Location optimization for tethered aerial base station serving mmWave high altitude UAVs

Pravallika Katragunta, Michel Barbeau, Joaquin Garcia-alfaro, Evangelos Kranakis, Venkata Srinivas Kothapalli

▶ **To cite this version:**

Pravallika Katragunta, Michel Barbeau, Joaquin Garcia-alfaro, Evangelos Kranakis, Venkata Srinivas Kothapalli. Location optimization for tethered aerial base station serving mmWave high altitude UAVs. IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), Aug 2024, Kingston, France. pp.271-276, 10.1109/CCECE59415.2024.10667117 . hal-04762101

HAL Id: hal-04762101
https://hal.science/hal-04762101v1

Submitted on 31 Oct 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Location Optimization for Tethered Aerial Base Station Serving mmWave High Altitude UAVs

Pravallika Katragunta*, Michel Barbeau*, Joaquin Garcia-Alfaro†,
Evangelos Kranakis*, and Venkata Srinivas Kothapalli‡

* School of Computer Science, Carleton University, K1S 5B6, Ottawa, Ontario, Canada

† Télécom SudParis, Institut Polytechnique de Paris, 91120, Palaiseau, France

‡ Ericsson Canada, K2K 2V6, Ottawa, Ontario, Canada

***Abstract*—Uncrewed Aerial Vehicle-User Equipment (UAV-UE) is integral to millimeter wave (mmWave)-based wireless cellular systems. UAV-UE at high altitudes encounter limited connectivity with terrestrial base stations. Tethered Aerial Base Stations (TABS) are viable alternatives to terrestrial base stations. Optimal placement of a TABS in a three-dimensional environment is necessary and critical to serve multiple moving UAV-UE units with reliable connectivity. In this work, we propose a contextual multi-armed bandit framework to learn the optimal TABS locations. We consider multiple UAV-UE units moving at high altitudes in an uplink mmWave setting. Under this framework, the TABS acts as a learning agent leveraging position information about served UAV-UE units to provide connectivity with minimum Signal to Noise Ratio (SNR) threshold requirements. We first compare the Upper Confidence Bound (UCB) and Thompson Sampling (TS)-based learning strategies against the traditional naive-based approach. Our simulation results show that the TS-based approach learns optimal locations with a 31% and 51% average regret-reduction ratio (ARR) over UCB and naive-based approaches, respectively. Also, the TS-based learning strategy for TABS reliably achieves the required SNR for UAV-UE units under multiple contexts, compared to a static TABS location.**

***Index Terms*—tethered aerial base station, uncrewed aerial vehicle, multi-armed bandit, mmWave communications.**

I. Introduction

Uncrewed Aerial Vehicle-User Equipment (UAV-UE) in cellular ecosystems play a vital role in Fifth-Generation (5G) and beyond wideband communications. Furthermore, the high mobility and cost-effective communication from Uncrewed Aerial Vehicles (UAVs) can enable a myriad of applications such as contactless delivery, defense, weather monitoring, and surveillance [1], [2]. The traditional connectivity of high altitude UAV-UE is limited due to fixed terrestrial Base Station (BS) locations. The BS antennas are optimized for terrestrial coverage causing interference to ground users [3]. A flying BS can provide a better service than a terrestrial BS [4], [5]. Fotouhi et al. focused their research work on providing service for ground users using flying BS [4], [5].The power source is a battery with a limited lifetime. The service is provided for a short time period. The focus of this paper is providing 5G service to UAV-UE. A flying BS for providing 5G service to UAV-UE may require frequent battery recharge to support. Instead, a Tethered Aerial Base Station (TABS) is a viable option to provide connectivity to high altitude UAV-UE (hereafter called UAVs).

A TABS is connected to a ground power source through a cable that provides both energy and data connectivity, thus enabling long flying time. Also, aerial communications with a ground BS is essentially free space with none of the typical terrestrial obstacles such as buildings and trees [3], [6]. This results in Line of Sight (LoS) communication for high-altitude UAVs. However, there is a higher degree of uplink interference to the neighboring ground BS and ground users.

TABLE I
UAV CELLULAR COMMUNICATION RESEARCH WORK.

BS	Cell devices	References	Challenges
Terrestrial	Ground users & UAVs	[3], [6]–[8]	Interference to ground users
Untethered drone	Ground users	[4], [5], [9]	Interference to ground users. Limited service time
Tethered drone	Ground users	[10]–[14]	Aerial users are not considered
	UAVs	Our work	Connectivity to UAVs

A TABS can mitigate uplink interference by moving closer towards UAVs and providing LoS communication. At the same time, serving multiple UAVs, while providing wide coverage to each of them, is a challenging problem. Hence, determining an optimal location for a TABS is necessary in order to serve multiple UAVs effectively in a Three-Dimensional (3D) environment. Classical location optimization approaches may not be adapted to dynamic constraints such as UAV mobility and large TABS to ground user separation distances. Hence, we consider learning approaches like Contextual Multi-Armed Bandit (CMAB) to solve TABS location optimization problems. We observe that simple learning architecture like CMAB is enough to guide TABS with satisfactory environmental connectivity and adaptability.

A. Contributions and Outline of the Paper

We first review the related work in different aspects of BSs investigated by other researchers, see table I. We highlight the new aspects of TABS that we are investigating. We propose a CMAB Reinforcement Learning (RL) framework to optimize the location of a TABS while serving multiple high altitude UAVs. Under this framework, we solve the location optimization objective using Upper Confidence Bound (UCB) and Thomson Sampling (TS)-based CMAB algorithms. We

compare their performance against the naive-based approach and static TABS location. This framework aims to optimize the TABS locations and provide connectivity to UAVs satisfying Signal to Noise Ratio (SNR) threshold requirements during their uplink communication. Our simulations show that the TS-based approach learns optimal locations with minimum regret and also achieves the SNR requirements for UAVs within multiple contexts, compared to a static TABS location.

The rest of the paper is organized as follows. Section II reviews the related work. Section III presents the system and communication model followed by the problem formulation. Section IV discusses implementation details. Section V provides simulation results. Section VI concludes the paper.

II. Related Work

Terrestrial BS-UAV communications have been extensively studied [3], [6]–[8]. Lin et al. conducted a field trial to enhance the applicability and performance of mobile networks for low-altitude drones [3]. The experimental results showed a decrease in Signal-to-Interference-Plus Noise Ratio (SINR) with increased drone flying altitude. This results in low spectral efficiency due to interference. The same authors present SINR measurements for three different altitudes, for a UAV in the presence of ground users. The results show strong interference in cells with drones flying at high altitudes, unlike cells that do not serve UAVs [6]. Challita et al. proposed an approach where multiple UAVs autonomously learn their path, transmit power levels, and association vectors with BS [7]. The approach is based on a dynamic non-cooperative game using deep RL. This idea mitigates the interference created by multiple UAVs while simultaneously improving the latency. The results are presented for drone altitudes up to 120 m. Susarla et al. proposed an RL-based beamforming approach [8]. The learning agent is a BS serving UAVs. Their work shows that the concept is practical with the current battery limitations.

Several works studied the use of drones as BS or relay nodes to serve ground User Equipment (UE) [4], [5], [9]. Fotouhi et al. improved the spectral efficiency of ground user communications by hovering the drone BS in 2D space at fixed altitudes [4], [5]. A drone BS, with dynamic positioning, improves the spectral efficiency but may offer only a limited service time due to battery capacity. In terms of energy consumption, a flying BS may be impractical for serving UAVs effectively moving in a 3D space at high altitudes [4]. In [9], Pourbaba et al. proposed a drone relay positioning approach to improve vehicular communications with a terrestrial BS. They model a Multi-Armed Bandit (MAB) approach using the state-of-art UCB algorithm to identify the optimal drone location for maximizing the total data rate in wireless networks. However, the work does not consider a multi-vehicular scenario. This may result in a contextual MAB to find the optimal drone location for each vehicle movement. The research of Fotouhi et al. has focused on untethered relay drones supporting ground communication [4]. Hence, we consider a TABS as an alternative to serve high-altitude UAVs with wired energy and data connectivity. It has mobility limitations to certain distances and altitudes. In contrast to an untethered BS, a TABS does not have the battery limitation.

Similar to the work in [9], we use a CMAB approach to identify the optimal location of a TABS serving multiple high altitude UAVs. The goal is to provide good communication to the UAVs. TABS-ground user communications have been extensively studied in the recent literature [10]–[14]. In [10], Mustafa et al. provided a comparative performance analysis of TABS over untethered drones to maximize the Quality of Service (QoS) in heavy-traffic regions. Similarly, Kishk et al. discussed the potential of TABS for cellular coverage and capacity enhancement for ground users [11]. Simulations have shown that a TABS with a 120 m long tether outperforms untethered drones. This is achieved by maximizing the coverage probability of ground users to nearly 30%. Lou et al. proposed a low complexity heuristic to find the optimal transmit power, 3D placement, and user association of a TABS. Their work demonstrated that power optimization could minimize the Electro Magnetic Force (EMF) exposure, in the environment, by more than 20%. It also achieves effective communication with ground users [13]. Lim et al. compared a performance-based multi-agent Q-learning approach over a conventional random action-based algorithm. The goal is to optimize the TABS trajectories, for maximizing the throughput in multi-cell users [14]. In [12], Mustafa et al. developed a mathematical model for 3D placement of a TABS to minimize the average path loss inside a hovering region. All these works convey that TABS location optimization is critical to effectively serving ground users.

In [15], Militaru et al. investigated the handover issues of Long Term Evolution (LTE) terrestrial networks at drone altitudes of 300 m to 400 m. Also, at high altitudes, UAVs create strong interference to neighboring cells [6]. Hence, in this work, we focus on using a TABS to provide service to UAVs at high altitudes under 5G uplink communications. Similar to the learning formulation proposed in [8], and using the CMAB approach, the TABS acts as a smart agent and find the optimal location in each context while serving multiple UAVs flying around 300 m to 400 m. Unlike a terrestrial BS, a TABS can be operational at high altitudes. It can be placed and relocated according to the traffic and channel conditions with the served UAVs. A small space like the rooftop of an urban building is sufficient for placing the Ground Station (GS) of a TABS. The GS consists of processing units, core network elements, and connections to energy resources. Unlike a permanently fixed terrestrial BS, a TABS can be quickly relocated from one rooftop to another. TABSs have also been practically used in multiple scenarios such as petroleum refineries for fire fighting exercises, in Rydercup events for monitoring and preventing intrusions, and in Port-of-Spain carnivals to provide non-stop coverage and live footage [16].

III. System Model

As shown in Fig. 1, we consider cellular millimeter-Wave (mmWave) Multiple-Input Multiple-Output (MIMO) uplink communication between a single TABS and multiple UAVs.

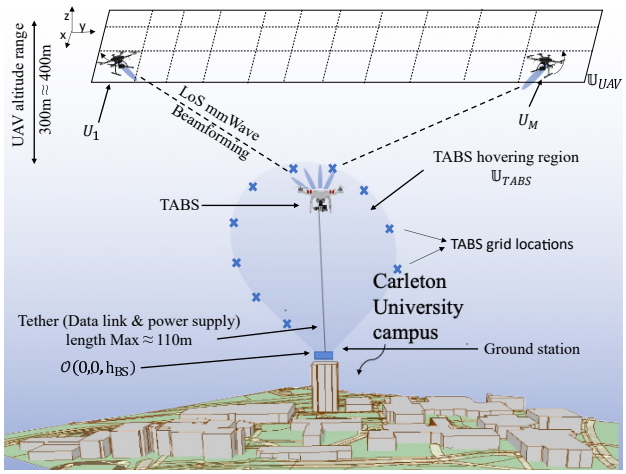

Fig. 1. System model considered around a Carleton University landscape with UAVs hovering at altitudes ranging from 300 m to 400 m.

Each UAV acts as a Transmitter (Tx) while the TABS acts as a Receiver (Rx) in a bounded 3D semi-spherical grid coverage area $\mathbb{U}_{\text{TABS}}$. Using a tether, the TABS is hovering attached to a GS at position $\mathcal{O}(0,0,h_{\text{BS}})$ in a grid environment. The TABS has elevation angle $\xi \in [0,\pi/2]$, azimuthal angle $\phi \in [-\pi,\pi]$, and maximum hovering radius δ equal to 110 m. A grid location in $l_{\text{TABS}} \in \mathbb{U}_{\text{TABS}}$ in the TABS hovering region is represented in Cartesian form as

$$(\delta\cos(\xi)\cos(\phi), \delta\cos(\xi)\sin(\phi), \delta\sin(\xi)+h_{\text{BS}}) \tag{1}$$

All the UAVs are moving randomly within the same 3D Cartesian grid region $\mathbb{U}_{\text{UAV}}$ at altitudes ranging from 300 m to 400 m.

The TABS communicates with the UAVs following the 5G New Radio (NR) standards. Every time a UAV moves to a random location, the SNR for the UAV-TABS link is measured. No interference across UAVs is assumed for simplicity. Hence, only SNR measurements are considered. Using a priori SNR measurements, the TABS learns the optimal location to support reliable 5G communication to each UAV. Different mobility models can be considered for UAVs to evaluate the performance. In this work, we do not require any specific mobility model as we select locations of moving UAVs randomly.

A. Communication Model

We consider LoS narrow band radio communication between each UAV (Tx) and the TABS (Rx). Each Tx and Rx is equipped with a single Radio Frequency (RF) chain consisting of N_t and N_r Uniform Linear Array (ULA) antennas, respectively. At any time instant, the TABS can serve only one UAV with a single RF chain of the antenna arrangement. Let θ_{tx} be the Angle of Departure (AoD) and θ_{rx} be the Angle of Arrival (AoA) at a UAV and the TABS, respectively. Let k be the time domain index of a sample of a transmitted signal. The baseband equivalent of the received signal is given by

$$y[k] = \underbrace{\sqrt{P_{tx}}\eta\ \boldsymbol{\omega}_{\text{R}}^H \mathbf{a}_R(\theta_{\text{rx}})\mathbf{a}_T^H(\theta_{\text{tx}})\boldsymbol{\omega}_{\text{T}} x[k]}_{r[k]} + \nu[k] \tag{2}$$

where P_{tx} is the transmission power, and η equal to $\left(\frac{4\pi d}{\lambda}\right)^2$ is the antenna channel gain under Free Space Path Loss (FSPL) conditions with d as the distance between the UAV and TABS, in meters, and $\boldsymbol{\omega}_{\text{R}} \in \mathbb{C}^{N_r}$, $\boldsymbol{\omega}_{\text{T}} \in \mathbb{C}^{N_t}$ are the transmit and receive unit-norm beamforming vectors given by

$$\boldsymbol{\omega_{R|T}}(\theta)|_{n=0}^{N-1} = \frac{1}{\sqrt{N}}\exp\left(j\frac{2\pi n\Delta}{\lambda}\sin\theta\right) \tag{3}$$

where Δ equal to $\lambda/2$ is the antenna element spacing, λ equal to c/f is the wavelength, c is the velocity of light, f is the mmWave carrier frequency. $\mathbf{a}_R(\theta_{\text{rx}}) \in \mathbb{C}^{N_r}$, $\mathbf{a}_T(\theta_{\text{tx}}) \in \mathbb{C}^{N_t}$ are array response vectors for the θ_{rx} and θ_{tx} radio links, respectively. The H exponent is the conjugate transpose operator. Here, $\mathbf{a}(\theta)|_{n=0}^{N-1} = \frac{1}{\sqrt{N}}\exp(j\frac{2\pi n\Delta}{\lambda}\sin\theta)$, where $\theta = \theta_{\text{rx}}, N = N_r$ and $\theta = \theta_{\text{tx}}, N = N_t$ for $\mathbf{a}_R(\theta_{\text{rx}})$ and $\mathbf{a}_T(\theta_{\text{tx}})$, respectively. $x[k]$ represents the k^{th} sample of the time-domain transmitted signal with bandwidth W and $\frac{1}{K}\sum_{k=0}^{\text{K}}|x[k]|^2 = 1$, $\nu[k] \sim \mathcal{CN}(0, WN_0)$ is the effective noise with zero mean and two-sided power spectral density $N_0/2$. In this work, we assume free space propagation between a UAV and a TABS with the LoS channel matrix $\mathbf{H}(\theta_{\text{tx}},\theta_{\text{rx}}) \triangleq \eta\ \mathbf{a}_R(\theta_{\text{rx}})\mathbf{a}_T^H(\theta_{\text{tx}})$. We define $r[k]$ equal to $\sqrt{P_{tx}}\boldsymbol{\omega}_{\text{R}}^H\mathbf{H}(\theta_{\text{tx}},\theta_{\text{rx}})\boldsymbol{\omega}_{\text{T}}x[k]$. Then, the SNR is given as

$$\text{SNR} = \frac{\frac{1}{K}\sum_{k=0}^{K}|r[k]|^2}{N_0 W}\ \text{dB}. \tag{4}$$

B. Problem Formulation

We consider mmWave uplink communications between M UAVs $(U_1, U_2, .., U_M)$ and a single TABS following the 5G NR framework. The TABS location optimization problem is modeled in the CMAB learning framework. The TABS acts as a learning agent and provides optimal connectivity to M randomly moving UAVs by adjusting its location each time inside $\mathbb{U}_{\text{TABS}}$. We consider L random grid locations for each UE during its mobility. These locations form contextual information for the learning agent. We represent the contextual information set B equal to $\{(U_1^l, U_2^l, ..., U_M^l)$, with $U_k^l \in \mathbb{U}_{\text{UAV}}, 1 \le k \le M, 1 \le l \le L\}$. The TABS grid locations in $\mathbb{U}_{\text{TABS}}$ are represented as the CMAB arms. This set is denoted as A. For each context $b \in B$, the agent plays an arm $a \in A$. The beamforming gain between the TABS and UAVs is evaluated using the SNR formulation in Eq. (4). Under this framework, r represents the reward associated with the obtained SNR measurements. The γ represents the SNR threshold requirement. The objective of this problem is to choose the optimal TABS location for context b by selecting the arm that yields the maximum reward, given by

$$\begin{aligned} a_b^* &= \arg\max_a \mathbb{E}[r(b,a)], \\ &s.t. \\ r(b,a) &= \begin{cases} 1 & \text{if } S_i(b,a) \ge \gamma, \forall i = \{1,2,...M\} \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \tag{5}$$

$S_i(b,a)$ is the SNR of the uplink between the BS and U_i for action a and context b. For each context b, the CMAB agent selects an arm at each round until the objective of Eq. (5)

is achieved. The average regret incurred by the agent for all contexts is defined as

$$R = \mathbb{E}\left[\sum_{i=1}^{T}(p_i \; - \; q_i)\right] \tag{6}$$

where p_i is the total maximum reward until round i, q_i is the cumulative reward obtained by the agent until round i, and T is the total number of rounds the agent plays. Following Eqs. (5) and (6), we implement the CMAB framework for TABS location optimization using the UCB and TS algorithms. We define the average regret-reduction ratio (ARR) metric as

$$\text{ARR} = \frac{100}{|C|}\sum_{c}\left(1 - \frac{R_{cmab}(c)}{R_{ref}(c)}\right) \tag{7}$$

to estimate the regret performance of the proposed CMAB framework over other referred learning schemes. We use this metric to analyze the results in Section V.

IV. Implementation

We discuss the implementation of the UCB and TS algorithms, between a single TABS and M UAVs. Each TABS location in $\mathrm{U}_{\mathrm{TABS}}$ is an arm of a bandit machine. At each time, we consider the TABS contextual information as described in Section III-B. The TABS learns the optimal arm for each context and establishes reliable 5G communication links with the M UAVs. Thus, the agent selects an arm from a given set of arms for each context and computes the reward following Eq. (5). The objective of CMAB is to identify and choose the optimal arm for each context with the largest expected reward.

A. The Upper Confidence Bound (UCB)-based Approach

We are the first to propose learning-based communications between TABS and high altitude UAVs. Hence, we consider the UCB approach used to learn UAV relay positioning [9] as the main contribution of our work. All the steps followed by UCB-based approach is shown in Algorithm 1.

Algorithm 1 *UCB-based MAB learning*

Input: Context set B, Arm set A
Initialization:
$SumR(b,a) \leftarrow 0$
$AverageR(b,a) \leftarrow 0$
$Count(b,a) \leftarrow 0$
for $b \leftarrow 1$ to $NumberOfContexts$ **do**
  for $j \leftarrow 1$ to $rounds$ **do**
    if $round \leq totalArms$ **then**
      $a \leftarrow round$
    else
      Calculate $UCB(b,a)$
      Select a with maximum UCB
      $Count(b,a) \leftarrow Count(b,a) + 1$
      Compute $r(b,a)$ following Eq. (5)
      $SumR(b,a) \leftarrow SumR(b,a) + r(b,a)$
      $AverageR(b,a) \leftarrow \frac{SumR(b,a)}{Count(b,a)}$

B. The Thomson Sampling (TS)-based Approach

TS is a Bayesian-type approach where the reward distribution is estimated considering a given prior distribution [17]. Unlike the UCB algorithm, TS selects the optimal arm with the highest probability at each time based on the available historical observations. In this work, we use the beta distribution for each arm as the prior probability distribution with positive shape parameters α and β in the range $[0, 1]$. We initialize both α and β with the same value. The reward values 0 and 1 are used to update the α and β parameters. Each time the agent pulls an arm, when it receives the best reward, the distribution of the arm is updated by incrementing the α value by one unit. Else, the distribution of the arm is updated by incrementing the β value by one unit. As time progresses, an accurate approximation of the distribution of the reward is obtained from the accumulated observations. In contrast to the UCB policies, TS can achieve significantly better performance. Another advantage of TS is that there is no need for parameter tuning. When there is a prior distribution of the rewards, and their update is computationally effective, using TS is preferable. All the steps followed by TS learning-based location optimization are shown in Algorithm 2.

Algorithm 2 *TS-based MAB learning*

Input: Context set B, Arm set A
Initialization:
$SumR(b,a) \leftarrow 0$
$AverageR(b,a) \leftarrow 0$
$Count(b,a) \leftarrow 0$
Beta Distribution$(\alpha, \beta) \leftarrow (1, 1)$
for $b \leftarrow 1$ to $NumberOfContexts$ **do**
  for $j \leftarrow 1$ to $rounds$ **do**
    Sampling from the distribution of each action
    Select a with maximum TS
    Same as Lines 13 to 19 of Algorithm 1
    if r = 1 **then**
      $\alpha(b,a) \leftarrow \alpha(b,a) + 1$
    else
      $\beta(b,a) \leftarrow \beta(b,a) + 1$

TABLE II
Simulation Parameters

Parameter	Value
mmWave carrier frequency f	30 GHz
antenna element spacing Δ	0.5λ
Transmit power P_{tx}	10 dBm
Bandwidth W	20 MHz
Transmit antenna elements N_{tx}	4
Receiver antenna elements N_{rx}	4
Noise power density N_0	-174 dBm/Hz
SNR Threshold γ	11 dB
TABS Max.hovering radius	110 m
TABS latitude angle	$0:180$
TABS longitude angle	$-180:180$
Coverage xloc, yloc UAV (in m)	[-250:10:250]
Coverage zloc UAV (in m)	[300:10:400]
$\mathbb{U}_{\mathrm{UAV}}$ (in m)	{xloc, yloc, zloc}
Number of UAVs M	2
Number of contexts $\lvert B\rvert$	10
Arms $\lvert A\rvert$	100
Rounds T	15000

V. Simulation Results

We implemented the CMAB approach for a single TABS and M UAVs following the UCB and TS algorithms. The simulation code is available in Github repository[1]. We simulated for scenarios where M equal to two UAVs each with L equal to 10 randomly selected grid positions from $\mathrm{U}_{\mathrm{UAV}}$. However, the proposed approach is not limited and can be extended to an arbitrary number of UAVs. We assume UAVs U_1 and U_2 moving randomly within the grid area $\mathbb{U}_{\mathrm{UAV}}$. As a result, the set B comprises 10 different contexts, as described in Section III-B. Similar to the approach in [9], we first compare

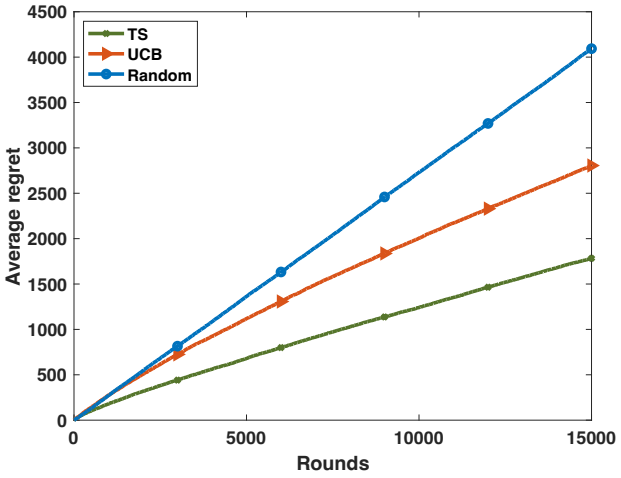

Fig. 2. The average regret plots for ten contexts for multiple training rounds using the UCB, TS, and naive-based approaches.

the regret performance of our UCB and TS learning-based TABS location optimization against a conventional naive-based approach. The naive-based approach randomly selects an arm without applying any learning strategy. We analyze the observed SNR measurements for learning-based optimal placement arms versus a static TABS location and a terrestrial BS location. Table II lists the parameters used for the simulations. In Fig. 2, the plots represent the average mean regrets over ten different U_1 and U_2 contextual location pairs ($b_i = (u_1^i, u_2^i)$ from B in section III-B) for the UCB, TS, and naive-based approaches. With an increase in rounds, we observe that the learning-based approaches accumulate relatively low average regrets compared to the naive-based approach. This shows that learning-based schemes are appropriate for optimal placement of a TABS to support high altitude multiple UAVs. Among these learning-based schemes, we notice that the TS strategy converge faster with an ARR of 31% and 51% compared to the UCB algorithm and naive-based scheme across multiple contexts, respectively. Thus, the TS algorithm helps in quick convergence of the TABS location optimization problem satisfying SNR threshold requirements, in contrast to UCB learning.

Figs. 3 and 4 show the subplots for ten U_1 and U_2 selected locations, namely, $U_k = \{u_k^1, u_k^2, ..., u_k^{10}\}, k = 1, 2$ for UCB

[1]https://github.com/Pravs288/Drone-communication.git

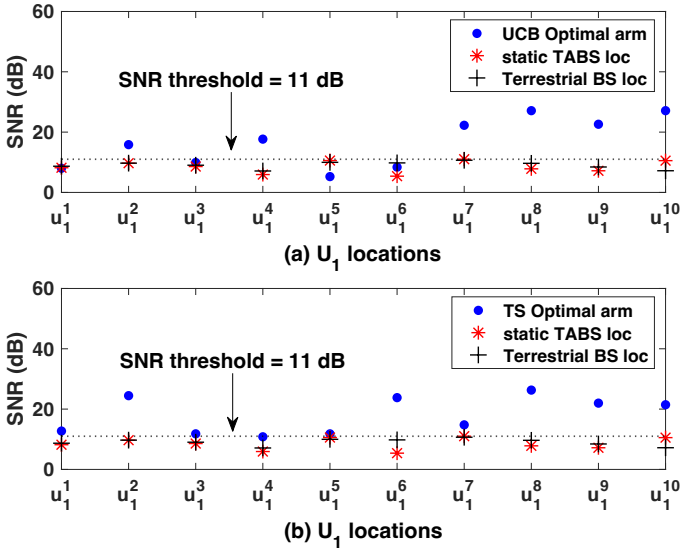

Fig. 3. SNR (dB) plots for the U_1 locations with the UCB optimal arms, TS optimal-arms, a static TABS location and a terrestrial BS location. The dotted line along the y-axis represents the SNR threshold requirement.

and TS optimal arms with a static TABS location and a terrestrial BS location. In each of these subplots, the achieve SNRs for the optimal UCB and TS arms are compared with the SNRs obtained for a static TABS location and a terrestrial BS location. This emphasizes the benefits of a TABS and location optimization versus a fixed terrestrial BS location. We can observe that both learning approaches achieve the SNR threshold for most of the U_1 and U_2 locations. Whereas, for a static TABS and a terrestrial BS, most of the U_1 and U_2 locations do not satisfy the SNR threshold. For the static case, we randomly select a location from the TABS grid and fix it. For a terrestrial BS, it is fixed location with 25 m altitude in the TABS grid.

With TS learning, we observe that all the ten U_1 and U_2 locations in Figs. 3 (b) and 4 (b) satisfy the SNR threshold γ, set to 11 dB. But in Figs. 3 (a) and 4 (a), six of the UCB optimal arms, namely $\mathrm{u}_1^1, \mathrm{u}_1^3, \mathrm{u}_1^5, \mathrm{u}_1^6$, and u_2^4, do not satisfy the SNR threshold. Under the static approach, only two out of ten U_1 and four out of ten U_2 locations reached the threshold requirement with a selective static TABS location. For a terrestrial BS location, only two out of ten U_1 and one out of ten U_2 locations achieved the SNR threshold. This is due to the long distances from the UAV locations to the terrestrial BS. To compare the TS learning against TABS location optimization, we analyze the average SNR of each context increasing their number and fixing their context size as shown in Fig 5 (a). Increasing context size with a fixed number of them is shown in Fig 5 (b). The results show that in both cases the TS optimal arms are always achieving the SNR threshold. These results demonstrate that compared to a terrestrial BS and a static TABS, the TS-based TABS location optimization strategy can provide reliable communications with good SNRs for high altitude UAVs.

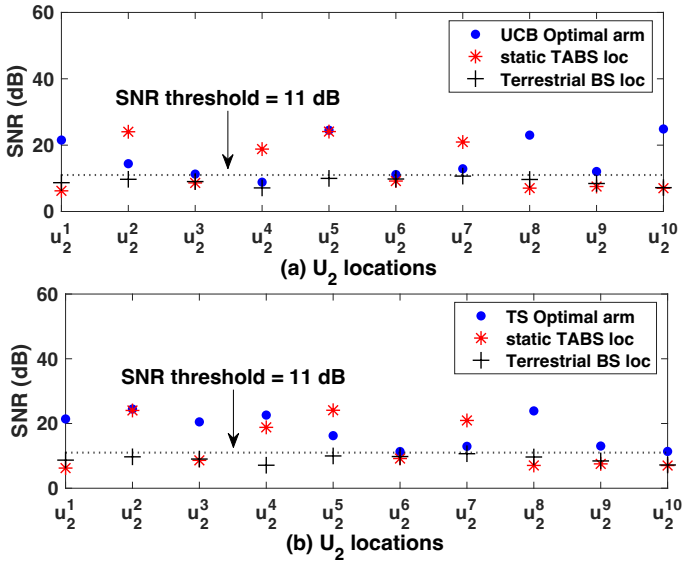

Fig. 4. SNR (dB) plots for the U_2 locations with UCB optimal-arms, TS optimal-arms, a static TABS location and a terrestrial BS location. The dotted line along the y-axis represent the SNR threshold requirement.

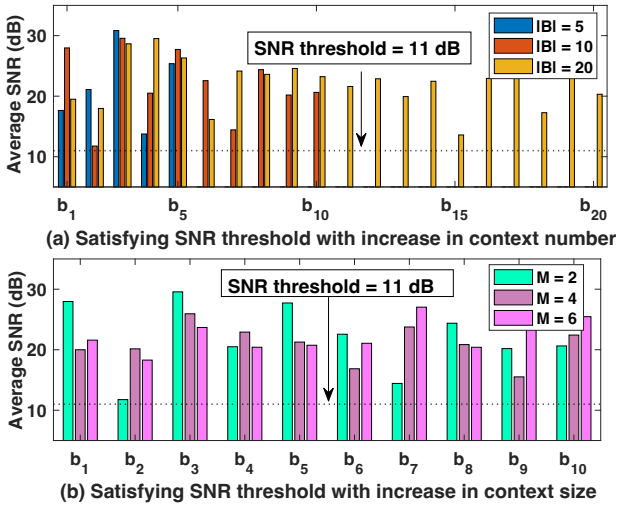

Fig. 5. Here, $|B|$ and M represent the total number of contexts and the number of UAVs considered in the system (context size), respectively. The X axis presents context number. Each context average SNR for (a) different context numbers with fixed context size, (b) different context size with fixed context number.

VI. Conclusion and Future Work

We proposed a CMAB-based TABS location optimization framework for high-altitude UAVs using 5G and beyond wireless systems. We investigated the CMAB-based UCB and TS learning strategies compared against the naive-based approach. We observed that the TS-based approach learns the optimal TABS locations with an ARR of 31% and 51% over the UCB and naive-based approaches, respectively. We also analyzed the performance of TS and UCB optimal arms against a static TABS location, respectively. We conclude that the TS-based location optimization strategy achieves reliable SNR requirements, between a TABS and high altitude UAVs uplink communications for multiple contextual locations. Having shown some promising results, we intend to extend the framework towards inclusion of multiple ground users, multiple TABS, and optimal coverage with interference mitigation, as future works.

Acknowledgments — This research was supported by Ericsson, Mitacs, and Natural Sciences and Engineering Research Council (NSERC) of Canada. The work has also been partially supported by the French National Research Agency under the France 2030 label (NF-HiSec ANR-22-PEFT-0009).

References

[1] X. Ren, S. Vashisht, G. S. Aujla, and P. Zhang, "Drone-edge coalesce for energy-aware and sustainable service delivery for smart city applications," *Sustainable Cities and Society*, vol. 77, p. 103505, 2022.

[2] M. Banafaa, Ö. Pepeoğlu, I. Shayea, A. Alhammadi, Z. Shamsan, M. A. Razaz, M. Alsagabi, and S. Al-Sowayan, "A comprehensive survey on 5g-and-beyond networks with uavs: Applications, emerging technologies, regulatory aspects, research trends and challenges," *IEEE Access*, 2024.

[3] X. Lin, R. Wiren, S. Euler, A. Sadam, H.-L. Määttänen, S. Muruganathan, S. Gao, Y.-P. E. Wang, J. Kauppi, Z. Zou *et al.*, "Mobile network-connected drones: Field trials, simulations, and design insights," *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 115–125, 2019.

[4] A. Fotouhi, M. Ding, and M. Hassan, "Dronecells: Improving spectral efficiency using drone-mounted flying base stations," *Journal of Network and Computer Applications*, vol. 174, p. 102895, 2021.

[5] ——, "Flying drone base stations for macro hotspots," *IEEE Access*, vol. 6, pp. 19 530–19 539, 2018.

[6] X. Lin, V. Yajnanarayana, S. D. Muruganathan, S. Gao, H. Asplund, H.-L. Maattanen, M. Bergstrom, S. Euler, and Y.-P. E. Wang, "The sky is not the limit: LTE for unmanned aerial vehicles," *IEEE Communications Magazine*, vol. 56, no. 4, pp. 204–210, 2018.

[7] U. Challita, W. Saad, and C. Bettstetter, "Interference management for cellular-connected UAVs: A deep reinforcement learning approach," *IEEE Transactions on Wireless Communications*, vol. 18, no. 4, pp. 2125–2140, 2019.

[8] P. Susarla, B. Gouda, Y. Deng, M. Juntti, O. Sílven, and A. Tölli, "Dqn-based beamforming for uplink mmwave cellular-connected uavs," in *2021 IEEE Global Communications Conference (GLOBECOM)*, 2021, pp. 1–6.

[9] P. Pourbaba, S. Ali, K. S. Manosha, and N. Rajatheva, "Multi-armed bandit learning for full-duplex UAV relay positioning for vehicular communications," in *2019 16th International Symposium on Wireless Communication Systems (ISWCS)*. IEEE, 2019, pp. 188–192.

[10] O. M. Bushnaq, M. A. Kishk, A. Celik, M.-S. Alouini, and T. Y. Al-Naffouri, "Optimal deployment of tethered drones for maximum cellular coverage in user clusters," in *IEEE Transactions on Wireless Communications*, vol. 20, no. 3, 2021, pp. 2092–2108.

[11] M. Kishk, A. Bader, and M.-S. Alouini, "Aerial Base Station Deployment in 6G Cellular Networks Using Tethered Drones: The Mobility and Endurance Tradeoff," in *IEEE Vehicular Technology Magazine*, vol. 15, no. 4, 2020, pp. 103–111.

[12] M. A. Kishk, A. Bader, and M.-S. Alouini, "On the 3D Placement of Airborne Base Stations Using Tethered UAVs," in *IEEE Transactions on Communications*, vol. 68, no. 8, 2020, pp. 5202–5215.

[13] Z. Lou, A. Elzanaty, and M.-S. Alouini, "Green tethered UAVs for EMF-aware cellular networks," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 4, pp. 1697–1711, 2021.

[14] S. Lim, H. Yu, and H. Lee, "Optimal tethered-UAV deployment in A2G communication networks: Multi-agent Q-learning approach," *IEEE Internet of Things Journal*, vol. 9, no. 19, pp. 18 539–18 549, 2022.

[15] L. G. Militaru, D. Popescu, and L. Ichim, "4G/LTE Issues of Low Altitude UAV Flying Systems," in *2020 24th International Conference on System Theory, Control and Computing (ICSTCC)*. IEEE, 2020, pp. 874–879.

[16] Elistair, "Orion: Tethered Drone for Surveillance and Communications," Accessed on February 3, 2023. [Online]. Available: https://elistair.com/orion-tethered-drone/

[17] D. J. Russo, B. Van Roy, A. Kazerouni, I. Osband, and Z. Wen, "A tutorial on Thompson sampling," *Foundations and Trends® in Machine Learning*, vol. 11, no. 1, pp. 1–96, 2018.