Adaptive Cross-Layer Resource Optimization in Heterogeneous Wireless Networks with Multi-Homing User Equipments

Weihua Wu, Qinghai Yang, Bingbing Li, and Kyung Sup Kwak

Abstract: **In this paper, we investigate the resource allocation problem in time-varying heterogeneous wireless networks (HetNet) with multi-homing user equipments (UE). The stochastic optimization model is employed to maximize the network utility, which is defined as the difference between the HetNet's throughput and the total energy consumption cost. In harmony with the hierarchical architecture of HetNet, the problem of stochastic optimization of resource allocation is decomposed into two subproblems by the Lyapunov optimization theory, associated with the flow control in transport layer and the power allocation in physical (PHY) layer, respectively. For avoiding the signaling overhead, outdated dynamic information, and scalability issues, the distributed resource allocation method is developed for solving the two subproblems based on the primal-dual decomposition theory. After that, the adaptive resource allocation algorithm is developed to accommodate the time-varying wireless network only according to the current network state information, i.e. the queue state information (QSI) at radio access networks (RAN) and the channel state information (CSI) of RANs-UE links. The tradeoff between network utility and delay is derived, where the increase of delay is approximately linear in V and the increase of network utility is at the speed of $1/V$ with a control parameter V. Extensive simulations are presented to show the effectiveness of our proposed scheme.**

Index Terms: **Cross-layer optimization, Lyapunov optimization theory, multi-homing resource allocation.**

I. INTRODUCTION

THE wireless industry is preparing for an astounding 1,000-fold increase in media applications generated by smartphones, tablets and machine-type communication devices in the next decades [1]. Supporting these media applications while maximizing the wireless network's resource (e.g., power, bandwidth) utilization is a significantly challenging task [2], [3]. Multi-homing service [4], [5] has been recognized as a promising technology to meet the balance between stringent quality-of-service (QoS) requirements for media transmission and efficient resource utilization. Multi-homing transmission enables user equipment (UE) to maintain multiple simultaneous network paths between the media content server and the UE by employing different radio access networks (RAN) in the heterogeneous wireless network (HetNet). Moreover, the media content server can schedule the traffic and balance the congestion across multiple paths in order to increase the QoS of media applications [6].

Despite the potential benefits of HetNet with multi-homing services, many research challenges remain to be addressed for the resource allocation, which plays an important role in traditional wireless networks [7]–[9]. Firstly, due to the fact that each UE can get its service from multiple RANs, a deliberate flow control scheme should be jointly designed with the physical resource allocation scheme to split the media traffic into multiple flows on the corresponding RANs. Secondly, practical network control decisions must be made under time varying channel conditions and stochastic media traffic arrival rates [10], hence a stochastic programming problem will be caused by these dynamics. Besides that, in traditional wireless networks [7]–[9], a system-level monitor serves as the centralized optimizer, which estimates the resource availability and environmental dynamics, optimizes the resource allocation strategy. Although, such approaches can determine the global optimal resource allocation strategy, it is often hard to collect the globally information on a large-scale system and solve the problem in a centralized way [11]. Accordingly, it makes much sense to design a distributed resource allocation scheme in the HetNet. Based on the analysis above, the mentioned factors present big challenges to solve the resource allocation problem in HetNet with multi-homing UEs.

Motivated by above considerations, we shall investigate the distributed resource allocation in time-varying HetNet with multi-homing UEs. To this end, we employ the stochastic optimization model to maximize the network utility, which is defined as the difference between the HetNet's throughput and the total energy consumption cost. In harmony with the hierarchical architecture of the HetNet, we decompose the problem of stochastic optimization of resource allocation by the Lyapunov optimization theory into two subproblems, which are associated with flow control in transport layer and power allocation in physical (PHY) layer. For allocating the wireless resource in HetNet, we solve the subproblems of flow control and power allocation.

The main contributions of this paper are outlined as follows:

- For solving the two subproblems, we develop the distributed resource allocation method based on the primal-dual decomposition technique [12]. More specifically, the distributed re-

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source allocation method does not need the exchange of channel state information (CSI) and queue state information (QSI) between different RANs.

- We design an adaptive cross-layer resource allocation algorithm to accommodate the dynamic wireless networks solely based on the current QSI and CSI but without requiring their prior knowledge.
- The tradeoff between network utility and delay is derived, where the increase of delay is approximately linear in V and the increase of network utility is at the speed of $1/V$ with the control parameter V.

The rest of the paper is organized as follows. Section II presents the related works. The system model and problem formulation are given in Section III. In Section IV, we give the cross-layer control strategy. The tradeoff between network utility and delay is analyzed in Section V. Section VI presents the simulation results to evaluate the proposed scheme. The conclusions are drawn in Section VII.

II. RELATED WORKS

There exists a large body of works conducted in resource allocation for the HetNet. For example, a stackelberg game was employed in [13] for the problems of resource allocation and interference management in heterogeneous networks. A limited-feedback two-phase resource allocation scheme was proposed in [14] to maximize the weighted sum of instantaneous rates of all users. The mobile associations and resource allocation scheme in [15] optimized the quality of experience (QoE)-aware energy efficiency and QoE-aware spectral efficiency in a HetNet. The proposed power control algorithm in [16] used the gradient ascent method to control the transmit power of microcell base stations for obtaining an upper bound of the maximum energy efficiency problem. A joint space-frequency resource allocation scheme was developed in [17], [18] for minimizing the total number of backlogged packets in each transmission instant. However, these resource allocation designs [13]–[18] cannot be directly used in the HetNet with multi-homing UEs, where a deliberate flow control scheme should be designed to split the media traffic into multiple flows on the corresponding RANs. With multi-homing UEs, a traffic splitting strategy was developed in [19] to guarantee a balance between energy consumption and rate based on the application service requirements. An energy management sub-system was proposed in [20] for UEs to support a sustainable multi-homing video transmission in a heterogeneous wireless access medium. The multi-homing media transmission scheme in [21] minimized the video distortion through congestion window adaption, flow rate allocation and data retransmission. The tradeoff between energy efficiency and spectral-efficiency was achieved in [22] by controlling the traffic splitting probability of a multi-homing media transmission process. A low complexity distributed user association algorithm is developed in [23] for fair user association while considering the QoS-provision for users. However, the aforementioned literatures are typically based on snapshot models and neglect the fact that practical resource allocation decisions must be made under time varying channel conditions and stochastic media content arrival rates. Considering the time-varying network conditions, a dynamic optimization algorithm was proposed in [24] for maximizing the average throughput of each UE. The dynamic power allocation algorithm in [25] achieved the maximum energy efficiency. Nevertheless, these strategies are operated in a centralized manner, which cannot be easily implemented in a HetNet without system-level monitor.

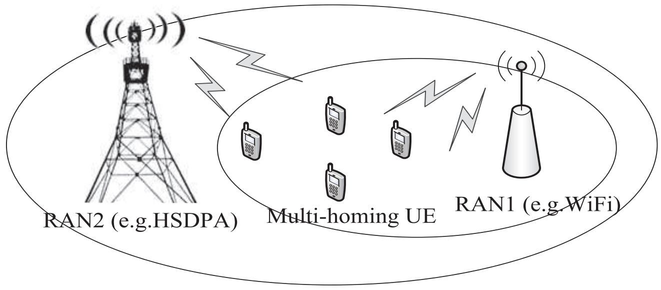

Fig. 1. System model of HetNet with multi-homing UEs.

III. SYSTEM MODEL

In this section, we first introduce the model of HetNet with multi-homing UEs. Next, we formulate the problem of resource allocation.

A. Network Model

We consider a HetNet integrating multiple RANs and UEs, as shown in Fig. 1. The RANs are connected to a flow controller by the backhaul links. The UE is equipped with multiple radio interfaces and multi-homing capable. As a result, the UE can establish communication with multiple RANs simultaneously. The end-to-end connection can be constructed by binding a pair of IP addresses from the media content server and the UE, respectively. For multi-homing transmission, a desired media content stream can be split into multiple flows by the flow controller. Let $N = \{1, 2, 3, \cdots\}$ denote the set of RANs and $M = \{1, 2, 3, \cdots\}$ denote the set of UEs. With the multi-homing capability, each UE m (RAN n) can simultaneously connect to the set of N_m RANs (M_n UEs) from the available RANs set N (UEs set M).

The HetNet is assumed to be operated in slotted time, with time-slots normalized to integer values $t \in \{0, 1, 2, \cdots\}$. Let $g_{n,m}(t)$ be the channel gain between RAN $n \in N$ and UE $m \in M$ at time-slot t. We assume that $\mathbf{g}(t) = [g_{n,m}(t)]_{n\in N, m\in M_n}$ is independently and identically distributed (i.i.d.) over different time-slots and that $\mathbf{g}(t)$ takes values in a finite state space $\mathcal{G}$. Let the stochastic process $A_m(t)$ denote the amount of data arrival at the flow controller for UE m at timeslot t. We assume that $\mathbf{A}(t) = [A_m(t)]_{m\in M}$ is i.i.d over different time-slots in a finite state place Λ and that $\mathbf{A}(t)$ has the average arrival rate $\boldsymbol{\lambda} = [\lambda_m]_{m\in M}$, i.e., $\mathbb{E}[A_m(t)] = \lambda_m, \forall m \in M$, where $\mathbb{E}[\cdot]$ is the expectation operator. In addition, we assume that both $\mathbf{g}(t)$ and $\mathbf{A}(t)$ remain constant for the duration of a time-slot, but potentially change between slots. In multi-homing networks, different RANs operate in different bandwidths (e.g., 2.4 GHz for WiFi, 1.8–2.3 GHz for high speed packet access (HSPA)) [5]. Thus the inter-RANs interference does not exist in multi-homing networks. Without loss of generality, and under the framework of the Shannon formula, the theoretical transmission rate between RAN $n \in N$ and UE $m \in M$ can be approximately represented as (unit: nats)

$$r_{n,m}(t) = \varepsilon_n B_n \log_2 \left(1 + \Gamma \frac{|g_{n,m}(t)|^2 p_{n,m}(t)}{B_n N_0}\right), \quad (1)$$

where $p_{n,m}(t)$ is the transmit power, ε_n is the network efficiency depending on the decoder efficiency of RAN, B_n is the bandwidth spacing in RAN n, Γ is the capacity gap from the Shannon channel capacity, and N_0 is the power spectral density of additive white Gaussian noise.

In the HetNet with multi-homing UEs, each media traffic is split and dispatched by the flow controller onto multiple RANs, the flow rate delivered through RAN n for UE m during time-slot t is defined as $\gamma_{n,m}(t)$. Then, we give the following constraint to ensure that the rate-aggregation of the flows should not be higher than that of arrivals

$$\sum_{n \in N_m} \gamma_{n,m}(t) \le A_m(t), \forall m \in M, \forall t > 0. \quad (2)$$

We assume that RAN n provides an infinite buffer[1] for backlogging the media content data and that the backlog in the infinite buffer at time-slot t is denoted by $Q_{n,m}(t)$. It should be noted that only the traffic data currently in the buffer of RANs at the beginning of time-slot t can be transmitted during that time-slot. Hence, the slot-to-slot dynamics of the queue backlog $Q_{n,m}(t)$ $(\forall t > 0, n \in N, m \in M_n)$ are formulated as

$$Q_{n,m}(t+1) = \max\{Q_{n,m}(t) - r_{n,m}(t), 0\} + \gamma_{n,m}(t). \quad (3)$$

The first term in (3) corresponds to the departure process and the second term corresponds to the arrival process. Due to the time-varying $\mathbf{g}(t)$ and the stochastic $\mathbf{A}(t)$, both the departure and arrival processes of the queues are stochastic, hence the queue backlogs are varying over time. Therefore, it is imperative to develop a general definition of queuing stability.

Definition 1: A queue is defined as strongly stable [26] if

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[Q_{n,m}(t)] < \infty. \quad (4)$$

Therefore, if the queue has a bounded time average backlog, we call it strongly stable. Then, a network is called strongly stable if all individual queues of the network are strongly stable. In the following discussions, we will use the term "stable" to refer to strongly stable.

Remark 1: Note that the average delay is proportional to the time averaged queue length from Little's Theorem [27]. Thus, we can depict the average delay by the time averaged queue length and further by network stability. Therefore, making the network stability is an important prerequisite for the resource allocation in HetNet.

B. Problem Formulation

It is reported that RANs consume the highest proportion of energy in HetNet [28]. It is noteworthy that more than 80% of the input energy in a typical wireless network is dissipated as heat. Generally, the useful output power is only around 5% to 20% of the input power [29]. Therefore, with respect to both financial and environmental aspects, excessive energy consumption has become a serious problem for the resource allocation in HetNet. Motivated from [10], [30], in this paper, we consider an energy-aware utility function for the HetNet, which is defined as the difference between the weighted throughput of RANs and the total energy consumption cost

$$U(t) = \sum_{n \in N} \beta_n \sum_{m \in M_n} w_{n,m} \log(\gamma_{n,m}(t) + e) - c \sum_{n \in N} \sum_{m \in M_n} p_{n,m}(t), \quad (5)$$

where c is the cost price of per unit power resource of all RANs, β_n is the income price of RAN n, $\omega_{n,m}$ is a positive weight for UE m to select RAN n. In (5), the first term is the total amount income earned by RANs, the second term is the total power consumption. This utility function not only presents the income and cost of the RANs but also achieves energy efficient wireless networks.

For maximizing the long-term utility of the whole network, the resource allocation problem in the HetNet with multi-homing UEs is formulated as

$$\max \ \overline{U} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[U(t)] \quad (6)$$

$$\text{s.t.} \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[Q_{n,m}(t)] < \infty, \forall n \in N, m \in M_n, \quad \text{(C1)}$$

$$\sum_{n \in N_m} \gamma_{n,m}(t) \le A_m(t), \forall m \in M, \quad \text{(C2)}$$

$$\sum_{m \in M_n} p_{n,m}(t) \le P_n^{\max}, \forall n \in N, \quad \text{(C3)}$$

$$p_{n,m}(t) \ge 0, \gamma_{n,m}(t) \ge 0, \forall n \in N, m \in M_n, \quad \text{(C4)}$$

where (C1) is the network stability constraint for guaranteeing a finite queue length for each queue, (C2) is the flow constraint to ensure that the rate-aggregation of multiple flows received at the UE cannot be more than that of arrivals, (C3) is the transmit power constraint of each RAN and $P_n^{\max}$ is the maximum allowed transmit power of RAN n, (C4) shows the nonnegative transmit power and flow rate.

Problem (6) can be viewed as a stochastic program. A solution is the algorithm for choosing flow rate variable $\boldsymbol{\gamma}(t) = [\gamma_{n,m}(t)]_{n \in N, m \in M_n}$ and transmit power variable $\mathbf{p}(t) = [p_{n,m}(t)]_{n \in N, m \in M_n}$ over time in reaction to the dynamic network state, such that all of the constraints are satisfied and the utility is maximized as large as possible. By jointly considering flow control and power allocation, problem (6) involves multiple layers in the protocol stack to optimize the utility and thus, it is a typical approach of cross-layer design. In the following section, we will develop practical dynamic flow control and power allocation strategy, which pushes the average network utility to the optimal solution of problem (6).

[1] This assumption is based on the reality that the RAN always has large cache space.

IV. ALGORITHM DESIGN FOR HETNET RESOURCE ALLOCATION

To solve optimization problem (6), we propose a dynamic optimization method to decompose the problem into two subproblems, which are associated with a flow control subproblem at the transport layer and a power allocation subproblem at the PHY layer, respectively. By solving the two subproblems, the adaptive resource allocation algorithm is developed to accommodate the dynamic wireless networks only according to the current QSI and CSI, which makes the algorithm easily implemented in practice.

A. Cross-Layer Control Scheme

The challenge behind optimization problem (6) is that we should find a resource allocation decision for stabilizing the queues while maximizing the network utility. Inspired by the recently developed Lyapunov *drift-plus-penalty* method [31], we solve the resource allocation problem starting from the analysis of queues. By controlling the arrival and departure process of the queues appropriately, the resource allocation decisions can stabilize the queues, whilst maximizing the network utility.

Let $\mathbf{Q}(t)$ denote the matrix containing the transmission queues $\{Q_{n,m}(t)|\forall n \in N, m \in M_n\}$. We define the quadratic Lyapunov function as $L(\mathbf{Q}(t)) = \mathbf{Q}(t)^H\mathbf{Q}(t)/2$, where $\mathbf{Q}(t)^H$ is the conjugation-transpose of $\mathbf{Q}(t)$. The conditional expected Lyapunov drift at time-slot t is defined by

$$\Delta(\mathbf{Q}(t)) :\triangleq \mathbb{E}[L(\mathbf{Q}(t+1))|\mathbf{Q}(t)] - E[L(\mathbf{Q}(t))], \tag{7}$$

where the expectation is taken over the randomness of departure and arrival processes of the queues.

Following from the Lyapunov optimization framework, we add the penalty term $-V\mathbb{E}[U(t)|\mathbf{Q}(t)]$ to (7) for obtaining the following *drift-plus-penalty* term

$$\Delta_V(\mathbf{Q}(t)) = \Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)]. \tag{8}$$

Here $V > 0$ is a control parameter and its practical understanding will be given in Section V.

Then, we have the following lemma regarding the *drift-plus-penalty* term.

Lemma 1: For any feasible resource allocation decision that can be implemented at time-slot t, we have

$$\begin{aligned}\Delta_V(\mathbf{Q}(t)) \le B - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \\ + \mathbb{E}[(\boldsymbol{\gamma}(t)-\mathbf{r}(t))^H\mathbf{Q}(t)|\mathbf{Q}(t)],\end{aligned} \tag{9}$$

where $\mathbf{r}(t)$ denotes the matrix $\{r_{n,m}(t)|\forall n \in N, m \in M_n\}$ and B is an upper bound on the term $[\mathbf{r}(t)^H\mathbf{r}(t) + \boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t)]/2$, which holds under the fact that both the wireless transmission rates and the flow rates satisfy the properties of boundness.

Proof: See Appendix A. □

Our dynamic resource allocation policy is designed to observe the current CSI $\mathbf{g}(t)$ and QSI $\mathbf{Q}(t)$, and as well to make the resource allocation decisions $\boldsymbol{\gamma}(t)$ and $\mathbf{p}(t)$ for minimizing the right-hand-side (RHS) of (9) at the current time. The non-constant part of the RHS of (9) can be written as

$$\begin{aligned}&VU(t) - \boldsymbol{\gamma}(t)^H\mathbf{Q}(t) + \mathbf{r}(t)^H\mathbf{Q}(t) \qquad (10)\\ &= \sum_{m\in M}\sum_{n\in N_m}\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) - \sum_{m\in M}\sum_{n\in N_m}Q_{n,m}(t)\gamma_{n,m}(t)\\ &+ \sum_{n\in N}\sum_{m\in N_m}Q_{n,m}(t)r_{n,m}(t) - Vc\sum_{n\in N}\sum_{m\in N_m}p_{n,m}(t).\end{aligned}$$

From (10), we observe that the second term is merely affected by the flow rate $\boldsymbol{\gamma}(t)$ and the third term is only affected by the transmit power $\mathbf{p}(t)$. Thus maximizing (10) can be decomposed into two subproblems, both of which have a clear operational meaning, and will be referred to as flow control subproblem and power allocation subproblem. The handling of each subproblem is described in the following subsections.

B. Flow Control

Considering the second term in (10) and the flow constraint (C2), there is no coupling in the term $\sum_{m\in M}$, which shows that flow control subproblems of different UEs are independent of each other. Thus, the flow control subproblem corresponding to UE $m \in M$ is represented as

$$\begin{aligned}\max\quad & V\sum_{n\in N_m}\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) - \sum_{n\in N_m}Q_{n,m}(t)\gamma_{n,m}(t)\\ \text{s.t.}\quad & \sum_{n\in N_m}\gamma_{n,m}(t) \le A_m(t), \gamma_{n,m}(t) \ge 0.\end{aligned} \tag{11}$$

Flow control subproblem (11) has a strictly concave objective function, and the flow rates are coupled by the linear constraint $\sum_{n\in N_m}\gamma_{n,m}(t) \le A_m(t)$. Therefore, the flow control subproblem can be decomposed by the dual decomposition method [12]. Relaxing the constraint by introducing Lagrangian multiplier $\mu_m(t)$ associated with $\sum_{n\in N_m}\gamma_{n,m}(t) \le A_m(t)$, it makes sense to form the Lagrangian as

$$L(\boldsymbol{\gamma}_m(t);\mu_m(t)) = \left\{\begin{array}{c}V\sum\limits_{n\in N_m}\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) - \sum\limits_{n\in N_m}Q_{n,m}(t)\gamma_{n,m}(t)\\ -\mu_m(t)(\sum\limits_{n\in N_m}\gamma_{n,m}(t) - A_m(t))\end{array}\right\}, \tag{12}$$

where $\boldsymbol{\gamma}_m(t) = [\gamma_{n,m}(t)]_{n\in N_m}$.

The dual function is given by

$$h_m(\mu_m(t)) = \max_{\gamma_{n,m}(t)\ge 0,\forall n\in N_m} L(\boldsymbol{\gamma}(t);\mu_m(t)), \tag{13}$$

and the dual problem of (11) is

$$\min_{\mu_m(t)\ge 0} h_m(\mu_m(t)). \tag{14}$$

The maximization problem of (13) can be written as

$$h_m(\mu_m(t)) = \sum_{n\in N_m}\max_{\gamma_{n,m}(t)\ge 0,\forall n\in N_m}\left\{\begin{array}{c}V\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) - Q_{n,m}(t)\gamma_{n,m}(t)\\ -\mu_m(t)\gamma_{n,m}(t) + \frac{\mu_m(t)A_m(t)}{|N_m|}\end{array}\right\}. \tag{15}$$

Thus, the optimal flow control for each RAN is obtained by solving

$$\max_{\gamma_{n,m}(t)\ge 0}\left\{\begin{array}{c}V\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) - Q_{n,m}(t)\gamma_{n,m}(t)\\ -\mu_m(t)\gamma_{n,m}(t) + \frac{\mu_m(t)A_m(t)}{|N_m|}\end{array}\right\}. \tag{16}$$

For a given $\mu_m(t)$, the flow rate $\gamma_{n,m}(t)$ can be calculated for each RAN by applying the Karush-Kuhn-Tucker (KKT) [32] conditions on (16), which results in

$$\gamma_{n,m}(t) = \left[\frac{V\beta_n w_{n,m}}{(Q_{n,m}(t)+\mu_m(t))} - e\right]^+, \tag{17}$$

where $[x]^+ = \max\{0, x\}$.

The optimal value of $\mu_m(t)$ is determined by solving the dual problem of (14). A subgradient method can be used to calculate the optimal value of $\mu_m(t)$, which is given by

$$\mu_m^{k+1}(t) = \left[\mu_m^k(t) + \delta\left(\sum_{n\in N_m}\gamma_{n,m}^k(t) - A_m(t)\right)\right]^+, \tag{18}$$

where δ is a positive scale stepsize and k is the iteration index. If the step size δ is sufficiently small, the dual variable $\mu_m^k(t)$ will converge to the dual optimal $\mu_m^*(t)$ as $k \to \infty$ and, since the duality gap for flow control subproblem (11) is zero and the solution to (17) is unique, the primal variable $\gamma_{n,m}(t)$ will also converge to the primal optimal variable $\gamma_{n,m}^*(t)$ [12], [33].

C. Power Allocation

Similar to the analysis of flow control subproblem, the power allocation subproblems of different RANs are independent of each other. Thus, the power allocation subproblem corresponding to RAN $n \in N$ is represented as

$$\max \left\{ \begin{array}{c} \sum\limits_{m\in M_n} Q_{n,m}(t)\varepsilon_n B_n \log_2\left(1+\Gamma\frac{|g_{n,m}(t)|^2 p_{n,m}(t)}{B_n N_0}\right) \\ -cV\sum\limits_{m\in M_n} p_{n,m}(t) \end{array} \right\}$$
$$\text{s.t.} \sum_{m\in M_n} p_{n,m}(t) \le P_n^{\max}, p_{n,m}(t) \ge 0. \tag{19}$$

Relaxing the constraint by introducing Lagrangian multiplier $\nu_n(t)$ associated with $\sum_{m\in M_n} p_{n,m}(t) \le P_n^{\max}$ at time-slot t, it makes sense to form the Lagrangian as

$$L(\mathbf{p}_n(t);\nu_n(t)) = \tag{20}$$
$$\left\{ \begin{array}{c} \sum\limits_{m\in M_n} Q_{n,m}(t)\varepsilon_n B_n \log_2\left(1+\Gamma\frac{|g_{n,m}(t)|^2 p_{n,m}(t)}{B_n N_0}\right) \\ -cV\sum\limits_{m\in M_n} p_{n,m}(t) - \nu_n(t)(\sum\limits_{m\in M_n} p_{n,m}(t) - P_n^{\max}) \end{array} \right\},$$

where $\mathbf{p}_n(t) = [p_{n,m}(t)]_{m\in M_n}$.

The dual function is given by

$$h(\nu_n(t)) = \max_{p_{n,m}(t)\ge 0, \forall m\in M_n} L(\mathbf{p}_n(t);\nu_n(t)), \tag{21}$$

and the dual problem of (19) is

$$\min_{\nu_n(t)\ge 0} h(\nu_n(t)). \tag{22}$$

The maximization problem of (21) can be written as

$$h(\nu_n(t)) = \sum_{m\in M_n} \max_{p_{n,m}(t)\ge 0, \forall m\in M_n} \tag{23}$$
$$\left\{ \begin{array}{c} Q_{n,m}(t)\varepsilon_n B_n \log_2\left(1+\Gamma\frac{|g_{n,m}(t)|^2 p_{n,m}(t)}{B_n N_0}\right) \\ -cVp_{n,m}(t) - \nu_n(t)p_{n,m}(t) + \frac{\nu_n(t)P_n^{\max}}{|M_n|}) \end{array} \right\}.$$

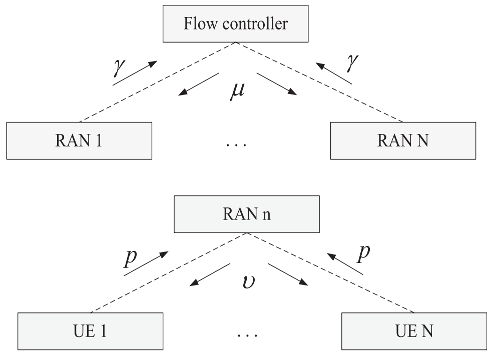

Fig. 2. Illustration of the control signaling in **Algorithm 1**.

Thus, the optimal power allocation for each UE is obtained by solving

$$\max_{p_{n,m}(t)\ge 0} \left\{ \begin{array}{c} Q_{n,m}(t)\varepsilon_n B_n \log_2\left(1+\Gamma\frac{|g_{n,m}(t)|^2 p_{n,m}(t)}{B_n N_0}\right) \\ -cVp_{n,m}(t) - \nu_n(t)p_{n,m}(t) + \frac{\nu_n(t)P_n^{\max}}{|M_n|}) \end{array} \right\}. \tag{24}$$

For a given $\nu_n(t)$, the transmit power $p_{n,m}(t)$ can be calculated for each UE by applying the KKT conditions on (24), which results in

$$p_{n,m}(t) = \left[\frac{Q_{n,m}(t)\varepsilon_n B_n}{(cV+\nu_n(t))\ln 2} - \frac{B_n N_0}{\Gamma|g_{n,m}(t)|^2}\right]^+. \tag{25}$$

The optimal value of $\nu_n(t)$ is determined by solving the dual problem of (22). A subgradient method can be used to calculate the optimal value of $\nu_n(t)$, which is given by

$$\nu_n^{k+1}(t) = \left[\nu_n^k(t) - \kappa\left(\sum_{m\in M_n} p_{n,m}^k(t) - P_n^{\max}\right)\right]^+, \tag{26}$$

where κ is a positive scale stepsize. The convergence analysis of the power allocation subproblem is the same as the flow control subproblem.

Based on the analysis above, the adaptive cross-layer resource allocation algorithm is given as **Algorithm 1**.

Our proposed ACRA algorithm has a distributed architecture, as illustrated in Fig. 2. At the transport layer, the flow controller updates the Lagrangian multiplier μ and sends it to the RANs for calculating the flow rates. The RAN computes $\gamma(t)$ using local QSI information and sends it to the flow controller for updating the Lagrangian multiplier μ. In this way, there is no need to exchange QSI information between flow controller and RANs, which will reduce the signaling overhead. At the PHY layer, the signaling overhead includes the Lagrangian multiplier ν from RANs to UEs, and the transmit power p returning from UEs to RANs.

V. TRADEOFF PERFORMANCE BETWEEN NETWORK UTILITY AND DELAY

In this section, we analyze the performance of ACRA algorithm. That is how the performance of the average network utility $\overline{U}$ will be and whether the network is stable under the proposed algorithm. Similar performance analysis can be found in

Algorithm 1 Adaptive cross-layer resource allocation (ACRA)

Step 1: At time-slot t, RANs observe $\mathbf{Q}(t)$, $\mathbf{g}(t)$ and run the following steps.
Step 2: Flow control in transport layer
Initialization: $\mu_m(t) > 0, k = 1, j = 0.$
while $j = 0$ **do**
  for each RAN $n \in N_m$ **do**
    $\gamma_{n,m}^{k+1}(t) = \left[\frac{V\beta_n w_{n,m}}{(Q_{n,m}(t)+\mu_m^k(t))} - e\right]^+;$
  end for
  if $||\boldsymbol{\gamma}_m^{k+1}(t) - \boldsymbol{\gamma}_m^k(t)|| > \epsilon$ **then**
    Flow controller
    $\mu_m^{k+1}(t) = \left[\mu_m^k(t) + \delta\left(\sum_{n\in N_m}\gamma_{n,m}^k(t) - A_m(t)\right)\right]^+;$
    $k = k + 1;$
  else
    $j = 1;$
  end if
end while
Step 3: Power allocation in PHY layer
Initialization: $k = 1, j = 0.$
while $j = 0$ **do**
  for each UE $m \in M_n$ **do**
    $p_{n,m}^{k+1}(t) = \left[\frac{Q_{n,m}(t)\varepsilon_n B_n}{(cV+\nu_n^k(t))\ln 2} - \frac{B_n N_0}{\Gamma|g_{n,m}(t)|^2}\right]^+;$
  end for
  if $||\mathbf{p}_n^{k+1}(t) - \mathbf{p}_n^k(t)|| > \epsilon$ **then**
    RAN $n \in \mathcal{N}$
    $\nu_n^{k+1}(t) = \left[\nu_n^k(t) - \kappa\left(\sum_{m\in M_n} p_{n,m}^k(t) - P_n^{\max}\right)\right]^+;$
    $k = k + 1;$
  else
    $j = 1;$
  end if
end while
Step 4: Update $Q_{n,m}(t)$ according to (3) based on $\gamma_{n,m}(t)$ and $p_{n,m}(t)$ obtained from **Step 2** and **Step 3**.

[24], [25], [34], they show that the average network utility and network stability are achieved by a certain i.i.d algorithm. However, the relationship between the i.i.d algorithm and their proposed algorithms is unclear. In this paper, we proposed a novel method for demonstrating the performance of the ACRA algorithm, which can be widely used in other Lyapunov drift-plus-penalty-based network optimization scenarios.

In the following analysis, some bound assumptions and concepts are given first, followed by performance discussion.

Let $s(t) = (\mathbf{A}(t), \mathbf{g}(t)) \in \mathcal{S}$ and $\alpha(t) = (\boldsymbol{\gamma}(t), \mathbf{p}(t)) \in \Omega$ denote the network state and resource allocation decision at timeslot t, respectively, where $\mathcal{S}$ is the network sate space and Ω is the set of feasible resource allocation decisions. Because the transmit power $\mathbf{p}(t)$ satisfies the property of boundness, the upper bound of $\mathbb{E}[\mathbf{r}(t)(\alpha(t), s(t))]$ can be depicted as:

$$\mathbb{E}[\mathbf{r}(t)(\alpha(t), s(t))] \leq \delta, \tag{27}$$

where δ is a finite constant.

Based on (5), it comes the bound

$$U_{\min} \leq \mathbb{E}[U(\alpha(t), s(t))] \leq U_{\max}, \tag{28}$$

where $U_{\min}$ and $U_{\max}$ are some finite constants.

These assumptions are based on the fact that all physical quantities are bounded from above and below in realistic systems and the assumptions will be useful for proving **Theorem 1** in the following discussion.

Under the assumption that the network state space $\mathcal{S}$ is finite state space, $s(t)$ is a stationary process and that $s(t)$ is i.i.d over different timeslots, there exists a stationary policy that chooses action $\tilde{\alpha}(t)$ independently every time-slot as a stationary and possibly randomized function of the current state $s(t)$ only (not include the QSI $\mathbf{Q}(t)$) for maximizing the current network utility $U(\tilde{\alpha}(t), s(t))$ under the constraints (C2)–(C4). Such policy is called s-only policy. Because $s(t)$ has the stationary distribution for all time-slots, the expectation of the flow rates and wireless link rates under s-only policy are the same for all time-slots.

To further reveal how the ACRA algorithm performs, we need the following lemmas, which will be used in proving **Theorem 1**.

Lemma 2: Suppose that $\boldsymbol{\lambda}$ is strictly interior to the capacity region Λ[2], and that $\boldsymbol{\lambda} + \varsigma$ is still in Λ for a positive ς, there exists an s-only policy that

$$\mathbb{E}\left[\tilde{r}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right] - \mathbb{E}\left[\tilde{\gamma}_{n,m}(t)(\tilde{\alpha}(t), s(t))\right] \geq \varsigma, \tag{29}$$

where $\tilde{r}_{n,m}(t)$ and $\tilde{\gamma}_{n,m}(t)$ are the resulting values under ω-only policy.

Proof: The proof is based on the definition of capacity region that there at least exists a resource allocation policy that stabilizes the HetNet under the average traffic arrival rate $\boldsymbol{\lambda}$. The detailed proof can be found in [31]. □

Now define the flow control function $\Phi(\alpha(t))$ and the power allocation function $\Psi(\alpha(t))$ as follows:

$$\Phi(\alpha(t)) :\triangleq \mathbb{E}\left[\begin{array}{c} V\sum_{n\in N_m}\beta_n w_{n,m}\log(\gamma_{n,m}(t)+e) \\ -\sum_{n\in N_m} Q_{n,m}(t)\gamma_{n,m}(t) \end{array}\right],$$

$$\Psi(\alpha(t)) :\triangleq \mathbb{E}\left[\sum_{m\in M_n} Q_{n,m}(t) r_{n,m}(t) - cV\sum_{m\in M_n} p_{n,m}(t)\right].$$

Lemma 3: The resource allocation decision $\hat{\alpha}(t)$ obtained by the ACRA algorithm has better performance in maximizing $\Phi(\alpha(t))$ and $\Psi(\alpha(t))$ than the s-only policy, i.e.,

$$\begin{aligned} \Phi(\hat{\alpha}(t)) &= \mathbb{E}\left[\begin{array}{c} V\sum_{n\in N_m}\beta_n w_{n,m}\log(\hat{\gamma}_{n,m}(t)+e) \\ -\sum_{n\in N_m} Q_{n,m}(t)\hat{\gamma}_{n,m}(t) \end{array}\right] \\ &\geq \mathbb{E}\left[\begin{array}{c} V\sum_{n\in N_m}\beta_n w_{n,m}\log(\tilde{\gamma}_{n,m}(t)+e) \\ -\sum_{n\in N_m} Q_{n,m}(t)\tilde{\gamma}_{n,m}(t) \end{array}\right] \\ &= \Phi(\tilde{\alpha}(t)); \\ \Psi(\hat{\alpha}(t)) &= \mathbb{E}\left[\sum_{m\in M_n} Q_{n,m}(t)\hat{r}_{n,m}(t) - cV\sum_{m\in M_n}\hat{p}_{n,m}(t)\right] \end{aligned}$$

[2]The capacity region Λ is defined as all of the average traffic arrival rates $\boldsymbol{\lambda}$ that can be stably supported by the HetNet, considering all possible resource allocation policies. If the arrival rate $\boldsymbol{\lambda}$ is outside of the capacity region Λ, we cannot find any resource allocation policies for stabilizing the HetNet.

$$\geq \mathbb{E}\left[\sum_{m\in M_n} Q_{n,m}(t)\tilde{r}_{n,m}(t) - cV\sum_{m\in M_n} \tilde{p}_{n,m}(t)\right]$$
$$= \Psi(\tilde{\alpha}(t));$$

Proof: The first inequality follows because the flow control subproblem in (11) maximizes $\Phi(\alpha(t))$ over all valid flow control decisions, including the particular s-only policy $\tilde{\alpha}(t)$, and the same reason is for the second inequality. □

Based on **Lemma 2** and **Lemma 3**, we obtain that the ACRA algorithm has the following performance.

Theorem 1: Suppose that $\boldsymbol{\lambda} + \varsigma$ is strictly in the capacity region Λ of the HetNet and $\mathbb{E}[L(\mathbf{Q}(0))] < \infty$, then for any control parameter $V > 0$, the proposed ACRA algorithm has the following properties:

(a) $\overline{U}$ has a lower bound that

$$\overline{U} \geq \overline{U}^{\mathrm{opt}} - \frac{B}{V}. \tag{30}$$

(b) The time averaged queue length is bounded by

$$\lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1}\sum_{n,m} \mathbb{E}[Q_{n,m}(t)] \leq \frac{B + V(U_{\max} - \overline{U}^{\mathrm{opt}})}{\varsigma}. \tag{31}$$

where $\sum_{n,m}$ is the abbreviation of $\sum_{n\in N}\sum_{m\in M_n}$ and $\overline{U}^{\mathrm{opt}}$ is the optimal utility of problem (6).

Proof: The proof is given in Appendix B □

Due to the fact that the average transmission delay of the media content is proportional to the average queue length from Little's Theorem [27], we can depict the average delay by the average queue length. From **Theorem 1** (a), we observe that the value of V can be chosen so that B/V is arbitrarily small, resulting in that $\overline{U}$ is arbitrarily close to $\overline{U}^{\mathrm{opt}}$. Moveover, the increase of $\overline{U}$ is at the speed of $1/V$ with the control parameter V. Meanwhile, the corresponding average delay (time average queues) increases linearly in V. As a result, the tradeoff between transmission delay and $\overline{U}$ is derived that we can balance the delay-$\overline{U}$ performance with the control parameter V.

VI. SIMULATION RESULTS

In this section, we present the simulation results to illustrate the performance of our proposed ACRA algorithm. Firstly, we illustrate the dynamic processes of the resource allocation decisions under the ACRA algorithm. Secondly, we verify the tradeoff between the time averaged queue length and the time averaged network utility by changing the control parameter V. Finally, we show the effectiveness of our proposed ACRA algorithm compared with the other schemes. In particular, there is no "standard" commonly accepted resource allocation scheme for the multi-homing service in HetNet. We then compare the performance of the proposed ACRA algorithm to the non multi-homing with max signal to noise ratio UE association (maxSNR-UA) algorithm and the multi-homing with uniform allocation (MHUA) algorithm, both of which are illustrated in [23] and [24], respectively. It should be noted that this is not the comparisons between our proposed ACRA algorithm and the whole schemes in [23] and [24]. Instead, it mainly focuses on showing the effectiveness of multi-homing service compared with the mentioned UE association schemes in [23], [24]. Specifically, in maxSNR-UA algorithm, the UE only accesses the RAN with the max signal to noise ratio, while in MHUA algorithm, the UE traffic is uniformly distributed among the connected RANs. Moreover, both the power allocations in maxSNR-UA and MHUA are executed as **Step 3** in **Algorithm 1**. By comparison with MHUA and maxSNR-UA, we will know the effectiveness of our proposed scheme.

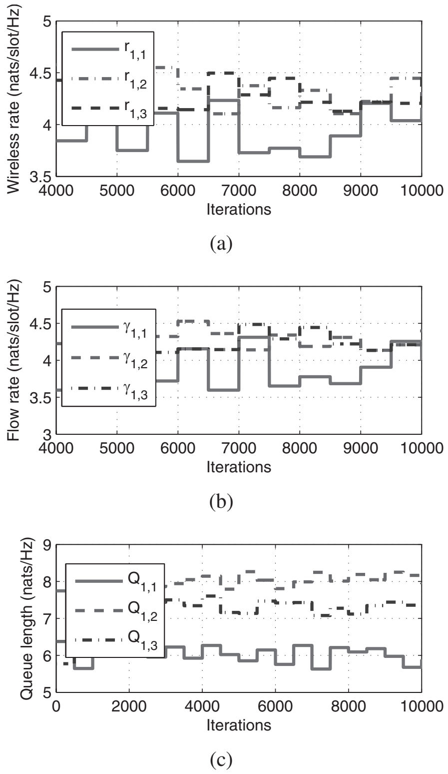

Fig. 3. Illustration of the queue processes, flow rates and wireless transmission rates under ACRA algorithm: (a) Wireless transmission rate, (b) flow rate, and (c) queue length.

For simplicity of simulations, we consider a normalized bandwidth spacing, i.e., $B_n = 1$. We model the channel process $h_{n,m}(t) = \Gamma|g_{n,m}(t)|^2/N_0$ as Gaussian random variables in the interval [10,15] and be i.i.d over different timeslots [32]. The instantaneous transmit power is upper bounded by 10 W, i.e., $P_n^{\max} = 10$ W. The arrival rate $A_m(t)$ of the media content is randomly distributed within a range of 10–12 nats/slot/Hz. The selection of step sizes has great effects on the convergence of flow control and power allocation algorithms. A relatively large step size will result in the vibration of the iteration algorithm around the optimal solution. Therefore, it is difficult for the algorithm to satisfy the break condition, i.e., $||\gamma_m^{k+1}(t) - \gamma_m^k(t)|| > \epsilon$ or $||\mathbf{p}_n^{k+1}(t) - \mathbf{p}_n^k(t)|| > \epsilon$, in **Algorithm 1**. However, too small step size would take a long time of iterations for the algorithm to satisfy the break condition. By making a lot of experiments and taking the above consideration into account, we found that $\kappa = 0.01$ and $\upsilon = 0.05$ are good choices for the convergence of flow control and power allocation algorithms, respectively. The convergence condition is set as $\epsilon = 0.01$. There are maximum 500 rounds during each timeslot.

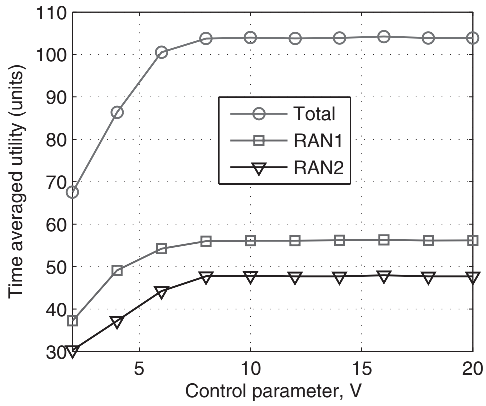

Fig. 4. Time averaged network utility versus control parameter V.

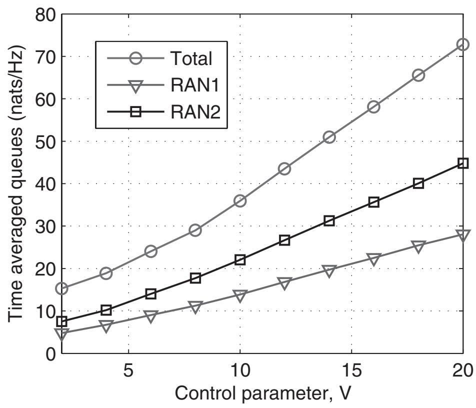

Fig. 5. Time averaged queue length versus control parameter V.

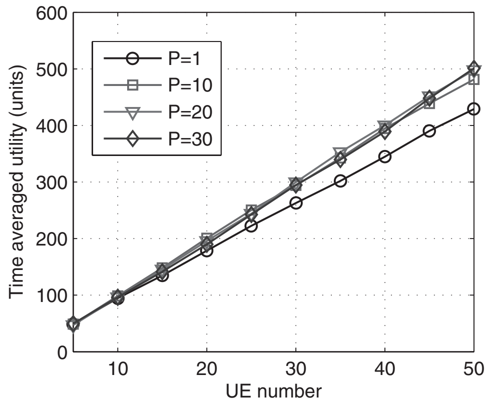

Fig. 6. Average network utility versus the number of UEs.

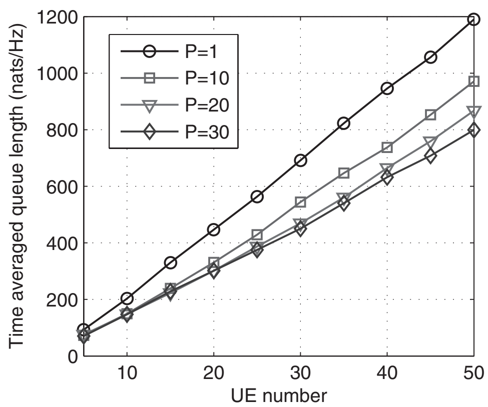

Fig. 7. Average network utility versus the number of UEs.

A. Dynamic Processes of Resource Allocation Decisions

Fig. 3 illustrates some dynamic processes for the resource allocation decisions under the ACRA algorithm. In this experiment, we use the HetNet having three RANs and five UEs. Due to the page limitation, we only plot the dynamic processes of RAN 1 over all time slots, the other RANs enjoy similar processes and they are omitted here. We first exhibit the dynamics of wireless transmission rates and flow rates in Fig. 3. It indicates that the transmit power and flow control decisions are made dynamically from slot to slot. By controlling the wireless transmission rates and flow rates appropriately, the resource allocation decisions can stabilize the queues, whilst maximizing the network utility. From the figure, we also observe that the backlogs of the transmission queues for RAN 1 are strictly bounded (always below 9 nats/Hz for instance), which implies strong stability for the transmission queues of RAN 1 and no network congestion occurred on the RAN.

B. Tradeoff Between Queue Length and Network Utility

Fig. 4 depicts that the time averaged network utility versus the control parameter V under the ACRA algorithm. We find that the time averaged network utility increases as V increases and that it increases to the optimum at the speed of $1/V$ as V increases. This consolidates the theoretical analysis in **Theorem 1** (a). Fig. 5 shows the time averaged queue length versus the control parameter V. Based on the solution that the time averaged queue length can be used to depict the average transmission delay [27], we obtain the conclusion that the average transmission delay under proposed algorithm increases as V increases. Moreover, the increase of average delay is approximately linear in V. Hence the result in **Theorem 1** (b) is verified. By contrast with Fig. 4, the proposed algorithm achieves a tradeoff between time averaged network utility and average delay. Based on the observation of simulation results, we obtain a significant rule for engineering design to flexibly balance the network utility-delay performance. We only need to adjust appropriate control parameter V to let the network in a predefined state.

Figs. 6 and 7 plot the time averaged utility and queue length under the ACRA algorithm versus the number of UEs, respectively. In this experiment, we assume that the RANs have the same maximum allowed transmit power, i.e., $P_n^{\max} = P, \forall n \in \mathcal{N}$. Fig. 6 shows that the time averaged utility increases with the increase of UE number. When the maximum allowed transmit power is small, the HetNet does not have enough resource for maximizing the network utility, hence it brings a smaller time averaged utility than others. When the maximum allowed transmit power is larger than 10 W, there will be no more time averaged utility gain by increasing the maximum allowed transmit power. That is because the optimization objective is an energy-aware utility function. The proposed algorithm finds the opti-

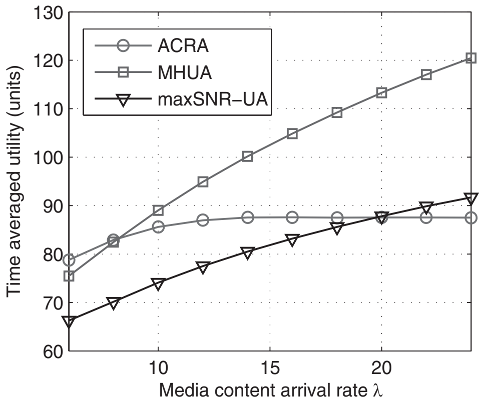

Fig. 8. Time averaged network utility versus media content arrival rate.

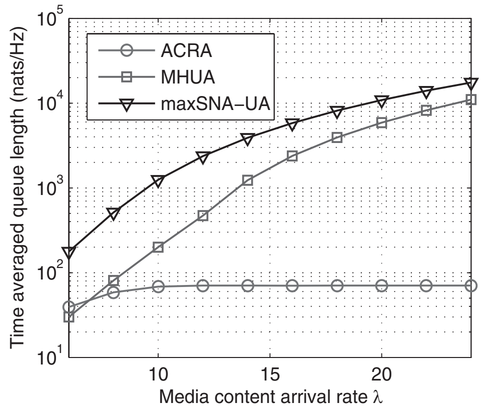

Fig. 9. Time averaged queue length versus media content arrival rate.

mal maximum allowed transmit power for the HetNet, which is probably around 10 W. Therefore, the time averaged utility is no longer improving by increasing the maximum allowed transmit power. Fig. 7 illustrates the time averaged queue length versus the number of UEs. The figure shows that the time averaged queue lengths increase with the increase of UE number. However, when the maximum allowed transmit power is lower than 10 W, the time averaged queue length increases sharply, i,e, the HetNet becomes instable. That is because the total transmit powers at RANs are upper bounded by $P_n^{\max}$. When $P_n^{\max}$ is smaller than 10 W, the HetNet cannot go on allocating the transmit power to support the UEs and hence, the system becomes instable.

C. Performance Comparison under Different Media Content Arrival Rate

In Figs. 8 and 9, we compare the performance of the ACRA algorithm with MHUA algorithm and maxSNR-UA algorithm. We observe from the figures that the time averaged network utilities under all of the algorithms increase with the increase of media content arrival rate. When the media content arrival rate is small, the proposed ACRA outperforms the other two algorithms. That is because the objective function of optimization problem (6) is an energy-aware utility function. From the Shannon formula, we know that the data rate is a logarithm function of the transmit power, hence the power consumption increases exponentially with the data rate. In maxSNR-UA algorithm, the UEs can only connect with one RAN, hence a lot of power will be consumed by the RAN. However, with multi-homing service, the UE's data requirement is split into different RANs. Each parallel flow is allocated with a proper rate, so that the power consumption can be effectively reduced. Although the data requirement is allocated among the RANs in MHUA algorithm, it still achieves a smaller utility than the ACRA algorithm due to its inefficient uniform allocation of the UE's data requirement. When the media content arrival rate is large enough, both MHUA and maxSNR-UA achieve larger utilities than our proposed ACRA algorithm. However, we observe from Fig. 9 that both MHUA and maxSNR-UA lead to terrible time averaged queue lengths. That is because they greedily maximize the network utility and neglect the network stability, hence result in extremely long time averaged queue lengths. On the contrary, our proposed ACRA is designed to maximize the network utility, whilst stabilizing the network. Therefore, it brings comprehensive excellent network performance. To sum up, both ACRA and MUHA achieve better performance on network utility and average delay than maxSNR-UA, hence demonstrating the effectiveness of multi-homing service in HetNet.

VII. CONCLUSIONS

In this paper, we designed an adaptive cross-layer resource allocation algorithm in the HetNet with multi-homing UEs. The long-term network utility maximization was characterized by a stochastic optimization model subject to the network stability constraint. In harmony with the hierarchical architecture of HetNet, the problem of stochastic optimization was decomposed into two subproblems, associated with the flow control in transport layer and the power control in PHY layer, respectively. We developed the distributed resource allocation method to solve the two subproblems for avoiding the signaling overhead, outdated dynamics information, and scalability issues. Then, the adaptive resource allocation algorithm was developed to accommodate the time-varying wireless network merely based on the current QSI and CSI. Further, we showed that the proposed algorithm yielded the network utility-delay tradeoff as $(V, 1/V)$ with the control parameter V from the theoretical analysis.

APPENDICES

I. PROOF OF LEMMA 1

Proof: Following from (8), we have

$$
\begin{aligned}
&L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t)) \\
&= \frac{1}{2}(\mathbf{Q}(t+1))^H \mathbf{Q}(t+1) - \frac{1}{2}(\mathbf{Q}(t))^H \mathbf{Q}(t) \\
&= \frac{1}{2}(\max[\mathbf{Q}(t) - \mathbf{r}(t), 0] + \boldsymbol{\gamma}(t))^H (\max[\mathbf{Q}(t) - \mathbf{r}(t), 0] + \boldsymbol{\gamma}(t)) \\
&- \frac{1}{2}(\mathbf{Q}(t))^H \mathbf{Q}(t)
\end{aligned}
$$

where we have used the queue evolution (3).

Noticing that for any non-negative scalar quantities Q, γ, and r the inequality

$$(\max\{Q-r,0\}+\gamma)^2 \le Q^2+r^2+\gamma^2+2Q(\gamma-r),$$

holds, we have

$$\begin{aligned} &L(\mathbf{Q}\,(t+1)) - L(\mathbf{Q}(t)) \qquad (32)\\ &\le \frac{1}{2}\mathbf{r}(t)^H\mathbf{r}(t) + \frac{1}{2}\boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t) + (\boldsymbol{\gamma}(t)-\mathbf{r}(t))^H\mathbf{Q}(t)\\ &\le B + (\boldsymbol{\gamma}(t)-\mathbf{r}(t))^H\mathbf{Q}(t), \end{aligned}$$

where B is an upper bound on the term $[\mathbf{r}(t)^H\mathbf{r}(t) + \boldsymbol{\gamma}(t)^H\boldsymbol{\gamma}(t)]/2$, which holds under the fact that both the flow rates and the wireless link transmission rates satisfy the properties of boundness.

Adding $-V\mathbb{E}[U(t)|\mathbf{Q}(t)]$ to both sides of (32) and taking an expectation, yields

$$\begin{aligned} &\Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \qquad (33)\\ &\le B - V\mathbb{E}[U(t)|\mathbf{Q}(t)] + \mathbb{E}[(\boldsymbol{\gamma}(t)-\mathbf{r}(t))^H\mathbf{Q}(t)|\mathbf{Q}(t)]. \end{aligned}$$

This completes the proof of **Lemma 1**. □

II. PROOF OF THEOREM 1

Proof: The ACRA algorithm is designed to minimize the RHS of (9), then we obtain

$$\begin{aligned} \Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \le B &\\ -V\mathbb{E}[U(\hat{\alpha}(t),\omega(t))|\mathbf{Q}(t)]&\\ +\mathbb{E}[(\boldsymbol{\gamma}(t)(\hat{\alpha}(t),\omega(t)) - \mathbf{r}(t)(\hat{\alpha}(t),\omega(t)))^H\mathbf{Q}(t)|\mathbf{Q}(t)].& \end{aligned}$$

Lemma 3 shows that $\Phi(\hat{\alpha}(t)) + \Psi(\hat{\alpha}(t)) \ge \Phi(\tilde{\alpha}(t)) + \Psi(\tilde{\alpha}(t))$, then we obtain

$$\begin{aligned} &V\mathbb{E}[U(\hat{\alpha}(t),\omega(t))|\mathbf{Q}(t)]\\ &\quad-\mathbb{E}[(\boldsymbol{\gamma}(t)(\hat{\alpha}(t),\omega(t)) - \mathbf{r}(t)(\hat{\alpha}(t),\omega(t)))^H\mathbf{Q}(t)|\mathbf{Q}(t)]\\ &\ge V\mathbb{E}[U(\tilde{\alpha}(t),\omega(t))|\mathbf{Q}(t)]\\ &\quad-\mathbb{E}[(\boldsymbol{\gamma}(t)(\tilde{\alpha}(t),\omega(t)) - \mathbf{r}(t)(\tilde{\alpha}(t),\omega(t)))^H\mathbf{Q}(t)|\mathbf{Q}(t)]. \end{aligned}$$

Applying **Lemma 2** in the equation above, we have

$$\begin{aligned} \Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \le B - V\mathbb{E}[U(\tilde{\alpha}(t),\omega(t))]&\\ -\varsigma\sum_{n,m}\mathbb{E}[Q_{n,m}(t)],& \end{aligned}$$

where $\sum_{n,m}$ is the simplification of $\sum_{n\in N}\sum_{m\in M_n}$.

We assume that there exists a ω-only policy that obtains the optimal utility $\overline{U}^{\text{opt}}$ of problem (6). Then, we obtain

$$\begin{aligned} \Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \le B - V\overline{U}^{\text{opt}}& \qquad (34)\\ -\varsigma\sum_{n,m}\mathbb{E}[Q_{n,m}(t)].& \end{aligned}$$

(a) The proof for time averaged utility.

By virtue of the fact that $\varsigma\sum_{n,m}\mathbb{E}[Q_{n,m}(t)]$ is positive, thus it can be omitted at the right-hand-side of (34). We obtain

$$\Delta(\mathbf{Q}(t)) - V\mathbb{E}[U(t)|\mathbf{Q}(t)] \le B - V\overline{U}^{\text{opt}}$$

Then, summing over $t \in \{0,1,\cdots,T-1\}$ for the equation above, we get

$$\begin{aligned} \mathbb{E}[L(\mathbf{Q}(T-1))] - \mathbb{E}[L(\mathbf{Q}(0))] - V\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)]&\\ \le BT - VT\overline{U}^{\text{opt}}.& \end{aligned}$$

Dividing by TV and using the fact that $\mathbb{E}[L(\mathbf{Q}(T-1))]$ is positive, we get

$$-\frac{\mathbb{E}[L(\mathbf{Q}(0))]}{TV} + \overline{U}^{\text{opt}} \le \frac{B}{V} + \frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)].$$

Taking limit as $T\to\infty$, we have

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)] \ge \overline{U}^{\text{opt}} - \frac{B}{V}.$$

There comes the solution that

$$\overline{U} \ge \overline{U}^{\text{opt}} - \frac{B}{V}.$$

(b) The proof for time average queues.

Summing (34) over $t \in \{0,1,\cdots,T-1\}$, we get

$$\begin{aligned} \mathbb{E}[L(\mathbf{Q}(T-1))] - \mathbb{E}[L(\mathbf{Q}(0))] - V\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)]&\\ \le BT - VT\overline{U}^{\text{opt}} - \varsigma\sum_{t=0}^{T-1}\sum_{n,m}\mathbb{E}[Q_{n,m}(t)].& \end{aligned}$$

Dividing by T and using the fact $\mathbb{E}[L(\mathbf{Q}(T-1))] > 0$, we get

$$\begin{aligned} -\frac{\mathbb{E}[L(\mathbf{Q}(0))]}{T} - V\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)]&\\ \le B - V\overline{U}^{\text{opt}} - \varsigma\frac{1}{T}\sum_{t=0}^{T-1}\sum_{n,m}\mathbb{E}[Q_{n,m}(t)].& \end{aligned}$$

Rearranging the above equation and taking the limit as $T\to\infty$, we have

$$\begin{aligned} \varsigma\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_{n,m}\mathbb{E}[Q_{n,m}(t)] \le B&\\ +V\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[U(t)|\mathbf{Q}(t)] - V\overline{U}^{\text{opt}}.& \end{aligned}$$

Using the bound assumption in (28) and dividing by ς, we have

$$\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\sum_{n,m}\mathbb{E}[Q_{n,m}(t)] \le \frac{B+V(\overline{U}_{\max}-\overline{U}^{\text{opt}})}{\varsigma}.$$

Thus the theorem for time averaged queues is proved. □

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