RAN Slicing in a UAV Network for eMBB Service Provision

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Abstract—This paper is concerned with a problem of radio access network (RAN) slicing in an unmanned aerial vehicle (UAV) network for enhanced mobile broadband (eMBB) service provision. Unlike the literature focusing on RAN resource sharing in a UAV network, this paper simultaneously considers the enforcement of network slicing and the share of RAN resources. Specifically, this paper formulates the problem of RAN slicing in a UAV network as a time sequence optimization problem with a goal of providing an energy-efficient and fair eMBB service under constraints of both eMBB user equipments’ quality of service requirements and UAVs’ energy consumption and trajectories. This problem is a mixed-integer-non-convex-programming problem that is highly challenging to mitigate. As such, this paper proposes a framework that needs to repeatedly and separately enforce network slicing and optimize RAN resource allocation for mitigating it by exploring the Lyapunov optimization. Besides, this paper leverages a successive convex approximate method to transform the non-convex RAN resource optimization problem into an approximate convex optimization one. Simulation results show that the proposed framework can achieve significant performance gains as compared with other benchmark algorithms.

I. INTRODUCTION

Emerging 5G mobile networks and upcoming 6G mobile networks are envisioned to support a wide range of services, significantly differing in their service requirements and device types, e.g., enhanced mobile broadband (eMBB), massive machine type communications (mMTC), ultra-reliable and low latency communications (URLLC) [1]. As a one-size fits all network architecture may be impossible to be feasible for such various services, a radio access network (RAN) slicing proposal, which turns physical RAN into multiple logical (or virtual) networks or slices, has attracted a great deal of interest from academia and industry. In RAN slicing, each slice is an end-to-end virtualized network instance and separately serves one service instance with custom-tailored network resources [2]. Although it is promising, the RAN slicing proposal is confronted with many crucial challenges, e.g., the efficient enforcement of network slicing and the efficient usage of shared RAN radio resources among different slice owners such that the utilization of RAN infrastructure can be improved [3].

A. Prior Works

Recently, many RAN slicing related work has been developed to tackle the aforementioned challenges [4]–[10]. For example, a framework of enforcing network slicing was proposed in [4]. This framework illustrated how RAN slicing could be implemented so that existing principles of radio access could be utilized. A slice-as-a-service system was proposed in [5] to study the slice enforcement problem via a multi-queuing system for diverse tenant requests. The work [4], [5], however, focused on the enforcement of network slicing and did not consider the efficient share of RAN resources.

As such, researchers investigated the issue of RAN resource sharing [6]–[9], for instance, the work in [6] proposed multiple RAN resource sharing methods using radio resource management functions that supported the split of radio resources among network slices. The potential advantages of allowing for non-orthogonal share of RAN resources in uplink communications from many ground eMBB, mMTC, and URLLC user equipments (UEs) to a base station was investigated in [7]. Besides, on the basis of a principle of puncturing radio resources, a risk-sensitiveness based framework of allocating resources to incoming URLLC traffic while minimizing the risk of eMBB transmission and ensuring the reliability of URLLC traffic was explored in [8].

Although the above work [4]–[9] effectively explores the RAN slicing among diverse slice owners, they do not simultaneously discuss the enforcement of network slicing and share of RAN resources. To mitigate this issue, a RAN slicing framework was developed in [11]. This framework first designed a programmable network slicing architecture based on a flexible RAN to enforce network slicing and then utilized a two-level medium access control (MAC) scheduler to abstract and share radio resources among network slices. Additionally, an offline reinforcement learning based network slicing strategy was first proposed to split radio resources and a heuristic method of allocating resources to eMBB and vehicle-to-everything (V2X) slices was then developed in [10].

B. Motivation and Contributions

All of the aforementioned RAN slicing schemes are developed for terrestrial radio access platforms and do not consider the case of network failure owing to infrastructure malfunction, flash crowd areas, etc.) In case of network failure, various
type of services will be interrupted which is fatal to 5G or 6G mobile networks. To alleviate the impact of network failure, the research community begins to show substantial interest towards the utilization of unmanned aerial vehicles (UAVs), which are promising for fast communication recovery, as radio access platforms in 5G or 6G mobile networks [11]. Under this background, RAN slicing for realizing service-oriented vision in a UAV network is starting to receive attention. For example, an architecture and possible applications of flying modes in a frame of a 5G network that supported network slicing and lightweight virtualization were investigated in [11]. A heterogeneous non-orthogonal multiple access scheme was developed in [12] to perform the network slicing for sharing non-orthogonal resources from a pool of eMBB, mMTC, and URLLC devices to a shared base station.

Unlike the work in [11], [12], this paper focuses on both the enforcement of network slicing and radio resource allocation (including the UAV transmit power and trajectory) for eMBB service provision. Particularly, the following main contributions are included:

- This paper simultaneously explores the enforcement of network slicing and share of RAN resources in a UAV network for eMBB service provision. Specifically, the enforcement of network slicing and share of RAN resources are formulated as an optimization problem with a goal of providing an energy-efficient and fair eMBB service under constraints of eMBB UEs’ quality of service (QoS) requirements and UAVs’ energy consumption and trajectories. Owing to the time-dependent feature, the formulated problem is non-trivial; it is confirmed as a mixed-integer-non-convex programming problem that is highly challenging to mitigate.

- Inspired by the superiority of Lyapunov optimization and Jensen’s inequality in tackling time sequence optimization problems, this paper equivalently transforms the formulated time sequence optimization problem into a time average optimization problem using the Jensen’s inequality with a goal of minimizing the Lyapunov drift while maximizing the energy-efficient and fair eMBB service provision under the UAV trajectory constraint.

- This paper proposes an effective framework of mitigating the transformed time average optimization problem, the principle of which is to repeatedly optimize this problem such that the Lyapunov queues are all mean-rate stable.

- This paper decomposes the enforcement of network slicing and share of RAN resources in the time average problem into three independent subproblems including the acceptance optimization of slice requests, UAV location optimization and UAV transmit power control. As the last two subproblems are non-convex a successive convex approximate method is explored to further transform them into approximate convex optimization problems.

- At last, this paper conducts a simulation verification of the proposed framework. Simulation results demonstrate the performance gains of the proposed framework compared with other benchmark algorithms.

The rest of this paper is organized as the following: Section II presents the system model used in this paper and formulates the problem of eMBB service provision. Section III describes the problem transformation in detail. Based on the derivation in Section III the solution to the formulated problem is developed in Section IV. Section V presents the simulation results, and this paper is concluded in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

This paper considers a UAV downlink communication scenario in a RAN slicing system. In this scenario, there are $M$ quasi-static eMBB UEs, each with one antenna, with known locations and $N$ UAVs, each with one antenna, acting as flying base stations. All UAVs connect to a centralized baseband unit (BBU) via fronthaul wireless links so that the RAN slicing can be implemented more smoothly. These UEs have different QoS requirements that are identified by their achievable data rates from UAVs. UE and UAV sets are denoted as $I = \{1, \ldots, M\}$ and $J = \{1, \ldots, N\}$, respectively. The time domain is assumed to be discretized and the communication task of UAVs will continue for an infinite sequence of steps, i.e., $t = \{1, 2, \ldots\}$. Owing to the limited number of UAVs and a UAV’s restricted communication range, UAVs need to adjust their locations continuously when executing tasks such that all ground UEs can be fairly served. Denote the location of UE $i$ as $x_i = [x_i, y_i]^T$ and the horizontal location of UAV $j$ at time slot $t$ as $x_j(t) = [x_j(t), y_j(t)]^T \in \mathcal{X}(t)$. We assume that all UAVs fly at the same and fixed altitude $y_j(t), j \in J$. Besides, considering that transmit powers of UAVs can be dynamically allocated so as to increase UEs’ receiving powers as well as alleviate co-tier interference, we will investigate the joint UAV trajectory design and power control. Because of the limitation on available UAV resources (e.g., transmit power, bandwidth) an acceptance optimization of network slice requests from UEs will be exploited as well.

Let $h_{ij}(t)$ be the power gain from UAV $j$ to UE $i$ at time slot $t$. Considering the limited UAV eMBB service capability and the improvement of system resource utilization, a network management and orchestration unit (briefly called RAN operator) in the RAN slicing system, which is responsible for creating, activating, and deleting network slices according to UEs’ QoS requirements, prefers to admitting a slice request from a UE with a great UAV-UE elevation angle. In this case, the air-to-ground path loss can be approximated as a free space path loss and we therefore adopt the Friis equation [13] to calculate $h_{ij}(t)$, i.e., $h_{ij}(t) = \frac{g_{ij}^x g_{ij}^r \zeta}{D_0^2}$, where $g_{ij}^x$ and $g_{ij}^r$ are transmitting and receiving antenna gains from UAV $j$ to UE $i$, respectively. $D_0$ is a far field reference distance, $\zeta = c/f_c$ is the carrier wavelength, $c$ is the speed of light and $f_c$ is the carrier frequency. $D_{ij}(t) = \sqrt{g_{ij}^x(t) + ||x_j(t) - x_i||^2}$ is a distance between UAV $j$ and UE $i$ at slot $t$.

For any UE $i \in I$, we denote its received signal-to-noise ratio from UAV $j$ at time slot $t$ by $\sinr_{ij}(t)$, which can be expressed as $\sinr_{ij}(t) = \frac{p_j(t) h_{ij}(t)}{\sigma^2 + h_{ij}(t)}$, where $p_j(t) \in \mathcal{P}$ is the instantaneous transmit power of $j$ at $t$, $h_{ij}(t) = \sum_{k \in J \setminus \{j\}} p_k(t) h_{ik}(t)$ is the co-tier interference caused by


other UAVs, $\sigma^2$ is the noise power. Further, owing to the inherently shared nature of radio channel and the potential interference that any transmitter may have on any receiver, slicing a RAN may be particularly challenging.

The time average transmit power of UAV $j$ with the first $t$ time slots can be written as $p_j(t) = \frac{1}{t} \sum_{\tau=1}^{t} p_j(\tau)$. Except for transmit powers, UAVs are subject to inherent circuit power consumption, which mainly includes power consumption of mixer, frequency synthesizer, and digital-to-analog converter. Denote $p_j^c$ as the circuit power of $j$ during a time slot, we model the energy consumption of $j$ at $t$ as,

$$ p_j^{tot}(t) = p_j(t) + p_j^c $$

which is upper-bounded by a constant $\bar{p}_j$, i.e., $p_j^{tot}(t) \leq \bar{p}_j$. Accordingly, the time average energy consumption of UAV $j$ within the first $t$ time slots can be written as,

$$ p_j^{tot}(t) = \bar{p}_j(t) + p_j^c $$

which is constrained with $\bar{p}_j^{tot}(t) \leq \bar{p}_j, \bar{p}_j$ is a constant.

Next, we define a network slice request set at time slot $t$ as $S(t)$. For any $s_{ij}(t) \in S(t)$, $s_{ij}(t) = 1$ indicates that a slice request that serving UE $i$ with UAV $j$ is accepted/admitted by the RAN operator at time slot $t$; otherwise, $s_{ij}(t) = 0$.

Owing to the movement of UAVs, eMBB UE $i$ $(i \in I)$ may be in the communication ranges of multi-UAV at slot $t$. We assume that at each $t$, a UE can be served by at most one UAV, and a UAV is allowed to deliver eMBB traffic to at most one UE, i.e., we consider the unicast eMBB service, and there is a single UE in an accepted slice, which can be extended to more UEs by grouping them into a class. Thus, we obtain

$$ 0 \leq \sum_{j \in J} s_{ij}(t) \leq 1, \quad 0 \leq \sum_{i \in I} s_{ij}(t) \leq 1 $$

For eMBB traffic, the blocklength may be sufficiently long and the decoding error probability may be significantly reduced by resorting to transmission schemes of low-rate codes that have enough redundancy. We therefore leverage the Shannon capacity which can characterize the decoding error probability to quantify the maximal achievable rate in eMBB services. Specifically, the maximal achievable rate of eMBB UE $i$ at time slot $t$ can take the following form

$$ u_i(t) = \sum_{j \in J} s_{ij}(t) \log_2 (1 + \sin r_{ij}(t)) $$

During the first $t$ time slots, the time average achievable rate of UE $i$ can then be written as $\bar{u}_i(t) = \frac{1}{t} \sum_{\tau=1}^{t} u_i(\tau)$.

Besides, as UEs require the minimum time average achievable data rates in practical communication scenarios we present the following constraint to guarantee that UEs’ minimum requirements can be satisfied, i.e., $\bar{u}_i(t) \geq u_i^c$.

During the flight, the distance between two consecutive waypoints on a UAV trajectory will be constrained by the UAV’s maximum speed. As such, the mathematical expression of the waypoint distance constraint can be written as $||x_j(t) - x_i(t-1)||^2 \leq e_{\max}^2$, where $e_{\max}$ is the UAV’s maximum flight distance during a slot. Additionally, for collision avoidance, the distance between any two UAVs at each slot should not be less than a safety distance. Mathematically, the expression can be written as $||x_j(t) - x_k(t)||^2 \geq d_{\min}^2$, where $d_{\min}$ is the minimum safety distance.

### B. Problem Formulation

Define $\phi(\bar{u}_1(t), \ldots, \bar{u}_M(t)) = \sum_{i=1}^{M} \log_2 (1 + \bar{u}_i(t))$ as a proportional fairness function of time average achievable data rates across all eMBB UEs. The maximization of $\phi(\bar{u}_1(t), \ldots, \bar{u}_M(t))$ will lead to that of UEs’ time average achievable data rates as well as UAVs’ fair coverage. Our goal is to achieve an energy-efficient and fair eMBB service in RAN slicing UAV communications by jointly optimizing the network slice request, UAV location, and UAV transmit power over all time slots. Combining with the above analysis, we can formulate a time sequence optimization problem as follows

Maximize $\lim_{t \to \infty} \phi(\bar{u}_1(t), \ldots, \bar{u}_M(t)) - \rho \sum_{j \in J} p_j^{tot}(t)$

s.t: $\lim_{t \to \infty} \bar{u}_i(t) \geq u_i^c, \forall i$

$\limsup_{t \to \infty} p_j^{tot}(t) \leq \bar{p}_j, \forall j$

$0 \leq \sum_{i \in I} s_{ij}(t) \leq 1, \forall i, t$

$0 \leq \sum_{j \in J} s_{ij}(t) \leq 1, \forall i, t$

$\|x_j(t) - x_j(t-1)\|^2 \leq e_{\max}^2, \forall j, t$

$\|x_j(t) - x_k(t)\|^2 \geq d_{\min}^2, \forall j, k \neq j, t$

$s_{ij}(t) \in \{0, 1\}, \forall i, j, t$

$p_j(t) \geq p_j^{\min}, \forall j, t$

where $x_j(0)$ represents the initial position of $j$, $\rho$ is a non-negative coefficient that weighs a trade-off between the system revenue and energy consumption, $p_j^{\min}$ is a small constant.

Since this problem includes logarithmic-quadratic-terms, non-convex-terms, continuous and integer variables, it is a mixed-integer-non-convex programming problem that may be NP-hard or even undecidable. Besides, via optimizing slice requests jointly with UAVs’ trajectories and powers, the goal of this problem is to: 1) maximize the achievable data rates over all UEs; 2) maximize the fair eMBB service over all UEs; 3) minimize the energy consumption of all UAVs; 4) alleviate the impact of interference on RAN slicing; 5) ensure the safety of UAV flight path; 6) strike a trade-off between the achieved data rates and the energy consumption. Thus, it is challenging to obtain the optimal solution to this problem.

In theory, some heuristic methods may be able to mitigate this problem. It is, however, impractical to explore heuristic methods since the duration of the communication service may be very long with $t \to \infty$, which entails unbearable high computational complexity for heuristic methods. Besides, any methods that attempt to mitigate this problem in a slot may be infeasible owing to the unbearable high problem dimensionality. Considering that the Lyapunov optimization can be leveraged to tackle time sequence optimization problem effectively by equivalently optimizing a time average optimization problem, we next design a Lyapunov optimization based framework to mitigate this problem.
### III. Problem Transformation

The key observation of (5a) is that it maximizes a nonlinear function of a time average term that can be transformed into a maximization of a time average of a nonlinear function via an auxiliary variable approach [15]. According to this observation, we first transform (5) into a time average problem and further transform it via the Lyapunov optimization.

**A. Transformation via the Jensen’s inequality**

Let \( \gamma(t) = (\gamma_1(t), \ldots, \gamma_M(t)) \) be an auxiliary vector with \( 0 \leq \gamma_i(t) \leq u_i^{\text{max}}, \forall i \in \mathcal{I}, t \). Define \( g(t) = \phi(\gamma(t)) \). According to the Jensen’s inequality we can achieve \( g(t) \leq \phi(\bar{\gamma}_1(t), \ldots, \bar{\gamma}_M(t)) \). Thus, (5) can be transformed into (6).

\[
\text{Maximize} \quad \lim_{t \to \infty} \left( \hat{g}(t) - \rho \sum_{j \in \mathcal{J}} p_j^{\text{tot}}(t) \right) \quad (6a)
\]

\[
\text{s.t.:} \quad \lim_{t \to \infty} \left[ u_i(t) - \bar{u}_i(t) \right] = 0, \forall i \quad (6b)
\]

\[
\lim_{t \to \infty} \left[ \bar{u}_i(t) - u_i \right] \geq 0, \forall i \quad (6c)
\]

\[
\limsup_{t \to \infty} \left[ \bar{p}_j - \bar{p}_j(t) \right] \geq 0, \forall j \quad (6d)
\]

\[
0 \leq \gamma_i(t) \leq u_i^{\text{max}}, \forall i, t \quad (6e)
\]

\[
\text{constraints (5c) - (5f) are satisfied} \quad (6f)
\]

Suppose all limits exist, the constraint (6b) is therefore equivalent to \( \bar{u}_i(t) = \gamma_i(t) \), \( \hat{g}(t) \leq \phi(\bar{u}_1(t), \ldots, \bar{u}_M(t)) \) can then be achieved. It means that the maximum value of the objective function of (3) is no greater than that of (5). Besides, the maximum value of the objective function of (5) can be obtained through letting \( \tilde{\gamma}_i(t) = \bar{u}_i(t) \) for each eMBB UE \( i \in \mathcal{I} \) and \( t \in \{1, 2, \ldots\} \) with \((\bar{u}_1(t), \ldots, \bar{u}_M(t))\) being the optimal time average achievable data rates of all eMBB UEs for (5) [15]. So, (5) and (6) are equivalent.

**B. Drift-Plus-Penalty**

We can observe that (6) only includes time average terms; thus, a drift-plus-penalty technique [15] is explored to alleviate (6). Specifically, we define virtual queues \( Q_i(t) \) for each \( i \in \mathcal{I} \) as the following form to enforce the constraint (6c):

\[
Q_i(t + 1) = Q_i(t) + u_i^c - u_i(t) \quad (7)
\]

Constraint (6c) is satisfied if the following mean-rate stability condition holds [15]

\[
\lim_{t \to \infty} E\left\{ \frac{\sum_{i \in \mathcal{I}} \left[ Z_i(t) \right]^+}{t} \right\} = 0 \quad (8)
\]

where the non-negative operation \( [x]^+ = \max\{x, 0\} \).

Besides, we define two virtual queues \( Z_i(t), H_j(t) \) for each \( i \in \mathcal{I} \) and \( j \in \mathcal{J} \) to enforce constraints (6b) and (6d) with

\[
Z_i(t + 1) = Z_i(t) + \gamma_i(t) - u_i(t) \quad (9)
\]

\[
H_j(t + 1) = H_j(t) + p_j^{\text{tot}}(t) - \bar{p}_j \quad (10)
\]

Similarly, constraints (6c), (6f) are satisfied if the following mean-rate stability conditions hold for each \( i \in \mathcal{I} \) and \( j \in \mathcal{J} \)

\[
\lim_{t \to \infty} E\left\{ \frac{\sum_{i \in \mathcal{I}} \left[ Z_i(t) \right]^+}{t} \right\} = 0 \quad (11)
\]

\[
\lim_{t \to \infty} E\left\{ \frac{\sum_{j \in \mathcal{J}} \left[ H_j(t) \right]^+}{t} \right\} = 0 \quad (12)
\]

For simplicity, we assume that all virtual queues are initialized to zero. We then define a Lyapunov function \( L(t) \) as a sum of square of all the three virtual queues \([Q_i(t)]^+, [Z_i(t)]^+, [H_j(t)]^+\) (divided by 2 for convenience) at slot \( t \) with \( L(t) \leq \frac{1}{2} \sum_{i \in \mathcal{I}} ([Q_i(t)]^+)^2 + \frac{1}{2} \sum_{j \in \mathcal{J}} ([Z_i(t)]^+)^2 + \frac{1}{2} \sum_{j \in \mathcal{J}} ([H_j(t)]^+)^2 \).

\( L(t) \) is a scalar measure of constraint violation. Intuitively, if the value of \( L(t) \) is small, the absolute values of all queues are small; otherwise, the absolute value of at least one queue is large. Additionally, we define a drift-plus-penalty function as \( \Delta(t) = V \left( g(t) - \rho \sum_{j \in \mathcal{J}} p_j^{\text{tot}}(t) \right) \), where \( \Delta(t) = L(t + 1) - L(t) \) represents a Lyapunov drift, \( \left( g(t) - \rho \sum_{j \in \mathcal{J}} p_j^{\text{tot}}(t) \right) \) is a “penalty”, and \( V \) is a non-negative penalty coefficient that weighs a trade-off between the constraint violation and the optimality. The function value satisfies the following lemma.

**Lemma 1.** At each time slot \( t \), the upper bound of the value of the drift-plus-penalty function \( \Delta(t) = V \left( g(t) - \rho \sum_{j \in \mathcal{J}} p_j^{\text{tot}}(t) \right) \) can take the following form

\[
\text{where, } B = \frac{1}{2} \sum_{i \in \mathcal{I}} (\bar{u}_i^{\text{max}})^2 + \sum_{j \in \mathcal{J}} (p_j^{\text{max}})^2/2
\]

**Proof.** See Appendix A.

**Remark:** In (22), the right-hand-side expression constitutes the upper bound of the drift-plus-penalty. As such, the minimization of the drift-plus-penalty can be approximated by minimizing its upper bound.

We therefore mitigate (6) by greedily minimizing the upper-bounded value of the drift-plus-penalty function at each \( t \). Meanwhile, at each \( t \), the upper-bound value can be decomposed into three independent terms including a constant term, an auxiliary variable term and a term consisting of UAs’ transmit power and eMBB UEs’ achievable data rates. Thus, the framework to mitigate (6) can be summarized as follows.

- At each \( t \), the BBU observes \( Q_i(t), Z_i(t), H_j(t) \).
- Choose \( \gamma_i(t) \) for every eMBB UE \( i \in \mathcal{I} \) to mitigate (22)

\[
\text{Minimize} \quad -V \phi(\gamma(t)) + \sum_{i \in \mathcal{I}} [Z_i(t)]^+ \gamma_i(t) \quad (23a)
\]

\[
\text{s.t.:} \quad \text{constraint (4b) is satisfied} \quad (23b)
\]

- Given the UAV location \( \mathcal{X}(t - 1) \), the BBU chooses \( \mathcal{S}(t), \mathcal{P}(t), \) and \( \mathcal{X}(t) \) to mitigate (24)

\[
\text{Maximize} \quad \sum_{j \in \mathcal{J}} \{V \rho + [H_j(t)]^+ \} p_j - \sum_{i \in \mathcal{I}} ([Q_i(t)]^+ + [Z_i(t)]^+) u_i(t) \quad (24a)
\]

\[
\text{s.t.:} \quad \text{constraints (5c) - (5f) are satisfied} \quad (24b)
\]

- Compute \( u_i(t) \) using (4). Update there virtual queues using (7), (9), and (10).

### IV. Problem Solution

As shown in the above framework, its implementation lies in the optimization of some problems. In this section, we present the detailed procedure for implementing it.
\[
\Delta(t) - V \left( g(t) - \rho \sum_{j \in \mathcal{J}} p_{j}^{\text{tot}}(t) \right) \leq B + \sum_{i \in \mathcal{I}} \left[ Q_i(t)^{+} u_i^c - \sum_{j \in \mathcal{J}} \left[ H_j(t)^{+} \delta_j - p_j^c \right] + V \rho \sum_{j \in \mathcal{J}} p_j^c \right]
- V \phi(\gamma_1(t), \ldots, \gamma_N(t)) + \sum_{i \in \mathcal{I}} \left[ Z_i(t)^{+} \gamma_i(t) \right]
\]

\[
\left. \begin{array}{c}
\text{auxiliary vector } \gamma(t) \text{ related term} \\
\text{constant term at } t
\end{array} \right]
\]

\[
\text{+ } \sum_{j \in \mathcal{J}} \left[ V \rho + [H_j(t)^{+}] \delta_j - \sum_{i \in \mathcal{I}} \left[ (Q_i(t)^{+} + [Z_i(t)^{+}]) u_i(t) \right] \right]
\]

power and achievable data rate related term

\[
(22)
\]

A. Solution to the problem (23)

As mentioned above, the proportional fairness function \( \phi(\gamma_1, \ldots, \gamma_N) = \sum_{i \in \mathcal{I}} \log_2(1 + \gamma_i) \) is a separable sum of individual logarithmic functions. Therefore, the mitigation of (23) is equivalent to a separate selection of the individual auxiliary variable \( \gamma_i(t) \in [0, u_i^{\max}] \) for each eMBB UE \( i \in \mathcal{I} \) that minimizes a convex function \( -V \log_2(1 + \gamma_i(t)) + [Z_i(t)^{+}] \gamma_i(t) \). Thus, the closed-form solution to (23) can be written as

\[
\gamma_i(t) = \begin{cases} 
\frac{u_i^{\max}}{\log_2(V)} - 1 \left. \begin{array}{c}
u_i^{\max} \\
\text{min} \left\{ \left. \begin{array}{c}
\nu_i^{\max} \\
\text{u_i^{\max}}
\end{array} \right\} \right. \right. \\
\left. \begin{array}{c}
\left. \begin{array}{c}
\text{for each eMBB UE set at time slot } t \in [1, T] \right. \\
\end{array} \right. \right. \\
\end{cases}
\]

\[
\gamma_i(t) = \begin{cases} 
\frac{u_i^{\max}}{\log_2(V)} - 1 \left. \begin{array}{c}
u_i^{\max} \\
\text{min} \left\{ \left. \begin{array}{c}
\nu_i^{\max} \\
\text{u_i^{\max}}
\end{array} \right\} \right. \right. \\
\left. \begin{array}{c}
\left. \begin{array}{c}
\text{for each eMBB UE set at time slot } t \in [1, T] \right. \\
\end{array} \right. \right. \\
\end{cases}
\]

(25)

B. Solution to the problem (24)

(24) includes logarithmic-quadratic-terms and continuous and integer variables. Besides, the constraint (5b) is non-convex; thus, (24) is a mixed-integer-non-convex programming problem that is highly challenging to mitigate directly (14). As such, we first attempt to optimize the acceptance of network slice requests. Supported by the optimal slices, UAV network resources including UAV trajectory and transmit power are then dynamically and efficiently allocated according to eMBB UEs’ QoS requirements. Further, the implementation scheme of RAN slicing in (2) is adopted in this paper which enforces the optimal slices via the RAN operator and manages radio resources through a slice context manager. Owing to the space limitation we omit the procedure of implementing the RAN slicing; the reader can refer to (2) for more details.

1) Acceptance Optimization of Slice Requests: Owing to the limitation on UAV’s eMBB service capability (e.g., limited by transmit power and bandwidth), and the high QoS requirements of eMBB UEs as well, the RAN operator cannot accept every incoming slice request. Thus, it has to properly select and admit slice requests to maximize eMBB UEs’ total achievable data rates. For any given UAV location and transmit power \( \mathcal{X}(t), \mathcal{P}(t) \), the acceptance of slice requests of (24) can be optimized by mitigating the following problem

Maximize \( \mathcal{X}(t), \{ \eta_i(t) \} \)

\[
\sum_{i \in \mathcal{I}_s(t)} \left[ (Q_i(t)^{+} + [Z_i(t)^{+}]) u_i(t) \right] \eta_i(t)
\]

s.t. constraints (5e), (5i) are satisfied

(28a)

(28b)

(28c)

Remark: If \( \eta_i^* \) is the optimal solution to (28) such that the constraint (28b) is satisfied with strict inequality, we can then decrease \( u_i(t) \) to make (28b) active, yet without changing the value of (28a). Therefore, (28) is equivalent to (27).

As \( h_{ij}(t) \) can be rewritten as \( h_{ij}(t) = \frac{\theta_{ij}}{r_{ij}} \), \( \theta_{ij} = \frac{g_{ij}^2 \sigma_{ij}^2 + 2 \sigma^2}{16 \pi^2} \), the achievable data rate of UE \( i \) can be expressed as \( u_i(t) = \sum_{j \in \mathcal{J}} \delta_{ij}(t) R_{ij}(t) \) with \( R_{ij}(t) = \log_2(\sigma^2) - \log_2(h_{ij}) \), where \( \delta_{ij}(t) = \max(0, [Q_i(t)^{+} + [Z_i(t)^{+}])] \).

\[
(28)
\]

(28) is not convex due to the non-convex constraints (5b), and (28b). Therefore, we may not find efficient methods to obtain the optimal solution to (28). Although (28b) is not concave with respect to (w.r.t) \( \delta_{ij}, \), we can observe that \( R_{ij}(t) \) is convex w.r.t \( \|x_{ik} - x_i\|^2 \). Accordingly, a slack variable \( B_{ik}(t) = \|x_{ik} - x_i\|^2 \) is involved to transform (28) into the following new problem
Maximize \( x(t), \{ \eta_i(t) \}, \{ B_{ik}(t) \} \sum_{i \in I(t)} \left\{ (Q_i(t))^+ + [Z_i(t)]^+ \right\} \eta_i(t) \) \tag{29a}

s.t. \( \sum_{j \in J} s_{ij}(t)(\tilde{R}_{ij}(t) + \tilde{R}_{j}(t)) \geq \eta_i(t), \forall i \in I(t), t \) \tag{29b}

\( B_{ik}(t) \leq ||x_k(t) - x_i||^2, \forall i \in I(t), k \neq i, j \) \tag{29c}

constraints \((5k), (51)\) are satisfied \tag{29d}

where \( \tilde{R}_{ij}(t) = -\log_2(\sigma^2 + \sum_{k \in J \setminus \{j\}} \frac{p_{k}(t)g_{ij}}{g_i(t) + B_{ik}(t)}) \).

Remark: Similar to (28), although a slack variable \( B_{ik}(t) \) is introduced, (29) is equivalent to (28). Unfortunately, (29) is still non-convex as \((5h), (29b), (29d)\) are non-convex.

To handle the non-convexity of (29), a successive convex approximate method is explored. It can be observed that \( \tilde{R}_{ij}(t) \) \((i \in I, j \in J)\) is convex w.r.t. \( ||x_k(t) - x_i||^2 \) and will be globally lower-bounded by its first-order Taylor expansion at any local point \( \{17\} \). Therefore, for a given local point at the \((r + 1)\)-th iteration \((r \geq 0)\), denoted by \( x_k^{(r)}(t) \), \( \tilde{R}_{ij}(t) \) is lower-bounded by

\[
\tilde{R}_{ij}(t) \geq \log_2 \left( \sigma^2 + \sum_{k \in J \setminus \{j\}} \frac{p_{k}(t)g_{ij}}{g_i(t) + (2\eta_i(t) - ||x_k^{(r)}(t) - x_i||^2)} \right) - \sum_{k \in J \setminus \{j\}} \frac{p_{k}(t)g_{ij}}{g_i(t) + (2\eta_i(t) - ||x_k^{(r)}(t) - x_i||^2)} \ln 2
\]

\[
= D_i^{(r)}(t) - \sum_{k \in J \setminus \{j\}} E_{ik}^{(r)}(t)(||x_k^{(r)}(t) - x_i||^2 - ||x_k^{(r)}(t) - x_i||^2)
\]

where \( D_i^{(r)}(t) = \log_2 \left( \sigma^2 + \sum_{k \in J \setminus \{j\}} \frac{p_{k}(t)g_{ij}}{g_i(t) + (2\eta_i(t) - ||x_k^{(r)}(t) - x_i||^2)} \right) \), and

\[
E_{ik}^{(r)}(t) = \frac{\left( \eta_i(t) - g_i(t) + (2\eta_i(t) - ||x_k^{(r)}(t) - x_i||^2) \right)}{\left( \sigma^2 + \sum_{k \in J \setminus \{j\}} \frac{p_{k}(t)g_{ij}}{g_i(t) + (2\eta_i(t) - ||x_k^{(r)}(t) - x_i||^2)} \right) \ln 2}
\]

Besides, for a given location point \( x_j^{(r)}(t), x_k^{(r)}(t) \), we can obtain the lower-bound of \( ||x_j(t) - x_k(t)||^2 \) via the first order Taylor expansion as described below.

\[
||x_j(t) - x_k(t)||^2 \geq -||x_j^{(r)}(t) - x_k^{(r)}(t)||^2 + 2(x_j^{(r)}(t) - x_k^{(r)}(t))^T(x_j(t) - x_k(t))
\]

Similarly, for a given location point \( x_k^{(r)}(t) \), \( ||x_k(t) - x_i||^2 \) is lower-bounded by

\[
||x_k(t) - x_i||^2 \geq ||x_k^{(r)}(t) - x_i||^2 + 2(x_k^{(r)}(t) - x_i)^T(x_k(t) - x_i)
\]

For any local point \( x^{(r)}(t) = \{ x_k^{(r)}(t) \} \), by referring to \( (30), (32) \) is approximated as

Maximize \( x(t), \{ \eta_i(t) \}, \{ B_{ik}(t) \} \sum_{i \in I(t)} \left\{ (Q_i(t))^+ + [Z_i(t)]^+ \right\} \eta_i(t) \) \tag{33a}

subject to:

\[
\sum_{j=1}^{N} s_{ij}(t) \left( D_i^{(r)}(t) - \sum_{k \in J \setminus \{j\}} E_{ik}^{(r)}(t) \right) (||x_k(t) - x_i||^2 - ||x_k^{(r)}(t) - x_i||^2) \right) + \sum_{j=1}^{N} s_{ij}(t) \tilde{R}_{ij}(t) \geq \eta_i(t), \forall i \in I(t)
\]

\[
B_{ik}(t) \leq ||x_k^{(r)}(t) - x_i||^2 + 2(x_k^{(r)}(t) - x_i)^T(x_k(t) - x_i), \forall i \in I(t), k \neq i, j \tag{33b}
\]

\[
-||x_j^{(r)}(t) - x_j^{(r)}(t)||^2 + 2(x_j^{(r)}(t) - x_j^{(r)}(t))^T \times (x_j(t) - x_j(t)) \geq d_{min}^2, \forall j, k \neq j, t \tag{33c}
\]

constraint \((5k), (51)\) is satisfied \tag{33e}

Remark: \((33)\) is now convex and can be efficiently mitigated by MOSEK \((16)\). Owing to the approximation, the feasible domain of \((33)\) is smaller than that of \((29)\); thus, the value of \((33a)\) is the upper-bound of that of \((29a)\).

3) UAV Transmit Power Control: For any given slice \( S(t) \) as well as UAV location \( x(t) \), the UAV transmit power of \( G \) can be optimized via mitigating the following problem

Maximize \( P(t), \{ \eta_i(t) \} \sum_{i \in I(t)} [H_i(t)]^+ p_j(t) + \sum_{i \in I(t)} \left\{ (Q_i(t))^+ + [Z_i(t)]^+ \right\} \eta_i(t) \) \tag{34a}

s.t. \( \sum_{j=1}^{N} s_{ij}(t) \log_2(1 + \frac{p_j(t)h_{ik}(t)}{\sigma^2 + \sum_{k \in J \setminus \{j\}} p_k(t)h_{ik}(t)}) \geq \eta_i(t), i \in I(t), t \) \tag{34b}

constraints \((51), (53)\) are satisfied \tag{34c}

Owing to the non-convex constraint \((34b), (34e)\) is non-convex; as a result, it is challenging to achieve its optimal solution. However, we observe that \((34e)\) is a difference of two concave functions w.r.t \( p_k(t) \). Accordingly, we adopt the successive convex approximate again to approximate \((34b)\).

Specifically, \( R_{ij}(t) \) can be rewritten as \( R_{ij}(t) = \tilde{R}_{ij}(t) - \tilde{R}_{i}(t) \), where \( R_{ij}(t) = \log_2 \left( \sigma^2 + \sum_{k \in J \setminus \{j\}} p_k(t)h_{ik}(t) \right) \).

For any local point \( P^{(r)}(t) = \{ p_j^{(r)}(t) \} \), via the first order Taylor expansion \( \tilde{R}_{ij}(t) \) is upper-bounded by

\[
\tilde{R}_{ij}(t) \leq \log_2 \left( \sigma^2 + \sum_{k \in J \setminus \{j\}} p_k^{(r)}(t)h_{ik}(t) \right) + \sum_{k \in J \setminus \{j\}} \left( \frac{p_k^{(r)}(t)}{h_{ik}(t)} \right) \ln 2 (p_k(t) - p_k^{(r)}(t)) = F_{ij}^{(r)}(t) + \sum_{k \in J \setminus \{j\}} G_{ik}^{(r)}(t) (p_k(t) - p_k^{(r)}(t)) \tag{35}
\]

where \( F_{ij}^{(r)}(t) = \log_2 \left( \sigma^2 + \sum_{k \in J \setminus \{j\}} p_k^{(r)}(t)h_{ik}(t) \right) \) and \( G_{ik}^{(r)}(t) = \left( \frac{\sigma^2 + \sum_{k \in J \setminus \{j\}} p_k^{(r)}(t)h_{ik}(t)}{h_{ik}(t)} \right) \ln 2 \)

We can thus write the lower-bound of \( R_{ij}(t) \) as \( R_{ij}(t) \geq \tilde{R}_{i}(t) - F_{ij}^{(r)}(t) - \sum_{k \in J \setminus \{j\}} G_{ik}^{(r)}(t) (p_k(t) - p_k^{(r)}(t)) \).
In summary, for any local point \( \mathcal{P}^{(r)}(t) \), the approximate problem of (34) can take the following form

\[
\text{Maximize} \quad -V \rho \sum_{j \in \mathcal{J}} p_j(t) - \sum_{j \in \mathcal{J}} [H_j(t)]^+ p_j(t) + \sum_{i \in \mathcal{I}} \left( (Q_i(t))^+ + [Z_i(t)]^+ \right) \eta_i(t) \tag{36a}
\]

subject to:

\[
\sum_{j=1}^{N} \left( s_{ij}(t) \bar{R}_i(t) - s_{ij}(t) F_i^{(r)}(t) \right) - \sum_{j=1}^{N} (s_{ij}(t) \times \sum_{k \in \mathcal{J} \setminus \{j\}} G_{ik}^{(r)}(t) (p_k(t) - p_k^{(r)})) \geq \eta_i(t), \forall i \in \mathcal{I}_x(t) \tag{36b}
\]

constraints (54), (55) are satisfied (36c)

Remark: (36) is now convex that can be efficiently alleviated by MOSEK [16]. Likewise, the utilization of the approximation results in that the feasible domain of (36) is smaller than that of (34). Therefore, the minimum value of (36a) is the upper-bound of that of (34a).

4) Iterative Acceptance, Location and Power Optimization:

Based on the above derivation, we next propose an iterative algorithm, named iterative acceptance, location and power optimization (IALPO), for (24) that is summarized as below.

Algorithm 1 Iterative Acceptance, Location and Power Optimization, IALPO

1: **Initialization:** Randomly initialize \( \mathcal{X}^{(0)}(t) \) and \( \mathcal{P}^{(0)}(t) \), let \( r = 0 \).
2: **repeat**
3: Solve problem (26) for given \( \mathcal{X}^{(r)}(t) \), \( \mathcal{P}^{(r)}(t) \), denote the optimal solution by \( \mathcal{S}^{(r+1)}(t) \)
4: Solve problem (33) for given \( \mathcal{S}^{(r+1)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t) \), denote the optimal solution by \( \mathcal{X}^{(r+1)}(t) \)
5: Solve problem (36) for given \( \mathcal{S}^{(r+1)}(t), \mathcal{X}^{(r+1)}(t), \mathcal{P}^{(r)}(t) \), denote the optimal solution by \( \mathcal{P}^{(r+1)}(t) \)
6: Update \( r = r + 1 \)
7: **until** Convergence or reach the maximum number of iteration \( r_{\max} \)

Given a local point \( (\mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t)) \), the obtained value of (26) at the \( (r+1) \)-th iteration, denoted by \( \Gamma(\mathcal{S}^{(r+1)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t)) \), is no greater than \( \Gamma(\mathcal{S}^{(r)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t)) \) via optimizing (26). Given a point \( (\mathcal{S}^{(r+1)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t)) \), we have,

\[
\Gamma(\mathcal{S}^{(r+1)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t)) \geq \Gamma(\mathcal{S}^{(r)}(t), \mathcal{X}^{(r)}(t), \mathcal{P}^{(r)}(t))
\]

for each eMBB UE \( i \) in \( \mathcal{I} \). Therefore, Algorithm 1 is convergent. However, Algorithm 1 cannot guarantee the optimal solution due to the exploration of successive convex approximate, and no optimality can be theoretically derived for it [17].

C. Repetitive Energy-Efficient and Fair eMBB Service

We then propose an efficient algorithm to mitigate the joint slice request, UAV location and transmit power optimization problem (5), which is summarized in Algorithm 2.

Algorithm 2 Repetitive Energy-Efficient and Fair eMBB Service, RE-EFS

1: **Initialization:** Let \( Q_i(1) = 0, Z_i(1) = 0, H_j(1) = 0 \), for each eMBB UE \( i \in \mathcal{I} \)
2: **for** each time slot \( t = 1, 2, \ldots, T \) **do**
3: Observe the virtual queues \( Q_i(t), Z_i(t) \), and \( H_j(t) \).
4: Compute \( \gamma_i(t) \) using (25) for each eMBB UE \( i \in \mathcal{I} \)
5: Find the network slice request \( S(t), \text{UAV location} \mathcal{A}(t) \), and UAV transmit power \( P(t) \) using Algorithm 1.
6: Calculate \( u_i(t) \) for each eMBB UE \( i \in \mathcal{I} \) using (4).
7: Calculate \( p_j^{\text{tot}}(t) \) for each UAV \( j \in \mathcal{J} \) using (11).
8: Update \( Q_i(t+1), Z_i(t+1), \text{and } H_j(t+1) \) using (7), (9), and (10), respectively.
9: **end for**

The computational complexity of Algorithm 2 relies on the complexity of Algorithm 1 and total time slots \( T \). Since Algorithm 1 only needs to mitigate convex problems the complexities of which are polynomial in the worst case, the computational complexity of Algorithm 2 is also polynomial. Lemma 1 points out that \( \Delta(t) \geq V_g(t) - \rho \sum_{j \in \mathcal{J}} p_j^{\text{tot}}(t) \) is upper-bounded at each time slot \( t \). The time average of \( L(t) \) then tends to be zero when \( t \to \infty \). Therefore, Algorithm 2 can make all virtual queues mean-rate stable and is convergent.

V. Simulation Results

In this section, extensive simulations are conducted to validate the effectiveness of the proposed algorithm.

A. Comparison Algorithms and Parameter Setting

To verify the effectiveness of the proposed algorithm, we compare it with the following two benchmark algorithms:

*Static UAV based algorithm:* At \( t = 1 \), it randomly generates horizontal locations for \( N \) UAVs (with an altitude of 100 m) in the geographical area. UAVs will hover throughout the simulation. At each slot, each UAV transmits signals with the maximum power, and UE \( i \in \mathcal{I} \) will access to an available UAV network, i.e., a UAV such that \( u_i(t) \geq u_i^* \) is satisfied, with an equal probability.

*Circular trajectory based algorithm:* Each UAV flies in a circular trajectory with a speed of 10 m/s. At the beginning of the simulation, UAVs (with an altitude of 100 m) are deployed in a line with an equal interval. The distance between two adjacent UAVs is \( 1/2N \) km. The horizontal locations of the first and the last UAVs are \( (1/2 + 1/|4N|, 1/2) \) km and \( (1 - 1/|4N|, 1/2) \) km, respectively, and turning radiuses of them are \( 1/|4N| \) km and \( 1/2 - 1/|4N| \) km. Each UAV transmits signals with the maximum power, and UE \( i \in \mathcal{I} \) will access to an available UAV network with an equal probability.

The parameter setting of the simulation is summarized as the following: Set the size of the considered geographical area be 1000 x 1000 m². A total of 50 eMBB UEs are uniformly distributed in this given area. These UEs are classified into
three categories according to their required data rates. A turntable game in [18] is used to identify the required data rate for each UE with $u_i \in \{0.1, 0.2, 0.4\}$ bps/Hz. Besides, $u_i^{\text{max}}$ is approximated as $\log_2(1 + (\bar{p}_j - p_j^c)\theta_i/(g_j^2(t)\sigma^2))$. More system parameters are listed as below: $T = 500$, $r_{\text{max}} = 500$, $p_j = 120$ mW, $\bar{p}_j = 120.5$ mW, $\sigma^2 = -110$ dBm/Hz, $p_j^c = 100$ mW, $f_c = 4.9$ GHz, $c = 3.0 \times 10^8$ m/s, $D_0 = 1$ m, $g_{ij} = 100$ m, $g_{ij}^{Rx} = 1$, $g_{ij}^{Tx} = 1$, $e_{\text{max}} = 50$ m, $d_{\text{min}} = 5$ m, $V = 0.01$, $\rho = 0.8$.

B. Performance Evaluation

Next, we proceed to the performance evaluation of all comparison algorithms. The following evaluation indexes are introduced to quantify the performance of all comparison algorithms:

**Queue stability:** Based on the definition of queue stability, we leverage variables $S_Q(t) = \max_{i \in I} \{ Q_i(t) \} / t$, $S_Z(t) = \max_{i \in I} \{ Z_i(t) \} / t$, and $S_H(t) = \max_{i \in I} \{ H_i(t) \} / t$ to measure the obtained queue stability of RE$^2$FS. Besides, with slight abuse of notation we denote $S_Q(t)$, $S_Z(t)$ and $S_H(t)$ by $S_Q$, $S_Z$ and $S_H$, respectively.

**Total achievable data rates:** It represents the obtained total achievable data rates of all eMBB UEs over the whole simulation process, i.e., $\sum_{t=1}^{T} \sum_{i \in I} u_i(t)\Delta t$. The duration $\Delta t$ greatly affects the performance of practical RAN slicing systems. It is difficult to select an appropriate duration and how to choose it may be an engineering problem rather than a mathematical one. For comparison, we let $\Delta t = 1$ s.

**Fairness:** The Jain’s fairness index is involved to measure the fairness of the resource allocation in the RAN slicing system, i.e., $(\sum_{i \in I} \bar{u}_i)^2 / M \sum_{i \in I} \bar{u}_i^2$, where $\bar{u}_i$ denotes the time average data rate of UE $i$ with $\bar{u}_i = 1/T \sum_{t=1}^{T} u_i(t)$.

**Energy efficiency:** Except for the fair eMBB service, energy-efficient eMBB service is also a goal of [S]; thus, we calculate the energy efficiency by (3).

Besides, for both benchmark algorithms, as a random slice request receiving scheme is applied to enable eMBB UEs’ network access requests, we run each of them for twenty-five times in the simulation. Correspondingly, we obtain twenty-five simulation results for each benchmark algorithm, and the following final simulation results are average ones.

1) **Queue Stability:** We first plot the tendency of the queue stability of the proposed RE$^2$FS algorithm. Fig. 1 illustrates there types of varying stability variables over $T$ time slots. From this figure, the following observations are achieved: a) All stability variables rapidly decrease over time slots. After a period of time, values of all queue stability variables are close to (or equal to) zero. b) According to the definition of queue stability, the obtained tendency shows that all the queues are mean-rate stable. c) RE$^2$FS can ensure that time average constraints (1), (2), and (6) are satisfied, i.e., the minimum required data rate of every eMBB UE is successfully provided in case of UAVs’ total energy consumption limitation.

2) **Total achievable data rates:** We plot the relationship among all comparison algorithms. Fig. 2 depicts the obtained total achievable data rates of all eMBB UEs during the whole simulation process by all comparison algorithms. From this figure, the following observations can be made: a) For all comparison algorithms, their achieved total data rates monotonically increase with the increase of the number of UAVs. This is not difficult to be understood. More UAVs imply more assignable network resources, e.g., transmit power, network bandwidth. Particularly, RE$^2$FS achieves a 1.8-fold total rates increase when the number of UAVs increases from two to seven. b) RE$^2$FS always obtains the greatest total achievable data rates. For example, compared with the static UAVs based algorithm, RE$^2$FS improves UEs’ total achievable data rates by 4.26-fold when two UAVs are deployed in the RAN slicing system. From the perspective of the obtained total achievable data rates, static UAVs based algorithm wins circular trajectory based algorithm by a narrow margin, e.g., the total data rates are improved by 27.51% when the number of UAVs is six. This result, however, may be closely related to system parameters such as the eMBB UEs’ location distribution and the size of the geographical area.

3) **Fairness:** Fig. 3 shows the average Jain’s fairness indexes gained by all comparison algorithms. From this figure, we can make the following two observations: a) Circular trajectory based algorithm overwhelms the proposed RE$^2$FS in terms of the fair eMBB service provision, e.g., the obtained fairness indexes of RE$^2$FS and circular trajectory based algorithm are 0.79 and 0.86, respectively, when three UAVs are deployed. This may be mainly due to the unique UAV flight trajectories that are exclusively designed for providing a

![Fig. 1. Average values of stability variables over time slots when $N = 2$.](image1.png)

![Fig. 2. Total achievable data rates of eMBB UEs vs. the number of UAVs.](image2.png)
fair eMBB service. The flight trajectories lead to a relatively balance distribution of eMBB UEs’ time average data rates. As shown in Fig. 4 however, circular trajectory based algorithm obtains the lowest energy efficiency. As such, we may say that the fair scheme applied in the algorithm is not worth promoting. b) Owing to the increasing signal interference, the fairness index obtained by static UAVs based algorithm monotonically decreases with the increase of the number of UAVs. For other two algorithms, the optimized/particular UAV flight trajectories alleviate the signal interference to some extent. As a result, their achieved fairness indexes may not decrease even though more UAVs are deployed.

4) Energy efficiency: At last, we study the impact of the number of UAVs on the achieved energy efficiency. Fig. 4 illustrates the achieved energy efficiency by all comparison algorithms with varying number of UAVs from two to seven. We can have the following observations from this figure: a) RE²FS achieves the greatest energy efficiency. For example, compared with the benchmark algorithms, the minimum improvement on the energy efficiency obtained by RE²FS is 13.65%. Besides, as the total achievable data rates of static UAVs based algorithm are greater than that of circular trajectory based algorithm (see Fig. 2) and both algorithms explore the same power control scheme, the energy efficiency of the former one is greater than that of the latter. b) For RE²FS, its achieved energy efficiency is reduced by 2.58% when the number of UAVs increases from two to seven. Although Fig. 2 shows that more UAVs contribute greater total data rates, they also consume more energy. The simulation results also verify that there is a trade-off between the reduction of energy consumption and the improvement of achievable data rates. As such, an appropriate number of UAVs is crucial for striking a good trade-off; yet it is out of the scope of this paper to identify this appropriate number. c) Except for the UAV trajectories, other differences between RE²FS and two benchmark algorithms lie in the power control scheme and the admission scheme of slice requests. Although benchmark algorithms transmit signals with the maximum transmit power, they do not achieve the greatest total data rates. This may result from the great signal interference. Owing to the exploration of power control and slice admission optimization, RE²FS not only achieves greater total data rates but consumes less energy.

Summarily, RAN slicing facilitates dynamic and efficient allocation of network resources to satisfy diverse QoS demands. Based on the RAN slicing, effective UAV trajectory design, transmit power control will help improve the network resource utilization and boost network capacity.

VI. CONCLUSION

This paper formulated the enforcement of network slicing and the share of RAN resources in a UAV network as a time sequence optimization problem with a goal of providing an energy-efficient and fair eMBB service under constraints of eMBB UEs’ QoS requirements and UAVs’ energy consumption and trajectories. The Lyapunov optimization and Jensen’s inequality were explored to transform it into a new optimization problem. To mitigate it, an algorithm separated and repeatedly optimizing the network slicing and the RAN resource allocation was developed. Simulation results verified that the proposed algorithm obtained a high level of fairness across eMBB UEs and improved the energy efficiency by at least 13.65% as compared with two benchmark algorithms.

APPENDIX

A. Proof of Lemma 7

We discuss the upper bound of \( \frac{1}{2}([Q_i(t+1)]^+)^2 \) in three cases. According to (7) and the non-negative operation, Case 1: when \( Q_i(t+1) \geq 0 \) and \( Q_i(t) \geq 0 \), we can obtain

\[
\frac{1}{2}([Q_i(t+1)]^+)^2 = \frac{1}{2}([Q_i(t)]^+)^2 + [Q_i(t)]^+(u_i^c - u_i(t)) + \frac{1}{2}(u_i^c - u_i(t))^2
\]  

(37)

Case 2: when \( Q_i(t+1) \geq 0 \) and \( Q_i(t) < 0 \), we can achieve \( u_i^c - u_i(t) > Q_i(t+1) \geq 0, [Q_i(t)]^+ = 0 \) and

\[
\frac{1}{2}([Q_i(t+1)]^+)^2 < \frac{1}{2}(u_i^c - u_i(t))^2
\]

\[
= \frac{1}{2}([Q_i(t)]^+)^2 + [Q_i(t)]^+(u_i^c - u_i(t)) + \frac{1}{2}(u_i^c - u_i(t))^2
\]  

(38)

Case 3: when \( Q_i(t+1) < 0 \), we can obtain

\[
\frac{1}{2}([Q_i(t+1)]^+)^2 = 0
\]

\[
\leq \frac{1}{2}([Q_i(t)]^+)^2 + (u_i^c - u_i(t))^2
\]

\[
= \frac{1}{2}([Q_i(t)]^+)^2 + [Q_i(t)]^+(u_i^c - u_i(t)) + \frac{1}{2}(u_i^c - u_i(t))^2
\]  

(39)
Therefore, we can have
\[
\frac{1}{2}([Q_i(t+1)]^+)^2 \leq \frac{1}{2}([Q_i(t)]^+)^2 + [Q_i(t)]^+(u_i^+ - u_i(t)) + \frac{1}{2}(u_i^+ - u_i(t))^2 \quad (40)
\]
Similarly, according to (2), (10) and the non-negative operation, we have
\[
\frac{1}{2}([Z_i(t+1)]^+)^2 = \frac{1}{2}([Z_i(t)]^+)^2 + [Z_i(t)]^+(\gamma_i(t) - u_i(t)) + \frac{1}{2}(\gamma_i(t) - u_i(t))^2 \quad (41)
\]
and
\[
\frac{1}{2}([H_j(t+1)]^+)^2 \leq \frac{1}{2}([H_j(t)]^+)^2 + [H_j(t)]^+(p_j(t) - \tilde{p}_j + p_j^2) + \frac{1}{2}(p_j(t) - \tilde{p}_j + p_j^2)^2 \quad (42)
\]
With inequalities (40)-(42), we can obtain a new inequality by utilizing the definition of Lyapunov drift. Next, we can achieve (22) by adding \(-V\left(g(t) - \sum_{j=1}^{N} p_j(t)\right)\) to both sides of the new inequality.

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