Efficient QoS Support for Robust Resource Allocation in Blockchain-Based Femtocell Networks

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***Abstract*—Blockchain-based femtocell networks aim to build decentralized frameworks which enable easy deployment and low power consumption, thus they have been seen promising technologies to make up the coverage of cellular networks in the next generation communication system. This article aims to employ power control to support quality-of-service provisioning, especially the guarantee for the transmission rate of a macrocell user (MUE) and the time delay of femtocell users (FUEs) in two-tier femtocell networks, where the MUE and FUEs share the same communication channel. We formulate the interactions among the macrocell base station and FUEs as a Stackelberg game to maximize the utilities of MUE and FUEs by obtaining the optimal power allocation and pricing strategy. Considering the uncertainty of channel gain which is expressed as a function of transmission distance, we propose a worst-case method to transform the uncertain optimization problem into a deterministic one. We then design two algorithms by considering the dynamics of FUEs, i.e., FUEs may join and leave femtocells. Numerical results verify the convergence and superior performance of our proposed algorithms.**

***Index Terms*—Blockchain, femtocell, quality of service, resource allocation, Stackelberg game.**

I. Introduction

With the advent of the era of the next generation communication (5G) system, when the demand for high-speed data grows significantly, the coverage of cellular networks has been extended largely. However, due to severe channel fading, especially when the signals penetrate buildings, the problem of indoor coverage poses a great challenge. To this end, femtocell which can make up the coverage of cellular networks has been seen as a promising technology due to the advantages of easy deployment and low power consumption [1]. Femtocells use the spectrum resource of macrocell for improvement of frequency spectrum utilization. However, femtocell networks still face some challenges. First of all, due to the small coverage of each femtocell and short distance between femtocells, communication users receive a variety of interferences, such as the intercell interference in each femtocell, cotier interference among femtocells, and cross-tier interference between femtocells and macrocell. Therefore, interference management is an urgent research topic to be investigated [2]. Secondly, with the popularity of mobile devices, electronic money transactions have received extensive attention in femtocell networks. However, in the traditional centralized transaction, the transaction consensus is reached through centralized third party which usually brings additional costs. To solve this problem, blockchain technology is introduced into femtocell networks. Blockchain, as the backbone technology of the current popular digital currency such as bitcoin, has become a promising decentralized data management framework [3], [4]. In order to ensure the validity of electronic transaction data in blockchain-based femtocell networks, mobile devices are required to complete proof of work, which requires a lot of computation. Even if mobile devices validate transactions through simplified payment verification (SPV) method, connections and requests with full node are inevitable, which has to meet low latency requirement.

Blockchain-based femtocell networks provide users convenient mobile communication services. However, there are still some challenges to push femtocell networks into practice. First, with the increasing number of users, how to guarantee the quality-of-service (QoS) requirements of both MUEs and FUEs has become an urgent problem. Different users may have different QoS requirements. For example, on the one hand, it is desired that a user delivers data with fast transmission rate, as providing the guarantee for transmission rate is required by a variety of streaming media-based applications. On the other hand, the dissemination of advertisements or coupons must meet a delay requirement [5], [6]. Data delivered beyond

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a delay requirement may lead to reduced or even useless value. Decentralized applications using blockchian technology are faced with the performance bottleneck of their underlying platform. For instance, Cryptokitties, a decentralized game built on ethereum, made the services of blokchain paralysis for a week. And mobile users' interests have been infringed as they cannot validate a transaction in time. Secondly, users in femtocell networks often move in the indoor environment, the transmission distances between users and base stations vary a lot. Therefore, transmission distance is an important factor to describe the complex channel environment, as the transmission distance is related to the channel gains of both indoor and outdoor transmissions.

II. Related Works

The methods of interference management are presented in literatures [7]–[11], i.e., power control, frequency reuse, multiple access technology. In [7], a downlink interference evaluation scheme is proposed to maximize user equipment throughput. In [8], a joint subcarrier and power allocation problem for uplink femtocell networks is considered. In this article, a temperature limit on the interference arising is imposed to suppress cross-tier interference. Power control is an effective way for interference management. Some schemes are presented to address power control problem in the following literatures. In [9], a stochastic approximation algorithm for downlink power control in femtocell networks is proposed. The authors focus on distributed femtocell base station (FBS) power control for cross-tier interference mitigation. The authors in [10] propose a distributed auction scheme to tackle the resource management and task scheduling in mobile systems. In [11], the interference avoidance problem among FBSs is examined by presenting two algorithms that maximize as much as possible the average achievable data rate per femtocell user (FUE). Implementing blockchain in mobile communication and devices are also widely researched by many startup blockchain companies. Sirin Labs has been developing the first blockchain smart phone, and every product of this company is committed to using their own blockchain. They promote use of digital currencies and decentralization through Sirin Labs Token (SRN) tokens. However, none of the above works consider QoS provisioning in blockchain-based femtocell networks.

Several works in the literatures have considered the resource allocation problem with QoS requirements in femtocell networks [12]–[16]. Moreover, game theoretic analysis is a reasonable approach to deal with resource allocation problem between players in a two-tier femtocell network. In [13], a distributed resource allocation that consists of subchannel and power-level allocation of the two-tier cognitive femtocell network is studied using a coalitional game, which dedicates to maximize the uplink sum rate under constraints of interference while maintaining the average delay requirement for users. In [14], a problem of joint users' uplink transmission power and data rate allocation in multiservice two-tier femtocell networks is tackled based on a supermodular game. The independent variables of power and rate are used to design utility functions to express users' QoS demands. In [15], a joint price and power allocation problem in the spectrum sharing femtocells networks is modeled based on Stackelberg game. Macrocell user (MUE) interference tolerance and its minimum rate requirement are taken as constraints in the utility functions. However, the works above have not considered the uncertainty of communication environment in two-tier networks. The uncertainties of the channel are inevitable and the robustness should be taken into consideration.

In this article, we propose to employ power control to support QoS provisioning, especially the guarantee for the transmission rate of a MUE and the time delay of FUEs in two-tier femtocell networks. In our article, we consider the channel gain uncertainty which includes the measurement error. We formulate the interactions among the macrocell base station (MBS) and FUEs as a Stackelberg game to maximize the utilities of MUE and FUEs by obtaining the optimal power allocation and pricing strategy. More specifically, MBS serves as a leader, and FUEs act as followers. The MBS shares its spectrum resource to FUEs, hence cochannel interference is produced by the FUEs. In this article, we propose to price the interference and charge the FUEs to restrain the interference introduced by FUEs. Therefore, the interference introduced by the FUEs can be regarded as the available resource used by FUEs. In order to avoid excessive interference from FUEs, MBS prices the interference to the FUEs, the FUEs determine their transmission powers and payments with the constraint of time delay maximizing their utilities. Considering the uncertainty of communication distance, we propose a worst-case method to transfer the uncertain optimization problem into a deterministic one, and design two algorithms. The main contributions are summarized as follows.

1) A joint power allocation and pricing strategy is proposed to guarantee the QoS requirements both of MUEs and FUEs, i.e., the transmission rate of MUE and time delay of FUEs. The improvement of QoS enables mobile users to validate a transaction in time in blockchain-based femtocell networks.
2) The uncertainties of channel gains are taken into consideration. A worst-case method is utilized to deal with this uncertain optimization problem and obtain closed-form expressions. The proposed resource allocation scheme is robust to the changing communication environment.
3) Based on the theoretical analysis, we give two distributed algorithms, which are suitable to the decentralized blockchain-based femtocell networks, by considering the dynamics of FUEs, i.e., FUEs may join and leave femtocells.

III. System Model and Problem Formulation

A. System Model

A two-tier network is considered which consists of one MBS and N femtocells. In this scenario, the MBS is interfered by the uplink transmission of FUEs located nearby. We assume single carrier-frequency division multiple access (SC-FDMA) is used for uplink transmission. Namely, there is only one active FUE on one subchannel in each femtocell, and there is no interference

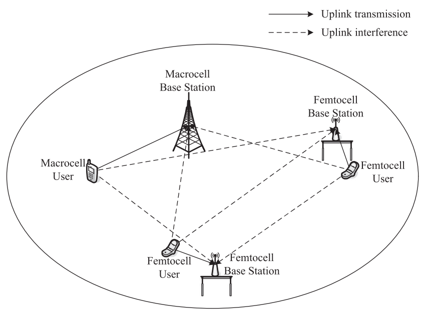

Fig. 1. Topology of two-tier network.

among FUEs in each femtocell. However, some FUEs in different femtocells may run in the same subchannel, there exists interference among FUEs in different femtocells. Additionally, as the FUEs in different subchannels do not interfere with each other, the resource allocation result for a single subchannel can be obtained first, then, it can be extended to other subchannels, according to the dual problem decomposition approach [17], in which resource allocation problem can be decomposed to multiple independent subproblems which are solved respectively. As shown in Fig. 1, the MBS and FBSs provide service for their corresponding users with coverage radius R_m and R_f, respectively. Let $h_{0,0}$ and $g_{i,i}$ denote the distances from MUE and FUE i to their corresponding base stations, respectively. Let h_i and $g_{i,j}$ denote the distances from MUE and FUE j to FBS i, respectively. And g_i denotes the distance from FUE i to MBS, $i, j \in \mathcal{I}, i \neq j, \mathcal{I} = \{1, 2, \ldots, N\}$.

B. The Uncertainty of Signal-to-Interference-Noise-Ratio (SINR)

In order to maintain the decentralization of blockchain, ethereum, bitcoin, and other public chain restrain their transactions per second (TPS) performance to ensure that even in common networks ordinary computers can participate in the network. The uncertainty of channel fading and poor quality of communication limits the number of transactions in the network. It is necessary to take the uncertainty into account when designing the resource allocation strategies. Let α and β denote the pass-loss exponent of outdoor and indoor transmissions, and $\alpha > \beta$. The channel gain in outdoor and cross-wall transmission is expressed as $H(|x|) = |x|^{-\alpha}$. The channel gain in indoor transmission is expressed as $H(|x|) = |x|^{-\beta}$. Here, $|x|$ denotes the distance from a user to the respective base station. $\boldsymbol{p} = \{p_1, p_2, \ldots, p_N\}$ denotes the vector of transmission powers for all FUEs, and $0 \leq p_i \leq p_i^{\max}$ $\forall i \in \{1, 2, \ldots, N\}$. p_0 denotes the transmission power of MUE, and $p_0 \geq 0$. Then the signal-to-interference-noise-ratio (SINR) of MUE and FUE i can be written as

$$\gamma_0 = \frac{p_0 h_{0,0}^{-\alpha}(e_0)}{\sum_{i=1}^{N} p_i g_i^{-\alpha}(e_i) + \sigma^2} \tag{1}$$

$$\gamma_i = \frac{p_i g_{i,i}^{-\beta}(e_{i,i})}{p_0 h_i^{-\alpha}(e_i) + \sum_{j=1, j\neq i}^{N} p_j g_{i,j}^{-\alpha}(e_{i,j}) + \sigma^2} \tag{2}$$

where σ^2 denotes the additive white Gaussian noise (AWGN). In this SINR model, it is assumed that the channel gain is affected by path loss. The uncertain transmission distance which includes measurement error is considered, which are denoted as $h_{0,0}(e_0)$, $g_{i,i}(e_{i,i})$, $h_i(e_i)$, $g_{i,j}(e_{i,j})$, and $g_i(e_i)$. It is assumed that the uncertainties are bounded, and the boundaries are denoted as ϵ_0, $\epsilon_{i,i}$, ϵ_i, $\epsilon_{i,j}$, ϵ_i, respectively. Then the channel gains can be expressed as $h_{0,0}(e_0) \in [\hat{h}_{0,0} - \epsilon_0, \hat{h}_{0,0} + \epsilon_0]$, $g_{i,i}(e_{i,i}) \in [\hat{g}_{i,i} - \epsilon_{i,i}, \hat{g}_{i,i} + \epsilon_{i,i}]$, $h_i(e_i) \in [\hat{h}_i - \epsilon_i, \hat{h}_i + \epsilon_i]$, $g_{i,j}(e_{i,j}) \in [\hat{g}_{i,j} - \epsilon_{i,j}, \hat{g}_{i,j} + \epsilon_{i,j}]$, and $g_i(e_i) \in [\hat{g}_i - \epsilon_i, \hat{g}_i + \epsilon_i]$, where $\hat{h}_{0,0}$, $\hat{g}_{i,i}$, $\hat{h}_i$, $\hat{g}_{i,j}$, $\hat{g}_i$ represent the estimated values of transmission distances. In this article, we attempt to study a robust resource allocation scheme considering the SINR uncertainty which is caused by the deviation of estimations.

C. Robust Stackelberg Game Formulation

Creating signature of transactions locally and sending them through mobile devices require considerable power consumption, thus optimized power allocation method can improve the QoS of blockchain-based mobile applications. In this section, we formulate the interactions among the MBS and FUEs as a Stackelberg game to maximize the utilities of users.

1) MBS Modeling: In femtocell networks, MUE as an authorized user shares its spectrum resource with nearby unauthorized users (FUEs). Due to the cochannel interference which is caused by the signal transmissions of FUEs, MUE prices the interference to guarantee the QoS of communication. Therefore, interference resource is available for purchase, and it can be utilized by FUEs. We formulate the interactions among the MUE and FUEs as a Stackelberg game, where MUE acts as a leader, and FUEs act as followers. MUE maximizes its utility by charging FUEs. Moreover, considering the constraint of transmission rate, i.e., the transmission rate of MUE should be larger than a transmission rate threshold. Therefore, the subgame of MUE is described as

Problem 1:

$$\begin{aligned} \max_{c_i \geq 0, p_0 \geq 0} \quad & U_0 = \sum_{i=1}^{N} c_i p_i g_i^{-\alpha}(e_i) - u_0(p_0 - \bar{p}_0) \\ \text{s.t.} \ & \log(1 + \gamma_0) \geq R^{\min} \quad \forall i \in \mathcal{I}, \end{aligned} \tag{3}$$

where $R^{\min}$ denotes the transmission rate threshold of MUE. The constraint in *Problem 1* indicates that the power of MUE, i.e., p_0 can be adjusted to guarantee its transmission rate. $\sum_{i=1}^{N} p_i g_i^{-\alpha}(e_i)$ denotes the total received interference of MBS caused by FUEs. c_i denotes the interference price imposed on FUE i. $\sum_{i=1}^{N} c_i p_i g_i^{-\alpha}(e_i)$ denotes the total revenue MBS obtained from the payments of FUEs. $(p_0 - \bar{p}_0)$ is the additional power that MBS needs to expend. u_0 is the price coefficient of additional power. $\bar{p}_0$ is the original power that MBS transmits when there is no FBS, i.e., $\log(1 + \frac{\bar{p}_0 h_{0,0}}{\sigma^2}) \geq R^{\min}$.

2) FUE Modeling: Interference prices which are collected from FUEs have been determined by MBS at first. FUEs as the unauthorized users, compete in a noncooperative manner to maximize their respective utilities. The utility function of a FUE is the difference between transmission rate and payment.

Considering the constraint of delay requirement, i.e., the time delay of each FUE should be smaller than the maximum time delay. The transmission power of each FUE is chosen by the following problem:

Problem 2:

$$\max_{p_i \geq 0} \quad U_i = \log(1+\gamma_i) - c_i p_i g_i^{-\alpha}(e_i)$$
$$\text{s.t. } D_i \leq D_i^{\max} \quad \forall i \in \mathcal{I} \tag{4}$$

where $D_i^{\max}$ denotes the time delay threshold of FUE i. The constraint in *Problem 2* suggests that the power of FUE i, i.e., p_i is allocated to guarantee its time delay requirement. Since we assume that there is only one FUE that is served by FBS within one time-slot, taking into account the M/M/1 queuing model [18], [19], the average time delay of FUE i is $D_i = \frac{1}{\kappa_i R_i - \lambda_i}$, where the data packet length follows exponential distribution with parameter κ_i, R_i is the data transmission rate represented as $R_i = \log(1+\gamma_i)$, where packet arrival follows a Poisson process with parameter λ_i.

IV. Robust Stackelberg Game Algorithm

In this proposed Stackelberg game, first, MBS as the leader declares its strategy. According to the leader's strategy, FUEs as the followers subsequently choose their strategies. Both MBS and FUEs make decisions to obtain the optimal utilities. MBS and FUEs compete with each other in a noncooperative manner, thus the game equilibrium (GE) can be obtained by addressing the Nash equilibrium (NE) of this noncooperative game. The GE is an operating point where both MBS and FUEs have no incentive to change their strategies unilaterally. In this section, we apply backward induction to gain the GE of the proposed robust Stackelberg game. First, based on the given $\boldsymbol{c}$, each FUE maximizes its utility to obtain the optimal p_i. Second, according to the obtained power response, MBS maximizes its utility to obtain the optimal $\boldsymbol{c}$.

A. Optimal Power Allocation Strategy for Femtocells

Blockchain-based mobile communication which usually involves transference of economic rights and interests demands high QoS standards. In our article, considering the fact that the channel gain uncertainty is taken into account in both objective functions and constraint conditions, we propose a worst-case method to transform the uncertain optimization *Problems 1* and *2* into deterministic ones. Then the subgame of FUE i is rewritten as the problem below

Problem 3:

$$\max_{\boldsymbol{p}} \min_{\boldsymbol{e}} \quad U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$$
$$\text{s.t.} \begin{cases} \min\limits_{\boldsymbol{e}} \quad D_i \leq D_i^{\max} & \forall i \in \mathcal{I} \\ 0 \leq p_i \leq p_i^{\max} & \forall i \in \mathcal{I} \end{cases} \tag{5}$$

where $\boldsymbol{e}$ represents the error of transmission distance. $p_i^{\max}$ denotes the power threshold of FUE i. The constraint of time delay can be concretely expressed as $\frac{1}{D_i^{\max}} \leq \kappa_i \log(1 + \frac{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}) - \lambda_i$ where $I_i(\boldsymbol{p}_{-i}) = p_0(\hat{h}_i - \epsilon_i)^{-\alpha} + \sum_{j\neq i} p_j(\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha} + \sigma^2, i,j \in \mathcal{I}$. Based on the uncertainty of transmission distance, it is noted that *Problem 2* is equivalent to the *Problem 4*

Problem 4:

$$\max_{\boldsymbol{p}} \quad U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c}) = \log\left(1 + \frac{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}\right) - c_i p_i(\hat{g}_i - \epsilon_i)^{-\alpha}$$
$$\text{s.t.} \begin{cases} \log\left(1 + \frac{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}\right) \geq e^{\Phi_i} - 1 \\ 0 \leq p_i \leq p_i^{\max}, \forall i \in \mathcal{I} \end{cases} \tag{6}$$

where $\Phi_i = \frac{1}{\kappa_i}(\frac{1}{D_i^{\max}} + \lambda_i)$.

In femtocell networks, a noncooperative competition problem can be formulated to investigate the behaviors of players, who compete with each other for maximizing their own utilities. Next, the existence and uniqueness of GE will be analyzed in the following theorem.

Proposition 1 ([20]): An NE exists in the Stackelberg game, if $\forall i \in \mathcal{I}$, the following requirements are met.

1) $\boldsymbol{p}$ is a nonempty convex and compact subset of some the Euclidean space $\mathcal{R}^N$.
2) $U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$ is continuous in $\boldsymbol{p}$ and concave in p_i.

Theorem 1: A GE exists in the proposed noncooperative game $\mathcal{G} = \{\mathcal{S}, \{p_i\}, \{U_i\}\}$, where $\mathcal{S}$ is the set of players.

Proof: 1) Since the convex set is a single point or a continuous line in one-dimensional space. For the strategy $p_i \in [0, p_i^{\max}]$, it is easy to see that $\{p_i\}$ is a nonempty, convex, and compact subset of the Euclidean space $\mathcal{R}^N$.

2) According to (6), it is evident that $U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$ is a continuous function of p_i. Subsequently, the first-order and second-order derivatives of $U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$ with respect to p_i are given as

$$\frac{\partial U_i}{\partial p_i} = \frac{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta} + I_i(\boldsymbol{p}_{-i})} - c_i(\hat{g}_i - \epsilon_i)^{-\alpha} \tag{7}$$
$$\frac{\partial^2 U_i}{\partial p_i^2} = \frac{-(\hat{g}_{i,i}+\epsilon_{i,i})^{-2\beta}}{\left[p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta} + I_i(\boldsymbol{p}_{-i})\right]^2} < 0 \tag{8}$$

Apparently, the second-order derivative of $U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$ with respect to p_i is always less than 0. Accordingly, $U_i(p_i, \boldsymbol{p}_{-i}, \boldsymbol{c})$ is concave in p_i. According to Proposition 1, a GE exists in the noncooperative game $\mathcal{G}$. ■

As solving the maximization of concave function is a convex optimization problem, *Problem 4* is a convex optimization problem and can be addressed using the method of dual decomposition. The Lagrangian function of the proposed nonlinear programming problem is constructed as (9)

$$L(p_i, \eta_i) = \log\left(1 + \frac{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}\right) - c_i p_i(\hat{g}_i - \epsilon_i)^{-\alpha} + \eta_i\left[\log\left(1 + \frac{p_i(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}\right) - \left(e^{\Phi_i} - 1\right)\right] \tag{9}$$

where η_i is the Lagrange multiplier. The dual problem of original optimization problem is given as

Problem 5:

$$\min_{\eta_i \geq 0} \quad q(\eta_i) = \min_{\eta_i \geq 0} \max_{\boldsymbol{p}} \quad L(p_i, \eta_i). \tag{10}$$

It is found that *Problem 5* is convex, and it can be solved by using a subgradient method. The subgradient of the dual function $q(\eta_i)$ is written as

$$H_{\eta_i} = \frac{\partial q(\eta_i)}{\partial \eta_i} = \log\left(1 + \frac{p_i(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}{I_i(\boldsymbol{p}_{-i})}\right) - \left(e^{\Phi_i} - 1\right). \tag{11}$$

Therefore, the Lagrange multiplier η_i is updated as the following iterative equation

$$\eta_i(t+1) = \left[\eta_i(t) - y_1(t) H_{\eta_i}\right]^+ \tag{12}$$

where $[X]^+ = \max\{0, X\}$. t denotes the iteration step. y_1 denotes the step size which is positive.

By using the Karush–Kuhn–Tucker conditions in optimization theory, the optimal allocated power of FUE i can be obtained by taking the partial derivative of $L(p_i, \eta_i)$ w.r.t. p_i, that is

$$p_i = \frac{1 + \eta_i}{c_i(\hat{g}_i - \epsilon_i)^{-\alpha}} - \frac{I_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}. \tag{13}$$

Theorem 2: The NE of the noncooperative game $\mathcal{G}$ is unique.

Proof: It can be found that transmitting power of FUE i is possible only when

$$c_i < \frac{(1 + \eta_i)(\hat{g}_i - \epsilon_i)^{\alpha}}{I_i(\boldsymbol{p}_{-i})(\hat{g}_{i,i} + \epsilon_{i,i})^{\beta}}. \tag{14}$$

At this time, FUE i transmits its power with the best power response with (13) relative to other FUEs. Thus NE p_i^* is the local optimum in $[0, p_i^{\max}]$, it is unique and equal to p_i. By contrast, if interference price is set too high, the transmission power of FUE i will be zero, resulting in stopping work of FUE i. Hence, the optimal solution of (9) is given by

$$p_i^* = \min\left\{\left[\frac{1 + \eta_i}{c_i(\hat{g}_i - \epsilon_i)^{-\alpha}} - \frac{I_i^*(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}\right]^+, p_i^{\max}\right\} \tag{15}$$

where $[x]^+ = \max[0, x]$. $I_i^*(\boldsymbol{p}_{-i}) = p_0(\hat{h}_i - \epsilon_i)^{-\alpha} + \sum_{j \neq i} p_j^* (\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha} + \sigma^2, i, j \in \mathcal{I}$.

Moreover, the formulation (15) is rewritten as a power allocation iteration of the form $\boldsymbol{p}(t+1) = \boldsymbol{A}(\boldsymbol{p}(t))$. Here, $\boldsymbol{A}(\boldsymbol{p}(t))$ is the power update strategy for FUE i. Thus, the individual power update strategy is described as

$$p_i^{(t+1)} = \min\left\{\left[\frac{1 + \eta_i^{(t)}}{c_i(\hat{g}_i - \epsilon_i)^{-\alpha}} - \frac{I_i^{(t)}(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}\right]^+, p_i^{\max}\right\}. \tag{16}$$

Let $\boldsymbol{p}_{-i}(t) = [p_j(t)]_{j \in \mathcal{I}, j \neq i}$ denotes the vector that is composed of $p_j(t), j \in \mathcal{I}$. We can obtain $\boldsymbol{G}_{-i}\boldsymbol{p}_{-i}(t) = \sum_{j=1, j\neq i}^{N} (\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha} p_j(t)$, where $\boldsymbol{G}_{-i} = [(\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha}]^T_{j \in \mathcal{I}, j \neq i}$. Define $\triangle p_i(t) = p_i(t) - p_i^*$, here p_i^* denotes the optimal transmission power of FUE i. From (16), the following equation can be obtained

$$\begin{aligned}|\triangle p_i(t+1)| = |p_i(t+1) - p_i^*| &= \left|\frac{\boldsymbol{G}_{-i}}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}} \triangle \boldsymbol{p}_{-i}(t)\right| \\ &\leq \left\|\frac{\boldsymbol{G}_{-i}}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}\right\|_\infty \|\triangle \boldsymbol{p}_{-i}(t)\|_\infty\end{aligned} \tag{17}$$

where $\triangle \boldsymbol{p}_{-i}(t) = [\triangle p_j(t)]_{j \in \mathcal{I}, j \neq i}$. In two-tier femtocell networks, the distance from FUE i to its corresponding FBS is close, there is $(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta} > (\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha}, j \neq i$. It can be easily obtained that $\|\frac{\boldsymbol{G}_{-i}}{(\hat{g}_{i,i} + \epsilon_{i,i})^{-\beta}}\|_\infty < 1$. Consequently, $|\triangle p_i(t+1)|$ converges to zero . That means $p_i(t)$ can converge to a unique fixed point p_i^*. According to the definition of NE, NE of the noncooperative game $\mathcal{G}$ is unique. ■

B. Optimal Pricing Strategy for Macrocell

In this subsection, the solution of optimal price is determined in dynamic power adjustment scheme. Because of the interference prices collected from FUEs are the same, let $c_i = c$ which denotes the uniform interference price. As discussed above, considering the impact of distance uncertainty, a worst-case method is utilized to deal with *Problem 1* with the constraint of QoS requirement. Therefore, the subgame for MBS is reformulated as

Problem 6:

$$\begin{aligned}&\max_{c>0, p_0>0} \min_{\boldsymbol{e}} \quad U_0(\boldsymbol{c}, \boldsymbol{p}, p_0) \\ &\text{s.t.} \begin{cases}\min\limits_{\boldsymbol{e}} \quad \log(1 + \gamma_0) \leq R^{\min} \\ \text{Eq. (13)}\end{cases}\end{aligned} \tag{18}$$

With the worst-case method, the constraint of rate requirement is given as $\log(1 + \frac{p_0(\hat{h}_{0,0} + \epsilon_0)^{-\alpha}}{\sum_{i=1}^{N} p_i(\hat{g}_i - \epsilon_i)^{-\alpha} + \sigma^2}) \leq R^{\min}$.

In view of the uncertainty model of transmission distance, *Problem 6* can be converted into a deterministic convex optimization problem as follows:

Problem 7:

$$\begin{aligned}&\max_{c>0, p_0>0} \quad U_0(\boldsymbol{c}, \boldsymbol{p}, p_0) = \sum_{i=1}^{N} c p_i(\hat{g}_i - \epsilon_i)^{-\alpha} - u_0(p_0 - \bar{p}_0) \\ &\text{s.t.} \begin{cases}\dfrac{p_0(\hat{h}_{0,0} + \epsilon_0)^{-\alpha}}{\sum_{i=1}^{N} p_i(\hat{g}_i - \epsilon_i)^{-\alpha} + \sigma^2} \geq e^{R^{\min}} - 1 \\ \text{Eq. (13)}\end{cases}\end{aligned} \tag{19}$$

It is found that the robust allocation problem above is a convex optimization problem. The detailed procedure of the best response of MBS is indicated in the following analysis. The Lagrange function of *Problem 7* is formulated as (20), where ξ is Lagrange multiplier. Karush-Kuhn-Tucker (KKT) conditions of *Problem 7* are represented as (21) shown at the bottom of this page.

$$L(\boldsymbol{c}, p_0, \xi) = \sum_{i=1}^{N}\left((1+\eta_i) - \frac{c(\hat{g}_i - \epsilon_i)^{-\alpha} I_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) - u_0(p_0 - \bar{p}_0) + \xi\left[\frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N} p_i(\hat{g}_i - \epsilon_i)^{-\alpha} + \sigma^2} - \left(e^{R^{\min}} - 1\right)\right]. \tag{20}$$

From (21)(a), it is easy to obtain that $\xi > 0$. Therefore, the power p_0 can be determined by (21)(b) shown at the bottom of this page, that is

$$p_0(\boldsymbol{p}) = \frac{\left(e^{R^{\min}} - 1\right)\left(\sum_{i=1}^{N} p_i(\hat{g}_i - \epsilon_i)^{-\alpha} + \sigma^2\right)}{(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}. \tag{22}$$

By replacing p_i with the obtained optimal power from (13) in the above equality, the formulation of p_0 with respect to c is derived as

$$p_0(\boldsymbol{c}) = H\sum_{i=1}^{N}\left(\frac{1+\eta_i}{c} - \frac{(\hat{g}_i - \epsilon_i)^{-\alpha}\tilde{I}_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) + H\sigma^2 \tag{23}$$

where $\tilde{I}_i(\boldsymbol{p}_{-i}) = \sum_{j\neq i} p_j(\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha} + \sigma^2$. $H = \frac{e^{R^{\min}} - 1}{(\hat{h}_{0,0}+\epsilon_0)^{-\alpha} + \left(e^{R^{\min}}-1\right)\sum_{i=1}^{N}\frac{(\hat{g}_i-\epsilon_i)^{-\alpha}(\hat{h}_i-\epsilon_i)^{-\alpha}}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}}$.

By substituting (23) into the formula (13), it can also obtain the formulation of p_i as function of the only variable c as (24) shown at the bottom of this page, where $\tilde{I}_i^*(\boldsymbol{p}_{-i}) = \sum_{j\neq i} p_j^*(\hat{g}_{i,j} - \epsilon_{i,j})^{-\alpha} + \sigma^2$.

The values of p_0 and p_i in (23) and (24) respectively are put into the objective function (19), then *Problem 7* can be rewritten as (25) shown at the bottom of this page.

Theorem 3: The NE of the Stackelberg game is unique.

Proof: According to (25), it is evident that $U_0(\boldsymbol{c})$ is a continuous function of c. It can be proved the second-order derivative of $U_0(\boldsymbol{c})$ with respect to c is always less than 0. Accordingly, $U_0(\boldsymbol{c})$ in *Problem 7* is a concave function with respect to c. Hence, there exists an NE in the game.

Since the objective function above is a concave function, the optimal price can be calculated by solving $\frac{\partial U_0(\boldsymbol{c})}{\partial c} = 0$. Thus, the optimum solution of *Problem 8* is (26), where $A_i^* = \frac{(\hat{g}_i-\epsilon_i)^{-\alpha}\tilde{I}_i^*(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}$. Furthermore, the iterative formula of interference price can be acquired. As the proof is similar as the one in Theorem 2, the interference price can converge to a unique fixed point. Therefore, the proposed Stackelberg game between MBS and FUEs exists an unique NE. ■

$$c^* = \sqrt{\frac{u_0 H\sum_{i=1}^{N}(1+\eta_i)}{\sum_{i=1}^{N} A_i^* + \sum_{i=1}^{N}\frac{(\hat{g}_i-\epsilon_i)^{-\alpha}(\hat{h}_i-\epsilon_i)^{-\alpha}H}{(\hat{g}_{i,i}-\epsilon_{i,i})^{-\beta}}\left(\sigma^2 - \sum_{i=1}^{N} A_i^*\right)}}. \tag{26}$$

V. Algorithm Design

A. Dynamic Power Allocation and Pricing Algorithm

The detailed procedure of the proposed power allocation and price strategy for the case that the number of FUEs keeps unchanged is given in Algorithm 1.

Theorem 4: Algorithm 1 is used to change the tolerable interference threshold by regulating the power of MUE when $\Gamma < \max_i Y_i\sum_{i=1}^{N}(1+\eta_i) - \sum_{i=1}^{N} Y_i$, where $\Gamma = \frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{e^{R^{\min}}-1} - \sigma^2$ denotes the maximum tolerable interference, $Y_i = \frac{(\hat{g}_i-\epsilon_i)^{-\alpha}I_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}$.

$$\begin{cases} \dfrac{\partial L(\boldsymbol{c}, p_0, \xi)}{\partial p_0} = -\sum_{i=1}^{N}\dfrac{c(\hat{h}_i-\epsilon_i)^{-\alpha}(\hat{g}_i-\epsilon_i)^{-\alpha}}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}} - u_0 + \dfrac{\xi(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N}\left(\frac{1+\eta_i}{c} - \frac{I_i(\boldsymbol{p}_{-i})(\hat{g}_i-\epsilon_i)^{-\alpha}}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) + \sigma^2} = 0 & (a) \\ \xi\left[\dfrac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N} p_i(\hat{g}_i-\epsilon_i)^{-\alpha} + \sigma^2} - \left(e^{R^{\min}}-1\right)\right] = 0 \quad (\xi \geq 0) & (b) \end{cases} \tag{21}$$

$$p_i^*(\boldsymbol{c}) = \left[\frac{1+\eta_i}{c(\hat{g}_i-\epsilon_i)^{-\alpha}} - \frac{\tilde{I}_i^*(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}} - \frac{(\hat{h}_i-\epsilon_i)^{-\alpha}H}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\sum_{i=1}^{N}\left(\frac{1+\eta_i}{c} - \frac{(\hat{g}_i-\epsilon_i)^{-\alpha}\tilde{I}_i^*(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) - \frac{(\hat{h}_i-\epsilon_i)^{-\alpha}H\sigma^2}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right]^+ \tag{24}$$

Problem 8:

$$\max_{c>0} \quad U_0(\boldsymbol{c}) = \sum_{i=1}^{N}\left[(1+\eta_i) - \frac{c(\hat{g}_i-\epsilon_i)^{-\alpha}\tilde{I}_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}} - \frac{(\hat{g}_i-\epsilon_i)^{-\alpha}(\hat{h}_i-\epsilon_i)^{-\alpha}H}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\left(\sum_{i=1}^{N}\left((1+\eta_i) - \frac{c(\hat{g}_i-\epsilon_i)^{-\alpha}\tilde{I}_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) + c\sigma^2\right)\right] - u_0 H\left(\sum_{i=1}^{N}\left(\frac{(1+\eta_i)}{c} - \frac{(\hat{g}_i-\epsilon_i)^{-\alpha}\tilde{I}_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right) + \sigma^2\right) \tag{25}$$

Algorithm 1: Dynamic Power Allocation and Pricing Algorithm.

```
Initialize: p_i > 0, c > 0, p_0 > 0, η_i^(1) > 0, y_1^(1) > 0.
while p_i and c are not converged do
  repeat
    For ∀i ∈ I = {1, 2, ..., N}, FUE i receives the
    uniform interference price from MBS. Then, FUE i
    computes p_i^(t+1) according to the (24).
    Multiplier η_i^(t+1) is computed according to (12).
    And y_1^(t+1) = y_1^(t) / t.
    The MBS receives the feedback information from
    FUEs and computes the price according to (26).
    p_0^(t+1) is computed according to (23).
    Let t = t + 1.
  until ||p_i^(t+1) − p_i^(t)||_∞ ≤ ε and ||c^(t+1) − c^(t)||_∞ ≤ ε
end while
```

Proof: For $c > 0, \zeta > 0$, according to KKT conditions, from *Problem 7*, we can get

$$\zeta\left[\frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N} p_i(\hat{g}_i-\epsilon_i)^{-\alpha}+\sigma^2}-\left(e^{R^{\min}}-1\right)\right]=0. \tag{27}$$

Replacing the value of p_i from (13) in (27), we obtain $\sum_{i=1}^{N}\left[\frac{1+\eta_i}{c}-Y_i\right]-\Gamma=0$. Replacing the value of c from (35), we can acquire $\sqrt{\zeta\sum_{i=1}^{N}(1+\eta_i)}=\frac{\sum_{i=1}^{N}(1+\eta_i)\sum_{i=1}^{N}\sqrt{Y_i}}{\sum_{i=1}^{N}Y_i+\Gamma}$. Then, we can get

$$c=\frac{\sum_{i=1}^{N}(1+\eta_i)}{\sum_{i=1}^{N}Y_i+\Gamma}. \tag{28}$$

It can be known that condition (14) can guarantee the communication of each FUE. Replacing the value of c from (28) in (14), it can be obtained

$$\Gamma>\frac{\max_i Y_i\sum_{i=1}^{N}(1+\eta_i)}{1+\eta_i}-\sum_{i=1}^{N}Y_i \tag{29}$$

where $\max_i Y_i=\max\{Y_i\}\ \forall i\in\mathcal{I}$. On the contrary, when $\Gamma<\frac{\max_i Y_i\sum_{i=1}^{N}(1+\eta_i)}{1+\eta_i}-\sum_{i=1}^{N}Y_i$, there exists no FUE which can communicate in the network. Thus Algorithm 1 is used to change the tolerable interference threshold by regulating the power of MUE. Then the power of FUEs are redistributed for being accommodated. ∎

B. Fixed Power Allocation and Pricing Algorithm

In indoor environment, the number of users varies, it is natural in practice because FUEs may leave or join femtocells at any time. Therefore, we propose a flexible MUE power adjustment algorithm in this article, aiming at accommodating the dynamic of FUEs and guaranteeing the QoS of FUEs, at the same time, reducing the energy consumption of MUE.

In dynamic power allocation and pricing algorithm, the transmission power of MUE p_0 is taken as a variable, and is solved in *Problem 1*. However, in fixed power allocation and pricing algorithm, p_0 is set as a fixed value, the component $u_0(p_0-\bar{p}_0)$ in objective function can be ignored. Thus, the problem for MBS is simplified and reformulated as follows:

$$\max_{c>0,p_0>0}\quad U_0(\boldsymbol{c},\boldsymbol{p},p_0)=\sum_{i=1}^{N}cp_i(\hat{g}_i-\epsilon_i)^{-\alpha}$$
$$\text{s.t.}\begin{cases}\frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N}p_i(\hat{g}_i-\epsilon_i)^{-\alpha}+\sigma^2}\geq e^{R^{\min}}-1\\ \text{Eq. (20)}\end{cases}. \tag{30}$$

It can be observed that the above problem is a convex optimization problem. It can be solved by constructing a Lagrangian function which is presented as (31), where ζ is the Lagrange multiplier

$$L(\boldsymbol{c},\zeta)=\sum_{i=1}^{N}\left((1+\eta_i)-\frac{c(\hat{g}_i-\epsilon_i)^{-\alpha}I_i(\boldsymbol{p}_{-i})}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}\right)+\zeta\left[\frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N}p_i(\hat{g}_i-\epsilon_i)^{-\alpha}+\sigma^2}-\left(e^{R^{\min}}-1\right)\right]. \tag{31}$$

The dual problem of (31) is formulated as

$$\min_{\zeta\geq 0}\quad f(\zeta)=\min_{\zeta\geq 0}\max_{\boldsymbol{c}}\quad L(\boldsymbol{c},\zeta). \tag{32}$$

Problem (32) is convex, and the subgradient method is utilized to solve this problem. The subgradient of this dual function $f(\zeta)$ is

$$H_\zeta=\frac{\partial f(\zeta)}{\partial\zeta}=\frac{p_0(\hat{h}_{0,0}+\epsilon_0)^{-\alpha}}{\sum_{i=1}^{N}p_i(\hat{g}_i-\epsilon_i)^{-\alpha}+\sigma^2}-\left(e^{R^{\min}}-1\right). \tag{33}$$

Consequently, the Lagrange multiplier ζ is updated as

$$\zeta(t+1)=\left[\zeta(t)-y_2(t)H_\zeta\right]^+ \tag{34}$$

where $[X]^+=\max\{0,X\}$, y_2 is the positive step size.

On account of KKT conditions, the optimal interference price is calculated by $\frac{\partial L(\boldsymbol{c},\zeta)}{\partial c}=0$. Hence c^* can be determined according to (35), and the pricing algorithm with fixed power is shown in Algorithm 2

$$c^*=\sqrt{\frac{\zeta\sum_{i=1}^{N}(1+\eta_i)}{\sum_{i=1}^{N}\frac{(\hat{g}_i-\epsilon_i)^{-\alpha}}{(\hat{g}_{i,i}+\epsilon_{i,i})^{-\beta}}I_i(\boldsymbol{p}_{-i})}}. \tag{35}$$

Remark 1: In the proposed scheme, the tolerable interference of MUE is treated as a kind of available resource, a Stackelberg game model between MUE and FUEs is established with pricing mechanism. The proposed algorithms are adaptive for dynamic FUEs. MUE does not need to regulate its power to fit FUEs, while the transmission powers of FUEs are updated according to their corresponding interference prices. In this scenario, Algorithm 2 is used. When the requirements of FUEs cannot be satisfied by pricing mechanism, e.g., some FUEs join or leave femtocells, MUE adjusts its power to coordinate with FUEs. In this case, Algorithm 1 is used.

TABLE I
SYSTEM PARAMETERS

Variable	N	R_m	R_f	p_i^{max}	α	β
Value	10	300 m	10 m	0.5 Watt	3.7	3
Variable	σ^2	λ_i	κ_i	u_0	c	D^{th}
Value	10^{-12} dB	200 packets/s	100 bits	0.1	1000	0.01 s

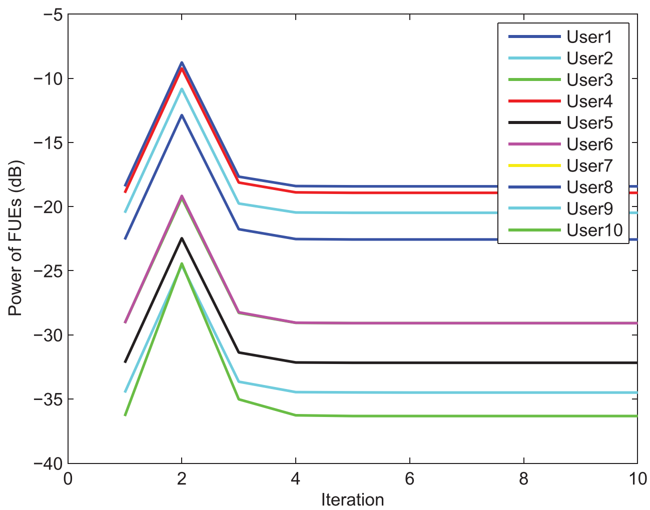

Fig. 2. FUEs' power under dynamic power allocation.

Algorithm 2: Fixed Power Allocation and Pricing Algorithm.

1: Initialize: $(p_i, c, \eta_i^{(1)}, \zeta^{(1)}, y_1^{(1)}, y_2^{(1)}) > 0$.
2: **while** p_i and c are not converged **do**
3:   **repeat**
4:     For $\forall i \in \mathcal{I} = \{1, 2, \ldots, N\}$, FUE i receives the uniform interference price from MBS. Then, FUE i computes $p_i^{(t+1)}$ according to the (24).
5:     Multiplier $\eta_i^{(t+1)}$ is computed according to (12). And $y_1^{(t+1)} = \frac{y_1^{(t)}}{t}$.
6:     The MBS receives the feedback information from FUEs, and updates the price according to (35).
7:     Multiplier $\zeta^{(t+1)}$ is computed according to (34). And $y_2^{(t+1)} = \frac{y_2^{(t)}}{t}$.
8:     Let $t = t + 1$.
9:   **until** $\|p_i^{(t+1)} - p_i^{(t)}\|_\infty \leq \epsilon$ and $\|c^{(t+1)} - c^{(t)}\|_\infty \leq \epsilon$
10: **end while**

VI. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

In the simulation, MUE and FUEs are randomly distributed. Referring to [15], [18], the parameters are given in Table I.

A. Simulation under Dynamic Power Allocation

In this part, we test the performance under dynamic power allocation algorithm, where the transmission power of MUE is regulated with the change of interference price. There is one MBS and $N = 10$ FBSs in the network. Considering the uncertainty of distance, the transmission distances vary within a certain interval, $\pm 5\%$ around each measured value. Fig. 2 illustrates the convergence of FUEs' powers under the proposed algorithm. It can be seen that the power of each FUE converges in several iterations. Fig. 3 demonstrates that the power of MUE converges quickly as $Y^{th} = 0.5$, 1.0, and 1.5 bps/Hz, respectively. As shown in the figure, MUE' power for higher transmission rate requirement, i.e., $Y^{th} = 1.5$ bps/Hz, is higher than the one for the lower rate requirement. This is because with higher transmission rate requirement, MUE needs more power to meet higher SINR demand. Similarly, the convergence of price is shown in Fig. 4.

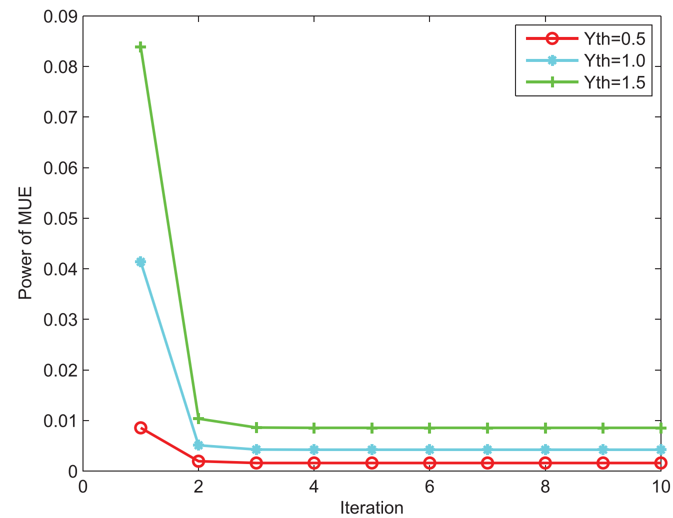

Fig. 3. MUE's power under dynamic power allocation.

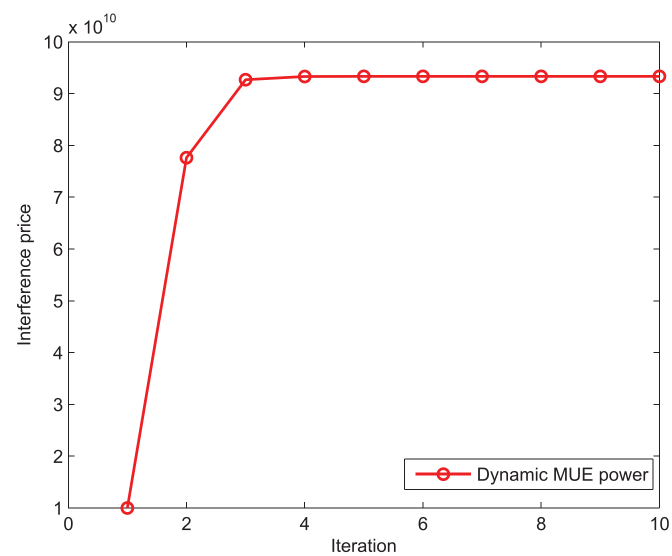

Fig. 4. Price under dynamic power allocation.

B. Simulation With Fixed Power Allocation

We analyze the performance under fixed power allocation algorithm. From Fig. 5, it is observed that the power of each FUE converges to an equilibrium. The convergence of price is shown in Fig. 6, where the prices vary with the changing transmission rate requirement Y^{th}. The higher prices are taken

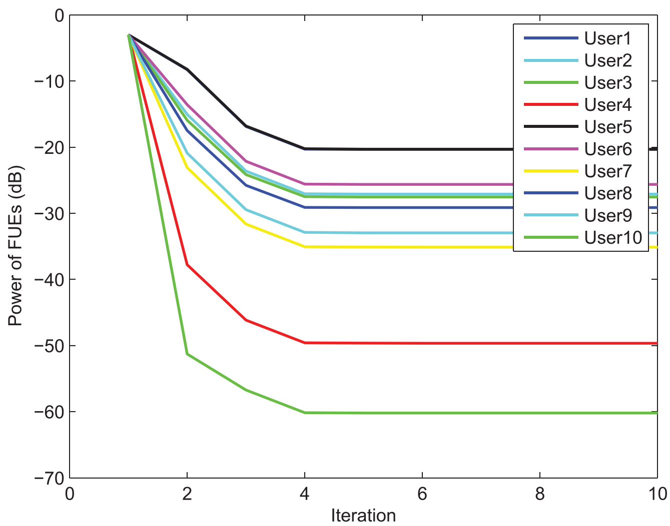

Fig. 5. FUEs' power under fixed power allocation.

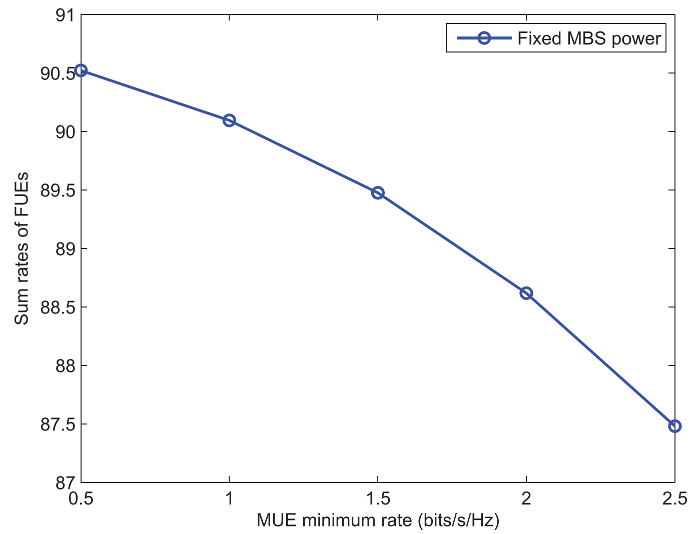

Fig. 7. FUEs' total transmission rate under fixed allocation.

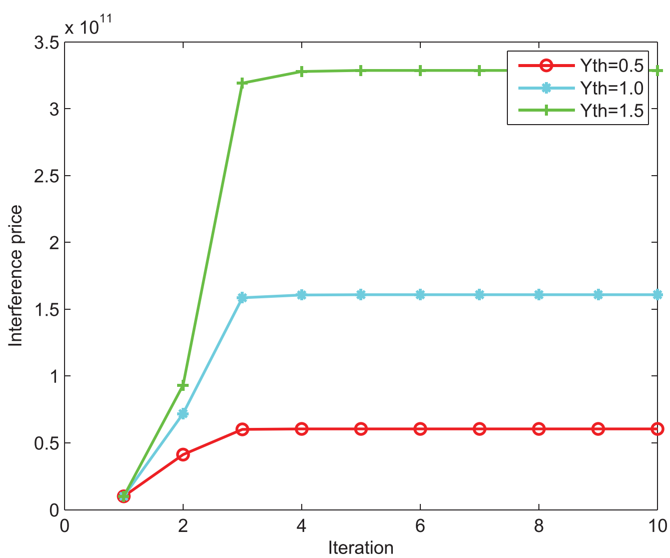

Fig. 6. Price under fixed power allocation.

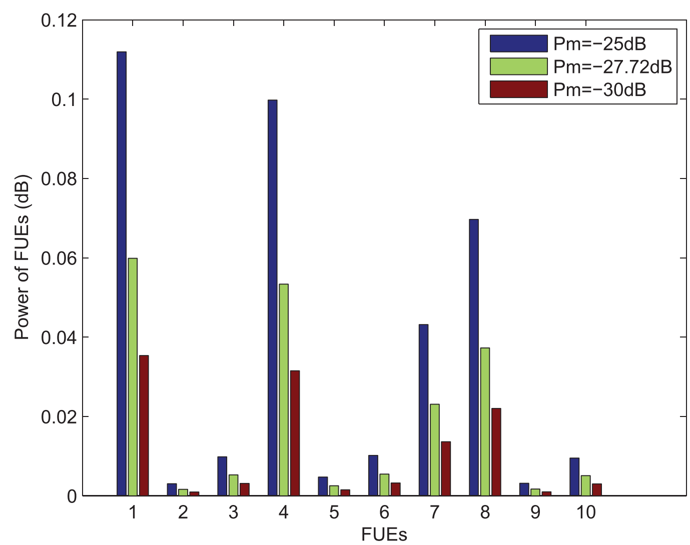

Fig. 8. FUEs' powers under different MUE's powers.

with increasing Y^{th}, because the total suffered interference of MBS is reduced when the transmission rate requirement increases. So MBS needs to charge more to maximize its utility.

It is found from Fig. 7 that total transmission rate of FUEs decrease with the increase of MUE's transmission rate requirement. The total utility of FUEs also show the same tendency, which is omitted due to the space limit. Higher MUE's transmission rate requirement causes higher interference price, resulting in the increase of FUEs' costs. And fewer FUEs are willing to share the spectrum resource of MBS. In Figs. 8 and 9, the performance of FUEs are presented with different powers of MUE. Under the same topology of Algorithm 1, it can be obtained the optimal transmission power of MUE is $P_m = -27.72$ dB. At the same time, the fixed transmission powers $P_m = -25$ dB and $P_m = -30$ dB are chosen to make a comparative analysis. The value of P_m is selected for the purpose of normal operation of FUE devices. It is shown in Fig. 8 that the transmission power of FUEs are higher with the increase of P_m. When $P_m = -25$ dB, the maximum transmission power of FUEs are obtained. In Fig. 9, it is found that the utilities of FUEs are not significantly different, which indicates that if MUE transmits with its optimal power, the communication rate of FUEs can be guaranteed as much as possible alongside the tradeoff between energy consumption and transmission rate.

C. Simulations With MUE Power Adjustment

In this scenario, the number of FBS does not change frequently, Algorithm 2 is used to allocate transmission power and interference price of FUEs. When FUEs joins in the femtocell or FBSs access the macrocell, the tolerable interference of MBS

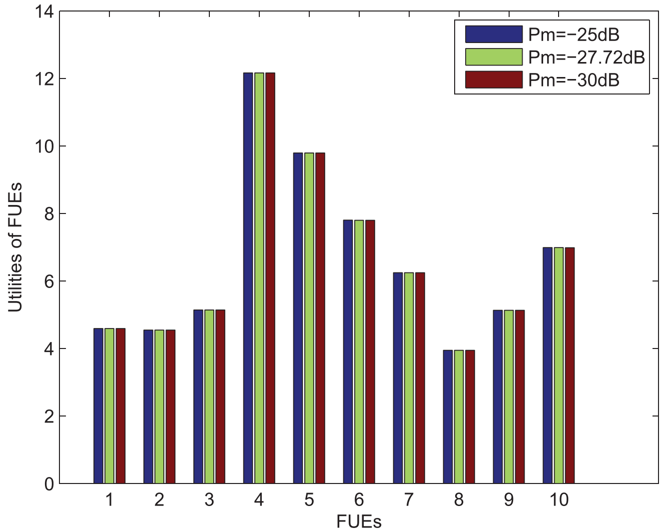

Fig. 9. FUEs' utilities under different MUE's powers.

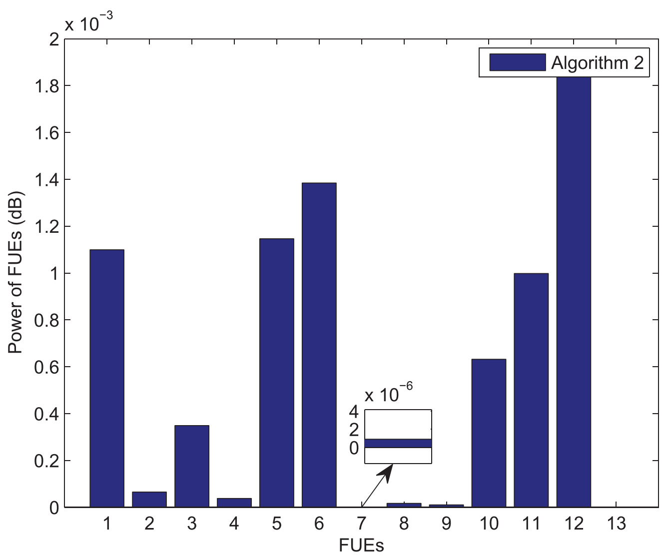

Fig. 10. FUE power in algorithm 2.

would exceed the threshold. Hence, the power of MUE p_0 should be regulated to adjust the interference threshold.

In this part, the simulations are given where there are three new FBSs accessing to the network. At first, Algorithm 2 is used under fixed transmission power $P_m = -20$ dB to allocate powers of FUEs. The values of Γ and $\max_i Y_i \sum_{i=1}^{N}(1+\eta_i) - \sum_{i=1}^{N} Y_i$ are computed as $2.3641e^{-11}$ and $3.3377e^{-10}$, respectively. It is evident that $\Gamma < \max_i Y_i \sum_{i=1}^{N}(1+\eta_i) - \sum_{i=1}^{N} Y_i$. In Fig. 10, the transmission powers of FUEs are provided. It can be seen that the power of FUE 13 is zero, that means FUE 13 cannot work. Therefore, Algorithm 1 is switched to reallocate the powers of FUEs by regulating the power of MUE. In Fig. 11, the powers of FUEs after MUE power adjustment are indicated. It is found that the transmission powers of FUEs are reduced.

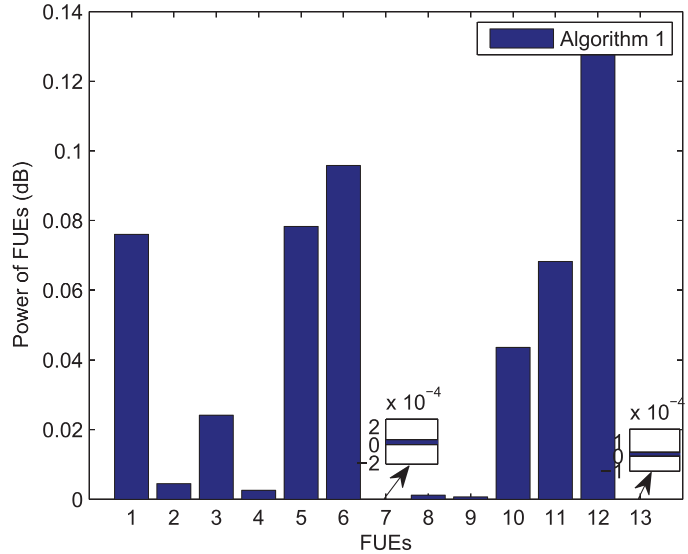

Fig. 11. FUE power in Algorithm 1.

VII. Conclusion

In this article, the proposed power control scheme improved data transmission and guaranteed the relay requirement, thus enhancing the QoS of blockchain-based mobile applications. Mobile users were able to query a transaction in time and optimization of power enabled miners to validate blocks with lower energy consumption. A Stackelberg game was modeled to analyze the behaviors between MBS and FUEs. The MBS set interference prices to FUEs to maximize its utility and guarantee its transmission rate requirement. Based on the interference prices, FUEs determined their powers to optimize their utilities subject to the delay constraint. The proposed robust power allocation and pricing problem with distance uncertainty was addressed using a worst-case method. Furthermore, two algorithms were designed by considering the dynamics of FUEs.

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