IEEE Access
Multidisciplinary Rapid Review Open Access Journal

Received April 24, 2019, accepted May 16, 2019, date of publication May 27, 2019, date of current version June 6, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2919290

A QoE-Oriented Scheduling Scheme for Energy-Efficient Computation Offloading in UAV Cloud System

ANG GAO[1], YANSU HU[2], WEI LIANG[1], YIZHI LIN[3], LIXIN LI[1], AND XU LI[1]
[1]School of Electronics and Information, Northwestern Polytechnical University, Xi'an 710072, China
[2]School of Electronics and Control, Chang'an University, Xi'an 710064, China
[3]School of Electrical and Electronic Engineering, University of Bristol, Bristol BS8 1UB, U.K.

Corresponding author: Ang Gao (gaoang@nwpu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61601365, in part by the China Postdoctoral Science Foundation under Grant 2017M623243, and in part by the Natural Science Basic Research Plan in Shaanxi Province of China under Grant 2018BSHYDZZ26 and Grant 2019ZDLGY130202.

ABSTRACT Air ground integrated mobile cloud computing (MCC) provides UAVs with more flexibility and resilience from the cloud computing architecture. However, the increasing aerial mobile data requires heterogeneous quality of experience (QoE) for aerial accessing network. In addition, for the persistent flying, energy efficiency during the computation offloading should also be under consideration. This paper proposes an energy-efficient resource allocation scheme with the ability of QoE enhancement. Various aerial offloading data with different QoE requirements is stored and relayed in the multi-queueing architecture. Hence offloading rate differentiation is utilized to ensure the high-priority data a better QoE. The satisfaction function is designed with respect to energy efficiency and actual performance experienced by UAV. By using the Lyapunov optimization technique, the problem can be decoupled into two independent sub-problems. The first one is rate control associated with multi-queueing architecture in ground base-station (GBS) that manages the aerial offloading data from the UAVs according to the queue state information. The second one is resource allocation associated with the strategy of subcarrier assignment and power allocation according to the channel state information. The experiments demonstrate the algorithm has great properties such as maximization of the UAVs' satisfaction, the reliable heterogeneous QoE support and enhancement of the UAVs' transmission energy efficiency.

INDEX TERMS Mobile cloud computing, unmanned aerial vehicle, computation offloading, quality of experience, energy efficiency.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), especially mini-drones, have attracted much attention for their flexible deployment, agile management, and low cost. UAV cloud [1]or UAV-based Mobile Cloud Computing (UAV-MCC) system, as well as air ground integrated mobile edge network (AGMEN) [2]–[4], provides a promising approach that enhances the performance of computation-intensive application by offering computation offloading opportunities to every individual drone or ground vehicle via aerial-to-aerial (A2A) and aerial-to-ground (A2G) communication.

Recent researches on UAV cloud [1] or UAV-aided network [5], [6] feature in treating UAV as an aerial moving relay system or an UAV-mounted cloudlet. However, such dramatic variety relayed data from sensors in a range makes multiple UAVs hard to afford. Computation-intensive aerial applications on UAV itself like simultaneous localization and mapping (SLAM), virtual reality(VR) and video/audio transmission, also generate a large mount of data, which results in such an issue that the performance of aerial applications on UAVs can be enhanced by offloading tasks to the cloud [1], [7]. Computation-intensive aerial applications are divided into a series of tasks, and then dispatched to the resource-rich cloud infrastructure for fast processing.

Comparing with general cloud, the smart drones in UAV cloud could not only offload tasks to cloud, but also share information and cooperate with each other through a flying ad hoc network (FANET) as well as cellular based network.

The associate editor coordinating the review of this manuscript and approving it for publication was Najah Abuali.

Although the cloud-based approach can significantly augment computational capability for UAVs, a large amount of offloading data makes the wireless A2G Link a new bottleneck that affects the performance of aerial application. The main problems and characteristics of wireless resource management in UAV cloud offloading are summarized as follows:

1) UAVs differ in processing capacity, mission environment and tasks emergency, and different types of aerial applications may generate heterogeneous user-perceived quality of service (QoS), which is also known as quality of experience (QoE). For example, SLAM and control signals should be superior to the general sensing data transmission. While lower-changing data such as temperature and moisture measurements is corresponding more delay-tolerant than that of fast-changing data such as real-time video and audio stream.
2) The communication model for wireless can either be WiFi access point [8]–[10], or Femtocell network or a macrocell in cellular network. Although 5th Generation (5G) communication technology as well as LTE can provide higher accessing rate for cloud, the rapid growth of aerial application and service puts forward higher requirements for network. Especially that offloading transmission always bursts for the uncertain nature of UAV missions and fast-changing environment, it is unnecessary and impossible to predict and reserve enough subcarriers or bandwidth to meet the QoE requirements.
3) Energy efficiency should be considered in the wireless task offloading scheme [4]. All kinds of aerial applications gradually come across the bottlenecks of common shared wireless channels, especially in the cellular mobile communication system. If too many drones choose to offload the computation simultaneously, they may suffer severe interference, large delay and network congestion. The uncontrolled retransmission causes unwanted energy wasting. For small UAVs with limited aerial platform carriage, less power wasting will enhance the aerial loiter endurance [11], which is important to the practicability of UAVs.

Therefore, it is a great challenge to improve the wireless accessing efficiency under the dual constraints of limited energy consumption and heterogeneous aerial QoE. The mobility, as well as the uncertainty of aerial applicant offloading, makes the problem more complicated. So it is very hard to arrange the resource ahead of time precisely. In general, the resource allocation in wireless network access is a dynamic optimization or a feedback control problem. To the best of our knowledge, most of the researches have solved QoE and energy efficiency in communication as two independent problems.

1) No matter QoS or QoE, the instinctive idea is to arrange more resource to high priority users according to their actual QoE. Frequency division duplex (FDD) and either orthogonal or non-orthogonal multiple access (NOMA) schemes are used during the design of QoE/QoS mapping and monitoring in 5G architecture [12]–[14]. Generally, utility functions are used to map one or several QoS metrics to QoE, and then are modelled as optimization problems. Approaches for solving optimizations include game [15], [16], machine learning for control [7], [17] and convex optimization [4]. The resource for allocation may be the access preambles [18], contention window [7], transmission power [7], [17], bandwidth [19] and caching in the sky [4].
2) Energy efficient or green wireless communication is another appealing challenge [20]. High energy efficiency in communication will improve the limited endurance of UAVs [21]. Bit allocation optimization [6] is proposed for minimizing the mobile energy consumption in UAV-MCC, which means only parts of the aerial tasks can be offloaded to cloudlet with the constrains of power and trajectory for relay. In cellular relay network, energy efficiency can also be improved by cognitive radio [22] or masssive MIMO [23]. Some researches aim at assessing energy efficiency and QoE in typical cellular network by subcarrier selection and bandwidth allocation without the consideration of heterogeneous application QoE [19], [24].

Nevertheless, aerial application offloading with QoE support and energy efficiency can not be solved by the simple combination of aforementioned methods. In particular, the jointed optimization of the wireless resource allocation and heterogeneous QoE, are tackled with the aims of maximizing the throughput under mobility constraints and a decode-store-and-forward scheme in ground base-station (GBS). This paper proposes an Energy-Efficient Differentiated QoE resource allocation (EE&Diff-QoE) scheme for UAV-MCC, which aims at minimizing the total mobile energy consumptions while satisfying heterogeneous QoE requirements.

In the algorithm, heterogeneous QoE support and energy efficiency are two vital optimization targets. The main contributions of this paper are as follows:

1) First, consider the overall process of aerial application offloading in UAV-MCC and model it as a multi-queueing architecture (also known as performance isolation [19]), so stability and continuity of queues are under consideration during the resource scheduling. Queue state information (QSI) and channel state information (CSI) are applied as feedback variables to assist the algorithm to maintain the stability of queues.
2) Second, with application ranking and measurement of UAVs' satisfaction, the problem can be decoupled into two independent issues by Lyapunov method. One is aerial offloading rate control at GBS for heterogeneous QoE support. The other is subcarriers assignment and power allocation at UAVs for energy efficiency. So the

TABLE 1. Notation.

N	Number of UAV or type of aerial traffic
K	Number of subchannel or subcarrier
w_n	Ranking/Priority of UAV n
$\omega_{n,k}(t)$	Assignment indicator of subcarrier k to UAV n
$Q_n(t)$	Queue length of n^{th} aerial traffic in BGS
λ_n	Offloading rate of n^{th} aerial traffic
$R_n(t)$	Accepting/Service rate of n^{th} aerial traffic
$\mu_n(t)$	Transmission/Arriving rate of n^{th} aerial traffic
$p_{n,k}(t)$	Power assigned to n^{th} aerial traffic on subcarrier k
$h_{n,k}(t)$	Channel gain square of subcarrier k to n^{th} aerial traffic
$P_{n,\max}$	Maximum transmission power of UAV n
$s_n(t)$	Satisfaction of n^{th} aerial traffic
β_1	Weight of throughput in utility function
β_2	Weight of energy efficiency in utility function
$Y_n(t)$	Virtual power queue of UAV n at slot t
$\boldsymbol{G}(t)$	Strategy elements composed by accepting rate, transmission power and subcarrier assignment indicator
$\mathcal{L}(\cdot)$	Lyapunov function
$\Delta\mathcal{L}(t)$	Lyapunov function drift between slot $t+1$ and t
V	Weight of utility function in Lyapunov optimization
$L(\cdot)$	Largrangian function
$\lambda_{n,k}$	Largrangian multiplier

proposed scheduling scheme can be solved and implemented by typical mathematical optimization.

The rest of this paper is organized as follows. In Chapter II, the model of EE&Diff-QoE algorithm in UAV-MCC is detailed. The mathematical discription of EE&Diff-QoE is in Chapter III. In Chapter IV, a series of simulations are carried out to test the performance of EE&Diff-QoE algorithm. Additionally the results of these experiments with analysis are also presented in this section. The conclusion is illustrated in Chapter V. Table 1 lists main notations used in the paper.

II. SYSTEM MODEL

A. COMMUNICATION MODEL

The communication model for wireless access in UAV-MCC is shown in Fig. 1. Supposing there exist a wireless access GBS, through which the UAVs in range can offload tasks to cloud. GBS can be either a WiFI or 4G/5G Femtocell or Macrocell access point. Supposing that there are N drones with different aerial applications to be offloaded, and there are K subcarriers or subchannels in the system. Data arrives in GBS randomly at every time slot and is queued separately according to traffic type. The priorities of UAVs and QoE requirements may be pre-fixed or dynamically negotiated and broadcasted by high-level protocol, which is not in the scope of this paper.

Every kind of aerial applications' data arrival is independently and identically distributed (i.i.d). To support differentiated service, the data received by GBS is temporarily stored in isolated queues waiting to be relayed in the manner of First-InFirst-Out(FIFO). Additionally, queueing theory also has been used to model and analyze this mutil-queueing system [25]. At each time slot t, the arriving data from drones is Poisson distribution with rate μ_n. $Q_n(t)$ denotes the queue length of aerial traffic n, then $\boldsymbol{Q}(t) = \{Q_n(t)\}$ represents all queue state information at GBS.

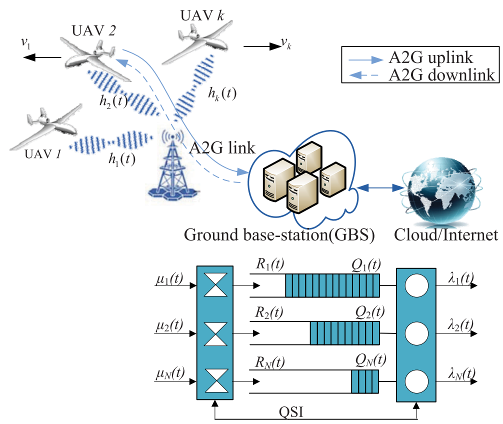


FIGURE 1. System model.

The service rate of different aerial applications is controlled at GBS by rate controller, which is tend to accept high priority aerial data. The queue length is finite. So if the queue is fulfilled, GBS will reject corresponding newly arrived data. The rate control subsystem is detailed in Section III-B.1. Power assignment and subcarriers selection are implemented by resource allocation subsystem, which enforces the final resource allocation and dominates the QoE. The resource allocation subsystem is detailed in Section III-B.2. In this paper, aerial application with larger queue backlog or better channel condition or higher priority will be assigned higher transmission power and more subcarriers [26].

B. A2G COMMUNICATION IN PHYSICAL LAYER

UAVs offload their aerial application data to cloud through A2G cellular network. Generally, the A2G uplink and downlink are asymmetric, because UAV offloading by A2G uplink contains large amount of computation-intensive data, while cloud only returns simple processing results by A2G downlink [2]. The paper only considers the A2G uplink that dominates the QoE of offloading.

Supposing that there are K subcarriers and N UAVs in cellulaer UAV-MCC system that operates in a time-slot fashion. A subcarrier can only be used by one UAV in a time slot. $\omega_{n,k}(t) \in \{0, 1\}$ is the subcarrier assignment indicator. $\omega_{n,k}(t) = 1$ denotes that subcarrier k is allocated to drone n at the time slot t.

$$\sum_{n=1}^{N} \omega_{n,k}(t) \leq 1, \quad \forall n, t \tag{1}$$

$\mu_n(t)$ is the total A2G uplink transmission rate from n^{th} UAV to GBS at the entrance of queue, which is also known as the arriving rate in queue theory. One UAV can use multiple subcarriers in a time slot.

$$\mu_n(t) = \sum_{k=1}^{K} \omega_{n,k}(t) \log_2(1 + \frac{p_{n,k}(t)h_{n,k}(t)}{n_0 B}), \quad \forall n, t \tag{2}$$

$p_{n,k}(t)$ denotes the transmission power of drone n on subcarrier k at time slot t, and $h_{n,k}(t)$ denotes the corresponding channel gain square. n_0 is power spectrum density of AWGN and B is subcarrier bandwidth. $h_{n,k}(t)$ is i.i.d, and $\boldsymbol{H}(t) = \{h_{n,k}(t)\}$ is a $N \times K$-dimensional channel gain matrix for all users and subcarriers.

In addition, the average transmit power of UAV is also up-bounded by average power $P_{n,\max}$.

$$0 \leq \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{P_n(t)\} \leq P_{n,\max} \tag{3}$$

where $P_n(t) = \sum_{k=1}^{K} \omega_{n,k}(t) p_{n,k}(t)$ is the transmit power vector.

C. QoE SATISFACTION FUNCTION

Let w_n denote the priority of n^{th} UAV, which can be achieved by sorting and assigning them with different weight according to their aerial applications' QoE. For example, a remote augmented reality (AR) which needs 10Mbps rate for offloading will be assigned a larger w_k. In practise, the determination of weigh w_n can also be pre-fixed or dynamically negotiated by other protocols, which is out of scope of this paper. In small UAV system, the accepting rate at GBS and power-saving in UAV are of equally importance for persistence flying.

Without loss of generality, it is supposed that every UAV only offloads one kind of aerial application data. Notice that for each UAV, different subcarrier set and different transmission power will lead to different offloading rate.

There are many mean opinion score (MOS) based metrics for QoE evaluation [14] in 5G communication system, which combines send bit rate (SBR), packet error rate (PER) and frame rate (FR) into one MOS value. However, UAV-MCC offloading rate is the most important for mission success. For some real-time applications, too low offloading rate will induce the crucial delay and lead to the failure of aerial task. In order to guarantee aerial applications' QoE with consideration of energy efficiency, in this paper, an increasing, concave, and continuous function is used to measure aerial applications/drones' satisfaction. There is evidence that user experience and satisfaction follow logarithmic laws [27]. Additionally, we use a positive weight β_1 and β_2 to strike a balance between transmission rate and energy efficiency [28], [29]. In this way, the satisfaction function for UAV n is defined as

$$s_n(t) = \beta_1 w_n log_2(R_n(t)) + \beta_2 \frac{\mu_n(t)}{\sum_{k=1}^{K} \omega_{n,k}(t) p_{n,k}(t)} \tag{4}$$

Equ. (4) is made up of two parts. The first item in the left represents offloading rate, which is actually related to the service rate $R_n(t)$ and the queue length $Q_n(t)$. The second item represents the energy efficiency. The weights of these two criteria are represented by $\beta_1, \beta_2, (\beta_1 + \beta_2) = 1$. Although every UAV expects a higher service rate, it is still limited by the data arrival rate μ_n. Consequently, the up boundary of service rate at time slot t is

$$0 \leq R_n(t) \leq \mu_n, \quad \forall n, t \tag{5}$$

This inequality constraints that the aerial service rate cannot exceed the transmission rate.

D. QUEUEING SYSTEM AT GBS

GBS is actually a multi-queueing system, which accepts the aerial data from UAV and relays them to cloud via a fibre cable in manner of FIFO. $Q_n(t)$ denotes the queue length of n^{th} aerial offloading data. The growth rate of queue is data accepting arrival rate from drones, i.e. R_n, while the reduce rate of queue is actually offloading rate of drones, i.e. λ_n. So the recursive formula for queue length can be obtained as follows [30]:

$$Q_n(t+1) = \max[Q_n(t) - \lambda_n(t), 0] + R_n(t) \tag{6}$$

Considering the actual transmission, to keep the aerial application integration and continuity, the queue mean rate should be stable.

$$\lim_{T\to\infty} \frac{\mathbb{E}\{Q_n(t)\}}{T} = 0 \tag{7}$$

E. PROBLEM FORMULATION

EE&Diff-QoE algorithm optimizes aerial application' satisfaction by applying subcarrier allocation and power control schemes for varying channel state. The problem can be described as:

$$\begin{aligned}
\max_{\boldsymbol{R}(t),\boldsymbol{W}(t),\boldsymbol{P}(t)} \quad & \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T-1} \mathbb{E}\{\sum_{n=1}^{N} s_n(t)\} \\
\text{s.t. } & \omega_{n,k}(t) \in \{0,1\}, \quad \forall n,k,t && \text{(C1)} \\
& \sum_{n=1}^{N} \omega_{n,k}(t) \leq 1, \quad \forall n,t && \text{(C2)} \\
& 0 \leq \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}\{P_n(t)\} \leq P_{n,\max} && \text{(C3)} \\
& \lim_{T\to\infty} \frac{\mathbb{E}\{Q_n(t)\}}{T} = 0 && \text{(C4)} \\
& 0 \leq p_{n,k}(t) \leq \infty, \quad \forall n,k,t && \text{(C5)} \\
& 0 \leq R_n(t) \leq \mu_n, \quad \forall n,t && \text{(C6)}
\end{aligned} \tag{8}$$

C1, C2 are conditions of subcarriers, which constrains that each subcarrier can only be allocated to one UAV once a time. C3, C4 ensure the rate stable of virtual power queues and actual data queues. C5 constrains that the transmission power can not be infinite. C6 constrains that service rate could not exceed the data arriving rate.

$$\boldsymbol{R}(t) = \{R_n(t)\}, \quad \boldsymbol{W}(t) = \{\omega_{n,k}(t)\}, \ \boldsymbol{P}(t) = \{p_{n,k}(t)\}$$

are strategy elements controlled by EE&Diff-QoE algorithm. By Lyapunov method, Problem(8) above can be decoupled into two optimization sub-problems.

1) The first one is offloading rate control subsystem, which determinates the service rate $\boldsymbol{R}(t)$ for each aerial application according to queue backlog $\boldsymbol{Q}(t)$, data arriving rate μ_n and users' priority w_n, i.e. aerial applications' QoE level.
2) The second one is resource allocation subsystem, according to the results of offloading rate control, QSI

$\boldsymbol{Q}(t)$ and CSI $\boldsymbol{H}(t)$, while assignment indicator matrix $\boldsymbol{W}(t)$ and transmission power matrix $\boldsymbol{P}(t)$ are optimised by assigning larger transmission power and more better subcarriers to drones who are able to achieve higher energy efficiency.

Thus EE&Diff-QoE algorithm can solve two sub-problems separately and finally offer the QoE-differentiation with high energy efficiency.

III. EE&DIFF-QoE ALGORITHM

A. LYAPUNOV OPTIMIZATION

The queueing system should be stable, so Lyapunov method [26], [30] is used to ensure the life-span and stability in a long term. For every UAV, the transmission power $P_n(t)$ can only change in a continuity, so virtual power queue is introduced based on the maximum limitation of transmission power $P_{n,\max}$ [24], which can convert C3 into a virtual power queue stability like C4. The virtual power queue at UAV n is defined as

$$Y_n(t+1) = \max[Y_n(t) - P_{n,\max}, 0] + P_n(t) \tag{9}$$

Only if both $\boldsymbol{Q}(t)$ and $\boldsymbol{Y}(t)$ are stable, this multi-queueing system is robustness in terms of stability of the average queue size and power continuity.

Lyapunov function is defined as

$$\mathcal{L}(\boldsymbol{G}(t)) = \frac{1}{2}\sum_{n=1}^{N}[Q_n(t)]^2 + \frac{1}{2}\sum_{n=1}^{N}[Y_n(t)]^2 \tag{10}$$

$\boldsymbol{G}(t)$ represents the strategy of EE&Diff-QoE algorithm, which is composed of $\boldsymbol{R}(t)$, $\boldsymbol{W}(t)$, and $\boldsymbol{P}(t)$. From Equ.(10), Lyapunov function drift is also defined as

$$\Delta\boldsymbol{\mathcal{L}}(t) \triangleq \mathbb{E}\{\mathcal{L}(\boldsymbol{G}(t+1)) - \mathcal{L}(\boldsymbol{G}(t))\} \tag{11}$$

where the expectation depends on the EE&Diff-QoE algorithm and strategy $\boldsymbol{G}(t)$ made in reaction. According to the definition of $Q_n(t)$ and $Y_n(t)$, the up-bound of $\Delta\boldsymbol{\mathcal{L}}(t)$ exists and satisfies

$$\Delta\mathcal{L}(t) \leq B + \mathbb{E}\{\sum_{n=1}^{N} Q_n(t)(R_n(t) - \lambda_n(t)) + \sum_{n=1}^{N} Y_n(t)(P_n(t) - P_{n,\max})\} \tag{12}$$

where $B = \mathbb{E}\{\sum_n^N \frac{{R_n}^2(t)+{\lambda_n}^2(t)}{2}\} + \mathbb{E}\{\sum_n^N \frac{P_n^2(t)+P_{n,\max}^2}{2}\}$ is defined as a finite constant to simplify the right-hand-side of Equ.(12) above.

Minimizing $\Delta\mathcal{L}(t)$ at every control slot is also known as minimizing the Lyapunov dift, which can only help to meet the stability of backlog in virtual power and actual queues in according with constrains C3, C4. To optimize Problem (8), the objective function $F[s_n(t)] = -Vs_n(t)$ is mapped as a penalty [26]. Instead of taking action to greedily minimize $\Delta\boldsymbol{\mathcal{L}}(t)$ in Equ. (12), actions are taken every time to greedily minimize the *drift-plus-penalty* expression by EE&Diff-QoE algorithm. Lemma 1 stated blow provides an up boundary.

Lemma 1: Supposing $h_{n,k}$ is i.i.d, for all possible $\boldsymbol{G}$ with given non-negative V, the drift-plus-penalty item has the following up boundary:

$$\Delta\mathcal{L}(G(t))+\mathbb{E}\left\{F[s_n(t)]\right\} \leq B + \mathbb{E}\left\{\sum_{n=1}^{N} Q_n(t)\left(R_n(t) - \lambda_n(t)\right)\right\} + \mathbb{E}\{\sum_{n=1}^{N} Y_n(t)(P_n(t) - P_{n,\max})\} - V\mathbb{E}\{s_n(t)\} \tag{13}$$

Proof: See Appendix A for the proof. □

V is a non-negative constant parameter that controls the tradeoff between $\Delta\boldsymbol{\mathcal{L}}(t)$ and the satisfaction function. A bigger V indicates a greater willing to maximize the satisfaction function value $s_n(t)$ with the expense of larger queue backlog. Lemma 1 is the system drift up boundary. To ensure the system stable and optimal, the up boundary should be as small as possible, and the original problem could be transformed into the minimum optimization problems with conditions C1,C2,C5, and C6 as follows:

$$\begin{aligned} \min\ & \mathbb{E}\{\sum_{n=1}^{N} Q_n(t)(R_n(t) - \lambda_n(t))\} - V\mathbb{E}\{s_n(t)\} \\ & + \mathbb{E}\{\sum_{n=1}^{N} Y_n(t)(P_n(t) - P_{n,\max})\} \\ \text{s.t. } & \tilde{\text{C}}1,\text{C}2,\text{C}5, \quad \text{and C6} \\ & \boldsymbol{Q}(t) \quad \text{and } \boldsymbol{Y}(t) \text{ are mean rate stable.} \end{aligned} \tag{14}$$

By introducing the conception of virtual queue, the constrain of power expenditure C3 is satisfied if $Y_n(t)$ is mean rate stable and continuity.

As mentioned before, $\boldsymbol{R}(t)$, $\boldsymbol{W}(t)$, and $\boldsymbol{P}(t)$ are strategy elements decided by EE&Diff-QoE algorithm. Equ.(14) can be divided into the summation of two parts. The first part only relates to vector $\boldsymbol{R}(t)$ and the second part relates to matrices $\boldsymbol{W}(t)$, $\boldsymbol{P}(t)$. So Problem (14) can be transformed to one minimization P1 with respect to $R_n(t)$, and one maximization problem P2 with respect to $\omega_{n,k}(t)$ and $p_{n,k}(t)$, i.e. 1) P1. Offloading rate control to achieve aerial application QoE-differentiation with the condition C6. 2) P2. Resource allocation to guarantee the high energy efficiency with the constrains C1,C2,C4,C5. The details of P1 and P2 are in the following Section III-B.1 and Section III-B.2.

B. EE&DIFF-QoE ALGORITHM DESIGN

In this section, convex optimization and KKT condition are used to obtain the solution of these two parts. In P1, the optimization target is a simple convex function with respect to $R_n(t)$ and condition C6, so the minimization can be solved by directly taking derivative to $R_n(t)$.

In P2, we take the energy efficiency as the most important element of solution. Since P2 can be treated as a concave problem, KKT condition is used to solve the global maximization. To solve the transcendental formula, both proof by contradiction and dichotomy methods are employed.

1) AERIAL OFFLOADING RATE CONTROL

$R_n(t)$ is mainly based on the QoE requirements and queue backlog. The algorithm proposed will allow high-priority aerial application to enjoy a better service rate. The rate differentiation problem is formulated as

$$\begin{aligned} \text{P1}: &\min_{R_n(t)} \mathbb{E}\{\sum_{n=1}^{N} Q_n(t)R_n(t)\} - V\beta_1 w_n \mathbb{E}\{\log_2 R_n(t)\} \\ &\text{s.t. C6} \end{aligned} \tag{15}$$

Obviously, Problem (15) has a minimum value, because $s_n(t)$ is a downward convex function to $R_n(t)$. Taking the derivative of $\sum_{n=1}^{N} Q_n(t)R_n(t) - V_n\beta_1 \log_2 R_n(t)$ with respect to $R_n(t)$ and setting the derivation to zero, there is

$$Q_n(t) - \frac{\beta_1 V w_n}{R_n(t)\ln 2} = 0 \tag{16}$$

So it is obtained that

$$R_n(t) = \begin{cases} \dfrac{\beta_1 V w_n}{Q_n(t)\ln 2}, & R_n(t) < \mu_n \\ \mu_n, & R_n(t) \geq \mu_n \end{cases} \tag{17}$$

It is obviously that the service rate is limited by A2G transmission rate from UAVs to GBS.

2) ENERGY-EFFICIENT RESOURCE ALLOCATION

In this subsystem, proper power and subcarriers are assigned to UAVs for high energy efficiency. The minimum problem is converted into a maximization by taking negative to the initial Equ. (14):

$$\begin{aligned} \text{P2}: \max_{\omega_{n,k}(t), p_{n,k}(t)} &\sum_{n=1}^{N} Q_n(t)\lambda_n(t) + V\beta_2 \frac{\mu_n(t)}{\sum_k^K \omega_{n,k}(t)p_{n,k}(t)} \\ &- \sum_{n=1}^{N}\sum_{k=1}^{K} Y_n(t)\omega_{n,k}(t)p_{n,k}(t) \\ &+ \sum_{n=1}^{N} Y_n(t)P_{n,\max} \\ \text{s.t.}\ \ &\text{C1,C2, and C5} \end{aligned} \tag{18}$$

Resource allocation P2 is a mixed combinatorial problem because it involves both binary variables $\omega_{n,k}(t)$ and continuous variables $p_{n,k}(t)$, which can be solved by brust-force exhaustive searching with complexity of $O(N^K)$. By applying a continuous relaxation approach [31]–[34], i.e. relaxing $\omega_{n,k}$ to $\widetilde{\omega}_{n,k} \in [0, 1]$, Equ.(18) becomes an upward concave function with respect to $\omega_{n,k}(t)$ and $p_{n,k}(t)$, so that P2 can be converted to a concave optimization problem.

Proof: For the prove of concavity, See Appendix B. □

Consequently, the maximization objective is a concave function with inequality constraints, so that KKT condition can be used to solve the optimization problem. Lagrangian multiplier $\lambda_{n,k}$ is introduced to remove the constrain C5. By submitting Equ. (2) to Equ. (18), the Lagrangian function is constructed as

$$\begin{aligned} L(\boldsymbol{P}) = &\sum_{n=1}^{N} Q_n(t)\lambda_n(t) + V\beta_2 \frac{\widetilde{\omega}_{n,k}(t)\log_2[1 + \frac{p_{n,k}(t)h_{n,k}(t)}{\widetilde{\omega}_{n,k}(t)n_0 B}]}{\sum_k^K \widetilde{\omega}_{n,k}(t)p_{n,k}(t)} \\ &- \sum_{n=1}^{N}\sum_{k=1}^{K} Y_n(t)\widetilde{\omega}_{n,k}(t)p_{n,k}(t) \\ &+ \sum_{n=1}^{N} Y_n(t)P_{n,\max} - \lambda_{n,k}p_{n,k}(t) \end{aligned} \tag{19}$$

$Q_n(t)$ and $Y_n(t)$ should be stable and continuous, $Y_n(t)$ is close to 0 with a long enough duration average. In this way, taking the derivative of $L(\boldsymbol{P})$ with respect to $p_{n,k}(t)$, and setting $\frac{\partial L(\boldsymbol{P})}{\partial p_{n,k}} = 0$ yields

$$\begin{aligned} \frac{\partial L(\boldsymbol{P})}{\partial p_{n,k}} = &V\beta_2 \frac{a}{\widetilde{\omega}_{n,k}p_{n,k}(1 + \frac{ap_{n,k}}{\widetilde{\omega}_{n,k}})\ln 2} \\ &- V\beta_2 \frac{\log_2(1 + \frac{ap_{n,k}}{\widetilde{\omega}_{n,k}})}{\widetilde{\omega}_{n,k}p_{n,k}^2} - \lambda_{n,k} = 0 \end{aligned} \tag{20}$$

where $a = h_{n,k}(t)/n_0 B$. Obviously, Equ. (20) is a transcendental formula that may have no analytical solution. So we take proof by contradiction:

1) Assuming that subcarrier k^* is assigned to user n, i.e. $\widetilde{\omega}_{n,k^*} = \omega_{n,k^*} = 1$. Equ. (20) can be rewritten as

$$\begin{aligned} \Gamma_{n,k}(p_{n,k}) = &V\beta_2 \frac{a}{p_{n,k}(1 + ap_{n,k})\ln 2} \\ &- V\beta_2 \frac{\log_2(1 + ap_{n,k})}{p_{n,k}^2} = 0 \end{aligned} \tag{21}$$

2) Equ. (21) can be solved by dichotomy [35]. By taking dichotomy searching, $\Gamma_{n,k}$ should have at least one zero point when $p_{n,k}^* \in [0.01, 0.05]$ Watts, because it is sustainable power range of typical 4G cellular communication. When zero point of $\Gamma_{n,k}$ is outside the interval, it means that power in subcarier k^* exceeds the affordable power. So set $p_{n,k}^*(t) = 0.035$ Watts (15.5dBm, typical 4G LTE subcarrier power) as the default solution.
3) With the power solution of $p_{n,k}^*(t)$ fixed, the allocation of subcarriers is a maximization of Lagrangian function. The Lagrangian Equ.(19) with respect to fixed $p_{n,k}^*(t)$ becomes

$$\begin{aligned} \arg\max_{k=1}^{K} L_{n,k}(\omega_{n,k}) = &V\beta_2 \frac{\omega_{n,k}\log_2(1 + a{p^*}_{n,k})}{{p^*}_{n,k}} \\ &- Y_n(t)\omega_{n,k}p_{n,k}^* \end{aligned} \tag{22}$$

4) If $k^* = \arg\max_{k=1}^{K} L_{n,k}(\omega_{n,k})$, which means subcarrier k^* can be assigned to user n with power $p_{n,k}^*(t)$; Otherwise,

$\omega_{n,k^*}(t) = 0$ and $p^*_{n,k}(t)$ is invalid, subcarrier k^* should not be used by UAV n.

So, at every time slot t, the subcarier k^* is assigned to UAV n to get the maximum $L_{n,k}(\omega_{n,k})$, where $p^*{}_{n,k}(t)$ is the optimal solution for power allocation. EE&Diff-QoE algorithm iterate all $L_{n,k}(\omega_{n,k})$ and find the maximum, then the solution of $\omega_{n,k}(t)$ is formulated as

$$\omega_{n,k}(t) = \begin{cases} 1, & \textit{if} \;\; k = k^* \\ 0, & \textit{otherwise} \end{cases} \tag{23}$$

Given the above, detailed EE&Diff-QoE with combination of both offloading rate control and energy-efficient resource allocation is summarized in Algorithm 1. The complexity mainly depends on the dichotomy searching for Equ.(21) in step 1, so the overall time complexity of EE&Diff-QoE is $O(\log_2 K)$.

Algorithm 1 EE&Diff-QoE Algorithm

```
Input: h_{n,k}(t), μ_{n,k}(t) and constant P_{n,max}, w_n, V
Output: ω_{n,k}, p_{n,k}, R_n
Initialize: t ← 0, Q(t) = 0, Y(t) = 0;
while t ≤ T do
    Q(t) ← update according to Equ.(6);
    Y(t) ← update according to Equ.(9);
    for n = 1 to N do
        for k = 1 to K do
            Solving Equ.(21) with respect to p_{n,k} by
            dichotomy searching when ω_{n,k} = 1;
            if 0.01 ≤ p_{n,k} ≤ 0.05 then
                p*_{n,k} = p_{n,k}
            end
            else
                p*_{n,k} = 0.035
            end
        end
    end
    for n = 1 to N do
        Solving Equ.(22) ;
        ω_{n,k} ← update according to Equ.(23);
    end
    for n = 1 to N do
        μ_n(t) ← update according to Equ.(2);
        R_n(t) ← update according to Equ.(17);
    end
    t ← t + 1;
end
```

C. PERFORMANCE ANALYSIS

It is obvious that $s_n(t)$ is a function of $\boldsymbol{G}(t) = \{\boldsymbol{R}(t), \boldsymbol{P}(t), \boldsymbol{W}(t)\}$, Where $\boldsymbol{G}(t)$ represents the strategy elements of EE&Diff-QoE algorithm. In additional, all the physical quantiles related to the procedure of aerial offloading are bounded in practical system, such as transmission power, service rate, arriving rate and etc. Given channel condition vector $\boldsymbol{H}(t)$, it is reasonable to assumed that all the mathematical expectation of $s_n(t)$ is bounded by :

$$s^{\min} \leq \mathbb{E}\{s_n(\boldsymbol{G}(t), \boldsymbol{H}(t))\} \leq s^{\max} \tag{24}$$

where $s^{\min}$ and $s^{\max}$ are finite constants related to $\boldsymbol{G}(t)$.

Lemma 2: There exist at least one solution for Problem (8) to satisfy C1-C6, and the bound of Equ. (24) holds. Given arbitrary small positive constant ϵ, for any $\delta > 0$, there also exit a stationary randomized algorithm that satisfies,

$$\mathbb{E}\{R^*_n(t) - \mu^*_n(t)|\boldsymbol{G}(t)\} \leq -\epsilon \tag{25}$$

$$\mathbb{E}\{Y^*_n(t) - P_{n,max}|\boldsymbol{G}(t)\} \leq -\delta \tag{26}$$

$$\mathbb{E}\{s^*_n(t)|\boldsymbol{G}(t)\} = s^{opt} \tag{27}$$

where $R^*_n(t)$, $\mu^*_n(t)$ and $s^*_n(t)$ are the corresponding accepting rate, transmission rate and user's satisfaction values with any alternative strategy solution $\boldsymbol{G}(t)$, s^{opt} is theoretical optimal of Problem (8).

Proof: A similar proof can be found in [26] pp. 92. □

Theorem 1: Supposing $h_{n,k}$ is i.i.d over time, for any given $V \leq 0$, if $\boldsymbol{Q}(0) \geq 0$ and $\boldsymbol{Y}(0) \geq 0$, the proposed EE&Diff-QoE with problem of Equ.(8), has the following properties:

1) ***Queue stability**: All queues at GBS, i.e. data queues $\boldsymbol{Q_n}$ and virtual power queues $\boldsymbol{Y}_n$ are mean rate stable.*
2) ***Satisfaction bound**: The bound of time averaged user's satisfaction, i.e. the optimization objective of EE&Diff-QoE satisfies:*

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T-1} \mathbb{E}\{s_n(t)\} \leq s^{opt} - \frac{B}{V} \tag{28}$$

3) ***Average backlog bound**: The time averaged backlog of queue is bounded:*

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T-1} \mathbb{E}\{\sum_{n}^{N} Q_n(t)\} \leq \frac{B+V(s^{max}-s^{opt})}{\epsilon} \tag{29}$$

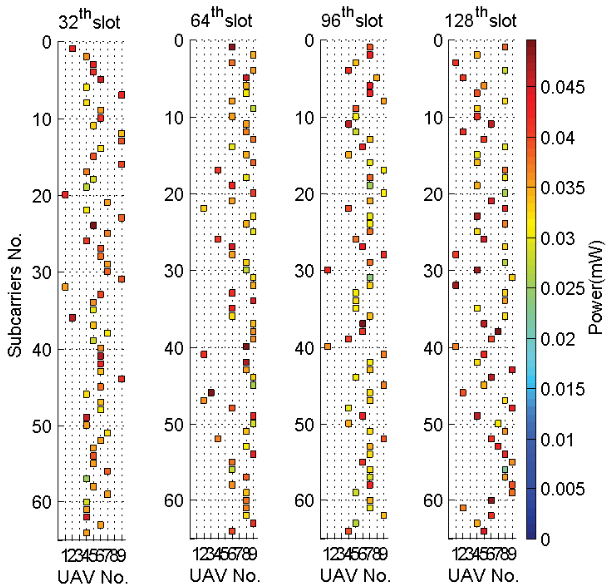
Proof: See Appendix C for the proof. □

Theorem 1 shows that if parameter V is sufficiently large, i.e. B/V is arbitrary small, yielding $s_n(t)$ is arbitrarily closed to the optimum. However, as V increases, the backlog bound of queues at GBS is consequently growing linear with V bounded by Equ.(29). In summary, pushing user's satisfaction close to the maximum value will sacrifice the queue backlog. So in practise, the selection of parameter V should tradeoff between satisfaction value and queue backlog. In Section IV-C, simulation in Figure 6 also shows the same result.

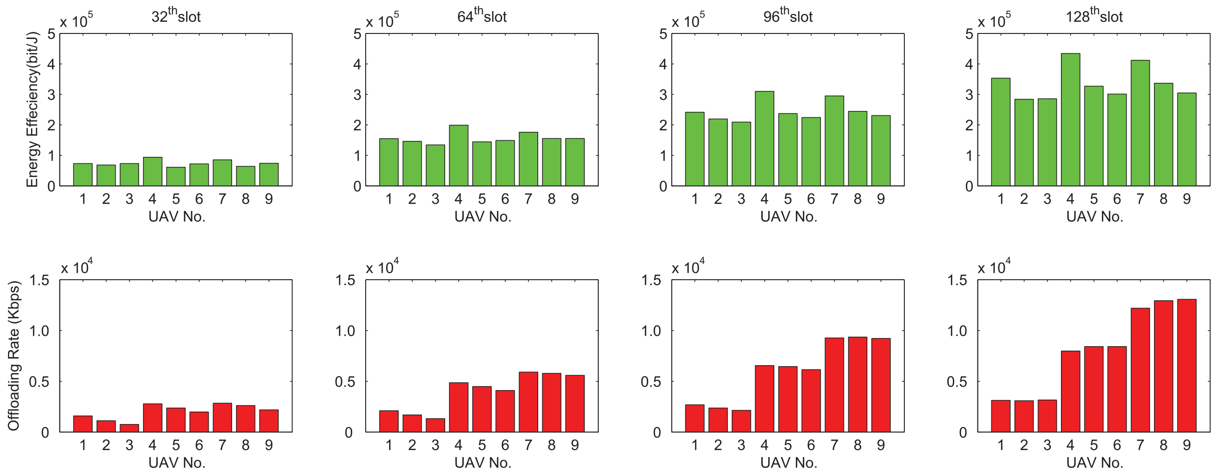
IV. SIMULATION RESULTS

A. SIMULATION CONFIGURATION

In this section, the performance, as well as feasibility and robustness of EE&Diff-QoE are estimated. There are $N = 9$ UAVs and $K = 64$ subcarriers in the system, and $P_{n,\max} = 2.5$ Watts for every UAV. The bandwidth of each subcarrier is 10kHz according to the existing 4G LTE system. The total time of simulation is 128 slots, and each slot lasts 10ms. To achieve aerial QoE-differentiation, we sort 9 UAVs into



(a)



(b)

FIGURE 2. Results of EE&Diff-QoE with mobile UAVs at different time slot. (a) subcarrier allocation and power assignment. (b) energy effeciency and offloading rate.

three groups, and weights of them are 2, 5, 10 respectively. UAVs in the same group are of same priority weight, i.e. $w_1 \ldots w_3 = 2$; $w_4 \ldots w_6 = 5$; $w_7 \cdots w_9 = 10$. In each group, one UAV moves far away to the GBS, one stays still and one approaches the GBS. In this situation, $h_{n,k}(t)$ will decline, keep and increase. We select distance changing from 300m to 400m, which implies that the maximum velocity of UAV is up to 280km/h, and it is in according with most civilian UAVs.

B. PERFORMANCE WITH TIME VARYING

Fig. 2 shows the results of simulation with mobile UAVs at every 32 slots. Fig.2(a) shows the detailed subcarrier allocation and power assignment, while Fig.2(b) shows the corresponding energy efficiency in bit per Jowel (bit/J) and offloading rate in kilobit per second (Kbps). The resource allocation strategy in a sample slot results from a comprehensive consideration of CSI, QSI, and the expectation of energy efficiency. The phenomenons as follows can be seen from the simulation.

1) In accord with the pre-setted weights of UAVs, the offloading rate, as well as the energy efficiency, are distinguished into three different groups. UAVs, whose w_n is larger, i.e. UAV 7, 8, 9, enjoy higher energy efficiency and offloading rate.
2) Fig.2(a) reveals that EE&Diff-QoE offers a scheme to transmit more data with less power consumption and achieve a better offloading rate. Subcarriers with good channel condition (SNR) could achieve higher rate with lower transmission power. Consequently, they may be assigned to high priority UAVs for better QoE. For example, in Fig.2(a) at 96th slot, "Good" subcarriers

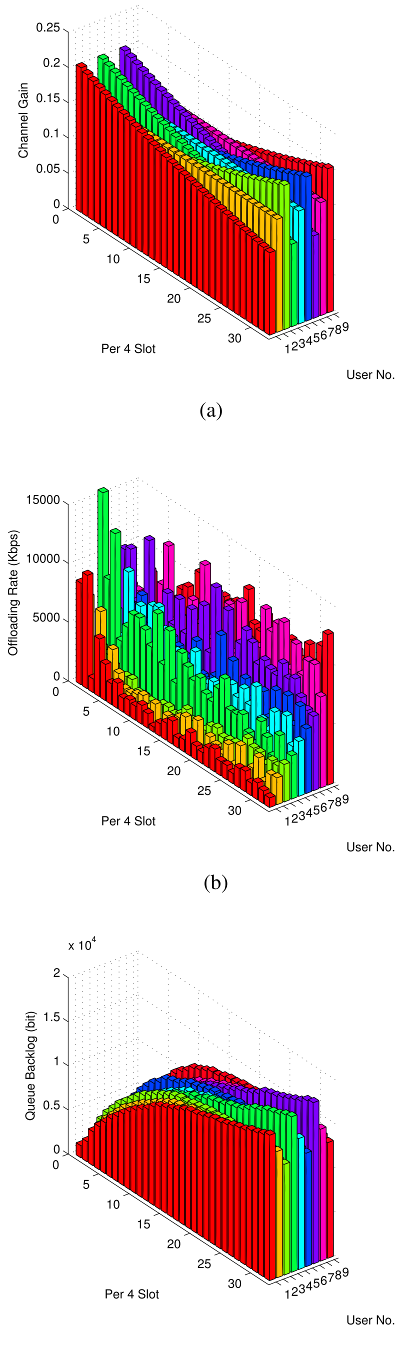


FIGURE 3. Channel condition and queue backlog changes with mobile UAVs at different time slot. (a) Channel Condition. (b) GBS Queue Backlog. (c) UAV Average Offloading Rate.

16, 19, 31, 59 are assigned to UAV 7 with lower transmission power (less than 0.03mW, which is marked by green grid).

3) As shown in Fig.2(a), the tendency can be roughly observed that UAV 7, 8, 9 who possess more "Good" subcarriers can achieve a better offloading rate with relatively lower transmission power. In other words, the high-priority aerial applications or UAVs could use more "Good" subcarriers, so that lower transmission power can still lead to a high offloading rate.

4) As shown in Fig.2(b), although EE&Diff-QoE algorithm provides heterogeneous QoE in aerial application offloading, offloading rate is still affected by the mobility of UAV. UAV 3, 6, 9 fly close to GBS, so the corresponding offloading rate is getting larger, and vice-versa for UAV 1,4, 7, which is because the mobility of UAVs affects channel condition/gain $h_{n,k}(t)$.

5) It should also be noticed that offloading rate increases with time, which is because at the very beginning of the simulation, queues at GBS are not fully padded. As queues are fulfilled at 96 and 128 slots, GBS is saturation. The output and input of queues get equilibration.

Fig. 3 depicts the detailed channel condition (in Fig.3(a)), queue backlog (in Fig.3(b)) and offloading rate (in Fig.3(c)) in a long term. The trend that UAVs' mobility affects the allocation strategy is shown again. UAVs moving far away from GBS will be assigned less resource. On the contrary, UAVs getting closer will acquire more power and subcarriers to offload aerial mission. Some fluctuation appears in the very beginning of the simulation, due to the initial zero state of multi-queueing architecture. After that, the system will become stable and reliable. In addition to the mobility, power and subcarriers are still strictly assigned according to UAVs' priority, which proves a good performance of heterogeneous QoE support.

Fig. 4 and Fig. 5 depict the resource assignment and CDF(Cumulative Distribution Function) of energy efficiency, offloading rate and queue backlog in the condition of fixed channel state, i.e. UAVs are hovering in the air. Comparing with the condition that UAV moves, queue backlog is the dominant factor that affects power allocation. Fig. 4 shows that queues with longer length are tend to be transmitted at a relatively higher power to make input and output balance. Fig. 5 shows CDFs for each grouped UAVs according to their priority, which proves again that EE&Diff-QoE can provide heterogeneous QoE with relatively larger average offloading rate, better energy efficiency and lower queue backlog for high priority UAVs, such as UAV 7, 8, 9. In additional, we also mark the corresponding mean μ and variance δ^2 with different colours in Fig. 5. To some extent, a relative smaller variances over means also proves the robustness of EE&Diff-QoE algorithm.

C. PERFORMANCE COMPARISON OF EE&DIFF-QoE

As aforementioned before, V is the parameter that trades off the queue backlog and user's satisfaction. In Fig.6, it is observed that V effects UAV satisfaction value and the corresponding queue backlog on GBS, i.e. sacrificing the queue backlog to enhance the satisfaction value, which is in accordance with the conclusions in Equ.(28) and Equ.(29). When $V \geq 500$, the satisfaction value is nearly indistinguishable, so 500 is selected as an optimal value for V in the simulation in Sec. IV-B. Nevertheless, no matter what V is, the satisfaction values of different UAVs and corresponding queue back-

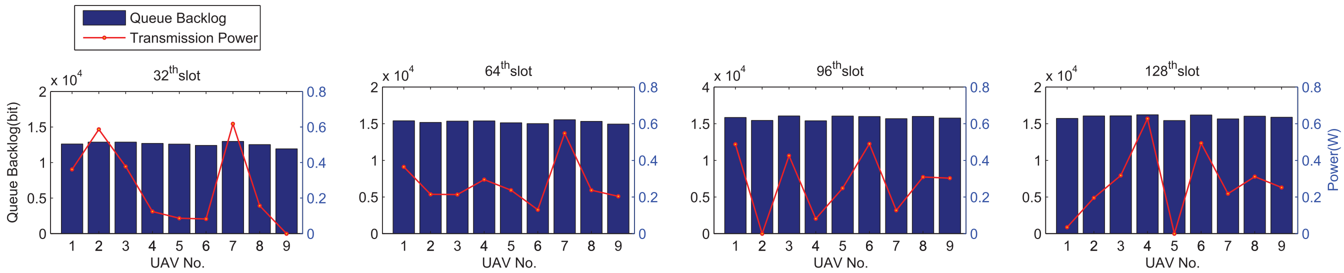


FIGURE 4. Resource assignment with fixed channel state.

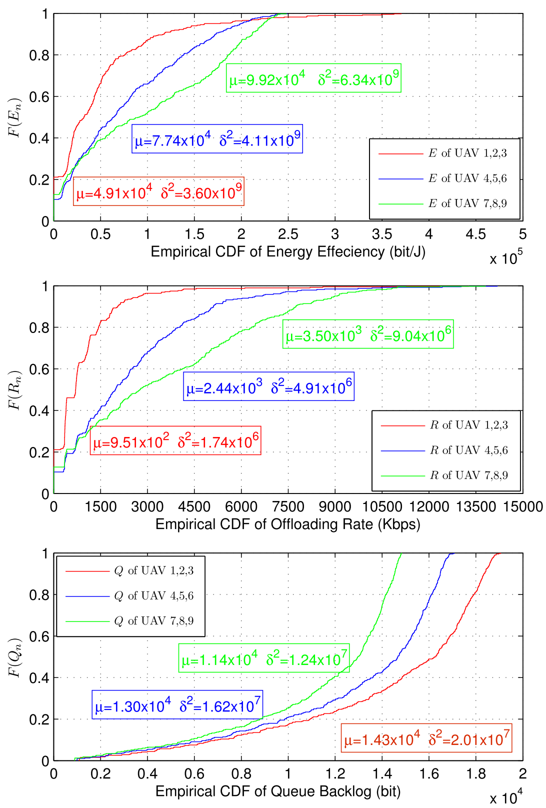


FIGURE 5. Empirical CDF of energy efficiency, offloading rates and queue backlog.

logs on GBS still show the differentiation in priorities, which proves again that EE&Diff-QoE can provide heterogeneous QoE.

The simulations above have proved that EE&Diff-QoE algorithm can provide heterogeneous QoE support with the jointed consideration of aerial application priority, channel states and energy efficiency. In the following, we implements a performance comparison with other two typical kinds of power allocation algorithm. The first one is a common quality-aware power allocation scheme (PF Quality-Aware) [14], which is actually based on proportional fairness (PF) that makes the throughput ration constant. The second one is aiming at maximize the instantaneous total throughput of all users (Throughput-optimal), whose basic ideal is based on weighted water-filling power algorithm. In the comparison, the total UAV satisfaction (TotSat), i.e. $\sum_{n=1}^{N} s_n(t)$ is used

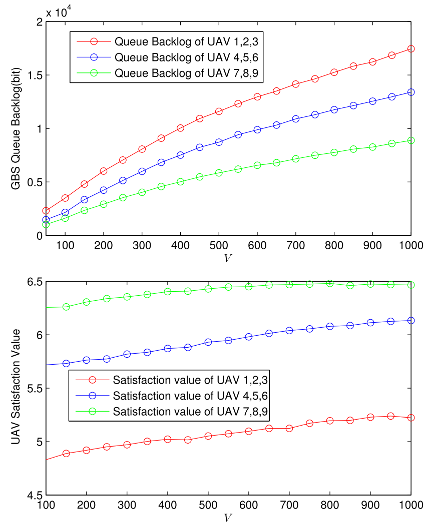


FIGURE 6. Effect of V on queue backlog and utility value.

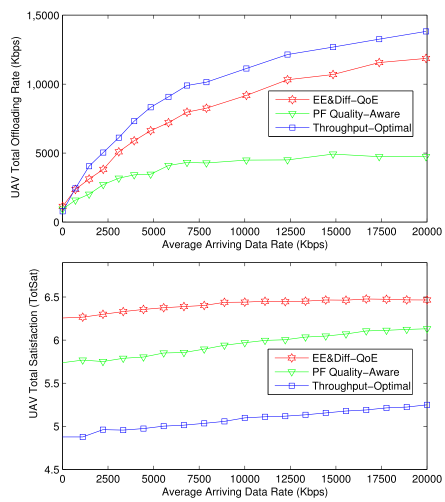


FIGURE 7. Performance comparison of EE&Diff-QoE.

to evaluated the global performances [14], [19] of UAV-MCC system. The following phenomenons show the advantages of EE&Diff-QoE algorithm.

1) As shown in Fig.7, with the increasing of average arriving aerial data at GBS, the total offloading rate are enhanced.

2) Throughput-optimal has the biggest total offloading rate, but without the consideration of energy efficiency and heterogeneous QoE leads to the worst TotSat in three algorithms. It is because that larger transmission power and better subcarriers may be arranged to lower priority user, while the low service rate makes lower priority user suffer a longer queueing time, which deteriorates the offloading rate.
3) On the contrary, PF Quality-Aware provides limited consideration of QoE, so its TotSat is better than water-filling based throughput-optimal.
4) EE&Diff-QoE has the biggest TotSat for its fully combination of user ranking and queue stability. Also, the total offloading rate in EE&Diff-QoE is closed to that with water-filling based throughput-optima strategy.

It is noticed that solely maximizing total offloading rate (throughput) of GBS deteriorates the global performances of TotSat, i.e. water-filling based throughput-optimal scheme. And solely simply PF based QoE-aware scheme also over-sacrifices the total offloading rate. The results above demonstrate EE&Diff-QoE has the advantage of maximizing the aggregate UAVs' satisfaction with little throughput degradation.

V. CONCLUSION

This paper proposes a high energy-efficient resource allocation scheme with QoE differentiation in UAV-MCC system. This adaptive algorithm offers a scheduling scheme with respect to mobility of UAVs as well as channel condition. EE&Diff-QoE comes up with a new satisfaction function with consideration of both actual performance experienced and energy efficiency. By taking Lyapunov optimization, EE&Diff-QoE algorithm decouples the resource allocation optimization into two subproblems. The first optimized object is QoE of aerial offloading, which is measured by the time average throughput. The queues of aerial application in GBS with high priority is allowed to be transmitted and relayed to cloud at a higher speed. The other optimized object is energy efficiency, which is achieved by selecting the channels with good condition and being transmitted at a lower power. In this way, EE&Diff-QoE can support an energy-efficient offloading rate for mobile UAVs. Simulation results confirm the reliable performance and feasibility of EE&Diff-QoE in dynamic aerial channel condition and different transmission data rate.

APPENDIX A
PROOF OF LEMMA 1

Lemma 3: For any nonnegative real number Q, b and A, there holds that $[max(Q-b,0)+A]^2 \leq Q^2+b^2+A^2+2Q(A-b)$ [26]

By taking usages of Lemma 3, there is

$$
\begin{aligned}
\Delta\mathcal{L}(t) &\triangleq \mathbb{E}\{\mathcal{L}(\boldsymbol{G}(t+1))-\mathcal{L}(\boldsymbol{G}(t))\} \\
&= \frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{Q_n^2(t+1)-Q_n^2(t)\} \\
&\quad+\frac{1}{2}\sum_{n=1}^{N}\mathbb{E}\{Y_n^2(t+1)-Y_n^2(t)\} \\
&\leq B(t)+\mathbb{E}\{\sum_{n=1}^{N}Q_n(t)(R_n(t)-\lambda_n(t)) \\
&\quad+\sum_{n=1}^{N}Y_n(t)(P_n(t)-P_{n,\max})\} \qquad (30)
\end{aligned}
$$

where

$$
B=\mathbb{E}\{\sum_n^N\frac{R_n^2(t)+\lambda_n^2(t)}{2}\}+\mathbb{E}\{\sum_n^N\frac{P_n^2(t)+P_{n,\max}^2}{2}\}
$$

Adding the penltay term of $V\mathbb{E}\{s_n(t)\}$ to Equ.(30) proves Equ.(13).

APPENDIX B
PROOF OF CONCAVITY OF RESOURCE ALLOCATION SUBPROBLEM

By relaxing $\omega_{n,k}$ to $\widetilde{\omega}_{n,k} \in [0,1]$ as the subcarriers' time sharing factor [34], the users are allowed to time-share each subcarrier over a large number symbols. The objective Equ. (18) in P2. can be reformulated as

$$
\begin{aligned}
\max_{\widetilde{\omega}_{nk}(t),p_{n,k}(t)} & \sum_{n=1}^{N}Q_n(t)\lambda_n(t)+V\beta_2\frac{\widetilde{\omega}_{n,k}\log_2[1+\frac{p_{n,k}(t)h_{n,k}(t)}{\widetilde{\omega}_{n,k}n_0B}]}{\sum_k^K\widetilde{\omega}_{n,k}(t)p_{n,k}(t)} \\
&-\sum_{n=1}^{N}\sum_{k=1}^{K}Y_n(t)\widetilde{\omega}_{n,k}(t)p_{n,k}(t) \\
&+\sum_{n=1}^{N}Y_n(t)P_{n,\max} \\
&\text{s.t. } 0\leq\widetilde{\omega}_{n,k}\leq 1 \quad \forall n,k,t \text{ (CC1)} \\
&0\leq\sum_{n=1}^{N}\widetilde{\omega}_{n,k}(t)\leq 1, \quad \forall n,t \text{ (CC2)} \\
&\text{(C5)}
\end{aligned}
$$

Assuming that $f(x)$ is concave, then its perspective function $bf(x/b)$ is still concave [36]. Since the function $\log_2[1+\frac{p_{n,k}h_{n,k}}{n_0\,B}]$ is concave, its perspective $\widetilde{\omega}_{n,k}\log_2[1+\frac{p_{n,k}h_{n,k}}{\widetilde{\omega}_{n,k}n_0B}]/\sum_k^K\widetilde{\omega}_{n,k}p_{n,k}$ is jointly concave with respect to $\widetilde{\boldsymbol{W}}(t)=\{\widetilde{\omega}_{n,k}\}$ and $\boldsymbol{P}(t)$. $\sum_{k=1}^K\sum_{n=1}^N\widetilde{\omega}_{n,k}p_{n,k}$ is a linear function. As the result, the objective function in the given optimization problem is jointly concave in $\widetilde{\boldsymbol{W}}$ and $\boldsymbol{P}$.

In addtion, CC1, CC2 and C5 are all linear constrains, therefore CC1, CC2 and C5 together construct a convex set. Thus, it is a concave optimization problem.

APPENDIX C
PROOF OF PERFORMANCE BOUND

Supposing $s_n^*(t)$ is a feasible solution of EE&Diff-QoE, in accordance with Lemma 1, there is

$$\begin{aligned}\Delta\mathcal{L}(\boldsymbol{G}(t)) &+ \mathbb{E}\{F[s_n^*(t)]\\ &\leq B + \mathbb{E}\{\sum_{n=1}^{N} Q_n(t)(R_n^*(t) - \lambda_n^*(t))\}\\ &\quad + \mathbb{E}\{\sum_{n=1}^{N} Y_n(t)(P_n^*(t) - P_{n,\max})\} - V\mathbb{E}\{s_n^*(t)\} \end{aligned} \tag{31}$$

Submitting Equ.(25),(26),(27) to Equ.(31), and taking $\delta \to 0$, yields that

$$\Delta\mathcal{L}(\boldsymbol{G}(t)) + \mathbb{E}\{F[s_n^*(t)]\} \leq B - \epsilon\sum_{n=1}^{N}\mathbb{E}\{Q_n(t)\} - V\mathbb{E}\{s^{\text{opt}}\} \tag{32}$$

Using iterated expectation over each sampling time $t \in \{0, 1, \ldots, T-1\}$ yields

$$\begin{aligned}\mathbb{E}\{\mathcal{L}(\boldsymbol{G}(T))\} - \mathbb{E}\{\mathcal{L}(\boldsymbol{G}(0))\} - \sum_{t=0}^{T-1} V\mathbb{E}\{s_n^*(t)\}\\ \leq T(B - Vs^{\text{opt}}) - \epsilon\sum_{t=0}^{T-1}\sum_{n=0}^{N-1}\mathbb{E}\{Q_n\}\end{aligned} \tag{33}$$

- Submitting Equ.(24), as well as the definition of Lyapunov function $\mathcal{L}(\boldsymbol{G}(t))$ in Equ. (10) into Equ.(33), there is

  $$\mathbb{E}\{\sum_{n=1}^{N} Y^2(T)\} \leq 2TB + 2VT(s^{\max} - s^{\text{opt}}) + 2\mathbb{E}\{\mathcal{L}(G(0))\}$$

  Dividing by T and taking a limits as $T \to \infty$ proves that

  $$\lim_{T\to\infty}\frac{\mathbb{E}\{\sum_n^N Y^2(T)\}}{T} = 0 \tag{34}$$

  Hence for every $Y_n^2 \geq 0$, there is

  $$\lim_{T\to\infty}\frac{\mathbb{E}\{|Y_n(T)|\}}{T} = 0 \tag{35}$$

  so every virtual power queue Y_n is mean rate stable. A similar proof can be applied for Q_n to satisfy C4 in Problem (8).
- Dividing Equ.(33) by TV, and for the fact that $\mathbb{E}\{\mathcal{L}(\boldsymbol{G}(T))\} \geq 0$ and $Q_n(t) \geq 0$, yields

  $$\lim_{T\to\infty}\frac{1}{T}\sum_{T=1}^{T-1}\mathbb{E}\{s(t)\} \geq s^{\text{opt}} - \frac{B}{V} - \frac{\mathbb{E}\{\mathcal{L}(G(0))\}}{TV} \tag{36}$$

  Taking the limits $T \to \infty$ proves Equ.(28).
- Similarly, rewrite Equ.(33), there is

$$\begin{aligned}\epsilon\sum_{t=0}^{T-1}\sum_{n}^{N}\mathbb{E}\{Q_n\} &\leq \mathbb{E}\{\mathcal{L}(\boldsymbol{G}(0))\}\\ &\quad + \sum_{t=0}^{T-1} V\mathbb{E}\{s(t)\} + T(B - Vs^{\text{opt}})\end{aligned} \tag{37}$$

Dividing by ϵT and taking $T \to \infty$, yields that

$$\lim_{T\to\infty}\sum_{t=0}^{T-1}\sum_{n}^{N}\mathbb{E}\{Q_n(t)\} \leq \frac{B + V(s^{\max} - s^{\min})}{\epsilon}$$

which proves Equ.(29).

REFERENCES

[1] F. Luo, C. Jiang, S. Yu, J. Wang, Y. Li, and Y. Ren, "Stability of cloud-based UAV systems supporting big data acquisition and processing," *IEEE Trans. Cloud Comput.*, to be published.

[2] N. Cheng, W. Xu, W. Shi, Y. Zhou, N. Lu, H. Zhou, and X. Shen, "Air-ground integrated mobile edge networks: Architecture, challenges, and opportunities," *IEEE Commun. Mag.*, vol. 56, no. 8, pp. 26–32, Aug. 2018.

[3] G. Hu, W. P. Tay, and Y. Wen, "Cloud robotics: Architecture, challenges and applications," *IEEE Netw.*, vol. 26, no. 3, pp. 21–28, May 2012.

[4] X. Xu, Y. Zeng, Y. L. Guan, and R. Zhang, "Overcoming endurance issue: UAV-enabled communications with proactive caching," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 6, pp. 1231–1244, Jun. 2018.

[5] Y. Zhou, N. Cheng, N. Lu, and X. S. Shen, "Multi-UAV-aided networks: Aerial-ground cooperative vehicular networking architecture," *IEEE Veh. Technol. Mag.*, vol. 10, no. 4, pp. 36–44, Dec. 2015.

[6] S. Jeong, O. Simeone, and J. Kang, "Mobile edge computing via a UAV-mounted cloudlet: Optimization of bit allocation and path planning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 3, pp. 2049–2063, Mar. 2018. doi: 10.1109/TVT.2017.2706308.

[7] A. Gao, Y. Hu, L. Li, and X. Li, "BP network control for resource allocation and QoS ensurance in UAV cloud," *J. Sensors*, vol. 2018, Apr. 2018, Art. no. 1419843. doi: 10.1155/2018/1419843.

[8] N. Cheng, N. Lu, N. Zhang, X. S. Zhang, X. Shen, and J. W. Mark, "Opportunistic WiFi offloading in vehicular environment: A game-theory approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 7, pp. 1944–1955, Jul. 2016.

[9] G. Gao, M. Xiao, J. Wu, K. Han, L. Huang, and Z. Zhao, "Opportunistic mobile data offloading with deadline constraints," *IEEE Trans. Parallel Distrib. Syst.*, vol. 28, no. 12, pp. 3584–3599, Dec. 2017.

[10] Y. He, M. Chen, B. Ge, and M. Guizani, "On WiFi offloading in heterogeneous networks: Various incentives and trade-off strategies," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2345–2385, 4th Quart.,2016.

[11] Z. S. Niu, S. Zhou, S. D. Zhou, and X. F. A. Zhong, "Energy efficiency and resource optimized hyper-cellular mobile communication system architecture and its technical challenges," *Sci. Sinica*, vol. 42, no. 10, pp. 1191–1203, 2012.

[12] M. Gramaglia, I. Digon, V. Friderikos, D. von Hugo, C. Mannweiler, M. A. Puente, K. Samdanis, and B. Sayadi, "Flexible connectivity and QoE/QoS management for 5G networks: The 5G NORMA view," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, May 2016, pp. 373–379.

[13] T. P. C. de Andrade, C. A. Astudillo, and N. L. S. da Fonseca, "Allocation of control resources for machine-to-machine and human-to-human communications over LTE/LTE-A networks," *IEEE Internet Things J.*, vol. 3, no. 3, pp. 366–377, Jun. 2016.

[14] N. Wang, S. Gong, Z. Fei, and J. Kuang, "A QoE-based jointly subcarrier and power allocation for multiuser multiservice networks," *Sci. China Inf. Sci.*, vol. 59, no. 12, 2016. doi: 10.1007/s11432-016-5552-6.

[15] X. Chen, "Decentralized computation offloading game for mobile cloud computing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 4, pp. 974–983, Apr. 2015.

[16] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2795–2808, Oct. 2016.

[17] A. Martin, J. Egaña, J. Flórez, J. Montalbán, I. G. Olaizola, M. Quartulli, R. Viola, and M. Zorrilla, "Network resource allocation system for qoe-aware delivery of media services in 5G networks," *IEEE Trans. Broadcast.*, vol. 64, no. 2, pp. 561–574, Jun. 2018. doi: 10.1109/TBC.2018.2828608.

[18] M. Vilgelm, H. M. Gürsu, W. Kellerer, and M. Reisslein, "LATMAPA: Load-adaptive throughput- maximizing preamble allocation for prioritization in 5G random access," *IEEE Access*, vol. 5, pp. 1103–1116, 2017.

[19] Y. Guo, Q. Yang, F. R. Yu, and V. C. M. Leung, "Dynamic quality adaptation and bandwidth allocation for adaptive streaming over time-varying wireless networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 12, pp. 8077–8091, Dec. 2017.

[20] D. Rapone, D. Sabella, and M. Fodrini, "Energy efficiency solutions for the mobile network evolution towards 5G: An operator perspective," in *Proc. Sustain. Internet ICT Sustainability*, 2015, pp. 1–9.
[21] M. E. Mkiramweni and C. Yang, "Energy efficiency optimization for wireless unmanned aerial vehicle communication networks: A bargaining game approach," in *Proc. 10th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2018, pp. 1–6.
[22] X. Hong, J. Wang, C.-X. Wang, and J. Shi, "Cognitive radio in 5G: A perspective on energy-spectral efficiency trade-off," *IEEE Commun. Mag.*, vol. 52, no. 7, pp. 46–53, Jul. 2014.
[23] S. Cui, A. J. Goldsmith, and A. Bahai, "Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 22, no. 6, pp. 1089–1098, Aug. 2004.
[24] Y. Guo, Q. Yang, and K. S. Kwak, "Quality-oriented rate control and resource allocation in time-varying OFDMA networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 3, pp. 2324–2338, Mar. 2017.
[25] T. Qiu, L. Feng, F. Xia, G. Wu, and Y. Zhou, "A packet buffer evaluation method exploiting queueing theory for wireless sensor networks," *Comput. Sci. Inf. Syst.*, vol. 8, no. 4, pp. 1028–1049, 2011.
[26] M. J. Neely, "Stochastic network optimization with application to communication and queueing systems," *Synthesis Lectures Commun. Netw.*, vol. 3, no. 1, pp. 1–211, 2010.
[27] P. Reichl, B. Tuffin, and R. Schatz, "Logarithmic laws in service quality perception: Where microeconomics meets psychophysics and quality of experience," *Telecommun. Syst.*, vol. 52, no. 2, pp. 587–600, Feb. 2013. doi: 10.1007/s11235-011-9503-7.
[28] Y. Wang, X. Dai, J. M. Wang, and B. Bensaou, "Iterative greedy algorithms for energy efficient LTE small cell networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2016, pp. 1–6.
[29] X. Zhang, J. Zhang, Y. Huang, and W. Wang, "On the study of fundamental trade-offs between QoE and energy efficiency in wireless networks," *Trans. Emerg. Telecommun. Technol.*, vol. 24, no. 3, pp. 259–265, 2013.
[30] J. Li, M. Peng, Y. Yu, and Z. Ding, "Energy-efficient joint congestion control and resource optimization in heterogeneous cloud radio access networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 9873–9887, Dec. 2016.
[31] Z. Shen, J. G. Andrews, and B. L. Evans, "Adaptive resource allocation in multiuser OFDM systems with proportional rate constraints," *IEEE Trans. Wireless Commun.*, vol. 4, no. 6, pp. 2726–2737, Nov. 2005.
[32] L. M. C. Hoo, B. Halder, J. Tellado, and J. M. Cioffi, "Multiuser transmit optimization for multicarrier broadcast channels: Asymptotic FDMA capacity region and algorithms," *IEEE Trans. Commun.*, vol. 52, no. 6, pp. 922–930, Jun. 2004.
[33] W. Yu and J. M. Cioffi, "FDMA capacity of Gaussian multiple-access channels with ISI," *IEEE Trans. Commun.*, vol. 50, no. 1, pp. 102–111, Jan. 2002.
[34] C. Y. Wong, R. S. Cheng, K. B. Lataief, and R. D. Murch, "Multiuser OFDM with adaptive subcarrier, bit, and power allocation," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 10, pp. 1747–1758, Oct. 1999.
[35] G. A. de S. Cavalcanti, R. R. Obelheiro, and G. Koslovski, "Optimal resource allocation for survivable virtual infrastructures," in *Proc. 10th Int. Conf. Design Reliable Commun. Netw. (DRCN)*, Apr. 2014, pp. 1–8.
[36] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

ANG GAO received the Ph.D. degree in control theory and control engineering from the School of Automation, Northwestern Polytechnical University, Xi'an, China, in 2011, where he currently serves as an Associate Professor with the School of Electronics and Information. His research interests include QoS control, resource management, and allocation in wireless communication and cloud.

YANSU HU received the Ph.D. degree in control theory and control engineering from the School of Automation, Northwestern Polytechnical University, Xi'an, China, in 2012. She currently serves as an Associate Professor with the School of Electronics and Control, Chang'an University. Her research interests include networked control and resource allocation in cloud computing.

WEI LIANG received the Ph.D. degree in wireless communication from the University of Southampton, Southampton, U.K, in 2015. She was a Postdoctoral Research Fellow with Lancaster University, from 2015 to 2018. She currently serves as an Associate Professor with the School of Electronics and Information, Northwestern Polytechnical University. Her research interests include adaptive coded modulation, network coding, matching theory, game theory, non-orthogonal multiple access, and machine learning.

YIZHI LIN received the B.E. degree in electronic information engineering from Northwestern Polytechnical University, Xi'an, China. He is currently pursuing the M.S. degree in wireless communication and signal processing with the University of Bristol, UK. His research interest includes optimal resource allocation scheme in cellular systems and cloud.

LIXIN LI received the Ph.D. degree in information and communication engineering from Northwestern Polytechnical University, Xi'an, China, in 2008. He was a Visiting Scholar with the University of Houston, TX, USA, in 2017. He currently serves as an Associate Professor with the School of Electronics and Information, Northwestern Polytechnical University. His research interests include network coding, power control, and resource management in wireless communication.

XU LI received the Ph.D. degree in signal and information processing from Northwestern Polytechnical University, Xi'an, China, in 2010. He was a Marie Currie Research Fellow with the School of Computer Science, University of Lincoln, U.K., from 2015 to 2016. He currently serves as an Associate Professor with the School of Electronics and Information, Northwestern Polytechnical University. His research interests include image fusion and optimization method.