Security-Aware Cross-Layer Resource Allocation for Heterogeneous Wireless Networks

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***Abstract*— In this paper, a security-aware energy-efficient resource allocation is modeled as a fractional programming problem for heterogeneous multi-homing networks. The security-aware resource allocation is formulated as a secrecy energy efficiency maximization problem subject to the average packet delay, the average packet dropping probability, and the total available power consumption. In order to guarantee the packet-level quality of service (QoS), first, the average packet delay and the average packet dropping probability requirement for each mobile terminal at the link layer are transformed into a minimum secrecy rate constraint at the physical layer. Then, the non-convex secrecy energy efficiency maximization problem is approximated by a convex problem through epigraph representation. A security-aware energy-efficient resource allocation algorithm is then proposed leveraging dual-decomposition method and bi-section search method. Finally, a heuristic security-aware resource allocation algorithm is proposed to serve as a benchmark. Simulation results demonstrate that the proposed security-aware energy-efficient resource allocation algorithm not only improves the secrecy energy efficiency and throughput, but also guarantees the packet-level QoS.**

***Index Terms*— Heterogeneous networks, cross-layer resource allocation, dual decomposition, packet delay, packet dropping probability.**

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I. Introduction

THE future wireless communication networks are expected to aggregate the spectrum resource of heterogeneous wireless networks to support high-quality communication services for mobile terminals (MTs) [1]. In the fifth generation (5G) communication system, there exist some promising candidate technologies, e.g., heterogeneous wireless network, non-orthogonal multiple access (NOMA), and massive multiple input and multiple output (MIMO) [2]–[5]. With the advance of multi-homing technologies, each MT is able to connect to available wireless networks via different radio interfaces, and the data stream for each MT is split into multiple sub-streams, which are transmitted simultaneously over different types of wireless networks [6], [7].

In heterogeneous multi-homing network, each MT has the requirement for secure communication over all available radio interfaces. Therefore, security issue becomes critical. Especially, physical layer security (PLS) is one of the important techniques against attacks from heterogeneous wireless medium based on information-theoretic approaches. For example, PLS can achieve secrecy via channel coding and advanced signal processing techniques. In comparison with conventional cryptography-based approaches, the advantage of PLS is to achieve *perfect secrecy* [8]. The performance of PLS is characterized by the achievable secrecy transmission rate defined as the non-zero transmission rate at which perfectly secure information can be transmitted with arbitrarily small error probability. As a result, PLS is an excellent candidate for heterogeneous multi-homing networks providing both security and quality of experience [9]–[11].

In order to utilize the radio resource efficiently, the resource allocation algorithms can be divided into three categories. The first category is the resource allocation problem based on single access technology for heterogeneous wireless networks [12]–[18]. In this scenario, each MT can connect to only one base station (BS). The second category is the resource allocation for heterogeneous wireless networks with multi-homing technology [19]–[24], which exploits the diversity among different radio interfaces for each MT [18]. The third category is the security-aware resource allocation with multi-homing technology which aims for not only reliable but also secure communications established among the legitimate parties in the presence of eavesdroppers [25]–[28].

The optimization objectives in the first category include, e.g., spectral efficiency [12], [14], energy efficiency [15], [16], and cross-layer design [13], [17], [18]. In [12], the resource allocation supporting multiple quality of service (QoS) classes for heterogeneous femtocell networks was investigated with a greedy algorithm. In order to maximize the spectral efficiency, a joint subchannel and power allocation algorithm was proposed for heterogeneous femtocell networks in [14]. For the energy-efficient resource allocation, a power minimization algorithm for interference mitigation was proposed in [15] for heterogeneous femtocell networks. In [16], a joint subcarrier assignment, power allocation and base station selection scheme for heterogeneous femtocell networks was proposed. For the cross-layer design, a cross-layer resource allocation algorithm was presented [17], taking both the data-link layer and the physical layer requirements into account. In [18], a joint resource allocation and call admission control problem for heterogeneous femtocell networks was solved by semi-Markov decision process and game theory. A joint resource allocation and call admission control algorithm was proposed for orthogonal frequency division multiple access (OFDMA) femtocell networks in [13].

For heterogeneous wireless networks with the multi-homing technology, an uplink decentralized joint bandwidth and power allocation algorithm was proposed in [19] utilizing the dual decomposition method. In [20], an uplink optimal resource allocation algorithm with delay-constraint service and best-effort service was proposed. In addition, resource allocation considering max-min fairness and proportional fairness were, respectively, studied in [21] and in [22]. On the other hand, an optimal joint bandwidth and power allocation algorithm maximizing the energy efficiency was proposed in [23] through a parameter-free approach. In [24], a joint bandwidth and power allocation scheme was also proposed utilizing dual decomposition.

For security-aware resource allocation in wireless network, security-aware max-min joint subchannel and power allocation was designed for multiuser OFDMA system in [25] with one eavesdropper. For OFDMA network, security-aware resource allocation algorithm with multiple untrusted MTs in the presence of a friendly jammer was proposed in [26]. In [27], the secret key agreement for MTs connected through parallel fading channels was considered, and the security-aware resource allocations were designed therein with full and partial eavesdropper's channel state information (CSI), respectively. In [28], secure resource allocations for OFDMA two-way relay wireless sensor networks were investigated without and with cooperative jamming, respectively.

One limitation of the above work for secure resource allocation in heterogeneous multi-homing networks is that they ignore the impact of the packet delay and the packet dropping probability on the secrecy transmission. In order to guarantee the security-aware packet-level QoS, the queue buffer occupancy at the link layer should also be analyzed, because this affects the resource allocation at the physical layer. In this paper, we investigate the security-aware energy efficiency maximization problem subject to the packet-level QoS constraints for heterogeneous multi-homing networks. We summarize the contributions of this paper as follows. (i) An energy-efficient packet-QoS-aware resource allocation problem is formulated as a fractional programming to jointly allocate subchannels, power and radio interface to each MT, subject to the average packet delay constraint, the average packet dropping probability constraint, and the total available power constraint. (ii) We transform the packet-level QoS into the required minimum secrecy transmission rate based on the packet arrival rate. (iii) A security-aware resource allocation algorithm is proposed using Lagrangian dual decomposition method, and a heuristic joint subchannel and power allocation algorithm is also developed to reduce computational complexity. (iv) Simulation results reveal that the proposed security-aware energy-efficient resource allocation algorithm not only improves the energy efficiency, but also guarantees the packet-level QoS.

The rest of the paper is organized as follows. The system description and optimization formulation are given in Section II. A security-aware cross-layer subchannel and power allocation algorithm is proposed in Section III. A heuristic low-complexity security-aware subchannel and power allocation algorithm is presented in Section IV. Section V provides the computation complexity analysis for the proposed algorithms. Finally, simulation results and conclusions are given in Section VI and Section VII, respectively.

II. System Model and Optimization Problem Formulation

In this section, the system description and the power consumption model are given first. Then, a security-aware energy-efficient resource allocation problem is formulated to ensuring the packet-level QoS for heterogeneous multi-homing networks. Finally, the analysis on packet dropping probability and packet delay is presented to simplify the problem.

A. System Description

Consider $\mathcal{N} = \{1, 2, \cdots, N\}$ of wireless networks, which are operated by different wireless technologies and different operators. In each network, there is a set of $\mathcal{S}_n = \{1, 2, \cdots, S_n\}$ BSs for network n in the geographical region. At the physical layer, orthogonal frequency division multiplexing (OFDM) technology is adopted, and the bandwidth is divided into many orthogonal subchannels. The subchannel set in network n for BS s is $\mathcal{K}_{ns} = \{1, 2, \cdots, K_{ns}\}$. ρ^k_{nsm} is the subchannel allocation indicator for network n BS s MT m over the kth subchannel. If $\rho^k_{nsm} = 1$, the subchannel k at network n with BS s is allocated to MT m; otherwise, $\rho^k_{nsm} = 0$. In the same network, there are $\mathcal{M} = \{1, 2, \cdots, M\}$ MTs in the geographical region and $\mathcal{M}_{ns} = \{1, 2, \cdots, M_{ns}\} \in \mathcal{M}$ is a subset of MTs, which lie in the coverage area of BS s in network n. As shown in Fig. 1, we consider secrecy downlink transmission between the BSs and the associated MTs in their respective coverage region in the presence of one external eavesdropper. The eavesdropper attempts to intercept the legitimate transmission across all the subchannels. Using multiple radio interfaces, each MT can communicate with multiple BSs simultaneously. In this work, we focus on the resource

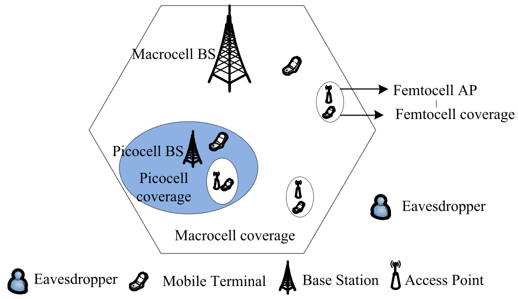

Fig. 1. Heterogeneous wireless networks.

allocation for multi-homing heterogeneous wireless networks. Consequently, we assume that orthogonal spectrum resources are used at different BSs and no interference occurs among different BSs. Additionally, this assumption follows the existing references for heterogeneous wireless networks, e.g., [6], [24]. Consider real-time traffic application, the packet-level QoS for the real-time traffic is packet delay and packet dropping probability. Each MT has real-time traffic flow to transmit via near BSs. In the control center, the incoming packets for each MT are queued in its own buffer [29]. Time is partitioned into time slots, as $\mathcal{T} = \{1, 2, \cdots\}$, with equal duration T_0.

The eavesdropper aims for wiretapping the transmitted signal within all the data-bearing subchannels. The eavesdropper's channel is assumed to be known by the controller.[1] Although we consider only one eavesdropper in this work, the proposed security-aware energy-efficient resource allocation scheme can be applied to the scenario with multiple eavesdroppers but with some proper changes. Multi-Eves scenarios differentiate from single Eve ones mainly in that multi-Eve case corresponds to a different achievable secrecy rate formula, which could be referred to papers [32]–[34], e.g., eqn. (11) in [34]. The reason we considered the one-Eve case is because this is the most simple model in which our formulated problem has not yet been well understood. Once this simple one-Eve case is understood, we believe there is no significant technical difficulties in modifying the current algorithm to solve the multi-Eves problem. Hence, the more general case with multiple Eves will be left for the future work.

A flat-fading model is assumed where each subchannel remains constant within its bandwidth and varies from subchannel to subchannel. h_{nsm}^k is the channel gain of the kth subchannel from network n BS s to MT m, and g_{nsk} is the channel gain of the kth subchannel from network n BS s to the eavesdropper $\forall k \in \mathcal{K}_{ns}$, $\forall n \in \mathcal{N}$, $\forall s \in \mathcal{S}_n$, and $\forall m \in \mathcal{M}_{ns}$. We assume h_{nsm}^k is perfectly known for resource allocation. At the beginning of each time slot, a centralized controller collects all the required information including CSI and queuing state information (QSI), and then conduct the resource allocation algorithm to select some packets in the queue such that the packet-level QoS is satisfied.

[1]Despite of being passive, the eavesdropping channel is still possible to be detected and then known by the controller [30], [31].

The secrecy transmission rate at the kth subchannel for network n BS s to communicate with MT m is

$$R_{nsm}^k = \begin{cases} R_{se}, & if\ h_{nsm}^k > g_{nsk} \\ 0, & if\ \ h_{nsm}^k \le g_{nsk} \end{cases} \tag{1}$$

and

$$R_{se} = B_{ns} \log_2 \left(\frac{B_{ns} n_0 + P_{nsm}^k h_{nsm}^k}{B_{ns} n_0 + P_{nsm}^k g_{nsk}} \right), \tag{2}$$

where P_{nsm}^k is the power allocated to the kth subchannel for BS s to communicate with MT m at network n, B_{ns} is the bandwidth of each subchannel for network n BS s, and n_0 is the one-sided noise power spectral density.

B. Power Consumption Model

The circuit power consumption for each BS consists of two components [35]: the first component is fixed power consumption for each BS, where P_{RF} is the radio frequency power consumption and P_{BB} is the baseband unit power consumption; and the second component is dynamic power consumption, where ξ is the power amplifier efficiency and σ_{feed} is the loss incurred by the antenna feed. Hence, the total power consumption, P_{ns}, for network n BS s is defined as

$$P_{ns} = \frac{\frac{\sum\limits_{m \in \mathcal{M}_{ns}} \sum\limits_{k \in \mathcal{K}_{ns}} \rho_{nsm}^k P_{nsm}^k}{\xi(1-\sigma_{\text{feed}})} + P_{\text{RF}} + P_{\text{BB}}}{(1-\sigma_{\text{DC}})\,(1-\sigma_{\text{MS}})\,(1-\sigma_{\text{cool}})} \tag{3}$$

where σ_{DC}, σ_{MS}, and σ_{cool} are the losses incurred by DC-DC power supply, main supply and active cooling, respectively.

C. Packet Dropping Probability and Average Packet Delay

To analyze the dropping probability and the average packet delay, in this section, we introduce the queuing model for each MT m. The service time for each packet at MT m, denoted by X_m, follows a distribution given by Appendix A. Assume that the queuing buffer is modeled as an M/G/1 system [36], and that the packet arrivals at the MT m follow Poisson process with an average rate of λ_m (packets/s). $Q_m(t)$ denotes the number of the packets in the queue buffer for MT m at the beginning of time slot t; $\pi_m(t)$ is the number of dropped packets at the beginning of time slot t owing to exceeding the maximum packet delay; and $v_m(t)$ is the packet arrival rate during the time slot t. Moreover, the queue length (in number of packets), $Q_m(t+1)$, for MT m at the beginning of time slot $(t+1)$ is given as below with the length of each packet denoted by P_L (in bits) [29].

$$\begin{aligned} Q_m(t+1) &= Q_m(t) - \pi_m(t) \\ &\quad - \left\lfloor \frac{T_0 \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{k\in\mathcal{K}_{ns}} \rho_{nsm}^k R_{nsm}^k}{P_L} \right\rfloor + v_m(t) T_0 \end{aligned} \tag{4}$$

where $\lfloor x \rfloor$ rounds the elements of x to the nearest integer less than or equal to x. If we use the transmission rate rather than the secrecy rate in (4), the average packet dropping probability and the average packet delay can not be guaranteed. This is due to the fact that the transmission rate is larger than the secrecy rate. If we adopt the transmission rate, the analysis results for the average packet dropping probability and the average packet delay are smaller than the practical results. Consequently, we adopt the secrecy rate in (1) to analyze the average packet dropping probability and the average packet delay.

The average packet dropping probability for MT m is required not to exceed the maximum packet dropping probability, i.e.,

$$\bar{u}_m \leq u_m, \quad \forall m \in \mathcal{M}, \tag{5}$$

where $\bar{u}_m$ is the average packet dropping probability for MT m, and u_m is the maximum permissive packet dropping probability for MT m.

The average packet delay for MT m is also required to be no larger than the maximum packet delay, i.e.,

$$\overline{d}_m \leq d_m, \quad \forall m \in \mathcal{M}, \tag{6}$$

where $\overline{d}_m$ is the average packet delay for MT m, and d_m is the maximum packet delay for MT m.

Due to the fact that the required average packet delay and average packet dropping probability at the link layer are not directly related to the subchannel and power allocations at the physical layer, we analyze their relationship in the following two subsections.

1) Packet Dropping Probability: At the beginning of each time slot, a packet will be dropped if the packet exceeds the maximum packet delay. The average packet dropping probability, $\overline{u}_m$, for MT m is defined as (7) [36].

$$\bar{u}_m = \frac{\mathrm{E}\left[\pi_m\left(t\right)\right]}{\mathrm{E}\left[v_m\left(t\right)\right]T_0}. \tag{7}$$

where $\mathrm{E}\left[\pi_m\left(t\right)\right]$ can be obtained from Eq. (4).

In order to satisfy the average packet dropping probability constraint in (5) and the equation (4), the required minimum secrecy transmission rate of MT m satisfies

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n}\sum_{k\in\mathcal{K}_{ns}}\rho_{nsm}^k R_{nsm}^k \geq \alpha_m' \tag{8}$$

where $\alpha_m' = P_L\left(1-u_m\right)\mathrm{E}\left[v_m\left(t\right)\right]$.

2) Average Packet Delay: The average waiting time for an M/G/1 system is defined as below [36].

$$\mathrm{E}\left\{W_m\right\} = \frac{\mathrm{E}\left[V_m\left(t\right)\right]\mathrm{E}\left\{X_m^2\right\}}{2\left(1-\mathrm{E}\left[V_m\left(t\right)\right]\mathrm{E}\left\{X_m\right\}\right)}. \tag{9}$$

With $\mathrm{E}\left\{X_m^2\right\} \geq \mathrm{E}^2\left\{X_m\right\}$, the lower bound of the average waiting time, $\mathrm{E}\left\{W_m\right\}$, is given by:

$$\mathrm{E}\left\{W_m\right\} \geq \frac{\mathrm{E}\left[V_m\left(t\right)\right]\left(\mathrm{E}^2\left\{X_m\right\}\right)}{2\left(1-\mathrm{E}\left[V_m\left(t\right)\right]\mathrm{E}\left\{X_m\right\}\right)}. \tag{10}$$

Combining with $\overline{d}_m = \mathrm{E}\left\{W_m\right\} + \mathrm{E}\left\{X_m\right\}$, we obtain the upper bound of the average service time as follows:

$$\mathrm{E}\left\{X_m\right\} \leq \frac{1+d_m\mathrm{E}\left[V_m\left(t\right)\right]-\sqrt{1+\left(d_m\mathrm{E}\left[V_m\left(t\right)\right]\right)^2}}{\mathrm{E}\left[V_m\left(t\right)\right]}. \tag{11}$$

After some manipulations, the average delay requirement given by (6) with the equation (4) is transformed into a constraint in terms of the required secrecy transmission rate of MT m expressed as:

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n}\sum_{k\in\mathcal{K}_{ns}}\rho_{nsm}^k R_{nsm}^k \geq \alpha_m'', \tag{12}$$

where $\alpha_m'' = \frac{P_L\mathrm{E}[V_m(t)]}{1+d_m\mathrm{E}[V_m(t)]-\sqrt{1+(d_m\mathrm{E}[V_m(t)])^2}}$.

In a sum, combining with (8) and (12), an equivalent minimum transmission rate constraint is given by:

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n}\sum_{k\in\mathcal{K}_{ns}}\rho_{nsm}^k R_{nsm}^k \geq \alpha_m, \tag{13}$$

where $\alpha_m = max\left(\alpha_m', \alpha_m''\right)$.

D. Optimization Formulation

In this paper, we investigate the security-aware resource allocation problem with packet-QoS constraints for heterogeneous multi-homing networks. Based on the aforementioned, the security-aware resource scheduler jointly allocates subchannel and power for different MTs across different radio interfaces, subject to the total power constraint at each BS, the packet dropping probability constraint as well the average packet delay constraint. The subchannel allocation at network n BS s should fall in the feasible region, i.e.,

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n}\sum_{m\in\mathcal{M}_{ns}}\rho_{nsm}^k \leq 1,\ \rho_{nsm}^k \geq 0, \tag{14}$$

where ρ_{nsm}^k is a continuous variable. The total power consumption, P_{ns}, at network n BS s satisfies the maximum power constraint, i.e.,

$$\frac{\frac{\sum\limits_{m\in\mathcal{M}_{ns}}\sum\limits_{k\in\mathcal{K}_{ns}}\rho_{nsm}^k P_{nsm}^k}{\xi(1-\sigma_{\mathrm{feed}})} + P_{\mathrm{RF}} + P_{\mathrm{BB}}}{\left(1-\sigma_{\mathrm{DC}}\right)\left(1-\sigma_{\mathrm{MS}}\right)\left(1-\sigma_{\mathrm{cool}}\right)} \leq P_{ns}^T,\ \forall n\in\mathcal{N},\ s\in\mathcal{S}_n \tag{15}$$

where P_{ns}^T is the total available power at network n BS s.

Define the secrecy energy efficiency in bits/sec/Watt, denoted by η, as the ratio of the total achievable secrecy transmission rate over the total power consumption, i.e.,

$$\eta = \frac{\sum\limits_{n\in\mathcal{N}}\sum\limits_{s\in\mathcal{S}_n}\sum\limits_{m\in\mathcal{M}_{ns}}\sum\limits_{k\in\mathcal{K}_{ns}}\rho_{nsm}^k R_{nsm}^k}{\sum\limits_{n\in\mathcal{N}}\sum\limits_{s\in\mathcal{S}_n}P_{ns}}. \tag{16}$$

Consequently, the security-aware energy-efficient subchannel and power allocation problem for the considered downlink multi-homing network is formulated as:

$$\begin{aligned}\mathrm{OP1}\ &\max_{\rho_{nsm}^k, P_{nsm}^k}\ \eta \\ &\quad \text{s.t. } (13),\ (14),\ (15),\quad P_{nsm}^k \geq 0,\end{aligned} \tag{17}$$

where problem (17) is shown to be a fractional programming.

III. Security-Aware Cross-Layer Resource Allocation

In this section, we solve the security-aware energy-efficient resource allocation problem (17) guaranteeing packet-level QoS constraints for heterogeneous multi-homing networks. Firstly, we transform the fractional programming problem (17) into the tri-convex programming with the polynomial form. Then, we adopt the dual decomposition method and the binary search method to obtain the security-aware subchannel and power allocation. Finally, we propose a joint security-aware subchannel and power allocation algorithm.

A. Equivalent Transformation in Epigraph Form

Problem (17) has an equivalent transformation via its epigraph form [37], i.e.,

$$\begin{aligned} \text{OP2} \quad & \max_{\rho_{nsm}^k,\ P_{nsm}^k, y} \ y \\ & \text{s.t. } y \leq \eta,\ (13),\ (14),\ (15) \\ & \quad P_{nsm}^k \geq 0, \quad y \geq 0. \end{aligned} \tag{18}$$

Collecting ρ_{nsm}^k and P_{nsm}^k into two vectors $\mathcal{B}$ and $\mathcal{P}$, (18) can be analyzed geometrically as an optimization problem in the graph space $\{\mathcal{B}, \mathcal{P}, y\}$. Consequently, we maximize y over the epigraph $\{\mathcal{B}, \mathcal{P}, y\}$, where $\mathcal{B}$ is the subchannel allocation set, and $\mathcal{P}$ is the power allocation set. Additionally, the first constraint in (18) can be transformed into

$$\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}} \rho_{nsm}^k R_{nsm}^k - y \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} P_{ns} \geq 0. \tag{19}$$

where problem (18) is a tri-convex optimization problem,[2] which can be proven in appendix B. Since problem (18) is a tri-convex optimization problem, we solve the variables y, P_{nsm}^k, and ρ_{nsm}^k, separately. Firstly, the variables P_{nsm}^k, and ρ_{nsm}^k are solved via the dual decomposition method with the fixed variable y. Then, y is obtained via binary search method.

B. Security-Aware Resource Allocation With Packet QoS Constraint

In this section, we solve the security-aware resource allocation problem with packet QoS guaranteed for heterogeneous multi-homing networks. Firstly, we obtain the solutions P_{nsm}^k and ρ_{nsm}^k via the dual decomposition method. With the fixed variable y, the Lagrangian function for problem (18) is

$$\begin{aligned} & L\left(u, v_{ns}^k, w_{ns}, l_m, \rho_{nsm}^k, P_{nsm}^k\right) \\ & \quad = y + \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} v_{ns}^k f_1 \\ & \qquad + \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} w_{ns} f_2 + \sum_{m\in\mathcal{M}} l_m f_3 + u f_4 \end{aligned} \tag{20}$$

where v_{ns}^k, w_{ns}, l_m, and u are Lagrangian multipliers associated with (14), (15), (13) and (19), respectively.

[2] In this work, the tri-convex optimization problem is similar with bi-convex, i.e., the optimization problem is convex with any one variable when fixed the other two variables.

The dual function, $h\left(u, v_{ns}^k, w_{ns}, l_m\right)$, is

$$\begin{aligned} & h\left(u, v_{ns}^k, w_{ns}, l_m\right) \\ & \quad = \begin{cases} \max\limits_{\rho_{nsm}^k, P_{nsm}^k} & L\left(u, v_{ns}^k, w_{ns}, l_m, \rho_{nsm}^k, P_{nsm}^k\right) \\ \text{s.t. } \rho_{nsm}^k \geq 0, & P_{nsm}^k \geq 0. \end{cases} \end{aligned} \tag{21}$$

Additionally, the dual problem is

$$\begin{aligned} \text{OP3} \quad & \min_{u, v_{ns}^k, w_{ns}, l_m} \ h\left(u, v_{ns}^k, w_{ns}, l_m\right) \\ & \text{s.t. } u \geq 0, \quad v_{ns}^k \geq 0,\ w_{ns} \geq 0,\ l_m \geq 0. \end{aligned} \tag{22}$$

For network n BS s, the Lagrangian function (20) can be decoupled into to

$$\begin{aligned} L_{ns} = & \ y + u\left(\sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}} \rho_{nsm}^k R_{nsm}^k - y P_{ns}\right) \\ & - P_{ns} w_{ns} + l_m \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}} \rho_{nsm}^k R_{nsm}^k \\ & - \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}} \rho_{nsm}^k v_{ns}^k. \end{aligned} \tag{23}$$

Consequently, each BS could solve its own utility maximization problem, i.e.,

$$\begin{aligned} \text{OP4} \quad & \max_{\rho_{nsm}^k,\ P_{nsm}^k} \ L_{ns} \\ & \text{s.t. } \rho_{nsm}^k \geq 0, \quad P_{nsm}^k \geq 0. \end{aligned} \tag{24}$$

The optimum power allocation, P_{nsm}^k, for fixed values ρ_{nsm}^k, y, u, v_{ns}^k, w_{ns} and l_m can be calculated with (25) by applying KKT condition on the optimization problem (24).

$$\frac{\partial L_{ns}}{\partial P_{nsm}^k} = 0. \tag{25}$$

From (25), we can obtain

$$P_{nsm}^k = \left[\frac{\sqrt{b^2 - 4ac}}{2a} - \frac{b}{2a}\right]^+ \tag{26}$$

and

$$\begin{cases} a = h_{nsm}^k g_{nsk} \\ b = \left(h_{nsm}^k + g_{nsk}\right) B_{ns} n_0 \\ c = \left(B_{ns} n_0\right)^2 - \dfrac{\left(h_{nsm}^k - g_{nsk}\right)\left(B_{ns}\right)^2 n_0}{A \ln 2} \\ A = \dfrac{\left(w_{ns} + uy\right)}{\left(u + l_m\right)} f_\sigma \\ f_\sigma = \dfrac{1}{\xi\left(1 - \sigma_{\text{feed}}\right)\left(1 - \sigma_{\text{DC}}\right)\left(1 - \sigma_{\text{MS}}\right)\left(1 - \sigma_{\text{cool}}\right)} \end{cases} \tag{27}$$

where $[x]^+$ is a projection of x on the positive orthant.

With the fixed values P_{nsm}^k, y, u, v_{ns}^k, w_{ns}, and l_m, the Lagrangian function L_{ns} for network n BS s is linear with respect to the variable ρ_{nsm}^k, and ρ_{nsm}^k falls in the interval $[0, 1]$. Hence, when $\partial L_{ns}/\partial \rho_{nsm}^k > 0$, the maximum value can be obtained via $\rho_{nsm}^k = 1$. On the other hand, when $\partial L_{ns}/\partial \rho_{nsm}^k < 0$, the maximum value can be obtained via $\rho_{nsm}^k = 0$.

$$\frac{\partial L_{ns}}{\partial \rho_{nsm}^k} = H_{nsm}^k - v_{ns}^k \tag{28}$$

and

$$H_{nsm}^{k} = R_{nsm}^{k}\left(l_m + y\right) - \left(w_{ns} + uy\right) P_{nsm}^{k} f_{\sigma}. \quad (29)$$

Subchannel k at network n BS s is assigned to MT m with the largest H_{nsm}^{k}, that is,

$$\rho_{nsm^*}^{k} = 1 \left| m^* = \max_{m} H_{nsm}^{k}. \right. \quad (30)$$

The optimum values u, w_{ns} and l_m can be calculated by solving the dual problem (22). For a non-differentiable dual function, a sub-gradient descent method can be applied to calculate the values for u, w_{ns} and l_m, i.e.,

$$\begin{cases} w_{ns}\left(i+1\right) = \left[w_{ns}\left(i\right) - \varepsilon_1\left(i\right) f_2\right]^{+} \\ l_m\left(i+1\right) = \left[l_m\left(i\right) - \varepsilon_2\left(i\right) f_3\right]^{+} \\ u\left(i+1\right) = \left[u\left(i\right) - \varepsilon_3\left(i\right) f_4\right]^{+} \end{cases} \quad (31)$$

where i is the iteration index. Since the subchannel allocation is given in (30), it is not necessary to update the Lagrangian variable v_{ns}^{k}. $\varepsilon_1\left(i\right)$, $\varepsilon_2\left(i\right)$, and $\varepsilon_3\left(i\right)$ are the step sizes of iteration i, and the step sizes should satisfy the condition,

$$\sum_{i=1}^{\infty} \varepsilon_j\left(i\right) = \infty, \lim_{i\to\infty} \varepsilon_j\left(i\right) = 0, \quad \forall j \in \left\{1, 2, 3\right\}. \quad (32)$$

where $\varepsilon_j\left(i\right)$ can be set with $\frac{1}{i}$.

The gradient of (31) satisfies the Lipchitz continuity condition [38], and the resource allocation P_{nsm}^{k} and ρ_{nsm}^{k} in (26) and (30) converges to the optimum solution [38]. The security-aware cross-layer resource allocation can be obtained by algorithm 1 and algorithm 2. Algorithm 1 is the outer loop, and algorithm 2 is the inner loop. In algorithm 1, the variable y is solved based on the bi-section method with the given variables P_{nsm}^{k} and ρ_{nsm}^{k}. If $y \le \eta$, set $Y_{\min}\left(j\right) = y\left(j\right)$; else, $Y_{\max}\left(j\right) = y\left(j\right)$. In algorithm 2, the power allocation and subchannel allocation P_{nsm}^{k} and ρ_{nsm}^{k} are obtained via the dual decomposition method with the fixed variable y. Additionally, the power allocation and subchannel allocation in algorithm 2 is a recursive algorithm and converges to the optimum solutions by updating the Lagrangian multipliers via (31) with the fixed y [38]. ε_y is an arbitrarily small positive number, and I_{max} is the maximum iteration number. $l_m\left(i\right)$, $u\left(i\right)$ and $w_{ns}\left(i\right)$ are the Lagrangian multipliers at the ith iteration. $Y_{\min}\left(j\right)$, $Y_{\max}\left(j\right)$, and $y\left(j\right)$ are the variable values at the jth iteration, and $y\left(j-1\right)$ is the variable value at the $(j-1)$th iteration.

Algorithm 1 Security-Aware Cross-Layer Resource Allocation Algorithm

Require: u_m, d_m, P_L and T_0.
Ensure: y, ρ_{nsm}^{k} and P_{nsm}^{k}.
1: Initialize ε_y, α_m, $Y_{\min}\left(j\right) = 0$, $Y_{\max}\left(j\right)$, $y\left(j\right) = Y_{\max}\left(j\right)/2$, and $j = 1$.
2: **repeat**
3: Use Algorithm 2 to obtain ρ_{nsm}^{k} and P_{nsm}^{k}.
4: Set $j = j+1$, and update $Y_{\min}\left(j\right)$, $Y_{\max}\left(j\right)$, and $y\left(j\right) = \left(Y_{\min}\left(j\right) + Y_{\max}\left(j\right)\right)/2$.
5: **if** $\left|y\left(j\right) - y\left(j-1\right)\right| \le \varepsilon_y$. **then**
6: Set $y = y\left(j\right)$. Output y, ρ_{nsm}^{k} and P_{nsm}^{k}.
7: **else**
8: Go to step 3.
9: **end if**
10: **until**

Algorithm 2 Subchannel and Power Allocation Algorithm With Fixed y

Require: P_{ns}^{T}, B_{ns}, α_m, and $y\left(j\right)$.
Ensure: ρ_{nsm}^{k} and P_{nsm}^{k}.
1: Initialize $l_m\left(i\right)$, $u\left(i\right)$, $w_{ns}\left(i\right)$, ρ_{nsm}^{k}, P_{nsm}^{k}, I_{max}, and $i = 1$.
2: **repeat**
3: Calculate ρ_{nsm}^{k}, P_{nsm}^{k}, and R_{nsm}^{k}.
4: **if** $\alpha_m \le \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{k\in\mathcal{K}_{ns}} R_{nsm}^{k}$ and $i = I_{max}$ **then**
5: Go to step 10.
6: **else**
7: Set $i = i+1$, and update $w_{ns}\left(i\right)$, $u\left(i\right)$, and $l_m\left(i\right)$. Go to step 3.
8: **end if**
9: **until**
10: Output ρ_{nsm}^{k} and P_{nsm}^{k}.

IV. Heuristic Algorithm

Although algorithm 1 and algorithm 2 can obtain the security-aware subchannel and power allocation, it has enormous computational complexity. This motivates us to develop a heuristic algorithm for heterogeneous multi-homing networks to reduce the computational complexity. In this section, we design a heuristic algorithm firstly. Then, the computational complexities for the proposed and heuristic algorithms are given in the simulation.

The security-aware heuristic algorithm is given in algorithm 3, which contains two stages. At the first stage, the total power at each BS is allocated equally among different MTs and among different radio interfaces at each MT. Then, MT m^* with the minimum secrecy transmission rate is selected. Additionally, the k^*th subchannel in network n^* BS s^* with the largest secrecy transmission rate is selected for MT m^*. The subchannel allocation procedure is repeated until all MTs satisfy the minimum secrecy transmission rate requirement. At the second stage, the k^*th subchannel in network n^* BS s^* with the maximum energy efficiency margin is selected for MT m^*, and the subchannel allocation procedure is repeated until all the subchannels are allocated or the network energy efficiency can not be decreased. $\hat{R}_{nsm}^{k}$ is the temporary secrecy transmission rate for network n BS s MT m over the kth subchannel, $\hat{\eta}_{nsm}^{k}$ is the temporary network energy efficiency when the subchannel is allocated to network n BS s MT m over the kth subchannel, and η_{nsm}^{k} is the network energy efficiency when the subchannel is allocated to network n BS s MT m over the kth subchannel. $\mathcal{K}_{remain}$ is the remaining vacant subchannel set. $R_m = \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{k\in\mathcal{K}_{ns}} \rho_{nsm}^{k} R_{nsm}^{k}$ is the secure transmission rate for MT m.

Algorithm 3 Heuristic Security-Aware Algorithm

Require: P^T_{ns}, B_{ns}, α_m, $\mathcal{K}_{remain}$, P_L, and T_0.
Ensure: ρ^k_{nsm} and P^k_{nsm}.
1: Initialize ρ^k_{nsm}, $\hat{R}^k_{nsm}$, P^k_{nsm}, η^k_{nsm}, $\hat{\eta}^k_{nsm}$, and R^k_{nsm}.
2: **repeat**
3: Find $m^* = \min_{m\in\mathcal{M}} R_m$ and $(n^*, s^*, k^*) = \max_{(n,s,k)\in\mathcal{N},\mathcal{S}_n,\mathcal{K}_{ns}} \hat{R}^k_{nsm^*}$.
4: **if** $\alpha^*_m \leq R^*_m$ **then**
5: Update $\rho^{k^*}_{n^*s^*m^*} = 1$, $\mathcal{K}_{remain} = \mathcal{K}_{remain} - (n^*, s^*, k^*)$, and go to step 9.
6: **end if**
7: **until**
8: **repeat**
9: Find $(n^*, s^*, k^*, m^*) = \max_{(n,s,k,m)\in\mathcal{N},\mathcal{S}_n,\mathcal{K}_{ns},\mathcal{M}} (\eta^k_{nsm} - \hat{\eta}^k_{nsm})$.
10: **if** $\mathcal{K}_{remain} \neq \emptyset$ **then**
11: Update $\rho^{k^*}_{n^*s^*m^*} = 1$, $\mathcal{K}_{remain} = \mathcal{K}_{remain} - (n^*, s^*, k^*)$, and go to step 9.
12: **else**
13: Go to step 16.
14: **end if**
15: **until**
16: Output ρ^k_{nsm} and P^k_{nsm} .

V. Performance Evaluation

This section presents the simulation results for algorithm, i.e., algorithm 1 combined with algorithm 2. We consider a geographical region that is covered by a macrocell BS and two femtocell BSs. The macrocell BS has a coverage area of 500 m, while each femtocell BS has a coverage area of 21 m. There exists an eavesdropper in heterogeneous multi-homing networks, and the distance from the eavesdropper to the macrocell BS is 900 m. Additionally, the distances from the eavesdropper to the two femtocell BSs are both 922 m, and the distances from the macrocell BS to the two femtocell BSs are both 200 m. The fast fading follows the Rayleigh fading. Due to the overlapped coverage among macrocell BS and two femtocell BSs, three service areas can be distinguished. In the first and second areas, MTs can get service from both macrocell BS and one femtocell BS. In the third service area, MTs can get service only from macrocell BS. There are both 16 subchannels at the physical layer for macrocell and femtocell. The maximum packet dropping probability is $u_m = 0.01$, and the packet length is $P_L = 1000$ bit. The one-side noise spectral density is $n_0 = -174$ dBm/Hz, and the time slot is $T_0 = 40$ ms. The power consumption parameters are adopted in [35]. In order to compare with the and heuristic algorithms, two benchmark algorithms, i.e., optimal power allocation algorithm and optimal subchannel allocation algorithm, are proposed. In the optimal power allocation algorithm, each BS allocates the transmission power to minimize the consumed energy per bit based on the dual decomposition method and the binary search method with the fixed subchannel allocation. In the optimal subchannel allocation algorithm, each BS allocates the subchannels to minimize the consumed energy per bit according to the dual decomposition method and the binary search method with the fixed power allocation. Since the formulated tri-convex programming problem is not a rigorous convex optimization problem, the strictly optimal solution is hardly obtained. Consequently, we use the exhausted search to find the asymptotically optimal solution in a small-scale scenario.

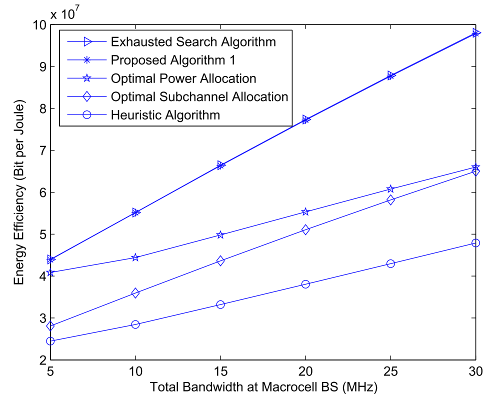

Fig. 2. Energy efficiency vs. total bandwidth at macrocell BS.

We evaluate the impact of total bandwidth at macrocell BS on energy efficiency and heterogeneous networks throughput in Fig. 2 and Fig. 3, respectively. The heterogeneous networks throughput is defined as $\sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}} \rho^k_{nsm} R^k_{nsm}$. The number of MTs in each macrocell and each femtocell are both $M = 5$. The total bandwidth for each femtocell BS is 2 MHz, and the total available power for each macrocell BS and each femtocell BS are 3 W and 1W, respectively. Moreover, the arrival rate of video packet is 1.5×10^3 packets/s, and the maximum packet delay is $d_m = 30$ ms. From Fig. 2, we can see that the energy efficiency for the algorithm is largest and that for the heuristic algorithm is smallest. The energy efficiency for four algorithms increase with the total bandwidth at each macrocell BS, which can be explained that more bandwidth resource can improve the energy efficiency. Since the energy efficiency for the optimal power allocation algorithm outperforms that of the optimal subchannel allocation algorithm, the power allocation in the algorithm contributes the most impact to improve the energy efficiency. In Fig. 3, it can be seen that the heterogeneous networks throughput for the optimal subchannel allocation algorithm outperforms that for the algorithm. This it due to the fact that the algorithm improves the energy efficiency at the cost of heterogeneous networks throughput. Additionally, we can see that the energy efficiency and the heterogeneous networks throughput for the proposed algorithm 1 are very close to that of exhausted search algorithm in Fig. 2 and Fig. 3.

We evaluate the impact of packet arrival rate on energy efficiency and heterogeneous networks throughput in Fig. 4 and Fig. 5, respectively. The number of MTs in each macrocell and each femtocell are both $M = 5$. The total bandwidth resources for each femtocell BS and each macrocell BS is

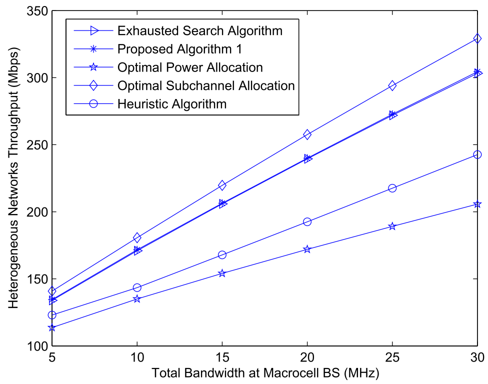

Fig. 3. Heterogeneous networks throughput vs. total bandwidth at macrocell BS.

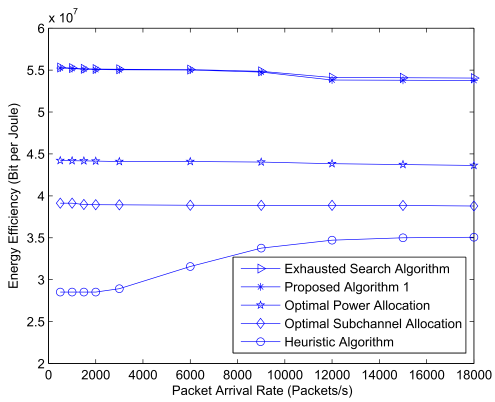

Fig. 4. Energy efficiency vs. packet arrival rate.

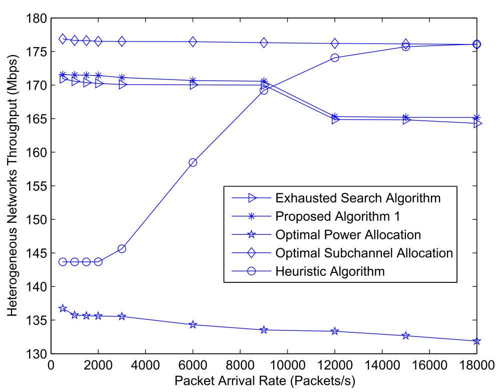

Fig. 5. Heterogeneous networks throughput vs. packet arrival rate.

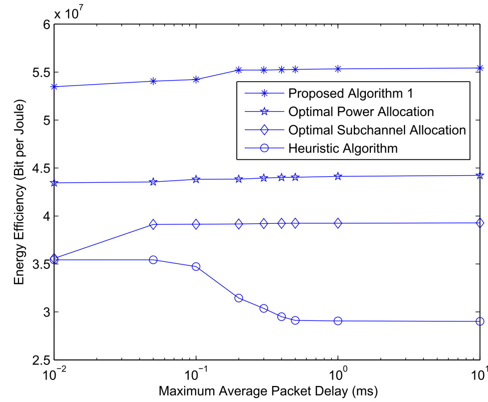

Fig. 6. Energy efficiency vs. maximum average packet delay.

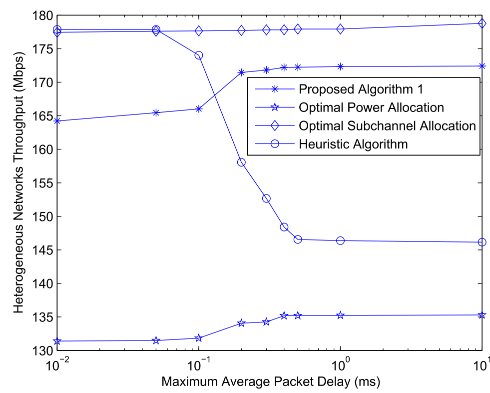

Fig. 7. Heterogeneous networks throughput vs. maximum average packet delay.

2 MHz and 10 MHz, respectively. The maximum packet delay is $d_m = 30$ ms. The total available power for each macrocell BS and each femtocell BS are 3 W and 1W, respectively. From Fig. 4 and Fig. 5, we can see that the energy efficiency for the algorithm, the optimal power allocation algorithm, and the optimal subchannel allocation algorithm decrease with the packet arrival rate, while the heterogeneous networks throughput for the algorithm, the optimal power allocation algorithm, and the optimal subchannel allocation algorithm decrease with the packet arrival rate. This is because increasing the packet arrival rate for each MT means increasing the required minimum transmission rate to maintain the target packet dropping rate and packet delay. Additionally, increasing the required minimum transmission rate needs more resources to guarantee the packet-level QoS. Consequently, the energy efficiency and throughput for the algorithm, the optimal power allocation algorithm, and the optimal subchannel allocation algorithm decrease. Since the heterogeneous networks throughput for the heuristic algorithm grows with the packet arrival rate, the energy efficiency for heuristic algorithm increases. Additionally, we can see that the energy efficiency and the heterogeneous networks throughput for the proposed algorithm 1 are very close to that of exhausted search algorithm in Fig. 4 and Fig. 5. On the other hand, the exhausted search algorithm sacrifices the throughput to improve the energy efficiency slightly.

We evaluate the impact of maximum average packet delay on energy efficiency and heterogeneous networks throughput in Fig. 6 and Fig. 7, respectively. The number of MTs in each macrocell and each femtocell are both $M = 5$. The total bandwidth resources for each femtocell BS and each macrocell BS is 2 MHz and 10 MHz, respectively. The total available power for each macrocell BS and each femtocell BS are 3 W and 1W, respectively. Moreover, the arrival rate of video packet is 1.5×10^3 packets/s. In Fig. 6 and Fig. 7, we can see that the energy efficiency for the algorithm, the optimal power allocation algorithm, and the optimal subchannel allocation algorithm increase with the maximum average packet delay,

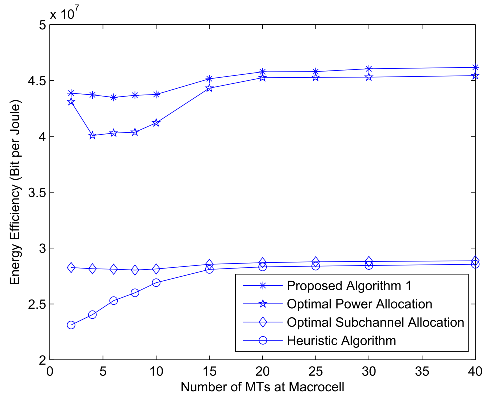

Fig. 8. Energy efficiency vs. number of MTs at macrocell.

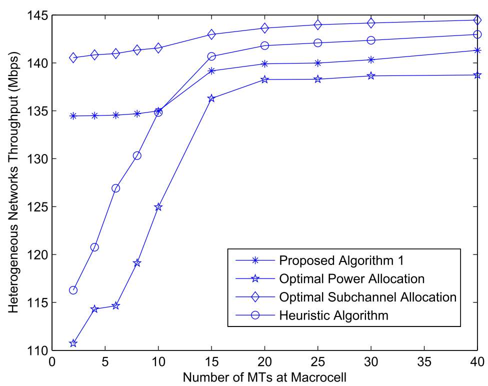

Fig. 9. Heterogeneous networks throughput vs. number of MTs at macrocell.

and the heterogeneous networks throughput for the algorithm, the optimal power allocation algorithm, and the optimal subchannel allocation algorithm grow with the maximum average packet delay. This can be explained that reducing the requirement of packet-level QoS can make more resources to improve the energy efficiency. Although the heterogeneous networks throughput for the optimal subchannel allocation algorithm is largest, it is obtained at the cost of sacrificing the energy efficiency. Since the heterogeneous networks throughput for the heuristic algorithm reduces with the maximum average packet delay, the energy efficiency for heuristic algorithm decreases with the maximum average packet delay.

We evaluate the impact of the number of MTs at macrocell on energy efficiency and heterogeneous networks throughput in Fig. 8 and Fig. 9, respectively. The number of MTs in each femtocell is $M = 5$. The total bandwidth resources for each femtocell BS and each macrocell BS is 2 MHz and 5 MHz, respectively. The total available power for each macrocell BS and each femtocell BS are 3 W and 1W, respectively. Moreover, the arrival rate of video packet is 1.5×10^3 packets/s, and the maximum packet delay is $d_m = 30$ ms. From Fig. 8 and Fig. 9, we can see that the heterogeneous networks throughput for the four algorithms increase with the number of MTs at macrocell. On the other hand, the energy efficiency for these algorithms increase with the number of MTs at macrocell. This is due to the fact that the multiuser diversity helps the users with the better channel state information to

TABLE I

COMPUTATIONAL COMPLEXITY

Number of MTs	Proposed Algorithm 1	Heuristic Algorithm
$M_{\text{macro}} = 3$	3.03×10^6	8.42×10^4
$M_{\text{macro}} = 5$	5.24×10^6	8.92×10^4
$M_{\text{macro}} = 7$	7.18×10^6	9.21×10^4
$M_{\text{macro}} = 10$	12.91×10^6	9.72×10^4

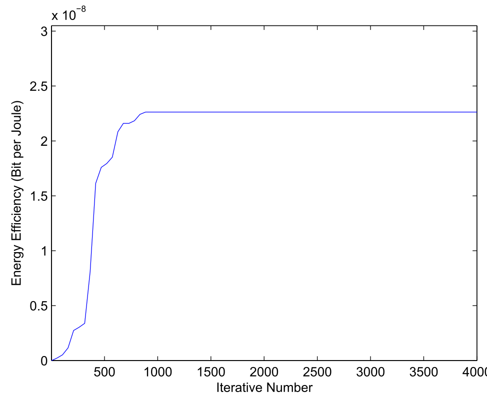

Fig. 10. Energy efficiency vs. iterative number.

obtain the resources. Consequently, increasing the number of MTs at macrocell improves the energy efficiency and the spectrum efficiency for heterogeneous multi-homing networks.

We evaluate the impact of the number of MTs at macrocell on computational complexity in Table I. In Fig. 10, we depict the convergence speed for the proposed security-awareness cross-layer resource allocation algorithm. The number of MTs in each femtocell is $M = 5$. The total bandwidth resources for each femtocell BS and each macrocell BS is 2 MHz and 5 MHz, respectively. The total available power for each macrocell BS and each femtocell BS are 3 W and 1W, respectively. Moreover, the arrival rate of video packet is 1.5×10^3 packets/s, and the maximum packet delay is $d_m = 30$ ms. In table I, we can see that the heuristic algorithm reduces the computational complexity at the cost of sacrificing the performance. On the other hand, the proposed algorithm 1 can fast converge to the stable solution. In Fig. 2-Fig. 10, it can be concluded that the proposed security-aware subchannel and power allocation algorithm not only improves the energy efficiency for heterogenous networks efficiently, but also obtains the better throughput.

VI. CONCLUSIONS

In this paper, we studied the security-aware energy-efficient cross-layer resource allocation problem for heterogeneous multi-homing networks. Each BS adjusted the subchannel assignment and power allocation to CSI at the physical layer and QSI at the link layer. The objective was to maximize the secrecy energy efficiency subject to the average packet delay, the average packet dropping probability, and the total available power constraints. The above optimization problem was formulated as a fractional programming, and an equivalent epigraph form was exploited to transform the factional programming into a tri-convex programming problem. The security-aware resource allocation algorithm was designed leveraging Lagrangian dual decomposition method, and a security-aware heuristic resource allocation algorithm was also proposed to reduce the computation complexity. Simulation results demonstrated that the proposed security-aware subchannel and power allocation scheme can improve the secrecy energy efficiency significantly in comparison with other benchmark schemes.

APPENDIX A

The service time, X_m, for MT m is determined by the maximum service time among different radio interfaces, i.e.,

$$X_m = \max_{n\in\mathcal{N}, s\in\mathcal{S}_n} \{X_{nsm}\} \tag{33}$$

where X_{nsm} is the service time for network n BS s MT m.

Since the service time, X_{nsm}, for different radio interfaces are independent, the CDF of service time, X_m, is defined by (34).

$$\begin{aligned}\Pr(X_m \le T_m) &= \Pr\left(\max_{n\in\mathcal{N}, s\in\mathcal{S}_n} \{X_{nsm}\} \le T_m\right)\\ &= \prod_{n\in\mathcal{N}, s\in\mathcal{S}_n} \Pr\{X_{nsm} \le T_m\}\end{aligned} \tag{34}$$

In (34), $\Pr\{X_{nsm} \le T_m\}$ is the probability of the service time, X_{nsm}, and is defined by (35).

$$\begin{aligned}&\Pr(X_{nsm} \le T_m)\\ &\quad= \Pr(X_{nsm} \le T_m | R_{nsm} \ge r_{nsm}) \Pr(R_{nsm} \ge r_{nsm})\\ &\qquad+ \Pr(X_{nsm} \le T_m | R_{nsm} < r_{nsm}) \Pr(R_{nsm} < r_{nsm})\\ &\quad= \Pr(X_{nsm} \le T_m | R_{nsm} \ge r_{nsm}) \Pr(R_{nsm} \ge r_{nsm})\end{aligned} \tag{35}$$

where r_{nsm} is the target transmission rate for network n BS s MT m.

Since $\Pr(X_{nsm} \le T_m | R_{nsm} \ge r_{nsm})$ and $\Pr(R_{nsm} \ge r_{nsm})$ follow the general distributions, $\Pr(X_{nsm} \le T_m)$ follows the general distribution.

APPENDIX B

Proof: We prove (18) is a tri-convex programming problem with the variables ρ^k_{nsm}, P^k_{nsm} and y. Define the objective function and the constraints in (18) as the functions g_1, f_1, f_2, f_3, and f_4, i.e.,

$$\begin{cases} g_1 = y\\ f_1 = 1 - \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{m\in\mathcal{M}_{ns}} \rho^k_{nsm}\\ f_2 = P^T_{ns} - P_{ns}\\ f_3 = \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{k\in\mathcal{K}_{ns}} \rho^k_{nsm} R^k_{nsm} - \alpha_m\\ f_4 = \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} \sum\limits_{m\in\mathcal{M}_{ns}} \sum\limits_{k\in\mathcal{K}_{ns}} \rho^k_{nsm} R^k_{nsm} - y \sum\limits_{n\in\mathcal{N}} \sum\limits_{s\in\mathcal{S}_n} P_{ns} \end{cases} \tag{36}$$

The second derivatives of g_1, f_1, f_2, f_3 and f_4 with respective to ρ^k_{nsm} are

$$\begin{cases} \dfrac{\partial^2 g_1}{\partial (\rho^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_1}{\partial (\rho^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_2}{\partial (\rho^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_3}{\partial (\rho^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_4}{\partial (\rho^k_{nsm})^2} = 0 \end{cases} \tag{37}$$

Given the variables P^k_{nsm} and y, the objective function is concave on ρ^k_{nsm}, and the constraints are concave according to (37). Hence, (18) is a convex programming problem with the variable ρ^k_{nsm}.

The second derivatives of g_1, f_1, f_2, f_3 and f_4 with respective to P^k_{nsm} are

$$\begin{cases} \dfrac{\partial^2 g_1}{\partial (P^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_1}{\partial (P^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_2}{\partial (P^k_{nsm})^2} = 0\\ \dfrac{\partial^2 f_3}{\partial (P^k_{nsm})^2} = \dfrac{\rho^k_{nsm} B_{ns} (g_{nsk})^2}{(B_{ns} n_0 + P^k_{nsm} g_{nsk})^2 \ln 2}\\ \qquad\qquad - \dfrac{\rho^k_{nsm} B_{ns} (h^k_{nsm})^2}{(B_{ns} n_0 + P^k_{nsm} h^k_{nsm})^2 \ln 2} \le 0\\ \dfrac{\partial^2 f_4}{\partial (P^k_{nsm})^2} = \dfrac{\rho^k_{nsm} B_{ns} (g_{nsk})^2}{(B_{ns} n_0 + P^k_{nsm} g_{nsk})^2 \ln 2}\\ \qquad\qquad - \dfrac{\rho^k_{nsm} B_{ns} (h^k_{nsm})^2}{(B_{ns} n_0 + P^k_{nsm} h^k_{nsm})^2 \ln 2} \le 0 \end{cases} \tag{38}$$

Given the variables ρ^k_{nsm} and y, the objective function is concave on P^k_{nsm}, and the constraints are concave according to (38). Hence, (18) is a convex programming problem with the variable P^k_{nsm}.

The second derivatives of g_1, f_1, f_2, f_3 and f_4 with respective to y are

$$\begin{cases} \dfrac{\partial^2 g_1}{\partial y^2} = 0\\ \dfrac{\partial^2 f_1}{\partial y^2} = 0\\ \dfrac{\partial^2 f_2}{\partial y^2} = 0\\ \dfrac{\partial^2 f_3}{\partial y^2} = 0\\ \dfrac{\partial^2 f_4}{\partial y^2} = 0 \end{cases} \tag{39}$$

Given the variables ρ^k_{nsm} and P^k_{nsm}, the objective function is concave on y, and the constraints are concave according to (39). Hence, (18) is a convex programming problem with the variable y. Consequently, problem (18) is a tri-convex programming problem with variables y, ρ_{nsm}^k and P_{nsm}^k.

References

[1] S. V. Hanly, C. Liu, and P. Whiting, "Capacity and stable scheduling in heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 6, pp. 1266–1279, Jun. 2015.

[2] S. Navaratnarajah, A. Saeed, M. Dianati, and M. A. Imran, "Energy efficiency in heterogeneous wireless access networks," *IEEE Wireless Commun.*, vol. 20, no. 5, pp. 37–43, Oct. 2013.

[3] S. Buljore *et al.*, "Architecture and enablers for optimized radio resource usage in heterogeneous wireless access networks: The IEEE 1900.4 working group," *IEEE Commun. Mag.*, vol. 47, no. 1, pp. 122–129, Jan. 2009.

[4] H. Zhang, N. Yang, K. Long, M. Pan, G. K. Karagiannidis, and V. C. M. Leung, "Secure communications in NOMA system: Subcarrier assignment and power allocation," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 7, pp. 1441–1452, Jul. 2018.

[5] C.-S. Lee and W.-H. Chung, "Hybrid RF-baseband precoding for cooperative multiuser massive MIMO systems with limited RF chains," *IEEE Trans. Commun.*, vol. 65, no. 4, pp. 1575–1589, Apr. 2017.

[6] M. Ismail and W. Zhuang, "A distributed multi-service resource allocation algorithm in heterogeneous wireless access medium," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 2, pp. 425–432, Feb. 2012.

[7] L. Xu, A. Nallanathan, and Y. Yang, "Video packet scheduling with stochastic QoS for cognitive heterogeneous networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7518–7526, Aug. 2017.

[8] A. D. Wyner, "The wire-tap channel," *Bell Syst. Tech. J.*, vol. 54, no. 8, pp. 1355–1387, 1975.

[9] W. Tong and S. Zhong, "A unified resource allocation framework for defending against pollution attacks in wireless network coding systems," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 10, pp. 2255–2267, Oct. 2016.

[10] S. Bayat, R. H. Y. Louie, Z. Han, B. Vucetic, and Y. Li, "Physical-layer security in distributed wireless networks using matching theory," *IEEE Trans. Inf. Forensics Security*, vol. 8, no. 5, pp. 717–732, May 2013.

[11] Y. Deng, L. Wang, M. Elkashlan, A. Nallanathan, and R. K. Mallik, "Physical layer security in three-tier wireless sensor networks: A stochastic geometry approach," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 6, pp. 1128–1138, Jun. 2016.

[12] Y.-S. Liang, W.-H. Chung, G.-K. Ni, I.-Y. Chen, H. Zhang, and S.-Y. Kuo, "Resource allocation with interference avoidance in OFDMA femtocell networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 5, pp. 2243–2255, Jun. 2012.

[13] A. Hatoum, R. Langar, N. Aitsaadi, R. Boutaba, and G. Pujolle, "Cluster-based resource management in OFDMA femtocell networks with Qos guarantees," *IEEE Trans. Veh. Technol.*, vol. 63, no. 5, pp. 2378–2391, Jun. 2014.

[14] R. Langar, S. Secci, R. Boutaba, and G. Pujolle, "An operations research game approach for resource and power allocation in cooperative femtocell networks," *IEEE Trans. Mobile Comput.*, vol. 14, no. 4, pp. 675–687, Apr. 2015.

[15] D. Lopez-Perez, X. Chu, A. V. Vasilakos, and H. Claussen, "Power minimization based resource allocation for interference mitigation in OFDMA femtocell networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 2, pp. 333–344, Feb. 2014.

[16] R. Estrada, A. Jarray, H. Otrok, Z. Dziong, and H. Barada, "Energy-efficient resource-allocation model for OFDMA macrocell/femtocell networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 7, pp. 3429–3437, Sep. 2013.

[17] N. Chakchouk and B. Hamdaoui, "Uplink performance characterization and analysis of two-tier femtocell networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 9, pp. 4057–4068, Nov. 2012.

[18] L. B. Le, D. Niyato, E. Hossain, D. I. Kim, and D. T. Hoang, "QoS-aware and energy-efficient resource management in OFDMA femtocells," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 180–194, Jan. 2013.

[19] Y. Choi, H. Kim, S.-W. Han, and Y. Han, "Joint resource allocation for parallel multi-radio access in heterogeneous wireless networks," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3324–3329, Nov. 2010.

[20] J. Miao, Z. Hu, C. Wang, R. Lian, and H. Tian, "Optimal resource allocation for multi-access in heterogeneous wireless networks," in *Proc. IEEE 75th Veh. Technol. Conf. (VTC)*, May 2012, pp. 1–5.

[21] P. Xue, P. Gong, J. H. Park, D. Park, and D. K. Kim, "Max-min fairness based radio resource management in fourth generation heterogeneous networks," in *Proc. IEEE ISCIT*, Sep. 2009, pp. 208–213.

[22] P. Xue, P. Gong, J. H. Park, D. Park, and D. K. Kim, "Radio resource management with proportional rate constraint in the heterogeneous networks," *IEEE Trans. Wireless Commun.*, vol. 11, no. 3, pp. 1066–1075, Mar. 2012.

[23] Q.-D. Vu, L.-N. Tran, M. Juntti, and E.-K. Hong, "Energy-efficient bandwidth and power allocation for multi-homing networks," *IEEE Trans. Signal Process.*, vol. 63, no. 7, pp. 1684–1699, Apr. 2015.

[24] M. Ismail and W. Zhuang, "Green radio communications in a heterogeneous wireless medium," *IEEE Wireless Commun.*, vol. 21, no. 3, pp. 128–135, Jun. 2014.

[25] S. Karachontzitis, S. Timotheou, I. Krikidis, and K. Berberidis, "Security-aware max–min resource allocation in multiuser OFDMA downlink," *IEEE Trans. Inf. Forensics Security*, vol. 10, no. 3, pp. 529–542, Mar. 2015.

[26] R. Saini, A. Jindal, and S. De, "Jammer-assisted resource allocation in secure OFDMA with untrusted users," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 5, pp. 1055–1070, May 2016.

[27] S. Tomasin and A. Dall'Arche, "Resource allocation for secret key agreement over parallel channels with full and partial eavesdropper CSI," *IEEE Trans. Inf. Forensics Security*, vol. 10, no. 11, pp. 2314–2324, Nov. 2015.

[28] H. Zhang, H. Xing, J. Cheng, A. Nallanathan, and V. C. M. Leung, "Secure resource allocation for OFDMA two-way relay wireless sensor networks without and with cooperative jamming," *IEEE Trans. Ind. Informat.*, vol. 12, no. 5, pp. 1714–1725, Oct. 2016.

[29] Z. Kong, Y.-K. Kwok, and J. Wang, "A low-complexity QoS-aware proportional fair multicarrier scheduling algorithm for OFDM systems," *IEEE Trans. Veh. Technol.*, vol. 58, no. 5, pp. 2225–2235, Jun. 2009.

[30] A. Chorti, S. M. Perlaza, Z. Han, and H. V. Poor, "On the resilience of wireless multiuser networks to passive and active eavesdroppers," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 1850–1863, Sep. 2013.

[31] A. Mukherjee and A. Lee Swindlehurst, "Detecting passive eavesdroppers in the MIMO wiretap channel," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2012, pp. 2809–2812.

[32] T.-X. Zheng, H.-M. Wang, Q. Yang, and M. H. Lee, "Safeguarding decentralized wireless networks using full-duplex jamming receivers," *IEEE Trans. Wireless Commun.*, vol. 16, no. 1, pp. 278–292, Jan. 2017.

[33] H.-M. Wang, T.-X. Zheng, J. Yuan, D. Towsley, and M. H. Lee, "Physical layer security in heterogeneous cellular networks," *IEEE Trans. Commun.*, vol. 64, no. 3, pp. 1204–1219, Mar. 2016.

[34] H. Xing, K.-K. Wong, A. Nallanathan, and R. Zhang, "Wireless powered cooperative jamming for secrecy multi-AF relaying networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 12, pp. 7971–7984, Dec. 2016.

[35] G. Auer *et al.*, "How much energy is needed to run a wireless network?" *IEEE Trans. Wireless Commun.*, vol. 18, no. 5, pp. 40–49, Oct. 2011.

[36] L. Kleinrock, *Queueing Systems*. Hoboken, NJ, USA: Wiley, Jun. 1975.

[37] M. Z. Shakir, M. A. Imran, K. A. Qaraqe, M.-S. Alouini, and A. V. Vasilakos, *Energy Management in Wireless Cellular and Ad-hoc Networks*. New York, NY, USA: Springer, 2016.

[38] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

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