Interference-Aware Energy-Efficient Resource Allocation for OFDMA-Based Heterogeneous Networks With Incomplete Channel State Information

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***Abstract*—Heterogeneous wireless networks are considered as promising technologies to improve energy efficiency. In heterogeneous networks, interference management is very important since the interference due to spectrum sharing can significantly degrade overall performance. In the existing work, various resource allocation methods are proposed to either improve energy efficiency or mitigate interference in orthogonal frequency-division multiple access (OFDMA)-based multicell networks. To the best of our knowledge, no research on resource allocation has jointly considered improving energy efficiency and performing interference control, especially using interference power constraint strategies. Furthermore, most existing work assumes that all of the channel state information (CSI) is known completely, which might not be realistic in heterogeneous networks due to the limited capacity of the backhaul links and varied ownership of network devices. In this paper, we propose a game-theoretical scheme using energy-efficient resource allocation and interference pricing for an interference-limited environment in heterogeneous networks. We formulate the problems of resource allocation and interference management as a Stackelberg game with incomplete CSI. A backward induction method is used to analyze the proposed game. A closed-form expression of the Stackelberg equilibrium (SE) is obtained for the proposed game with various interference power constraints. Simulation results are presented to show the effectiveness of the proposed scheme.**

***Index Terms*—Energy efficiency, game theory, heterogeneous networks, incomplete channel state information, interference management.**

I. INTRODUCTION

THE high energy consumption of cellular networks has had a significant impact on their service providers' operating expenses and on the level of the associated CO_2 emissions. The energy bill has become a significant portion of the service providers' operational expenditure, for example, about 10% in the mature European market and more than 30% in India [1]. The CO_2 emissions produced by wireless cellular networks are equivalent to those from more than 8 million cars [2], [3]. For service providers, improving energy efficiency can demonstrate their social responsibility in fighting climate change, and more importantly, it has significant economic benefits. Therefore, energy efficiency has gradually become a significant performance metric for wireless cellular networks [4]. Heterogeneous networks (e.g., deploying small cells in existing macrocells) have become an important technique to improve energy efficiency of cellular networks [5]. In heterogeneous networks, cells may use orthogonal frequency division multiple access OFDMA-based technology, the leading multiple-access strategy for 4G and beyond.

In heterogeneous networks, interference control is an important research area, particularly when small cells operate on the same frequency spectrum as macrocells. This type of spectrum sharing will cause cross-tier interference between macrocells and small cells. Meanwhile, small cells can share the same radio resources among themselves to improve spectrum efficiency, which will cause co-tier interference among small cells. Both cross-tier and co-tier interference can significantly degrade network performance. Without proper interference management, a significant amount of power will be wasted, and the overall energy efficiency of the network might become even worse than that of a network without small cells [6]. Existing interference control strategies for heterogeneous networks can be categorized into two general types: interference mitigation/cancelation strategies and interference power constraint strategies that originated from cognitive radio networks. In an interference power constraint strategy, the aggregate interference caused by the small cell to the macrocell users should be kept within an acceptable level [7].

Various methods have been proposed to alleviate or avoid interference in heterogeneous networks. Lopez-Perez *et al.* [8] studied self-configuration and self-optimization techniques for interference avoidance in OFDMA-based femtocell networks. Chandrasekhar and Andrews [9] proposed a decentralized spectrum allocation strategy for two-tier networks to minimize cross-tier interference. Lopez-Perez *et al.* [10] evaluated the main enhanced intercell interference coordination (eICIC)

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techniques developed for Release 10 of the third-generation partnership project (3GPP). Chandrasekhar *et al.* [11] proposed a distributed utility-based signal-to-interference-plus-noise ratio adaptation algorithm to alleviate cross-tier interference at the macrocell. Jo *et al.* [12] proposed two interference mitigation strategies in which femtocell users adjust their maximum transmit power using open- and closed-loop techniques to control the cross-tier interference at the macrocell base station (MBS). Park *et al.* [13] proposed an orthogonal random beamforming-based cross-tier interference reduction scheme for two-tier femtocell networks. The work by Kang *et al.* in [14] is one of the few studies using an interference power constraint strategy in heterogeneous networks.

Network resources, such as transmit power and subchannels, must be appropriately allocated among users to maximize the energy efficiency of the users or networks. Game theory has been widely employed in multiuser wireless networks to model the interactions between active users or base stations (BSs). Goodman and Mandayam [15] adopted a game-theoretical approach to solve the power control problem. Lasaulce *et al.* [16] analyzed the effect of hierarchy in energy-efficient power control games both on the individual user and overall network performance. Treust and Lasaulce [17] studied an energy-efficient distributed power control problem in wireless networks using a repeated game.

Energy-efficient resource allocation for multicell OFDMA-based networks has been recently investigated. In [18], the resource allocation problem is considered in the uplink of OFDMA multicell networks to maximize the users' energy effiency. Xie *et al.* [19] studied the energy-efficient spectrum sharing and power allocation problem in heterogeneous cognitive radio networks with femtocells using a Stackelberg game. In [20], noncooperative transmit power control and cooperative subcarrier allocation are jointly performed for energy efficiency maximization in a multicell OFDMA system. Miao *et al.* [21] investigated energy-efficient power optimization schemes for interference-limited communications using non-cooperative game theory. Han *et al.* [22] proposed a non-cooperative game to perform subchannel assignment, adaptive modulation, and power control for multicell OFDMA networks to minimize the users' transmitted power.

Resource allocation plays a very important role in interference management and energy efficiency. However, in most existing work on energy-efficient resource allocation, the objective is to improve energy efficiency of the users or the whole network, sometimes considering the effect of interference on energy efficiency. There are also some research works using resource allocation to address interference control problems in OFDMA-based multicell networks. Resource allocation is used to either improve energy efficiency or mitigate interference.

In addition, most existing work assumes that each BS or user has all others' channel state information (CSI) whenever making its resource allocation decisions. This assumption may not be realistic in heterogeneous networks for the following reasons. In heterogeneous networks, small-cell base stations (SCBSs) owned by individual subscribers are connected to the MBSs owned by operators using backhaul communication links that usually have limited capacity due to their deployment costs [23]. Moreover, these BSs and their users may not have protocols to share CSI between each other. Even if this kind of protocol exists, appropriate incentive mechanisms are still needed to ensure that the network devices truthfully exchange information, since their objectives might not be aligned [24]. Furthermore, even if they are willing to share information, the shared information is very likely to be outdated due to the limited capacity of the backhaul links, which can result in significant performance degradation [25], [26]. As a result, the complete CSI may be unknown to the others.

Incomplete CSI has a significant impact on the performance of not only heterogeneous networks but also wireless networks in general. Indeed, the capacity of channels with incomplete CSI is largely unknown in wireless networks. Game theory has well-developed mechanisms to address the impacts of incomplete CSI, which will give insights into the problems related to incomplete CSI from a new perspective [27].

In this paper, we design a game-theoretical resource allocation scheme considering both energy efficiency and interference control in heterogeneous wireless networks with incomplete CSI. To the best of our knowledge, no research on resource allocation has jointly considered improving energy efficiency and performing interference control using the interference power constraint strategies. Some distinct features of this paper are as follows.

- We adopt an interference power constraint strategy, where, in the downlink, SCBSs are allowed to transmit in the frequency bands of MBSs as long as the resulting interference to the MUs is kept below an acceptable level. Specifically, an interference pricing strategy is proposed for the MBSs to protect their users by keeping the aggregate interference from SCBSs below a target level. A similar scheme can be applied for the uplink. In the price-based strategy, the prices are computed as signals to reflect relations between resource demand and supply, where the interference tolerance margin at the MUs is used as the resource for which the MBS and the SCBSs compete.
- The SCBSs can design their resource allocation strategies individually based on the offered interference prices to maximize utility. Resource allocation is performed to improve the energy efficiency of the network and keep the interference to MUs within an acceptable level.
- We formulate the problems of interference control and energy-efficient resource allocation as a two-stage Stackelberg game with incomplete CSI. A backward induction method is used to analyze the proposed Stackelberg game, since it can capture the sequential dependence relations of the decisions in the stages of the game [28]. A closed-form expression of the Stackelberg equilibrium (SE) is obtained for the proposed game with various interference power constraints. We also compare the results with/without the complete CSI scenarios.

The rest of this paper is organized as follows: Section II describes the system model. The problems are formulated in Section III. Section IV analyzes the proposed game. Simulation results are discussed in Section V. Finally, Section VI presents our conclusions.

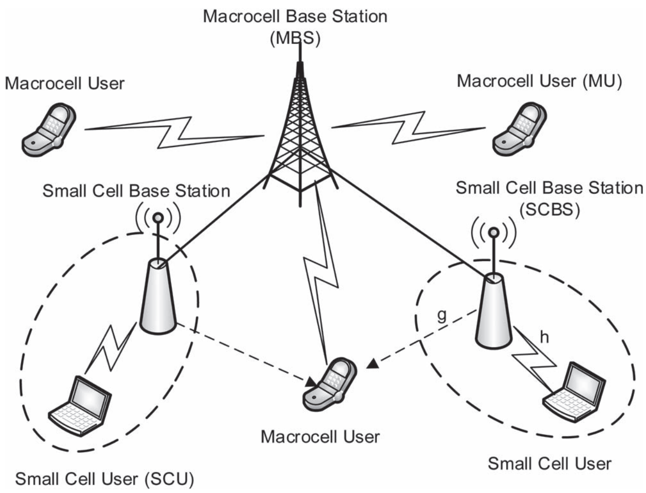

Fig. 1. Exemplary heterogeneous network.

II. System Model

We study the downlink transmission in a two-tier heterogeneous network, as shown in Fig. 1. In each service region, there is one MBS and N SCBSs, each of which is connected to the MBS over a broadband connection, such as a cable modem or a digital subscriber line (DSL) [29]. Let SCBS set $\mathbb{N} = \{1, \ldots, N\}$. In small cell n, the SCBS provides service for K_n users. We assume that the MBS is aware of spectrum access by the SCBSs, and the SCBSs can monitor the surrounding radio channel environment and are allowed to intelligently access the subchannels. The system is operated in a time-slotted manner. In each time slot, the spectrum resource licensed to the MBS is divided into multiple subchannels. The MUs use OFDMA technology to access the MBS.

The MBS and the SCBSs share a spectrum in the network. At each time slot, each subchannel of the MBS is allocated to one MU, and N nearby small cells can also use this subchannel, i.e., each SCBS assigns one most appropriate user to each subchannel during that time slot. Since the SCBSs share a spectrum with the MBS, the cross-tier interference will greatly restrict the network performance. Interference prices are proposed as a mechanism to allow the MBS to protect its MUs and meet their interference power constraints by charging the SCBSs. We assume that the maximum interference power that each macrocell user (MU) can tolerate is $\bar{Q}$, i.e., the aggregate interference from all the SCBSs should not be larger than $\bar{Q}$. The SCBSs will adaptively adjust the transmit power based on the channel condition and the interference prices offered by the MBS.

Due to the limited capacity of backhaul links and the competing interests of the MBSs and SCBSs, we consider that each MBS and SCBS only has the state information of the channels between itself and its own users, as well as the incident channels between its users and the other BSs [30]. However, each BS does not know the state information of the channels between other BSs and their users. In the scenario considered in this paper, the SCBSs are sparsely deployed, and therefore, the mutual interference between the small cells is negligible. In practice, this scenario is applicable to the small-cell networks deployed in the sparse areas, such as rural areas. However, the proposed schemes can be extended to the densely-deployed scenarios by taking the mutual interference between different SCBSs into account. We only demonstrate the situation of one subchannel, since we mainly focus on how the decisions in the MBS and SCBSs affect each other. The model can be extended to multiple subchannel situations using various techniques, such as the dual-decomposition technique [31].

To facilitate the communication of channel gain information, we assume that the channel gains are mapped into a finite set of states, which is widely used in the literature and practical networks [32], [33]. Nevertheless, our proposed scheme can be extended to the scenario where the channel gains are modeled as an infinite set of states. In our proposed scheme, the MBS does not know the exact value of the channel gain $h^{(n)}$, $n \in \mathbb{N}$, from SCBS n to its scheduled small-cell user (SCU), but it can collect the fixed distribution of the channel gain as defined in Assumption 1 from SCBS n, through the backhaul link. For SCBS n, the distribution of the channel gain $g^{(nm)}$ between itself and the scheduled MU served by MBS m is defined in Assumption 2, which can be collected from MBS m through the backhaul link.

Assumption 1: For MBS m, the channel gain $h^{(n)}$ between SCBS n and its scheduled SCU has R positive states, which are $h_1^{(n)}, \ldots, h_R^{(n)}$ with probability $\rho_1^{(n)}, \ldots, \rho_R^{(n)}$, respectively, and $\sum_{r=1}^{R} \rho_r^{(n)} = 1$. Without loss of generality, we assume that $h_1^{(n)} > \cdots > h_R^{(n)}$.

Assumption 2: For an arbitrary SCBS n, the channel gain $g^{(nm)}$ between SCBS n and the scheduled MU served by MBS m has S positive states, which are $g_1^{(nm)}, \ldots, g_S^{(nm)}$ with probability $\varphi_1^{(nm)}, \ldots, \varphi_S^{(nm)}$, respectively, and $\sum_{s=1}^{S} \varphi_s^{(nm)} = 1$.

III. Problem Formulation

In heterogeneous networks, BSs may not serve a common goal or belong to a single authority. One example scenario is that each small cell operates in a closed-access mode, where a set of subscribed home users is allowed to access the small cell. Therefore, a mechanism is needed so that the MBS can control the interference received by its MU from the SCBSs within the interference tolerance margin. On the other hand, if each SCBS pays for the interference it causes to the MU, each SCBS needs to decide which SCU to assign to each subchannel and its optimal transmission power. According to such characteristics, we employ a Stackelberg game [34] to jointly maximize the interference revenue of the MBS and the individual utilities of the SCBSs in the heterogeneous network. Stackelberg games, which are also known as the leader–follower games, are an extension of noncooperative games. In a Stackelber game, there is a group of players called leaders and of other players called followers. The leaders can anticipate and take into consideration the behavior of the followers and then act. After the actions of the leaders, the followers take their actions. In the proposed game, the MBS is the leader, and the SCBSs are the followers. The strategy of the MBS is to set interference prices, and those of the SCBSs involve both subchannel assignment and power allocation.

A. MBS Level Problem With Incomplete CSI

The MBS offers an interference price to each SCBS and tries to maximize the revenue obtained from selling the interference quota to SCBSs within the interference power constraints. The offered interference price to SCBS n, $n \in \mathbb{N}$, can be defined as y_n. There are two different kinds of interference power constraints: peak interference power constraints and average interference power constraints [35]. A peak interference power constraint is the short-term constraint that limits the peak interference power at each channel gain. An average interference power constraint, which is a long-term constraint, limits the average interference power over all different channel gains. In general, the average interference power constraint is preferable to the SCBSs, because it allows more flexibility for dynamically allocating transmit power over different channel gains. On the other hand, the peak interference power constraint is a better option for the MUs. However, the average interference power constraint can be also preferable to the MUs in terms of achievable limits of the ergodic and outage capacities [35].

In the scenario with peak interference power constraints, the revenue of the MBS obtained from all SCBSs can be calculated by

$$\mathcal{U}_m(\mathbf{y}) = \sum_{n=1}^{N} g^{(nm)} p_n \left(h^{(n)}, y_n\right) y_n, \tag{1}$$

where $\mathbf{y} = \{y_1, \ldots, y_N\}$ is the interference price vector, p_n denotes the transmit power for SCBS n, and it is a function of channel gain $h^{(n)}$ and interference price y_n. The optimization problem for the MBS can be formulated as

$$\max \mathcal{U}_m(\mathbf{y}) = \max_{\mathbf{y}\succeq 0} \left\{ \sum_{n=1}^{N} g^{(nm)} p_n \left(h^{(n)}, y_n\right) y_n \right\}, \tag{2}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} g^{(nm)} p_n \left(h^{(n)}, y_n\right) \le \bar{Q}, \tag{3}$$

where $\mathbf{y} \succeq 0$ means $y_n \ge 0, \forall n \in \mathbb{N}$. In our scheme, the average interference power constraint is used since the MBS does not know the exact value of the channel gain $h^{(n)}$ from SCBS n to its scheduled SCU, but it can collect the distribution of the channel gain. In the scenario with the average interference power constraint, the given optimization for the MBS can be converted into a problem that considers the expected revenue $\bar{\mathcal{U}}_m(\mathbf{y})$ in terms of various channel gains $\mathbf{h}$. Let subscript $\mathbf{h}$ of $\mathbb{E}$ indicate that the expectation is calculated with respect to $\mathbf{h}$. The optimization problem for the MBS can be reformulated as

$$\max \bar{\mathcal{U}}_m(\mathbf{y}) = \max_{\mathbf{y}\succeq 0} \left\{ \mathbb{E}_{\mathbf{h}} \left[\sum_{n=1}^{N} g^{(nm)} p_n \left(h^{(n)}, y_n\right) y_n \right] \right\}, \tag{4}$$

$$\text{s.t.} \quad \mathbb{E}_{\mathbf{h}} \left[\sum_{n=1}^{N} g^{(nm)} p_n \left(h^{(n)}, y_n\right) \right] \le \bar{Q}. \tag{5}$$

Therefore, the optimal interference price for the MBS is

$$\mathbf{y} = \arg\max_{\mathbf{y}\succeq 0} \left\{ \sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} p_n \left(h_r^{(n)}, y_n\right) y_n \right\}, \tag{6}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} p_n \left(h_r^{(n)}, y_n\right) \le \bar{Q}. \tag{7}$$

In the scenario where the channel gains are modeled as an infinite set of states, we assume that the random variable channel gain $h^{(n)}$ has a probability density function $t_n(h^{(n)})$. The expected revenue is given by the expectation of function $\mathcal{U}_m(\mathbf{y})$.

B. SCBS Level Game With Incomplete CSI

For energy-efficient communications, it is desirable to the maximize transmission rate and take the electricity cost into account [5], [36]. The energy efficiency metric used for each SCBS is its weighted transmission rate minus the weighted electricity cost [36], [37]. The electricity consumed by an SCBS can be divided into two parts: One part is independent of the transmit power and includes the circuit power, signal processing power, and so on; the other part is equal to the total transmit power over the power amplifier efficiency [38].

Based on the interference price provided by the MBS, each SCBS needs to allocate the subchannel to one appropriate SCU and adjust its transmit power to maximize its individual net utility. For example, when the weighted sum of the data rates of all of its SCUs are considered as its utility, each SCBS will assign the subchannel to the SCU who can yield the maximal weighted data rate. Therefore, our proposed method works well with different fairness mechanisms, which will be used to choose the appropriate SCU. Then, the resource allocation problem turns into a power allocation problem. In the following presentation, we do not consider interference caused by the MBS to the SCBSs' users. In the scenario where that interference needs to be considered, the interference and noise power as observed by a SCBS's user will be given by $\sigma_n^2 + p_m g^{(mn)}$ (σ_n^2 denotes the additive white Gaussian noise, p_m is the transmit power of the MBS, and $g^{(mn)}$ is the channel gain from MBS m to the scheduled user of SCBS n) instead of only σ_n^2. Therefore, the net utility function for SCBS n can be defined as [37], [39]

$$\mathcal{U}_n(p_n) = W \log\left(1 + \frac{p_n h^{(n)}}{\sigma_n^2}\right) - \mu_n x p_n - \lambda_n y_n g^{(nm)} p_n, \quad \forall n, \tag{8}$$

where W denotes the bandwidth of each subchannel. Without loss of generality, it is assumed that $\sigma_n^2 = \sigma^2, \forall n$, in the rest of this paper. Parameters μ_n and λ_n denote weights, which represent the tradeoff between the transmission rate, energy cost, and interference cost. In this paper, we consider the scenario where the weights are known in advance, which is called the *a priori* approach commonly used in the literature [40]. In a real-world application, these parameters need to be carefully chosen to match the characteristics of the SCBSs. The electricity price scale factor is denoted by x. In an SCBS, the dynamic electricity part dominates its electricity consumption, which is the opposite of the energy consumption pattern of MBSs [41]. Therefore, in utility function (8), only the dynamic part of the electricity consumption is considered. To extend our work to the densely deployed scenario, the net utility function for SCBS $n(\forall n)$ defined in (8) would be changed to

$$\mathcal{U}_n(p_n, \mathbf{p}_{-n}) = W \log\left(1 + \frac{p_n h^{(n)}}{\sigma^2 + \sum_{l\neq n} p_l h_{ln}}\right) - \mu_n x p_n - \lambda_n y_n g^{(nm)} p_n, \qquad \forall n, \quad (9)$$

where $\mathbf{p}_{-n}$ is a vector of power allocation for all SCBSs except SCBS n, i.e., $\mathbf{p}_{-n} = [p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N]^T$, and h_{ln} denotes the channel gain between SCBS l and the scheduled SCU in SCBS n.

In the sparsely deployed scenario, since SCBS n does not know the current channel gain $g^{(nm)}$, the net utility function can be reformulated as

$$\bar{\mathcal{U}}_n(p_n) = W \log\left(1 + \frac{p_n h^{(n)}}{\sigma^2}\right) - \mu_n x p_n - \lambda_n y_n p_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right), \qquad \forall n. \quad (10)$$

Therefore, the optimal transmit power for SCBS n is

$$p_n = \arg\max_{p_n \geq 0} \left\{ W \log\left(1 + \frac{p_n h^{(n)}}{\sigma^2}\right) - \mu_n x p_n - \lambda_n y_n p_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)\right\}. \quad (11)$$

In the scenario where the channel gains are modeled as an infinite set of states, we assume that the random variable channel gain $g^{(nm)}$ has a probability density function $z_{nm}(g^{(nm)})$. The expected channel gain is the expectation of the random variable $g^{(nm)}$.

IV. Analysis of the Proposed Stackelberg Game

Here, we will first analyze the proposed Stackelberg game and then obtain the SE of this game. A backward induction method is used to analyze the proposed game, since this approach can capture the sequential dependence of the decisions in the stages of the game. Finally, we investigate the same resource allocation problem in the complete CSI scenario and compare the performance in this scenario with that in the incomplete CSI scenario.

A. Analysis of the Resource Allocation Problem for the SCBSs

To maximize its net utility, each SCBS needs to adjust its transmit power p_n based on the provided interference price and the channel gain of its scheduled SCU. For an arbitrary SCBS n, its net utility function is a concave function of p_n since

$$\frac{\partial^2 \bar{\mathcal{U}}_n}{\partial p_n^2} = \frac{-W\left(h^{(n)}\right)^2}{\left(\sigma^2 + p_n h^{(n)}\right)^2} < 0. \quad (12)$$

Therefore, the optimal resource allocation strategy for SCBS n can be denoted as

$$p_n^* = \left(\frac{W}{\mu_n x + \lambda_n y_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2}{h^{(n)}}\right)^+, \quad (13)$$

with $(\cdot)^+ \triangleq \max(\cdot, 0)$. This is actually utility-based water-filling. We assume that the electricity price x is always less than $W h^{(n)}/(\sigma^2 \mu_n)$. The reason is that if the electricity price is higher than that, SCBS n will stop transmitting no matter what the provided interference price is. If the interference price y_n is too high (i.e., $y_n > (W h^{(n)}/\sigma^2 - \mu_n x)/(\lambda_n(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}))$), SCBS n will also stop transmitting. We also observe from (13) that given a fixed pricing policy, when the channel gain of the SCBS is higher, the SCBS performs a non-decreasing optimal resource allocation strategy.

To extend our work to the densely deployed scenario, the optimal resource allocation strategy for SCBS n could be denoted as

$$p_n^* = \left(\frac{W}{\mu_n x + \lambda_n y_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2 + \sum_{l\neq n} p_l h_{ln}}{h^{(n)}}\right)^+. \quad (14)$$

Since one SCBS's optimal resource allocation strategy is affected by others', noncooperative game theory [42] can be used to model the resource allocation problem of the SCBSs in the densely deployed scenario. One of the most commonly used solution concepts in a noncooperative game is called a Nash equilibrium, which is an equilibrium where every player plays the best-response strategy when taking others' decision into account.

Proposition 1: The best response of SCBS n is given by

$$p_n = \mathcal{BR}_n(\mathbf{p}_{-n}) \quad (15)$$

with

$$\mathcal{BR}_n(\mathbf{p}_{-n}) = \left(\frac{W}{\mu_n x + \lambda_n y_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2 + \sum_{l\neq n} p_l h_{ln}}{h^{(n)}}\right)^+. \quad (16)$$

The following iterative algorithm can be used to obtain the Nash equilibrium for this non-cooperative resource allocation game in the densely-deployed scenario.

Algorithm 1. Iterative Resource-Allocation Algorithm

1. Initialization: set $p_n = 0, \forall n \in \mathbb{N}$, iteration count $k = 0$
2. **Repeat** iterations
   (a) $k = k + 1$
   (b) **for** $n = 1$ to N SCBSs **do**
   (c) Estimate total interference plus noise level
   (d) $p_n[k] = \mathcal{BR}_n(p_1[k-1], \ldots, p_{n-1}[k-1], p_{n+1}[k-1], \ldots, p_N[k-1])$
   (e) **end for**
   (f) **until** $k \geq K_{\max}$ or $\|p_n[k]-p_n[k-1]\|/\|p_n[k-1]\| \leq \varepsilon, \forall n \in \mathbb{N}$
3. End iteration

where $K_{\max}$ is the maximum iteration count, and parameter ε is set to a small value, such as 0.0001.

B. Analysis of the Interference Price Problem for the MBS

To maximize its revenue, the MBS dynamically adapts the offered interference prices based on the energy-efficient resource allocation response of the SCBSs and the total interference power constraints. Since the response strategy of each SCBS is as explained in the previous section, (13) is substituted into (4) and (5). For an arbitrary SCBS n, we introduce the following indicator function:

$$V_r^{(n)} = \begin{cases} 1, & y_n \leq \dfrac{\frac{W h_r^{(n)}}{\sigma^2} - \mu_n x}{\lambda_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} \\ 0, & \text{otherwise.} \end{cases} \quad (17)$$

The utility function $\bar{U}_m(\mathbf{y})$ becomes a piecewise function, which is not totally differentiable. However, when given $V_r^{(n)}$, function $\bar{U}_m(\mathbf{y})$ becomes a continuous differentiable function. We let

$$L_r^{(n)} = \frac{\frac{W h_r^{(n)}}{\sigma^2} - \mu_n x}{\lambda_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)}, \qquad \forall n. \quad (18)$$

Note that $L_1^{(n)} > \cdots > L_R^{(n)}$, since we assume that $h_1^{(n)} > \cdots > h_R^{(n)}$. All $L_r^{(n)}$s need to be sorted in ascending order, and without loss generality, let $L_1^{(1)} > \cdots > L_R^{(1)} > L_1^{(2)} > \cdots > L_R^{(2)} > \cdots > L_R^{(N)}$. Hence, we obtain RN intervals $[0, L_R^{(N)}], \ldots, [L_2^{(1)}, L_1^{(1)}]$. Since for all convex optimization problems, their optimal solutions must satisfy the Karush–Kuhn–Tucker (KKT) conditions, the optimal interference price solutions must satisfy the KKT conditions as well. Therefore, the optimal interference price solutions within different range limits of interference power constraints can be obtained by solving the KKT conditions, as presented in Theorem 1, where $[\cdot]_a^b = \min(b, \max(\cdot, a))$. The Lagrange multiplier α within each range limit can be obtained using the binary search algorithm [43], which has low complexity. Thus

$$Q_0 = \sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} \times \left(\frac{W}{\mu_n x + \lambda_n f_n(0) \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}} \right), \quad (19)$$

$$Q_1 = \sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} \times \left(\frac{W}{\mu_n x + \lambda_n L_R^{(N)} \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}} \right), \quad (20)$$

$$\begin{aligned} Q_2 = &\sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} \times \left(\frac{W}{\mu_n x + \lambda_n L_{R-1}^{(N)} \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}} \right) \\ &- \rho_R^{(N)} g^{(Nm)} \times \left(\frac{W}{\mu_N x + \lambda_N L_{R-1}^{(N)} \left(\sum_{s=1}^{S} \varphi_s^{(Nm)} g_s^{(Nm)}\right)} - \frac{\sigma^2}{h_R^{(N)}} \right), \end{aligned} \quad (21)$$

$$Q_{NR-1} = \sum_{r=1}^{2} \rho_r^{(1)} g^{(1m)} \times \left(\frac{W}{\mu_1 x + \lambda_1 L_2^{(1)} \left(\sum_{s=1}^{S} \varphi_s^{(1m)} g_s^{(1m)}\right)} - \frac{\sigma^2}{h_r^{(1)}} \right), \quad (22)$$

$$Q_{NR} = \rho_1^{(1)} g^{(1m)} \times \left(\frac{W}{\mu_1 x + \lambda_1 L_1^{(1)} \left(\sum_{s=1}^{S} \varphi_s^{(1m)} g_s^{(1m)}\right)} - \frac{\sigma^2}{h_1^{(1)}} \right). \quad (23)$$

Theorem 2: For the MBS, the optimal interference price $\mathbf{y}^*$ can be obtained as follows.

1) When $\bar{Q} \geq Q_0$

$$y_n^* = f_n(0) = \left[\frac{\sqrt{\frac{W \mu_n x}{\sum_{r=1}^{R} \frac{\rho_r^{(n)} \sigma^2}{h_r^{(n)}}}} - \mu_n x}{\lambda_n \left(\sum_{s=1}^{S} \varphi_s^{(nm)} g_s^{(nm)}\right)} \right]_0^{L_R^{(N)}}. \quad (24)$$

2) When $Q_1 \le \bar{Q} < Q_0$

$$y_n^* = \left[\frac{\sqrt{\frac{W\left(\mu_n x + \alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{\sum_{r=1}^{R}\frac{\rho_r^{(n)}\sigma^2}{h_r^{(n)}}}} - \mu_n x}{\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)} \right]_0^{L_R^{(N)}}, \quad (25)$$

$$\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)} \times \left(\frac{W}{\mu_n x + \lambda_n y_n^*\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}}\right) - \bar{Q} = 0. \quad (26)$$

3) When $Q_2 \le \bar{Q} < Q_1$, we obtain (27) and (28), shown at the bottom of the page.

4) When $Q_{NR} \le \bar{Q} < Q_{NR-1}$

$$y_1^* = \left[\frac{\sqrt{\frac{\rho_1^{(1)}W\left(\mu_1 x + \alpha\lambda_1\left(\sum_{s=1}^{S}\varphi_s^{(1m)}g_s^{(1m)}\right)\right)}{\frac{\rho_1^{(1)}\sigma^2}{h_1^{(1)}}}} - \mu_1 x}{\lambda_1\left(\sum_{s=1}^{S}\varphi_s^{(1m)}g_s^{(1m)}\right)} \right]_{L_2^{(1)}}^{L_1^{(1)}},$$

$$\rho_1^{(1)}g^{(1m)}\left(\frac{W}{\mu_1 x + \lambda_1 y_1^*\left(\sum_{s=1}^{S}\varphi_s^{(1m)}g_s^{(1m)}\right)} - \frac{\sigma^2}{h_1^{(1)}}\right) - \bar{Q} = 0,$$

$$y_n^* = \infty, \qquad n \in \{2, \ldots, N\}.$$

Proof: See Appendix A. ■

The theorem intuitively shows that a higher threshold has the potential to admit more SCBSs, and the optimal interference prices decrease first with the increase in the threshold and then become constant, at which point the value of no longer affects the SCBSs' decisions.

Remark 1: From the system design perspective, the given results are very useful in practice. For example, if the MBS sets the interference price for a SCBS to ∞, this SCBS will not transmit. Moreover, if the system is designed to admit these N SCBSs, the tolerable interference power constraint $\bar{Q}$ needs to be set above this threshold, i.e.,

$$\sum_{n=1}^{N-1}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)} \times \left(\frac{W}{\mu_n x + \lambda_n L_1^{(N)}\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}}\right) + \rho_1^{(N)}g^{(Nm)} \times \left(\frac{W}{\mu_N x + \lambda_N L_1^{(N)}\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)} - \frac{\sigma^2}{h_1^{(N)}}\right).$$

C. Existence of the SE for the Proposed Stackelberg Game

The objective of the proposed Stackelberg game is to find the SE, from which neither the MBS nor the SCBSs have incentives to deviate. Here, we prove that the solutions p_n^* in (13) and $\mathbf{y}^*$

$$y_n^* = \left[\frac{\sqrt{\frac{W\left(\mu_n x + \alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{\sum_{r=1}^{R}\frac{\rho_r^{(n)}\sigma^2}{h_r^{(n)}}}} - \mu_n x}{\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)} \right]_0^{L_{R-1}^{(N)}}, \qquad n \in \{1, \ldots, N-1\}, \quad (27)$$

$$y_N^* = \left[\frac{\sqrt{\frac{\left(1-\rho_R^{(N)}\right)W\left(\mu_N x + \alpha\lambda_N\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)\right)}{\sum_{r=1}^{R-1}\frac{\rho_r^{(N)}\sigma^2}{h_r^{(N)}}}} - \mu_N x}{\lambda_N\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)} \right]_{L_R^{(N)}}^{L_{R-1}^{(N)}}, \quad (28)$$

$$\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\left(\frac{W}{\mu_n x + \lambda_n y_n^*\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)} - \frac{\sigma^2}{h_r^{(n)}}\right) - \rho_R^{(N)}g^{(Nm)}\left(\frac{W}{\mu_N x + \lambda_N y_N^*\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)} - \frac{\sigma^2}{h_R^{(N)}}\right) - \bar{Q} = 0$$

$$\vdots$$

presented in Theorem 2 are the SE for the proposed game. For the proposed game with incomplete CSI, the SE is defined as follows.

Definition 1: y_n^{SE} and p_n^{SE} are the SE of the proposed game if for every $n \in \mathbb{N}$, when y_n is fixed

$$\bar{\mathcal{U}}_n\left(p_n^{\mathrm{SE}}\right) = \sup_{p_n \geq 0} \bar{\mathcal{U}}_n(p_n), \tag{29}$$

and for every $n \in \mathbb{N}$, when p_n is fixed

$$\bar{\mathcal{U}}_m\left(\{y_n^{\mathrm{SE}}\}\right) = \sup_{y_n \geq 0} \bar{\mathcal{U}}_m\left(\{y_n\}\right). \tag{30}$$

We will show that the optimal interference prices $\mathbf{y}^*$ of (6) with constraint (7) can be obtained by solving (39) in the Appendix due to Property 1 [44].

Property 1: The Lagrangian $\mathcal{L}(\mathbf{y}, \alpha, \beta, \gamma)$ associated with the interference price problem is jointly concave in $\{y_n\}\ \forall n \in \mathbb{N}$, with $y_n \geq 0$, when p_n is calculated in (13).

Proof: See Appendix B. ∎

Due to Property 1, y_n^* in Theorem 2 is the global optimum solution, which can maximize the MBS's utility $\bar{\mathcal{U}}_m$. Therefore, y_n^* satisfies (30) and is the SE y_n^{SE}.

Property 2: The utility function $\bar{\mathcal{U}}_n$ of SCBS n is a concave function of its own transmit power p_n when the interference price offered by the MBS is fixed.

Proof: See Appendix C. ∎

Together with Property 1 and Property 2, we conclude the following Theorem 3.

Theorem 3: The pair of $\{y_n^*\}$, $n \in \mathbb{N}$, defined in Theorem 2, and $\{p_n^*\}$,$n \in \mathbb{N}$ in (13), is the SE for the proposed game.

In practice, the following steps can be performed to obtain the SE of the proposed Stackelberg game.

1) The MBS collects information about μ_n, λ_n and the distribution of the channel gain $h^{(n)}$ from SCBS n $(\forall n)$ through the backhaul link. SCBS n $(\forall n)$ collects the distribution of the channel gain $g^{(nm)}$ from the MBS through the backhaul link.
2) The MBS calculates the value of each $L_r^{(n)}$ $(\forall n)$ and uses them to compute the range limits defined in Theorem 2.
3) The MBS decides the optimal interference price y_n^* $(\forall n)$ based on the interference power constraint $\bar{Q}$ presented in Theorem 2. These optimal interference prices are then fed back to the SCBSs through the backhaul links.
4) After receiving its interference price, SCBS n $(\forall n)$ decides the optimal transmit power p_n^* according to (13).

D. Comparison With the Complete CSI Scenario

To demonstrate the performance of our proposed game-theoretical scheme, here, we will investigate the energy-efficient resource allocation and interference control problems in the complete CSI scenario. In this scenario, the MBS knows the channel gains of each SCBS to its scheduled SCU, and the SCBS knows the channel gain from itself to the scheduled MU. It is important to analyze how this scenario differs from the incomplete CSI scenario, since the complete CSI scenario gives the upper bound for the SE in the incomplete CSI scenario.

With complete CSI, the optimal resource allocation strategy for each SCBS can be calculated as follows:

$$p_n^* = \left(\frac{W}{\mu_n x + \lambda_n y_n g^{(nm)}} - \frac{\sigma^2}{h^{(n)}}\right)^+. \tag{31}$$

For the MBS, the optimal interference price $\mathbf{y}^*$ under different interference power constraints is presented in Theorem 4, which can be proved using the method presented in the incomplete CSI scenario. The Lagrange multiplier α can be obtained by using the binary search method [43].

Theorem 4: Assuming that $L_1 > \cdots > L_N$, where $L_n = (Wh^{(n)}/\sigma^2 - \mu_n x)/(\lambda_n g^{(nm)})$, the optimal interference price $\mathbf{y}^*$ can be obtained as follows.

1) When $\bar{Q} \geq \sum_{n=1}^N g^{(nm)}(W/(\mu_n x + \lambda_n f_n(0) g^{(nm)}) - \sigma^2/h^{(n)})$

$$y_n^* = f_n(0) = \left[\frac{\sqrt{\frac{W\mu_n x h^{(n)}}{\sigma^2}} - \mu_n x}{\lambda_n g^{(nm)}}\right]_0^{L_N}. \tag{32}$$

2) When $\sum_{n=1}^N g^{(nm)}(W/(\mu_n x + \lambda_n L_N g^{(nm)}) - \sigma^2/h^{(n)}) \leq \bar{Q} < \sum_{n=1}^N g^{(nm)}(W/(\mu_n x + \lambda_n f_n(0) g^{(nm)}) - \sigma^2/h^{(n)})$

$$y_n^* = f_n(\alpha) = \left[\frac{\sqrt{\frac{Wh^{(n)}\left(\mu_n x + \alpha\lambda_n g^{(nm)}\right)}{\sigma^2}} - \mu_n x}{\lambda_n g^{(nm)}}\right]_0^{L_N}, \tag{33}$$

$$\sum_{n=1}^N g^{(nm)}\left(\frac{W}{\mu_n x + \lambda_n y_n^* g^{(nm)}} - \frac{\sigma^2}{h^{(n)}}\right) - \bar{Q} = 0. \tag{34}$$

$$\vdots$$

3) When $g^{(1m)}(W/(\mu_1 x + \lambda_1 L_1 g^{(1m)}) - \sigma^2/h^{(1)}) \leq \bar{Q} < \sum_{n=1}^2 g^{(nm)}(W/(\mu_n x + \lambda_n L_2 g^{(nm)}) - \sigma^2/h^{(n)})$

$$y_1^* = f_1(\alpha) = \left[\frac{\sqrt{\frac{Wh^{(1)}\left(\mu_1 x + \alpha\lambda_1 g^{(1m)}\right)}{\sigma^2}} - \mu_1 x}{\lambda_1 g^{(1m)}}\right]_0^{L_1}, \tag{35}$$

$$g^{(1m)}\left(\frac{W}{\mu_1 x + \lambda_1 y_1^* g^{(1m)}} - \frac{\sigma^2}{h^{(1)}}\right) - \bar{Q} = 0. \tag{36}$$

$$y_n^* = \infty, \qquad n \in \{2, \ldots, N\}. \tag{37}$$

We will show a performance comparison between the complete CSI and the incomplete CSI scenarios in Section V.

V. Simulation Results and Discussions

We use computer simulations to evaluate the performance of the proposed scheme. We also compare the performance of our proposed scheme with incomplete CSI with that of an existing scheme [45], where all of the CSI is assumed to be known. We assume that there is one MBS and two SCBSs (SCBS_1 and SCBS_2) in the heterogeneous network, and each unknown channel gain has two states with the uniform probability. The parameters are set as follows: $W = 1$, $h^{(1)} = [1.0\ 0.9]$,

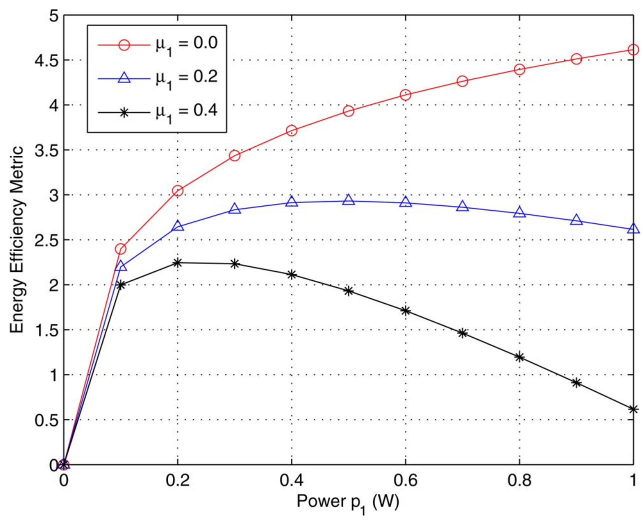

Fig. 2. Energy efficiency metric taking the power consumption cost into account during transmission (μ_1 denotes a weight, which represents the tradeoff between the transmission rate and the energy cost of SCBS_1).

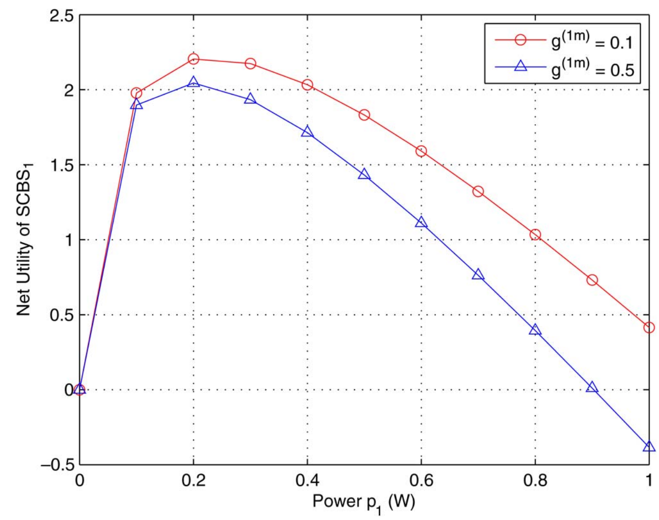

Fig. 3. Net utility of SCBS_1 with the change in the energy-efficient power allocation strategy ($g^{(1m)}$ is the channel gain between SCBS_1 and MU m).

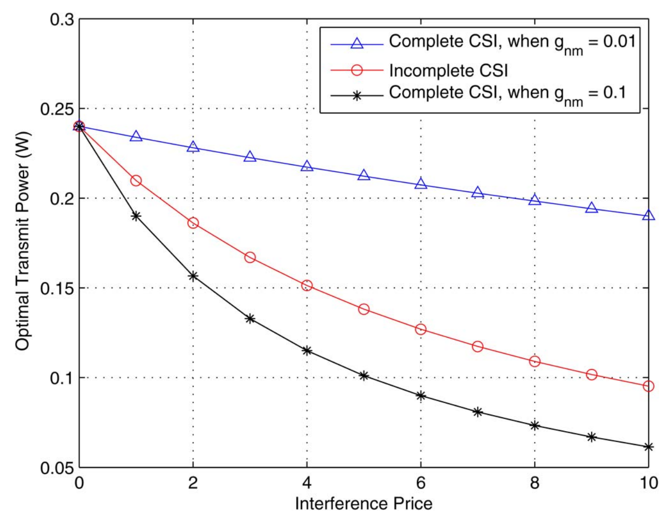

Fig. 4. Optimal transmit power for an SCBS with the variation of interference price.

$h^{(2)} = [1.0\ 0.8]$, $\sigma^2 = 0.2$, $\mu = 0.4$, $x = 1$, $\lambda = 2$, $g^{(1m)} = [0.05\ 0.1]$, and $g^{(2m)} = [0.1\ 0.3]$. These parameters stay the same in the following simulations, unless otherwise stated. Note that the exact shape of the figures in this section change with the parameters, but the insight remains the same.

We first study how the weight parameter μ affects SCBS's energy efficiency metric. When $\mu = 0$, maximizing the energy efficiency metric is equivalent to maximizing the transmission rate. As μ increases, there is a tradeoff between transmission rate and power consumption. Fig. 2 shows that the energy efficiency metric first increases with the transmit power and then decreases. For a given transmit power, the energy efficiency metric is a decreasing function of μ.

We study how an SCBS's net utility is affected by its energy-efficient power allocation decision and the corresponding channel gain $g^{(nm)}$. We also investigate how an SCBS should adapt its transmit power strategy based on the interference price offered by the MBS and under different CSI scenarios. Fig. 3 shows that the net utility function is a concave function, which matches the proof in Section IV-A. Therefore, there exists an optimal transmit power for each SCBS to maximize its net utility. With the increase in the transmit power, the net utility first increases due to the corresponding increase in the transmission rate and then decreases since the net utility gain on the transmission rate cannot balance the electricity cost and interference cost. For a given transmit power, the net utility is lower with a higher $g^{(nm)}$, since the SCBS has to pay more for its interference in this situation. Fig. 4 shows that each SCBS tries to decrease its interference cost by lowering its transmission power as the interference price increases. For the same interference price, higher $g^{(nm)}$ leads to higher total interference cost, due to higher interference. The figure also shows that the optimal transmit power in the incomplete CSI scenario is between the power values for the best and worst channel gains in the complete CSI scenario.

We then analyze how the optimal interference prices $\mathbf{y}^*$ and the optimal transmit power p_n^* change with the variation of the interference power margin $\bar{Q}$ in dB. Fig. 5 shows that when $\bar{Q}$ is below a threshold, only SCBS_1 is allowed to transmit, and the optimal interference price is offered to this SCBS. To prevent SCBS_2 from transmitting, the MBS offers it an infinite interference price. When $\bar{Q}$ passes the threshold, both SCBSs can perform the energy-efficient power allocation. The optimal interference prices decrease with the increase of $\bar{Q}$ first and then reach a stable level when the total caused interference is below $\bar{Q}$. For a given $\bar{Q}$, the optimal interference price of SCBS_1 is higher than that of SCBS_2, since the channel gain $g^{(1m)}$ is lower than $g^{(2m)}$. Fig. 7 shows that the optimal transmit power first increases and then becomes constant when the value of $\bar{Q}$ does not affect the SCBSs' decisions, since the optimal transmit power of each SCBS is a nondecreasing function of its offered optimal interference price, as shown in Fig. 5. When $\bar{Q}$ is below a threshold, SCBS_2 is not allowed to transmit, and therefore, the optimal transmit power is zero. The optimal transmit power of SCBS_2 begins lower than that of SCBS_1 but becomes higher, although its offered optimal interference price is still lower

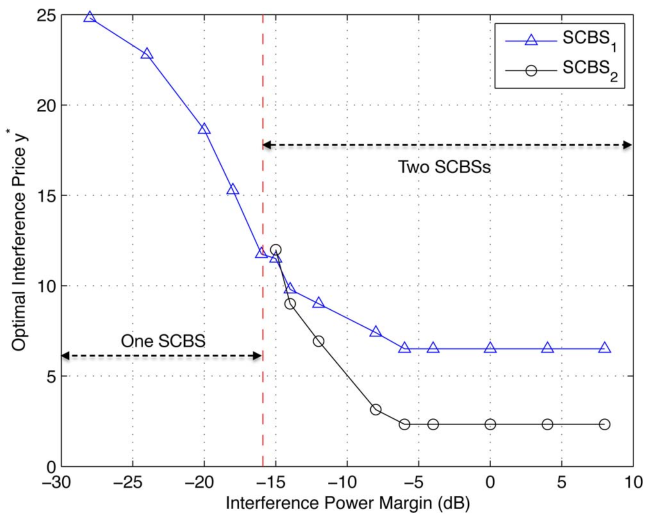

Fig. 5. Optimal interference prices for the SCBSs with the change in the interference power margin. The dashed red line marks the vertical asymptote of SCBS_2.

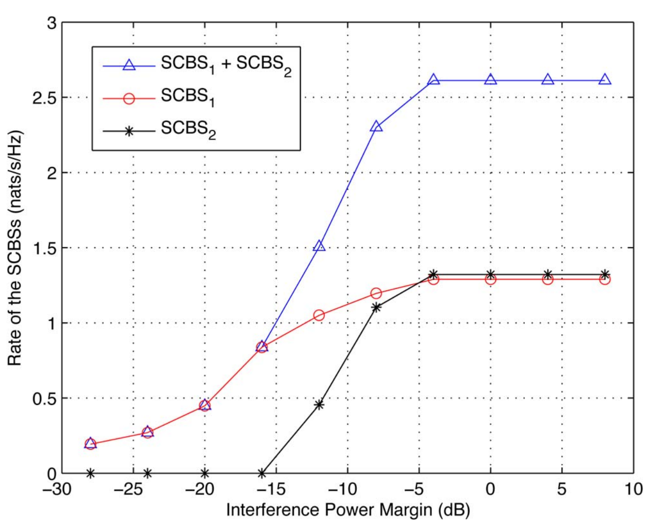

Fig. 6. Rate of the SCBSs with the variation of the interference power margin.

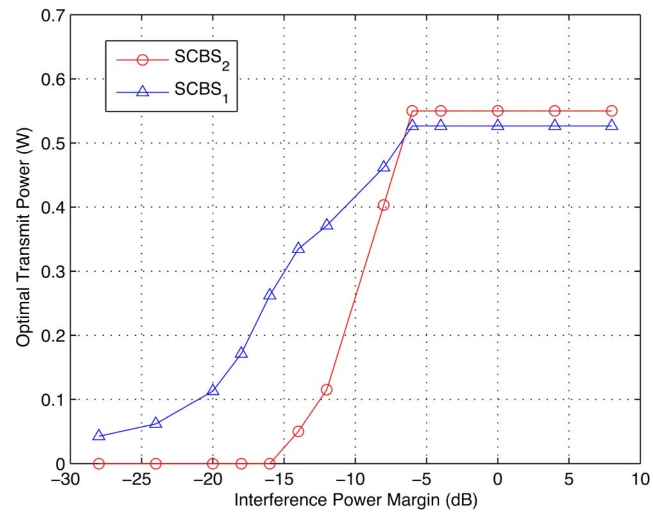

Fig. 7. Optimal transmit power for the SCBSs with the variation of the interference power margin.

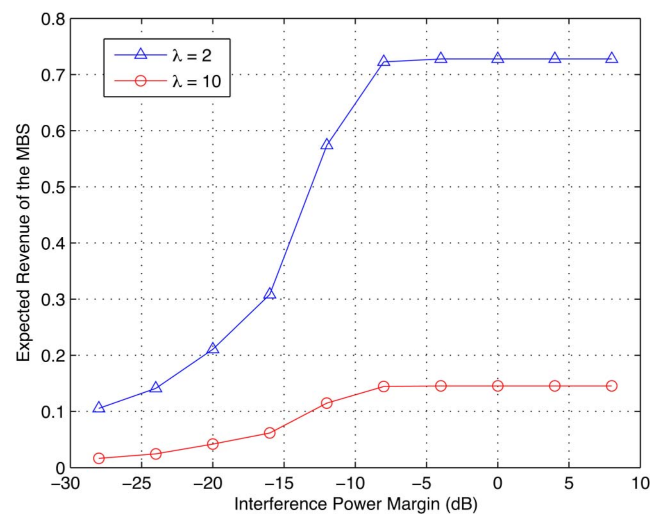

Fig. 8. Expected revenue of the MBS with the variation of the interference power margin (λ denotes a weight, which represents the tradeoff between the transmission rate and interference cost).

than that of SCBS_1. This is because the optimal transmit power depends not only on the optimal interference price but on the channel gains between the SCBSs and the MUs as well.

We analyze how the transmission rate of the SCBSs and the expected revenue of the MBS change with the interference power margin $\bar{Q}$. Fig. 6 shows that the transmission rate of each SCBS has the same trend as its corresponding optimal transmit power shown in Fig. 7, since the optimal transmit power determines the transmission rate. The figure shows that when $\bar{Q}$ is less than -15 dB, the curve of $\text{SCBS}_1 + \text{SCBS}_2$ merges with that of SCBS_1, since only SCBS_1 is allowed to transmit. Fig. 8 shows that with the increase of $\bar{Q}$, the expected revenue of the MBS first increases and then reaches a stable level. The reason is that with the increase of $\bar{Q}$, the MBS provides lower interference prices, and the SCBSs correspondingly increase their transmit power. The expected revenue keeps increasing until the value of $\bar{Q}$ is set to greater than or equal to some threshold (i.e., the total interference caused by the SCBSs with their optimal resource allocation strategies) and then has no impact on the BSs' decisions. The figure also shows that the weight parameter λ of the SCBSs has a negative impact on the expected revenue, since higher λ means lower optimal transmit power.

We compare the expected revenue of the MBS in our incomplete CSI scenario with that in the complete CSI scenario. We also compare the performance of our proposed scheme with that of an existing scheme [45], which is an energy-efficient resource allocation scheme for heterogeneous wireless networks assuming perfect CSI. A gradient-based iteration algorithm is used in [45] to obtain the solution to the resource allocation problem. In Fig. 9, the channel gains are set to the following: $g^{(1m)} = [0.3\ 0.4]$ and $g^{(2m)} = [0.5\ 0.7]$. The figure shows that the MBS receives higher revenue from the SCBSs when the CSI is known, since the MBS can make better interference price decisions with complete CSI. Therefore, it is beneficial for the MBS to carry on different incentive strategies to make the SCBSs share their channel gain information with it. When

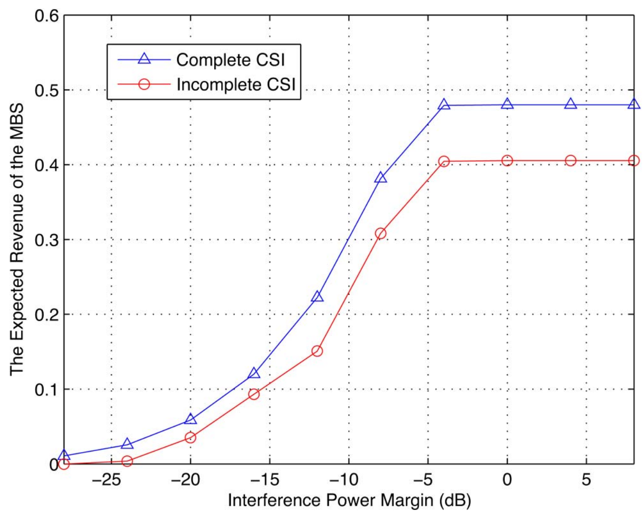

Fig. 9. Revenue of the MBS with the variation of the interference power margin.

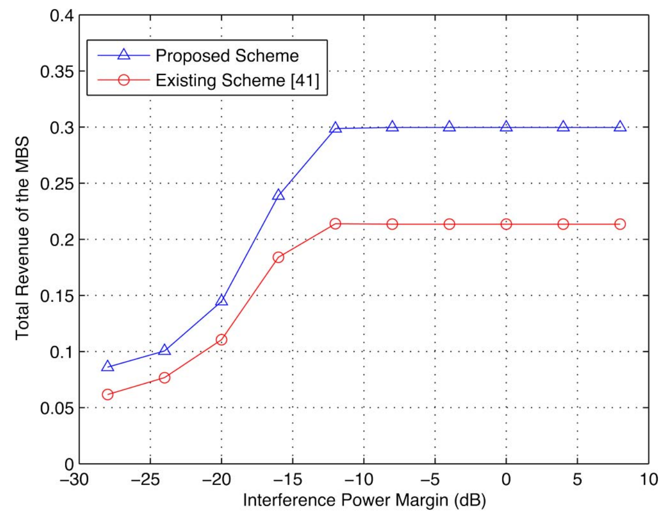

Fig. 11. Revenue of the MBS with the variation of the interference power margin.

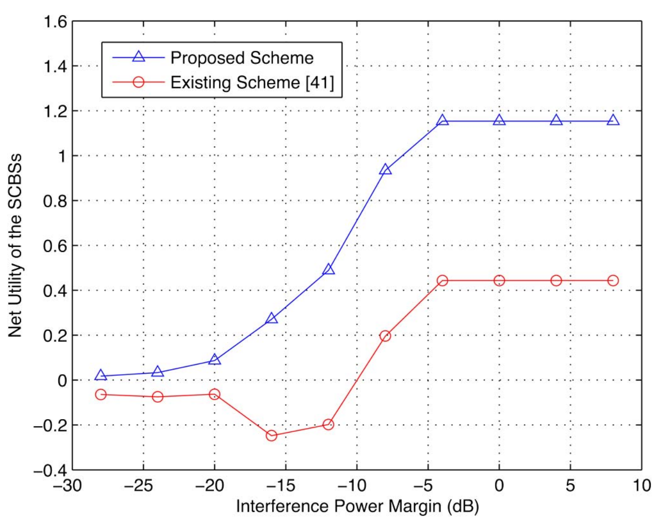

Fig. 10. Total net utility of the SCBSs with the variation of the interference power margin.

interference power margin $\bar{Q}$ reaches a certain level, the revenue of the MBS becomes stable, since the optimal interference price offered by the MBS becomes constant, and the optimal transmit power therefore becomes constant. In reality, it is difficult to know all of the CSI in real time due to the limited backhaul capacity. Fig. 10 shows that the SCBSs obtain higher net utility using our proposed scheme than the existing scheme. For the existing scheme, the total net utility of the SCBSs does not necessarily increase with the interference power constraint $\bar{Q}$, since the incomplete CSI leads the SCBSs to make suboptimal transmit power decisions. Fig. 11 also indicates that our proposed scheme performs better than the existing scheme in improving the total revenue of the MBS.

VI. Conclusion

In this paper, energy-efficient resource allocation has been studied for two-tier heterogeneous networks with limited backhaul capacity, where CSI is not known completely. To meet the interference power constraints of its MUs, the MBS offers nonuniform interference prices to the SCBSs. The SCBSs perform energy-efficient resource allocation to perform interference control and improve energy efficiency of the network. We formulated the problems of interference control and resource allocation in the heterogeneous network as a Stackelberg game with incomplete CSI. A backward induction method was used to analyze the proposed Stackelberg game. The closed-form solution of the proposed Stackelberg game was obtained with various interference power constraints. Then, we proved that the solutions are the SE for the proposed game. We presented a comparison study of the proposed scheme in an incomplete CSI scenario and a complete CSI scenario. Simulation results show that our proposed scheme is better than the the existing scheme in terms of the total net utility of the SCBSs and the total revenue of the MBS. The proposed scheme can be extended to the imperfect CSI scenario, e.g., with channel estimation errors. In this kind of scenarios, it is important to consider the uncertainty in the CSI distribution, and the robust optimization theory can be applied to solve the corresponding problem. Each uncertain parameter is modeled by the sum of its estimated value and the uncertain part [46]. When robust optimization is applied, the Stackelberg game and its equilibrium are referred to as the robust Stackelberg game and the robust SE, respectively.

Appendix A
Proof of Theorem 2

In the following, we demonstrate how to obtain the optimal interference prices when $\mathbf{y} \leq L_R^{(N)}$. The same method can be used to obtain the optimal interference prices in other intervals.

When $\mathbf{y} \leq L_R^{(N)}$, all $V_r^{(n)} = 1$. The Lagrangian associated with the given interference price problem can be written as [47],

$$\mathcal{L}(\mathbf{y}, \alpha, \beta, \gamma)$$
$$= \sum_{n=1}^{N} \sum_{r=1}^{R} \rho_r^{(n)} g^{(nm)} y_n$$

$$\times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)$$
$$-\alpha\left(\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)-\bar{Q}\right)$$
$$+\sum_{n=1}^{N}\beta_n y_n-\sum_{n=1}^{N}\gamma_n\left(y_n-\frac{\frac{Wh_R^{(N)}}{\sigma^2}-\mu_N x}{\lambda_N\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)}\right), \tag{38}$$

where α, β_n, and γ_n are non-negative dual variables associated with the constraints

$$\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)\le\bar{Q},\qquad y_n\ge 0,$$

and $y_n\le (Wh_R^{(N)}/\sigma^2-\mu_N x)/(\lambda_N(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}))$. Then, the KKT condition can be written as follows [47], [48]:

$$\frac{\partial\mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n}=0,\qquad\forall n, \tag{39}$$
$$\alpha\ge 0,\beta_n\ge 0,\gamma_n\ge 0,\qquad\forall n, \tag{40}$$
$$\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)\le\bar{Q}, \tag{41}$$
$$y_n\ge 0, y_n\le\frac{\frac{Wh_R^{(N)}}{\sigma^2}-\mu_N x}{\lambda_N\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)},\qquad\forall n, \tag{42}$$
$$\alpha\left(\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)-\bar{Q}\right)=0, \tag{43}$$
$$\beta_n y_n=0,\quad\forall n, \tag{44}$$
$$\gamma_n\left(y_n-\frac{\frac{Wh_R^{(N)}}{\sigma^2}-\mu_N x}{\lambda_N\left(\sum_{s=1}^{S}\varphi_s^{(Nm)}g_s^{(Nm)}\right)}\right)=0,\qquad\forall n. \tag{45}$$

According to (39)

$$\frac{\partial\mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n}=\frac{g^{(nm)}W\left(\mu_n x+\alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{\left(\mu_n x+\lambda_n y_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)^2}-\sum_{r=1}^{R}\frac{\rho_r^{(n)}g^{(nm)}\sigma^2}{h_r^{(n)}}+\beta_n-\gamma_n=0. \tag{46}$$

Lemma 5: $\beta_n=0,\forall n$.

Proof: Assume that $\beta_n\ne 0$. According to (44), $y_n=0$. According to (45), $\gamma_n=0$. Therefore, (46) and (43) can be rewritten as the following equations, respectively:

$$\frac{g^{(nm)}W\left(\mu_n x+\alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{(\mu_n x)^2}-\sum_{r=1}^{R}\frac{\rho_r^{(n)}g^{(nm)}\sigma^2}{h_r^{(n)}}+\beta_n=0. \tag{47}$$
$$\alpha\left(\sum_{n=1}^{N}\sum_{r=1}^{R}\rho_r^{(n)}g^{(nm)}\left(\frac{W}{\mu_n x}-\frac{\sigma^2}{h_r^{(n)}}\right)-\bar{Q}\right)=0. \tag{48}$$

Based on (47), (48) can be rewritten as

$$\alpha\left(\sum_{n=1}^{N}\left(\frac{-g^{(nm)}W\alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}{\mu_n^2x^2}-\beta_n\right)-\bar{Q}\right)=0. \tag{49}$$

Therefore, $\alpha=0$, and (47) can be rewritten as

$$\frac{g^{(nm)}W}{\mu_n x}-\sum_{r=1}^{R}\frac{\rho_r^{(n)}g^{(nm)}\sigma^2}{h_r^{(n)}}+\beta_n=0, \tag{50}$$

which contradicts $W/(\mu_n x)>\sigma^2/h_r^{(n)}$ since $\beta_n>0$. Therefore, $\beta_n=0,\forall n$. ■

Lemma 6: $\gamma_n=0,\forall n$.

Proof: If $\gamma_n\ne 0$, according to (46),

$$y_n=\frac{\sqrt{\frac{W\left(\mu_n x+\alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{\sum_{r=1}^{R}\frac{\rho_r^{(n)}\sigma^2}{h_r^{(n)}}+\frac{\gamma_n}{g^{(nm)}}}}-\mu_n x}{\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}, \tag{51}$$

which contradicts with (45). Therefore, $\gamma_n=0,\forall n$. ■

Therefore, the KKT conditions can be summarized as follows [48]:

$$y_n=f_n(\alpha)=\left[\frac{\sqrt{\frac{W\left(\mu_n x+\alpha\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)\right)}{\sum_{r=1}^{R}\frac{\rho_r^{(n)}\sigma^2}{h_r^{(n)}}}}-\mu_n x}{\lambda_n\left(\sum_{s=1}^{S}\varphi_s^{(nm)}g_s^{(nm)}\right)}\right]_0^{L_R^{(N)}}, \tag{52}$$

$$\frac{\partial^2 \mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n^2} = \frac{-2g^{(nm)}W\lambda_n\left(\mu_n x+\alpha\lambda_n\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)\right)\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)}{\left(\mu_n x+\lambda_n y_n\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)\right)^3} < 0, \quad (56)$$

$$\frac{\partial^2 \mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n \partial y_j} = 0, \qquad j\in\mathbb{N}, \qquad j\neq n. \quad (57)$$

$$\alpha\left(\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)} \times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)-\bar{Q}\right)=0, \quad (53)$$

$$\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)} \times\left(\frac{W}{\mu_n x+\lambda_n y_n\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)}-\frac{\sigma^2}{h_r^{(n)}}\right)\leq\bar{Q}, \quad (54)$$

where α has to be chosen so that conditions (53) and (54) are satisfied, and y_n is a function of α, denoted f_n. When $\alpha = 0$, y_n becomes

$$y_n = f_n(0) = \left[\frac{\sqrt{\frac{W\mu_n x}{\sum_{r=1}^R \frac{\rho_r^{(n)}\sigma^2}{h_r^{(n)}}}}-\mu_n x}{\lambda_n\left(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}\right)}\right]_0^{L_R^{(N)}}. \quad (55)$$

Based on (53), when $\bar{Q}\geq\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)}(W/(\mu_n x+\lambda_n f_n(0)(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}))-\sigma^2/h_r^{(n)})$, α must be 0. When $\bar{Q}<\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)}(W/(\mu_n x+\lambda_n f_n(0)(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}))-\sigma^2/h_r^{(n)})$, in order to meet the conditions in (52)–(54), $\alpha\neq 0$ and $\bar{Q}\geq\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)}\times(W/(\mu_n x+\lambda_n L_R^{(N)}(\sum_{s=1}^S \varphi_s^{(nm)} g_s^{(nm)}))-\sigma^2/h_r^{(n)})$. In this situation, the bisection search algorithm can be used to search for the optimal interference prices. When $\bar{Q}<\sum_{n=1}^N\sum_{r=1}^R \rho_r^{(n)} g^{(nm)}(W/(\mu_n x+\lambda_n L_R^{(N)}(\sum_{s=1}^S \varphi_s^{(nm)}\times g_s^{(nm)}))-\sigma^2/h_r^{(n)})$, no y_n meets the given KKT conditions.

Appendix B
Proof of Property 1

In the following, we demonstrate how to prove Property 1 when $\mathbf{y}\leq L_R^{(N)}$. The same method can be used to prove Property 1 in other intervals. Taking the second-orderderivatives of the Lagrangian, we obtain (56) and (57), shown at top of the page. Therefore

$$\frac{\partial^2 \mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n^2}\frac{\partial^2 \mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_j^2}-\left(\frac{\partial^2 \mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)}{\partial y_n \partial y_j}\right)^2>0, \quad \forall n\neq j. \quad (58)$$

Moreover, $\mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)$ is continuous in y_n; therefore, when $0\leq y_n\leq L_R^{(N)}$, $\mathcal{L}(\mathbf{y},\alpha,\beta,\gamma)$ is strictly concave in each $y_n(\forall n)$, and jointly concave over $\{y_n\}(n\in\mathbb{N})$ as well.

Appendix C
Proof of Property 2

Taking the second-order derivatives of utility $\bar{\mathcal{U}}_n$, we obtain

$$\frac{\partial^2\bar{\mathcal{U}}_n}{\partial p_n^2}=\frac{-W\left(h^{(n)}\right)^2}{\left(\sigma^2+p_n h^{(n)}\right)^2}<0. \quad (59)$$

Therefore, $\bar{\mathcal{U}}_n$ is a concave function of p_n.

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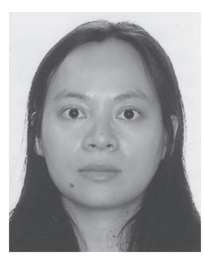

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