs	10
Transmission Frequency	28GHz
Tx Gain	11 dBi
Rx Gain	21 dBi
Requested Data Rate	1Kbps-10Mbps
UAV Height	100m
Number of RBs per UAV	275
RB Bandwidth RB_{RB}	180KHz

Algorithm 2 Coverage-Based User Allocation

```
input : n_uav_bs, n_ue, h_uav, range_dr, B_RB, R_j
Create UAV user list using K-Means algorithm
  Calculate the number of preferred R_i in Eq. 2

for UE i in UAV j Uplink list do
    if R_j >= R_i then
        R_j = R_j - R_i

        Update UAV resource available list
        break
    end
    else
        Reject UE i
    end
end
```

4. Simulation Results

Fig. 3 presents a comparative analysis of two distinct approaches: "Proposed Solution" and "Baseline Solution." This visual representation provides insight into each approach's performance, allowing for a comprehensive understanding of their respective strengths and weaknesses. The proposed solution exhibits a higher number of allocated users compared to the baseline solution. In contrast, the baseline solution has fewer allocated users. Notably, the proposed solution also features a larger proportion of reallocated users. The results are shown for accepted, rejected users, and reallocated users achieved by our proposal (Algorithm 1) and the baseline one (Algorithm 2), considering 10 executions. The green bar represents the users allocated to the UAV (their cluster), while the blue bar denotes users redirected to another UAV and successfully allocated. The red bar means rejected users due to insufficient resources. It is noted that almost all rejected users were reallocated to another UAV when our solution (Algorithm 1) is applied. On average, our solution successfully allocated around 99.5% users, while the baseline one achieved 90.0% of allocated users and 10% of rejected users.

Fig. 4 shows the average throughput and allocated users per UAV achieved by the solutions. The x-axis represents the UAV ID, 10 in total, while the double y-axis displays the average throughput in Mbps and the average allocated users. It is observed that the solutions present similar throughput and number of allocated users for UAVs from 0 to 4. This is attributed to the small number of users requesting resources in these clusters, resulting in no necessity to reallocate users to obtain radio resources from other UAVs. However, as we move towards larger clusters (UAVs 5-9), significant differences emerge between the two solutions. Algorithm 2 struggles to assign users and shows lower throughput compared to our solution (Algorithm 1). The number of allocated users per UAV is also depicted in the figure. Our proposed solution (Algorithm 1) consistently demonstrates a higher number of allocated users compared to Algorithm 2 , especially for larger clusters (UAVs 5-9), the proposed scheme has the highest average throughput, reaching 6.79 Gbps, 11.53 Gbps, 8.87 Gbps, 4.11 Gbps, and 12.33 Gbps, respectively. Hence, our solution (Algorithm 1) shows superior performance compared to Algorithm 2 in both user acceptance and throughput for larger clusters. Based on the analysis presented, we can conclude that our proposed solution (Algorithm 1) outperforms the baseline approach (Algorithm 2) in both user acceptance and throughput for larger clusters. The results suggest that our algorithm is more efficient in allocating users to UAVs, resulting in higher average throughput values.

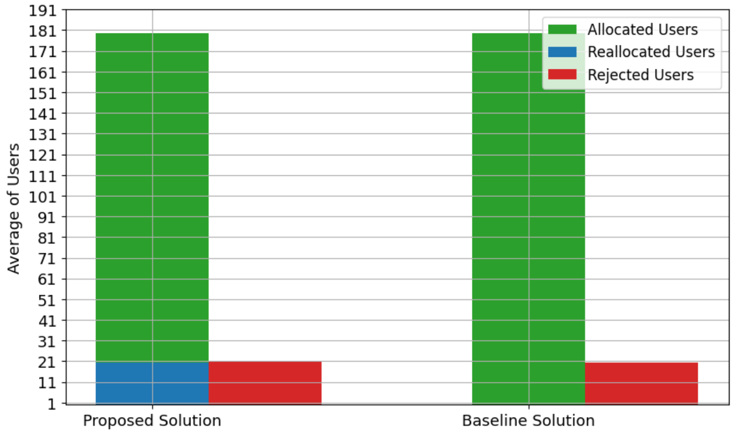

Figure 3. Algorithm's comparison

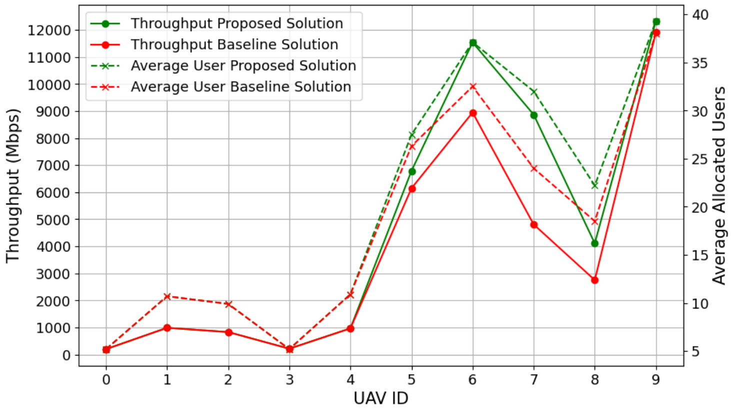

Figure 4. Average throughput and allocated users comparison per UAV-BS

5. Conclusion

Aerial Base Stations (ABS) utilizing Unmanned Aerial Vehicles (UAV) offer a promising approach for enhancing capacity and coverage in 5G and 6G networks. However, these systems introduce several challenges, including dynamic mobility patterns, energy constraints, and communication limitations, which complicate the assignment of users to UAVs when compared to terrestrial environments. This paper presents a clustering-based solution for user-to-UAV assignment, complemented by a reallocation strategy to prevent connection denials. Our findings indicate substantial improvements: the proposed method successfully allocated 99.5% of users, whereas the baseline achieved only 90%. Furthermore, our solution enhanced the average data rate by 910 Mbps, resulting in an average throughput of 4.68 Gbps, compared to the baseline's 3.77 Gbps. While these results are encouraging, it is important to acknowledge certain limitations. The current study assumes fixed UAV positions and a uniform distribution of users, which, although simplifying initial analyses, may not accurately represent real-world scenarios where users and UAVs exhibit dynamic behaviors. Factors such as energy constraints, communication limitations, and dynamic mobility patterns will need to be addressed in future work. Subsequent research will focus on developing advanced positioning algorithms to improve coverage, optimizing resource allocation for fewer UAVs, and incorporating trajectory optimization techniques to enhance overall network efficiency. These enhancements aim to provide a more comprehensive solution that more closely aligns with practical deployment scenarios.

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