# Security-Aware Proportional Fairness Resource Allocation for Cognitive Heterogeneous Networks

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***Abstract*—Cognitive radio and heterogeneous wireless networks are important candidate techniques for the fifth generation (5G) communication systems. On the other hand, propagation properties of radio channels in a physical layer are exploited to design efficient secure transmission schemes for 5G wireless networks. In this work, a security-aware joint power and subchannel allocation problem based on the inter-network cooperation is investigated at cognitive heterogeneous networks via imperfect spectral sensing. The security-aware joint power and subchannel allocation is subject to constraints in available subchannels, proportional fairness secrecy transmission rates among secondary mobile terminals (MTs), total interference power threshold, and total power for each secondary MT. In order to determine the impact of imperfect spectral sensing to resource allocation, we first represent the interference power at primary base station in terms of the misdetection probability and false alarm probability. Then, the security-aware power and subchannel allocation problem with inter-network cooperation is formulated as a biconvex optimization problem, and an optimal security-aware power and subchannel allocation algorithm is proposed utilizing the dual decomposition method. Compared to the heuristic power and subchannel allocation algorithms, numerical simulation results show that the proposed algorithms improve the total secrecy throughput and guarantee the proportional fairness among different secondary MTs.**

***Index Terms*—Cognitive heterogeneous networks, proportional fairness, security-aware resource allocation, inter-network cooperation, imperfect spectral sensing.**

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## I. Introduction

Different radio access technologies are applied in 5G communication systems, which may share the same wireless resources and constitute heterogeneous wireless networks [1]. Additionally, static spectrum allocation is inefficient in using the scarce spectrum resource [2]. In order to improve the spectral utilization efficiency, the cognitive radio technology is applied in heterogeneous wireless networks. Secondary mobile terminals (MTs) use the under-utilized licensed frequency bands to communicate with the infrastructure [3]. This motivates several international standards, e.g,. LTE-U, IEEE 802.11 af, and IEEE 802.22, to support and develop the cognitive radio networks [4]. Hence, cognitive heterogeneous networks are expected to integrate different primary networks and obtain spectral harvesting [5], [6]. To maximize user experience, a secondary MT takes advantage of multi-homing technology, where the transmission data stream at the secondary MT is split into multiple sub-streams, which use different radio interfaces to communicate with multiple secondary base stations (BSs) simultaneously [7], [8]. Consequently, adopting inter-network cooperation at cognitive heterogeneous networks is an important and useful scenario for 5G communication systems.

Secondary MTs also have the requirements of secure communication at cognitive heterogeneous networks. The security at physical layer is a promising approach to defend against attacks over the wireless networks. Designing efficient secure transmission schemes can efficiently safeguard the confidential and privacy communication data. Based on an information-theoretic approach, physical layer security can ensure secrecy via advanced signal processing techniques and/or channel codes [9]–[11]. With the undesired eavesdroppers, security performance is characterized by the nonzero transmission rate of perfectly secured information. From this perspective, physical layer security is promising to ensure both quality of experience and security for secondary MTs.

Resource management for cognitive radio network arises many unique challenges. The most important one is the interference between cognitive radio networks and primary wireless networks. Resource allocation for homogeneous or heterogeneous cognitive radio networks have been heavily investigated [12]–[25]. Recently, security-aware resource allocation mechanisms have gained attentions [23]–[25]. The existing security-aware resource allocation mechanisms limit the communication of secondary MTs. However, multi-homing technology has been shown to be beneficial for heterogeneous wireless networks with inter-network cooperation [26]. Consequently, extending multi-homing technology to the resource allocation problem with secure communication for cognitive heterogeneous networks requires further studies. Developing the security-aware proportional fairness resource allocation for cognitive heterogeneous networks not only considers the interference power to heterogeneous primary networks, but also utilizes the aggregated spectrum resources from multiple cognitive radio networks.

In this work, we study the security-aware joint power and subchannel allocation problem, based on imperfect spectral sensing, for cognitive heterogeneous networks. The main contributions of this work has three-fold: (i) We formulate a security-aware proportional fairness resource allocation problem with inter-network cooperation as a bi-convex optimization problem to allocate power and subchannel resources; (ii) We analyze the impact of the misdetection probability and the false alarm probability due to imperfect spectral sensing on the resource allocation problem; (iii) The optimal security-aware power and subchannel allocation algorithm is designed with the dual decomposition method, and the heuristic power and subchannel allocation algorithms are developed via the greedy method. Numerical simulation results demonstrate that the proposed algorithms guarantee the fairness among secondary MTs, and improve the total secrecy throughput, and are the robustness of the solution against estimation errors of eavesdropper's channel for cognitive heterogeneous networks.

In this work, the rest parts are organized as follows. Section II describes the related works and Section III gives the system model. The optimal security-aware proportional fairness power and subchannel allocation algorithm is presented in Section IV. A heuristic power and subchannel algorithm and an analysis of computational complexity are given in Section V. Finally, Sections VI and VII present performance evaluation and conclusions, respectively.

## II. Related Works

Existing resource allocation algorithms are divided into three categories for cognitive radio networks [12]–[25]. The first category are designed for single cognitive radio network, where the system contains a cognitive radio network and a primary wireless network [12]–[17]. The second category are designed for heterogeneous cognitive radio networks[18]–[22]. The third category of resource allocation algorithms are designed for security-aware cognitive radio network[23]–[25], [27]–[32].

In single cognitive radio network, resource allocation algorithms are divided into bandwidth allocation [12], [13], packet scheduling [14], [15], and joint bandwidth and power allocation [16], [17]. In [12], an optimal bandwidth allocation for secondary MTs via dynamically accessing licensed channels is proposed, and the optimal throughput for each secondary MT is analyzed. Different from [12], bandwidth allocation based on max-min criterion is investigated for cognitive mesh network [13]. For packet scheduling, a joint packet scheduling and connection admission scheme is proposed with non-real-time and real-time traffics for cognitive ad hoc network in [14]. In [15], a packet scheduling scheme is proposed to minimize the packet delay. For joint bandwidth and power allocation, a minimizing bandwidth-power product resource allocation algorithm is presented in [16]. Based on [16], maximizing the total ergodic capacity for secondary MTs has been studied with the constraints, i.e., total available bandwidth, average/peak transmit power at secondary MTs, and total interference power in [17].

In cognitive heterogeneous networks, resource allocation can be formulated to maximize spectral efficiency [18], [19], energy efficiency [20], [21], and fairness [22]. For maximizing spectral efficiency, a random subcarrier allocation algorithm is proposed based on supermodular game theory [18]. In [19], a joint resource allocation and spectral sensing framework is investigated to maximize the spectrum efficiency. Different from [18], [19], an energy-efficient resource allocation algorithm is solved with stackelberg game theory for cognitive heterogeneous femtocell networks [20]. Based on [20], smart grid is further considered in cognitive heterogeneous femtocell networks, and a stackelberg game framework with three-level structure is proposed to decide electricity price, interference price and energy-efficient power allocation [21]. For guaranteeing the fairness of secondary MTs, a fair resource allocation scheme with imperfect spectral sensing is proposed under cross-tier/co-tier interference constraints for cognitive heterogeneous femtocell network [22].

For security-aware resource allocation, an optimal resource allocation algorithm with multi-objective optimization is proposed at cognitive radio network [23]. In [24], an ergodic security-aware resource allocation problem is investigated with the presence of a set of passive eavesdroppers for cognitive relay-assisted orthogonal frequency division multiple access (OFDMA) network. A cooperative security-aware resource allocation is presented with guaranteeing secrecy transmission rate for cognitive radio network as long as secondary users preserve the secure communication of primary users with malicious eavesdroppers [25]. A user scheduling problem is investigated with the stochastic network optimization problem considering the security, reliability, and stability [27]. In [29], a resource allocation algorithm with secrecy outage probability constraint is proposed via the stochastic network optimization framework. For multiple eavesdroppers to overhear the primary user confidential messages, a security awareness resource allocation is proposed to maximize secondary user ergodic transmission rate subject to the primary user secrecy outage [28]. In [30], a novel nonmonetary trading model is designed for the secure communication issue at cognitive radio networks with nonaltruistic users. To maximize the secrecy throughput of the primary user, a joint beamforming, rate parameters of the wiretap code and power allocation is investigated for multi-input single-output cognitive radio network in slow fading channels [31]. In [32], a secure cooperative communication scheme is proposed via the dual decomposition method for orthogonal frequency-division multiple-access-based cognitive radio networks.

## III. System Model

Firstly, the system model is described for cognitive heterogeneous networks. Then, the imperfect spectral sensing and interference power models are given. Finally, we present the power model of secondary MT.

### A. System Model Description

There exists a geographical region with different wireless networks, which are used with different radio access technologies and operated via different service operators as shown in Fig. 1. For BS $s'$ in the primary network $n'$, there is a cognitive network $n$ secondary BS $s$ which can use the same spectrum of the primary BS opportunistically. In cognitive

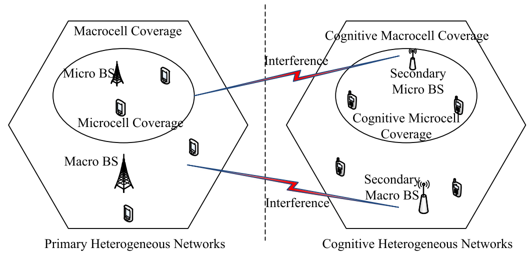


Fig. 1. Cognitive heterogeneous networks.

network $n \in \{1, 2, \ldots, N\}$, there exists a set of secondary base stations (BSs) $\mathcal{S}_n = \{1, 2, \ldots, S_n\}$. Additionally, an eavesdropper exists in the cognitive heterogeneous networks. Denote $\mathcal{M} = \{1, 2, \ldots, M\}$ by a set of all secondary MTs, and $\mathcal{M}_{ns} = \{1, 2, \ldots, M_{ns}\} \in \mathcal{M}$ is a subset of secondary MTs a cognitive network $n$ secondary BS $s$. In both the primary and cognitive networks, the OFDMA technology is adopted, and the bandwidth is divided into many orthogonal subchannels. The subchannel set of secondary BS $s$ in cognitive network $n$ is $\mathcal{K}_{ns}^{v} = \{1, 2, \ldots, K_{ns}^{v}\}$. Additionally, the transmission power for secondary MTs needs to be controlled with the interference temperature model [5]. Using multiple radio interfaces and the multi-homing mechanism, each secondary MT may communicate to multiple secondary BSs simultaneously. This is due to the fact that different secondary BSs have different coverage areas, and some coverage areas are overlapped with each other. In the overlapped areas, each secondary MT utilizes its multiple radio interfaces to communicate with multiple secondary BSs via different and orthogonal spectrum resources. Moreover, secondary MTs perform cooperative sensing [33], and the secondary BSs obtain the feedback for spectral sensing information to make the final spectral sensing result for the vacant subchannel set, $\mathcal{K}_{ns}^{v_0}$, as well as the unavailable subchannel set, $\mathcal{K}_{ns}^{v_1}$. In each cognitive radio network, the resource allocation results and spectral sensing information are exchanged with a common control channel, which is assumed always reliable and available.

The eavesdropper is passive, and wiretaps the transmission signal over all subchannels [34], [35]. The wireless channel gains between the eavesdropper (or secondary BS) and secondary MTs are assumed to be known perfectly, and the eavesdropper's channel and the secondary MTs' channel are independent [9]. Additionally, the instantaneous channel power gain is adopted for the security-aware proportional fairness resource allocation in this work, which is used in the existing security-aware resource allocation algorithms, e.g., [23], [25]. A block-fading model assumes that each subchannel remains constant and independent to other subchannels and varies across different blocks. $g_{nsm}^{k}(t)$ is the channel power gain at time slot $t$ from secondary MT $m$ to cognitive network $n$ secondary BS $s$ over subchannel $k$, while $\hat{f}_{nsm}^{k}(t)$ is the channel power gain at time slot $t$ from secondary MT $m$ in the coverage of cognitive network $n$ secondary BS $s$ to the eavesdropper over subchannel $k$. We assume $g_{nsm}^{k}(t)$ is perfectly known for resource allocation. Since the eavesdropper's channel, $f_{nsm}^{k}(t)$, can not be perfectly known, the secondary BSs can estimate the upper bound of channel power gain, $\hat{f}_{nsm}^{k}(t)$, between the eavesdropper and secondary BSs, and apply them in cross-layer resource allocation, conservatively.

The secrecy transmission rate over the $k$ subchannel at time slot $t$ for cognitive network $n$ secondary BS $s$ secondary MT $m$ is

$$R_{nsm}^{k,v_0}(t) = \begin{cases} R_{se}(t), & \text{if } g_{nsm}^{k}(t) > \hat{f}_{nsm}^{k}(t) \\ 0, & \text{if } g_{nsm}^{k}(t) \le \hat{f}_{nsm}^{k}(t) \end{cases} \tag{1}$$

and

$$R_{se}(t) = B_{ns} \log_2 \left( \frac{B_{ns} n_0 + P_{nsm}^{k}(t) g_{nsm}^{k}(t)}{B_{ns} n_0 + P_{nsm}^{k}(t) \hat{f}_{nsm}^{k}(t)} \right) \tag{2}$$

where $P_{nsm}^{k}(t)$ is the power allocated for secondary MT $m$ at time slot $t$ over subchannel $k$ to communicate with cognitive network $n$ secondary BS $s$, and $n_0$ is the one-sided noise power spectral density.

Consequently, the total secrecy transmission rate for secondary MT $m$ is

$$R_m(t) = \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{S}_n} \sum_{k \in \mathcal{K}_{ns}^{v_0}} \rho_{nsm}^{k} R_{nsm}^{k,v_0}(t) \tag{3}$$

where $\rho_{nsm}^{k}$ is the subchannel allocation indicator variable for cognitive network $n$ secondary BS $s$ secondary MT $m$ over subchannel $k$.

## B. Imperfect Spectral Sensing Model

In the spectral sensing, there are typically two types of errors, i.e., false alarm and misdetection. For misdetection, a subchannel is identified to be idle, but it is in fact used by a primary MT. For false alarm, a subchannel is sensed busy, but it is idle actually. The probabilities over the $k$th subchannel for misdetection and false alarm are $q_{ns}^{k}$ and $qF_{ns}^{k}$, respectively. Additionally, $q_{ns}^{k}$ and $qF_{ns}^{k}$ are obtained by cooperative spectrum sensing [36]. Obviously, misdetection leads to co-channel interference to the primary BS, and false alarm reduces spectral efficiency. $O_{ns}^{k}$ and $H_{ns}^{k}$ are the hypotheses of the presence and the absence for a certain primary MT signal over subchannel $k$ for cognitive network $n$ secondary BS $s$, respectively. $\overline{O}_{ns}^{k}$ and $\overline{H}_{ns}^{k}$ are the events that the $k$th subchannel for cognitive network $n$ secondary BS $s$ is unavailable or available based on spectral sensing information, respectively. Therefore, the probabilities of four possible cases for the spectrum sensing are

$$\begin{cases} \Pr\left\{ \overline{O}_{ns}^{k} \left| O_{ns}^{k} \right. \right\} = 1 - q_{ns}^{k} \\ \Pr\left\{ \overline{H}_{ns}^{k} \left| O_{ns}^{k} \right. \right\} = q_{ns}^{k} \\ \Pr\left\{ \overline{H}_{ns}^{k} \left| H_{ns}^{k} \right. \right\} = 1 - qF_{ns}^{k} \\ \Pr\left\{ \overline{O}_{ns}^{k} \left| H_{ns}^{k} \right. \right\} = qF_{ns}^{k}. \end{cases} \tag{4}$$

Define $\Pr_{ns}^{1,k}$ as the probability that the $k$th subchannel for network $n$ BS $s$ is truly used by a primary MT, while the secondary MT makes a correct judgement, i.e.,

$$\begin{cases} \Pr_{ns}^{1,k} = \frac{\Pr\left\{ \overline{O}_{ns}^{k} \left| O_{ns}^{k} \right. \right\} \Pr\left\{ O_{ns}^{k} \right\}}{\Omega_{nsk}^{1}} \\ \Omega_{nsk}^{1} = \Pr\left\{ \overline{O}_{ns}^{k} \left| O_{ns}^{k} \right. \right\} \Pr\left\{ O_{ns}^{k} \right\} \\ \qquad + \Pr\left\{ \overline{O}_{ns}^{k} \left| H_{ns}^{k} \right. \right\} \Pr\left\{ H_{ns}^{k} \right\}. \end{cases} \tag{5}$$

Define $\Pr_{ns}^{2,k}$ as the probability that the $k$th subchannel for network $n$ BS $s$ is truly occupied, when a secondary MT deems it as vacant, i.e.,

$$\begin{cases} \Pr_{ns}^{2,k} = \frac{\Pr\left\{\overline{H}_{ns}^{k} \left| O_{ns}^{k} \right.\right\} \Pr\left\{O_{ns}^{k}\right\}}{\Omega_{nsk}^{2}} \\ \Omega_{nsk}^{2} = \Pr\left\{\overline{H}_{ns}^{k} \left| H_{ns}^{k} \right.\right\} \Pr\left\{H_{ns}^{k}\right\} \\ \qquad + \Pr\left\{\overline{H}_{ns}^{k} \left| O_{ns}^{k} \right.\right\} \Pr\left\{O_{ns}^{k}\right\}. \end{cases} \tag{6}$$

### C. Interference Power Model

The bandwidth of each subchannel for cognitive network $n$ secondary BS $s$ is $B_{ns}$, and the spectrum over subchannel $j$ is from $f_s + (j-1) B_{ns}$ to $f_s + jB_{ns}$, where $f_s$ is the starting frequency for the first subchannel. When secondary MT $m$ uses the unit transmission power to transmit data over subchannel $k$, the interference $I_{nsm}^{kj}$, introduced to the $j$th subchannel from the $k$th subchannel at cognitive network $n$ secondary BS $s$, is

$$I_{nsm}^{kj} = \int_{(j-1)B_{ns}-(k-0.5)B_{ns}}^{jB_{ns}-(k-0.5)B_{ns}} h_{nsm}^{k}(t)\,\phi(f)df \tag{7}$$

where $h_{nsm}^{k}(t)$ is the channel power gain from cognitive network $n$ secondary BS $s$ MT $m$ to cognitive network $n$ secondary BS $s$ over subchannel $k$ at time slot $t$, and $\phi(f)$ is the power spectrum density, i.e.,

$$\phi(f) = T\left(\frac{\sin \pi f T}{\pi f T}\right)^2 \tag{8}$$

where $T$ is the duration of orthogonal frequency division multiplexing (OFDM) symbol.

Hence, the interference power $I_{nsm}^{k}$, introduced to the $k$th subchannel by accessing secondary MT $m$ at cognitive network $n$ secondary BS $s$ with the unit transmission power, is

$$I_{nsm}^{k} = \sum_{j\neq k, j\in\mathcal{K}_{ns}^{v0}} \Pr{}_{ns}^{2,j} I_{nsm}^{kj} + \sum_{j\in\mathcal{K}_{ns}^{v1}} \Pr{}_{ns}^{1,j} I_{nsm}^{kj}. \tag{9}$$

### D. Power Consumption Model

The power consumption at secondary MT contains two components, i.e., a fixed power consumption, $P_c$, and the transmission power consumption [37]. Therefore, the power consumption $P_m$ at time slot $t$ for secondary MT $m$ is

$$P_m(t) = P_c + \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n}\sum_{k\in\mathcal{K}_{ns}^{v0}} \rho_{nsm}^{k} P_{nsm}^{k}(t). \tag{10}$$

## IV. Security-Aware Power and Subchannel Allocation

In this section, we formulate the security-aware proportional fairness power and subchannel allocation problem at cognitive heterogeneous networks firstly. Then, the optimal security-aware power and subchannel allocation algorithm is proposed with the dual decomposition method.

### A. Security-Aware Proportional Fairness Resource Allocation Problem

The total power consumption, $P_m$, should satisfy the maximum power constraint for secondary MT $m$, i.e.,

$$P_m(t) \leq P_m^{\mathrm{T}}, \forall m \in \mathcal{M} \tag{11}$$

where $P_m^{\mathrm{T}}$ is the maximum power for secondary MT $m$.

Since the transmission distances between secondary MTs and secondary BSs are different, the transmission path loss are different for different secondary MTs. This phenomenon leads to the unfairness. Therefore, the proportional fairness secrecy transmission rates should be considered for secondary MTs [38], i.e.,

$$\frac{R_{m+1}(t)}{R_m(t)} = \frac{\varphi_{m+1}}{\varphi_m}, \forall m \in \mathcal{M} \tag{12}$$

where $\varphi_m$ is the proportional fairness weight at secondary MT $m$. The proportional fairness weights should be set according to the secondary user priority. If the secondary user has the higher priority, the proportional fairness weight should be large.

Additionally, the feasible region of subchannel allocation and the interference power at cognitive network $n$ secondary BS $s$ should be considered in (13) and (14), respectively.

$$\sum_{m\in\mathcal{M}_{ns}} \rho_{nsm}^{k} \leq 1, \forall n \in \mathcal{N}, k \in \mathcal{K}_{ns}^{v_0}, s \in \mathcal{S}_n \tag{13}$$

and

$$\sum_{m\in\mathcal{M}_{ns}}\sum_{k\in\mathcal{K}_{ns}^{v0}} \rho_{nsm}^{k} P_{nsm}^{k}(t) I_{nsm}^{k} \leq I_{ns}^{\mathrm{th}}, \forall n \in \mathcal{N}, s \in \mathcal{S}_n \tag{14}$$

where $I_{ns}^{\mathrm{th}}$ is the interference threshold for primary network $n'$ BS $s'$.

Hence, the security-aware power and subchannel allocation problem is formulated as

$$\begin{aligned} OP1 \quad & \max_{\rho_{nsm}^{k}, P_{nsm}^{k}(t)} \sum_{m\in\mathcal{M}} R_m(t) \\ & \text{s.t.}: (11), (12), (13), (14), \\ & \rho_{nsm}^{k} \in \{0,1\}, P_{nsm}^{k}(t) \geq 0 \end{aligned} \tag{15}$$

where $R_m(t)$ is the secrecy transmission rate at time slot $t$ for secondary user $m$.

Problem (15) contains the integer variable $\rho_{nsm}^{k}$ and the continuous variable $P_{nsm}^{k}(t)$, which is a NP-hard mixed integer non-linear programming problem. Hence, we transform problem (15) into a convex programming problem. Obviously, $\rho_{nsm}^{k}$ is an integer variable, and (13) is an integer constraint condition. In order to tackle the integer constraint, integer variables are relaxed into continuous ones via time-sharing. Refine $\rho_{nsm}^{k} \in [0,1]$ as the fraction of the $k$th subchannel at cognitive network $n$ secondary BS $s$ secondary MT $m$.

Except for relaxing the variable $\rho_{nsm}^{k}$, we transform the constraint (12) into a convex constraint condition. Since there are $M$ secondary MTs with delay-tolerance in the cognitive heterogeneous networks, constraint (12) includes $M-1$ independent equalities. To analyze and solve conveniently, the constraint in

(12) can be replaced by $M$ dependent inequalities, i.e.,

$$\frac{R_{[m+1]_M}(t)}{R_m(t)} \le \frac{\varphi_{[m+1]_M}}{\varphi_m}, \forall m \in \mathcal{M} \tag{16}$$

where $[\bullet]_M$ represents the modulus based on $M$.

The constraint in (16) can be transformed as

$$\varphi_{[m+1]_M} R_m(t) - \varphi_m R_{[m+1]_M}(t) \ge 0, \forall m \in \mathcal{M}. \tag{17}$$

Hence, (15) can be rewritten as

$$\begin{aligned} OP2 & \max_{\rho_{nsm}^k, P_{nsm}^k(t)} \sum_{m\in\mathcal{M}} R_m(t) \\ & \text{s.t.}: (11), (13), (14), (17) \\ & \rho_{nsm}^k \ge 0, P_{nsm}^k(t) \ge 0. \end{aligned} \tag{18}$$

where problem (18) is a bi-convex optimization problem, which can be proved in Appendix A. The bi-convex optimization is a generalization of convex optimization. In the bi-convex optimization, the objective function and the constraint set can be biconvex, which can find the global optimum [39].

### B. Optimal Security-Aware Power and Subchannel Allocation

In this section, we solve the security-aware joint power and subchannel allocation problem for cognitive heterogeneous networks. Additionally, we adopt the dual decomposition method to solve it. The Lagrangian function for primary problem (18) can be expressed as

$$\begin{aligned} & f\left(\alpha_{nsk}, u_m, v_m, \delta_{ns}, \rho_{nsm}^k, P_{nsm}^k(t)\right) \\ & = \sum_{m\in\mathcal{M}} u_m \left(\phi_{[m+1]_M} R_m(t) - \phi_m R_{[m+1]_M}(t)\right) \\ & \quad + \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \sum_{k\in\mathcal{K}_{ns}^{v_0}} \alpha_{nsk} \left(1 - \sum_{m\in\mathcal{M}_{ns}} \rho_{nsm}^k\right) \\ & \quad + \sum_{m\in\mathcal{M}_{ns}} v_m \left(P_m^{\mathrm{T}} - P_m(t)\right) + \sum_{m\in\mathcal{M}} R_m(t) \\ & \quad + \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \delta_{ns} \left(I_{ns}^{\mathrm{th}} - \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}^{v_0}} \rho_{nsm}^k P_{nsm}^k(t) I_{nsm}^k\right) \end{aligned} \tag{19}$$

where $\alpha_{nsk}$, $u_m$, $v_m$, and $\delta_{ns}$ are the Lagrangian multipliers.

With (19), the dual function $h(\alpha_{nsk}, u_m, v_m, \delta_{ns})$ can be expressed as

$$h(\alpha_{nsk}, u_m, v_m, \delta_{ns}) = \begin{cases} \max\limits_{P_{nsm}^k(t), \rho_{nsm}^k} f\left(\alpha_{nsk}, u_m, v_m, \delta_{ns}, \rho_{nsm}^k, P_{nsm}^k(t)\right) \\ \text{s.t.}: \rho_{nsm}^k \ge 0, P_{nsm}^k(t) \ge 0. \end{cases} \tag{20}$$

Additionally, the dual problem is

$$\begin{aligned} OP3 & \min_{\substack{\alpha_{nsk}, u_m \\ v_m, \delta_{ns}}} h(\alpha_{nsk}, u_m, v_m, \delta_{ns}) \\ & \text{s.t.}: \alpha_{nsk} \ge 0, u_m \ge 0, v_m \ge 0, \delta_{ns} \ge 0. \end{aligned} \tag{21}$$

For each secondary MT, the Lagrangian function (19) can be transformed as

$$\begin{aligned} f_m & = R_m(t) - v_m P_m(t) \\ & \quad - \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \delta_{ns} \sum_{k\in\mathcal{K}_{ns}^{v_0}} \rho_{nsm}^k P_{nsm}^k(t) I_{nsm}^k \\ & \quad - \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}_n} \sum_{k\in\mathcal{K}_{ns}^{v_0}} \alpha_{nsk} \rho_{nsm}^k + R_m(t) L_m \end{aligned} \tag{22}$$

and

$$L_m = u_m \varphi_{[m+1]_M} - u_{[m-1]_M} \varphi_{[m-1]_M}. \tag{23}$$

Hence, each secondary MT solves its own utility maximization problem, i.e.,

$$\begin{aligned} OP4 & \max_{\rho_{nsm}^k, P_{nsm}^k(t)} f_m \\ & \text{s.t.}: \rho_{nsm}^k \ge 0, P_{nsm}^k(t) \ge 0. \end{aligned} \tag{24}$$

The optimal power, $P_{nsm}^k(t)$, for the fixed values of $\rho_{nsm}^k$, $\alpha_{nsk}$, $u_m$, $v_m$, and $\delta_{ns}$ can be obtained via (25) by applying the KKT condition on (22).

$$\frac{\partial f_m}{\partial P_{nsm}^k(t)} = 0. \tag{25}$$

From (25), we can obtain

$$P_{nsm}^k(t) = \left[\frac{\sqrt{\Delta} - \left(f_{nsm}^k(t) + g_{nsm}^k(t)\right) B_{ns} n_0}{2 f_{nsm}^k(t) g_{nsm}^k(t)}\right]^+ \tag{26}$$

$$\Delta = 4 f_{nsm}^k(t) g_{nsm}^k(t) W_{nsm}^k \tag{27}$$

$$\quad + \left(f_{nsm}^k(t) - g_{nsm}^k(t)\right)^2 (B_{ns} n_0)^2 \tag{28}$$

and

$$W_{nsm}^k = \frac{(1 + L_m)\left(f_{nsm}^k(t) - g_{nsm}^k(t)\right)(B_{ns})^2 n_0}{\left(v_m + \delta_{ns} I_{nsm}^k\right)\ln 2} \tag{29}$$

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

With the fixed values $P_{nsm}^k(t)$, $u_m$, $v_m$, and $\delta_{ns}$, the Lagrangian function $f_m$ for secondary MT $m$ is linear with respect to the variable $\rho_{nsm}^k$, and $\rho_{nsm}^k$ falls in the interval [0, 1]. Hence, when $\partial L_{ns}/\partial \rho_{nsm}^k < 0$, the maximum value can be obtained via $\rho_{nsm}^k = 0$. On the other hand, when $\partial L_{ns}/\partial \rho_{nsm}^k > 0$, the maximum value can be obtained via $\rho_{nsm}^k = 1$. The criterion of subchannel allocation is

$$\frac{\partial f_m}{\partial \rho_{nsm}^k} = \begin{cases} > 0, \rho_{nsm}^k = 1 \\ 0, 0 < \rho_{nsm}^k < 1 \\ < 0, \rho_{nsm}^k = 0 \end{cases} \tag{30}$$

$$\frac{\partial f_m}{\partial \rho_{nsm}^k} = H_{nsm}^k - \alpha_{nsk} \tag{31}$$

and

$$H_{nsm}^k = (1 + L_m) R_{nsm}^{k,v_0}(t) - \left(v_m + \delta_{ns} I_{nsm}^k\right) P_{nsm}^k(t). \tag{32}$$

**Algorithm 1:** Optimal Security-Aware Power and Subchannel Allocation.

**Require:** $P_m^{\mathrm{T}}$, $\varphi_m$, and $I_{ns}^{\mathrm{th}}$.
**Ensure:** $\rho_{nsm}^k$ and $P_{nsm}^k(t)$.
1: Initialize $u_m(i)$, $v_m(i)$, $\delta_{ns}(i)$, $\rho_{nsm}^k$, $P_{nsm}^k(t)$, $I_{\max}$, and $i = 1$.
2: **repeat**
3: Calculate $P_{nsm}^k(t)$ and $\rho_{nsm}^k$ with (26) and (33).
4: **if** $\sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}^{v_0}} \rho_{nsm}^k P_{nsm}^k(t) I_{nsm}^k \le I_{ns}^{\mathrm{th}}$ and $i < I_{\max}$ **then**
5: Set $i = i + 1$, and update $u_m(i)$, $v_m(i)$, and $\delta_{ns}(i)$. Go to step 3.
6: **else**
7: Go to step 10.
8: **end if**
9: **until**
10: Output $\rho_{nsm}^k$ and $P_{nsm}^k(t)$.

Subchannel $k$ at secondary $ns$ is assigned to secondary MT $m$ with the largest $H_{nsm}^k$, that is,

$$\rho_{nsm^*}^k = 1 \Big| m^* = \max_m H_{nsm}^k. \tag{33}$$

The optimum values of $u_m$ , $v_m$, and $\delta_{ns}$ can be calculated by solving the dual problem (21). We use a gradient descent method to obtain the optimal values for $u_m$, $v_m$, and $\delta_{ns}$, i.e.,

$$\delta_{ns}(i+1) = [\delta_{ns}(i) - \Delta\varepsilon_1(i)\Delta\delta]^+ , \tag{34}$$

$$v_m(i+1) = [v_m(i) - \Delta\varepsilon_2(i)\Delta v]^+ , \tag{35}$$

$$u_m(i+1) = [u_m(i) - \Delta\varepsilon_3(i)\Delta u]^+ , \tag{36}$$

and

$$\begin{cases} \Delta v = P_m^{\mathrm{T}} - P_m(t) \\ \Delta u = \varphi_{[m+1]_M} R_m(t) - \varphi_m R_{[m+1]_M}(t) \\ \Delta\delta = I_{ns}^{\mathrm{th}} - \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}^{v_0}} C_{nsm}^k I_{nsm}^k \end{cases} \tag{37}$$

where $i$ is the iteration index, and $\Delta\varepsilon_j$, is a small step size. Since the Lipchitz continuity condition is satisfied, the convergence can be guaranteed by (34)–(37) [40]. Therefore, the resource allocation solution $\rho_{nsm}^k$ and $P_{nsm}^k(t)$ converges to the optimum solution.

Since the subchannel allocation is given in (33), it is not necessary to update the Lagrangian variable $\alpha_{nsk}$. $\varepsilon_1(i)$, $\varepsilon_2(i)$, and $\varepsilon_3(i)$ are the step sizes of iteration $i$, and the step sizes should satisfy the condition,

$$\sum_{i=1}^{\infty} \varepsilon_j(i) = \infty, \lim_{i\to\infty} \varepsilon_j(i) = 0, \forall j \in \{1,2,3\}. \tag{38}$$

Although (26) and (33) give the solution to the optimal security-aware power and subchannel allocation, an algorithm is designed to provide the execution structure. Consequently, Algorithm 1 is proposed as an implementation to obtain the optimal security-aware power and subchannel allocation. $\varepsilon_p$ is a small positive number and $I_{\max}$ is the maximum iteration number. $u_m(i)$, $\alpha_{nsk}(i)$, $\delta_{ns}(i)$ and $v_m(i)$ are the Lagrangian multipliers at the $(i)$th iteration.

**Algorithm 2:** Heuristic Subchannel Allocation.

**Require:** $P_m^{\mathrm{T}}$, $\varphi_m$, and $I_{ns}^{\mathrm{th}}$.
**Ensure:** $\rho_{nsm}^k$.
1: Initialize $\mathbf{\Omega}_{ns} = \{\mathcal{K}_{ns}^{v_0}\}$ , $\rho_{nsm}^k = 0$, $P_{nsm}^k(t)$, $\eta_m$, $R_m(t)$, and $Rt_{nsm}^{k,v_0}(t)$, $\forall n, s, m$.
2: **repeat**
3: Calculate $\eta_m = R_m(t)/\varphi_m$, and find $m^* = \min_{m\in\mathcal{M}} \eta_m$.
4: Secondary MT $m^*$ calculates $Rt_{nsm^*}^{k,v_0}(t)$, and finds $k^* = \max_{k\in\mathbf{\Omega}_{ns}} Rt_{nsm^*}^{k,v_0}(t)$.
5: **if** $\mathbf{\Omega}_{ns} \ne \emptyset$ and $\sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}^{v_0}} C_{nsm}^k I_{nsm}^k \le I_{ns}^{\mathrm{th}}$ **then**
6: Cognitive network $n$ secondary BS $s$ updates $\rho_{nsm^*}^{k^*} = 1$, and $\mathbf{\Omega}_{ns} \leftarrow \mathbf{\Omega}_{ns} - k^*$. Go to step 3.
7: **else**
8: Go to step 11.
9: **end if**
10: **until**
11: Output $\rho_{nsm}^k$.

## V. Heuristic Resource Allocation Algorithm And Complexity Analysis

In order to compare with Algorithm 1, we develop a heuristic security-aware resource allocation algorithm for cognitive heterogeneous networks with single access. This heuristic resource allocation algorithm is designed via the greedy method, which is inspired by the existing resource allocation algorithm in homogeneous OFDMA network, e.g., [41]. In this section, we first propose a heuristic security-aware algorithm with single access. Then, the computational complexity and signaling overhead are analyzed for the optimal and heuristic algorithms.

### A. Heuristic Security-Aware Algorithm

In the heuristic security-aware algorithm, its subchannel allocation and power allocation are designed separately. Hence, the heuristic security-aware algorithm includes a subchannel allocation algorithm and a power allocation algorithm. If the subchannel allocation and the power allocation for heuristic security-aware algorithm are designed in a recursive manner, the performance can be improved further. For simplicity, we adopt one recursive. For the subchannel allocation, the subchannel is allocated, based on the greedy method, to different secondary MTs with the equal power allocation. In the power allocation, the subchannel allocation is fixed, and the power is allocated for secondary MTs, by the greedy method to maximize the secrecy throughput. The subchannel allocation in the heuristic resource allocation algorithm is depicted in Algorithm 2. In Algorithm 2, the subchannel is assigned to secondary MT, who has the minimum normalized secrecy transmission rate in step 3. Additionally, the radio interface of the tagged secondary MT is selected with the largest secrecy transmission rate in step 4. The step 1 is the initialization parameters and step 5-step 9 check the terminal condition of Algorithm 2. The power allocation in heuristic resource allocation algorithm is similar with the subchannel allocation. The heuristic power algorithm is given in Algorithm 3. In Algorithm 3, the power is allocated to secondary MT, who has the minimum normalized secrecy

**Algorithm 3:** Heuristic Power Allocation.

**Require:** $P_m^{\mathrm{T}}$, $\varphi_m$, $\rho_{nsm}^k$, and $I_{ns}^{\mathrm{th}}$.
**Ensure:** $P_{nsm}^k(t)$.
1: Initialize $\mathbf{\Omega}_{ns} = \{\mathcal{K}_{ns}^{v_0}\}$, $\Delta P$, $Pt_{nsm}^k(t)$, $\eta_m$, $R_m(t)$, and $Rt_{nsm}^{k,v_0}(t), \forall n, s, m$.
2: **repeat**
3: Calculate $\eta_m = R_m(t)/\varphi_m$, and find $m^* = \min_{m\in\mathcal{M}} \eta_m$.
4: Secondary MT $m^*$ updates $Pt_{nsm^*}^k(t)$, $Rt_{nsm^*}^{k,v_0}(t)$ and $R_{nsm^*}^{k,v_0}(t)$. Find $k^* = \max_{k\in\mathbf{\Omega}_{ns}} (Rt_{nsm^*}^{k,v_0}(t) - R_{nsm^*}^{k,v_0}(t))$.
5: **if** $P_{m^*}(t) \leq P_{m^*}^{\mathrm{T}}$ and $\sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}_{ns}^{v_0}} C_{nsm}^k I_{nsm}^k \leq I_{ns}^{\mathrm{th}}$ **then**
6: Secondary MT $m^*$ updates $P_{nsm^*}^{k^*}(t) = P_{nsm^*}^{k^*}(t) + \Delta P$. Go to step 3.
7: **else**
8: Go to step 11.
9: **end if**
10: **until**
11: Output $P_{nsm}^k(t)$.

transmission rate in step 3. Additionally, the radio interface of the tagged secondary MT is selected with the largest secrecy transmission rate increment in step 4. The step 1 is the initialization parameters and step 5-step 9 check the terminal condition of Algorithm 3. $Rt_{nsm}^{k,v_0}(t)$ is the temporary transmission rate for cognitive network $n$ secondary BS $s$ MT $m$ over subchannel $k$ at time slot $t$, $\eta_m$ is the normalized secrecy throughput for secondary MT $m$, and $\mathbf{\Omega}_{ns}$ is the set of not allocated subchannels for cognitive network $n$ secondary BS $s$. $Pt_{nsm}^k(t)$ is the temporary power allocation. $\Delta P$ is the increment for power allocation.

### B. Computational Complexity and Signaling Overhead

In algorithm 1, the computational complexity is given by $O(O_I M^2 \sum_{n\in\mathcal{N}} |\mathcal{K}_{ns}^{v_0}|S_n)$. $O_I$ is the number of iterations for the convergence, and $|\mathcal{K}_{ns}^{v_0}|$ is the number of subchannel in cognitive network $n$ secondary BS $s$. Since the number of subchannel $|\mathcal{K}_{ns}^{v_0}|$ and the number of iterations $O_I$ are usually large, the proposed optimal algorithm can not be affordable when the size of cognitive heterogeneous networks is large. In heuristic security-aware algorithm, the computational complexity is $O((B_I + P_I)\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n} |\mathcal{K}_{ns}^{v_0}|M_{ns})$. $B_I$ and $P_I$ are the number of iterations for subchannel allocation and power allocation, respectively.

In the optimal algorithm, all secondary BSs broadcast $\alpha_{nsk}(i+1)$ and $\delta_{ns}(i+1)$, and each secondary MT broadcasts its $C_{nsm}^k I_{nsm}^k$ and $\rho_{nsm}^k$ to serving secondary BSs. Hence, the total signaling overhead is $O(O_I(2\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n} |\mathcal{K}_{ns}^{v_0}|M_{ns} + \sum_{n\in\mathcal{N}} |\mathcal{K}_{ns}^{v_0}|S_n + \sum_{n\in\mathcal{N}} S_n))$. In heuristic algorithm, secondary BS broadcasts to notice the tagged secondary MT, the tagged secondary MT broadcasts its $C_{nsm}^k I_{nsm}^k$ to serving secondary BSs and all secondary BSs exchange the information regarding $\eta_m$. Therefore, the signaling overhead is $O((B_I + P_I)(\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}_n} |\mathcal{K}_{ns}^{v_0}|M_{ns} + 2M))$.

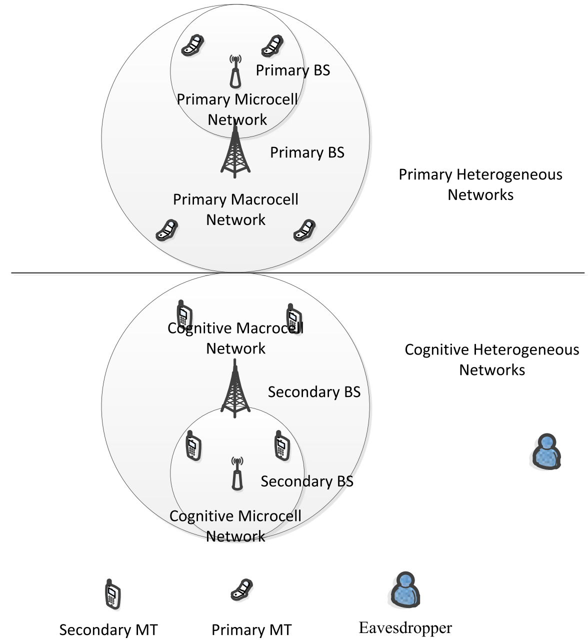


Fig. 2. Simulation Scenario Topology.

## VI. Performance Evaluation

The numerical simulation results are presented for the proposed algorithms in this section. Consider a geographical region with one cognitive microcell and one cognitive macrocell. The cognitive microcell has a coverage area of 200 m, while the cognitive macrocell has a coverage area of 400 m. An eavesdropper exists in cognitive heterogeneous networks, and the distances from the secondary microcell BS and the secondary macrocell BS to the eavesdropper are both 900 m. Secondary MTs can get services from both secondary microcell BS and secondary macrocell BS, and they are uniformly located in the coverage areas. The channel model is Rayleigh fading, and the path loss exponent is 4. The noise power is $10^{-19}$ W/Hz. The distance between macrocell BS and secondary macrocell BS is 800 m, and the distance between microcell BS and macrocell BS is 200 m. The simulation scenario topology is shown in Fig. 2. The probabilities of misdetection and false alarm for each subchannel are uniformly distributed [0.01, 0.05] and [0.05, 0.1], respectively. The probability is uniform distributed over [0, 1] for all primary MTs activity at each subchannel. The other simulation parameters are $P_c = 20$ dBm. Define $\eta = (\hat{f}_{nsm}^k(t)/f_{nsm}^k(t) - 1) \times 100\%$ as the channel estimation error indicator variable. In the simulation, the proposed optimal algorithm with multi-homing (OAMH) is compared with heuristic algorithm with single access (HASA), where OAMH is Algorithm 1 and HASA is Algorithm 2 and Algorithm 3. In the simulation, Monte Carlo method is applied.

We depict the interference threshold vs. the secrecy transmission rate, and Jain fair index in Fig. 3 and Fig. 4. Additionally, we depicts the interference threshold vs. the secrecy transmission rate with different channel estimate errors in Fig. 5. The number of secondary MTs in cognitive microcell and cognitive marcocell are both 5. The total power is 2 W for each secondary MT. The proportional fairness weights for secondary MTs in cognitive microcell and cognitive macrocell are both $\{2, 1, 1, 1, 1\}$.

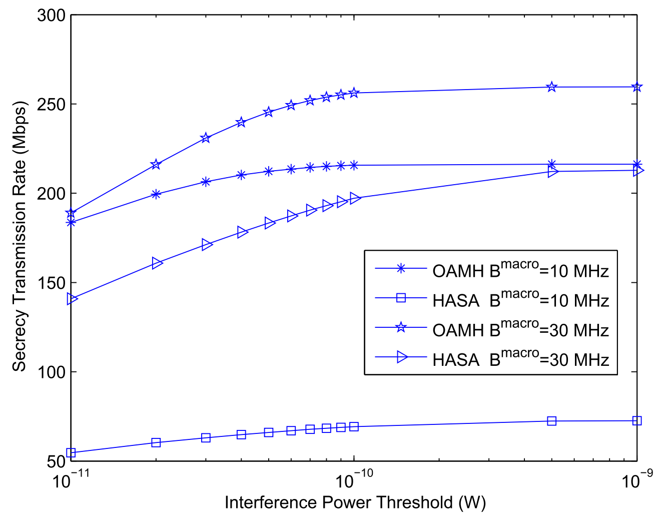


Fig. 3. Secrecy transmission rate vs. interference threshold.

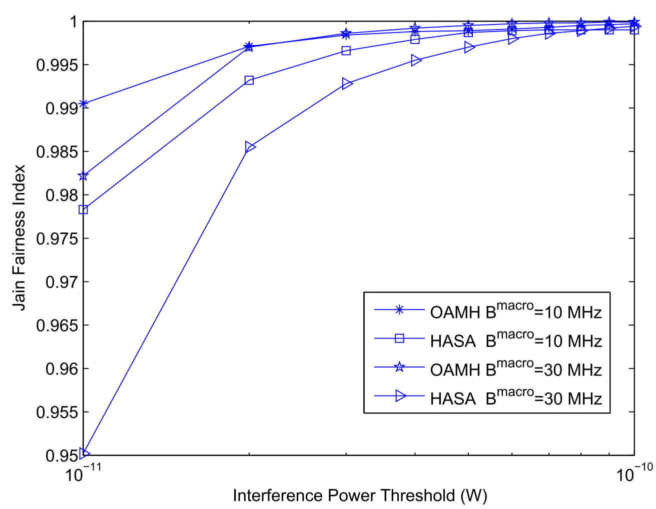


Fig. 4. Jain fair index vs. interference threshold.

The number of subchannels is $K^v_{ns} = 128$. The bandwidth for microcell is $B^{\mathrm{micro}} = 50$ MHz. In Fig. 3 and Fig. 4, the bandwidth for macrocell have two cases, i.e., $B^{\mathrm{macro}} = 10$ MHz and $B^{\mathrm{macro}} = 30$ MHz, and $\eta = 10\%$. In Fig. 5, $B^{\mathrm{macro}} = 30$ MHz, and the other simulation parameters are the same as Fig. 3 and Fig. 4. From Fig. 3, we observe that the secrecy throughput for OAMH and HASA increase with the growth of the interference threshold. Since the growth of the interference threshold not only increases the available power consumption, but also results in the growth of the capacity region. Additionally, the secrecy throughput for cognitive heterogeneous networks in case $B^{\mathrm{total}} = 30$ MHz is larger than that in case $B^{\mathrm{total}} = 10$ MHz. Based on the Shannon theory, increasing the bandwidth can improve the secrecy throughput for cognitive heterogeneous networks. In Fig. 4, it can be observed that Jain fairness index for OAMH is slightly larger than that of HASA, and they are both very close to 1, so they can guarantee the fairness. In Fig. 5, we can see that the secrecy transmission rate with $\eta = 15\%$ is close to that with $\eta = 5\%$ for both OAMH and HASA algorithms. Additionally, the secrecy transmission rate for both OAMH and

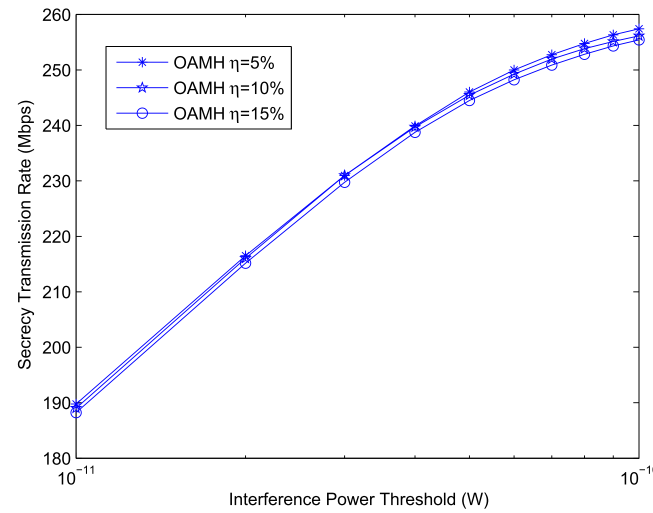


Fig. 5. Secrecy transmission rate with different channel estimate errors vs. interference threshold.

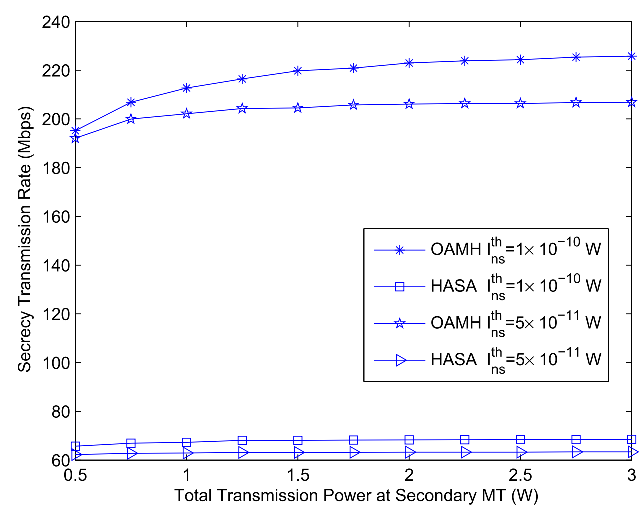


Fig. 6. Secrecy transmission rate vs. total transmission power.

HASA algorithms decrease with the channel estimation error indicator variable $\eta$. This is due to the fact that the channel estimation error indicator variable $\eta$ means the deviation degree between the upper bound of channel power gain, $\hat{f}^k_{nsm}(t)$, and $f^k_{nsm}(t)$. Additionally, increasing the variable $\eta$ means resource allocation is conservative.

We depict the total transmission power at each secondary MT vs. the secrecy transmission rate in Fig. 6, and the secrecy transmission rate of each secondary MT at cognitive macrocell vs. the secondary MT index in Fig. 7. Additionally, we plot the secrecy transmission rate of each secondary MT for OAMH vs. the secondary MT index at cognitive macrocell/microcell networks in Fig. 8. The number of secondary MTs in cognitive marcocell and cognitive microcell are both 5. The proportional fairness weights for secondary MTs in cognitive microcell and cognitive macrocell are both $\{2, 1, 1, 1, 1\}$. The number of subchannels is $K^v_{ns} = 128$. The bandwidth for microcell is $B^{\mathrm{micro}} = 50$ MHz, and the bandwidth for macrocell is $B^{\mathrm{macro}} = 10$ MHz. The interference power thresholds have two cases, i.e., $I^{\mathrm{th}}_{ns} = 1 \times 10^{-10}$ W and $I^{\mathrm{th}}_{ns} = 5 \times 10^{-11}$ W.

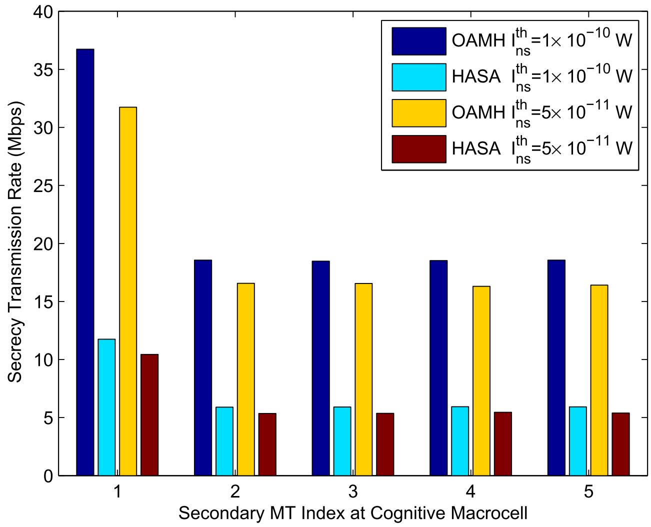


Fig. 7. Secrecy transmission rate of secondary MT vs. secondary MT index at cognitive macrocell.

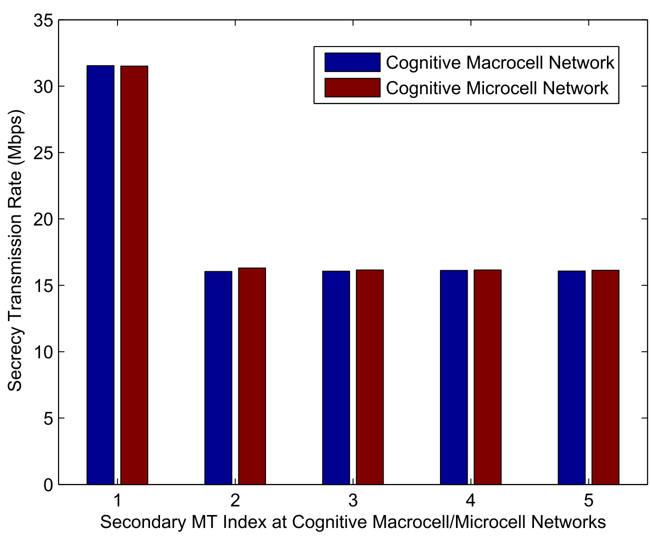


Fig. 8. Secrecy transmission rate of each secondary MT vs. secondary MT index at cognitive macrocell/microcell networks.

In Fig. 7, the total power for each secondary MT is 2 W, and the other simulation conditions are the same with Fig. 6. In Fig. 6 and Fig. 7, $\eta = 10\%$. In Fig. 8, $I_{ns}^{\rm th} = 2 \times 10^{-11}$ W, and $P_m^{\rm T} = 0.5$ W. As can be seen in Fig. 6, the secrecy throughput for OAMH and HASA increase along with the transmission power significantly, when the transmission power is small. However, the increasing trend for the secrecy throughput becomes slow when the transmission power is large. This is because the interference power threshold at primary BS limits the available power for secondary MTs. Additionally, the secrecy throughput for both algorithms with $I_{ns}^{\rm th} = 5 \times 10^{-11}$ W is smaller than that with $I_{ns}^{\rm th} = 1 \times 10^{-10}$W. This can be explained that relaxing the interference threshold at primary BS can improve the secrecy throughput for cognitive heterogeneous networks. It is shown in Fig. 7 that OAMH and HASA can guarantee the fairness for secondary MTs very well. Additionally, the secrecy throughput

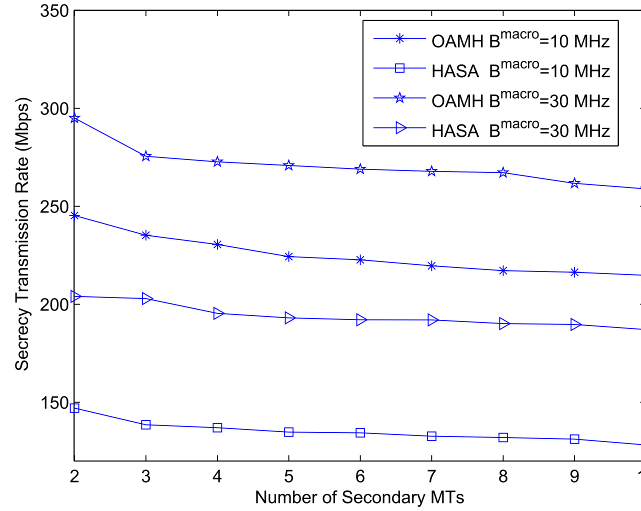


Fig. 9. Secrecy transmission rate vs. number of secondary MTs.

of OAMH is larger than that of HASA significantly. This is due to the fact that multi-homing technology improves the secrecy throughput of OAMH, significantly. In Fig. 8, we can see that OAMH not only guarantees the fairness among different secondary MTs, but also guarantees the fairness among different networks.

The impact of the number of secondary MTs on the secrecy transmission rate is evaluated in Fig. 9. The number of subchannels is $K_{ns}^v = 128$. The interference power threshold at macrocell and microcell BSs are both $1 \times 10^{-10}$ W. In cognitive microcell and cognitive macrocell, the proportional fairness weight for the first secondary MT is 2, and that for the other secondary MTs are 1. The total power for secondary MT is $P_m^{\rm T} = 2$ W. The bandwidth for microcell is $B^{\rm micro} = 50$ MHz. Additionally, the bandwidth for macrocell are $B^{\rm macro} = 10$ MHz and $B^{\rm macro} = 30$ MHz. From Fig. 9, it can be seen that the secrecy throughput of cognitive heterogeneous networks decreases with increasing the number of secondary MTs. This is due to the fact that the secondary MT with the bad channel state information influences the secrecy throughput to guarantee the proportional fairness when the number of secondary MTs increases. From Fig. 3 to Fig. 9, we can conclude that OAMH guarantees the proportional fairness secrecy transmission rates among secondary MTs, and improves the secrecy throughput for cognitive heterogeneous networks.

## VII. Conclusions

In this paper, we studied the uplink security-aware proportional fairness power and subchannel allocation problem for cognitive heterogeneous networks with inter-network cooperation. Each secondary MT adjusts radio power and subchannel according to imperfect spectral sensing and channel state information, so as to maximize the secrecy throughput under the QoS constraints. To solve the above bi-convex optimization problem, an optimal security-aware power and subchannel allocation algorithm was proposed via the dual decomposition method. Finally, the heuristic power and subchannel allocation algorithms were proposed by the greedy method. Numerical simulation results show that the proposed optimal algorithm not only guarantees the fairness among different secondary MTs, but also improves the secrecy throughput and is the robustness of the solution against estimation errors of eavesdropper's channel.

For the resource allocation study of cognitive heterogeneous networks, there are several open issues in future. Firstly, the channel state information between secondary (CSI) BS and secondary MTs is known perfectly, and the determined resource allocation problem is solved in this work. The stochastic CSI is obtained easily and chance-constrained resource allocation problem needs to be investigated for cognitive heterogeneous networks. Secondly, only one eavesdropper is considered in this work. If there exist several eavesdroppers in cognitive heterogeneous networks, how these several eavesdroppers affect the resource allocation needs to be further investigated.

## Appendix A
## Proof of Proposition 1

*Proof*: We prove (18) is a bi-convex programming problem with variables $\rho^k_{nsm}$ and $P^k_{nsm}(t)$. 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.,

$$\begin{cases} g_1 = \sum_{m\in\mathcal{M}} R_m(t) \\ f_1 = P_m^{\mathrm{T}} - P_m(t) \\ f_2 = \varphi_{[m+1]_M} R_m(t) - \varphi_m R_{[m+1]_M}(t) \\ f_3 = 1 - \sum_{m\in\mathcal{M}_{ns}} \rho^k_{nsm} \\ f_4 = I^{\mathrm{th}}_{ns} - \sum_{m\in\mathcal{M}_{ns}} \sum_{k\in\mathcal{K}^{v0}_{ns}} \rho^k_{nsm} P^k_{nsm}(t) I^k_{nsm} \end{cases} \tag{39}$$

Given the variable $P^k_{nsm}(t)$, the second derivatives of $g_1$, $f_1$, $f_2$, $f_3$ and $f_4$ with respective to $\rho^k_{nsm}$ are equal to zeros. Consequently, the objective function and the constraints are concave on $\rho^k_{nsm}$. Consequently, (18) is a convex programming problem with variable $\rho^k_{nsm}$.

Given the variable $\rho^k_{nsm}$, the second derivatives of $g_1$, $f_1$, $f_2$, $f_3$ and $f_4$ with respective to $P^k_{nsm}(t)$ are

$$\begin{cases} \frac{\partial^2 g_1}{\partial (P^k_{nsm}(t))^2} = \frac{\rho^k_{nsm} B_{ns} \left(f^k_{nsm}(t)\right)^2}{(B_{ns} n_0 + P^k_{nsm}(t) f^k_{nsm}(t))^2 \ln 2} \\ \qquad - \frac{\rho^k_{nsm} B_{ns} \left(g^k_{nsm}(t)\right)^2}{(B_{ns} n_0 + P^k_{nsm}(t) g^k_{nsm}(t))^2 \ln 2} \le 0 \\ \frac{\partial^2 f_1}{\partial (P^k_{nsm}(t))^2} = 0 \\ \frac{\partial^2 f_2}{\partial (P^k_{nsm}(t))^2} = \frac{\varphi_{[m+1]_M} \rho^k_{nsm} B_{ns} \left(f^k_{nsm}(t)\right)^2}{(B_{ns} n_0 + P^k_{nsm}(t) f^k_{nsm}(t))^2 \ln 2} \\ \qquad - \frac{\varphi_{[m+1]_M} \rho^k_{nsm} B_{ns} \left(g^k_{nsm}(t)\right)^2}{(B_{ns} n_0 + P^k_{nsm}(t) g^k_{nsm}(t))^2 \ln 2} \le 0 \\ \frac{\partial^2 f_3}{\partial (P^k_{nsm}(t))^2} = 0 \\ \frac{\partial^2 f_3}{\partial (P^k_{nsm}(t))^2} = 0 \\ \frac{\partial^2 f_4}{\partial (P^k_{nsm}(t))^2} = 0 \end{cases} \tag{40}$$

From (40), the objective function and the constraints are concave on $P^k_{nsm}(t)$. Consequently, (18) is a convex programming problem with variable $P^k_{nsm}(t)$. Hence, (18) is a bi-convex programming problem with variables $\rho^k_{nsm}$ and $P^k_{nsm}(t)$.

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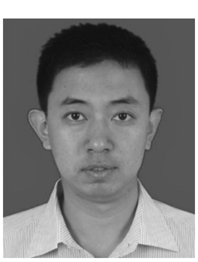

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