Resource Allocation for Mobile Data Offloading Through Third-Party Cognitive Small Cells

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Abstract. Mobile data offloading is considered as an effective way to solve the network overloading issue. In this paper, we study the mobile data offloading problem through a third-party cognitive small cell providing data offloading service to a macrocell. Particularly, four scenarios, namely, successive interference cancellation (SIC) available at neither the macrocell base station (MBS) nor the small cell BS (SBS), SIC available at both the MBS and the SBS, SIC available at only the MBS, and SIC available at only the SBS are considered. For all the four scenarios, iterative optimization based data offloading schemes are proposed. We show that the proposed data offloading schemes outperform the corresponding schemes without data offloading. We also show that equipping SIC at the SBS is more beneficial compared to equipping SIC at the MBS.

Keywords: Cognitive radio · Mobile data offloading
Successive interference cancellation

1 Introduction

Mobile phones and wireless mobile communications are developing very rapidly in recent years. The unprecedented increase in mobile data traffic has created many challenges for cellular networks, such as the network overloading issue. Mobile users in overloaded cellular networks will undergo degraded mobile services, such as high call blocking probability and low data rate. In this respect, mobile data offloading is an effective method to solve the network overloading issue by offloading part of the data traffic load off the main cellular networks [5].

This work was supported by the National Science and Technology Major Project of China (Grant No. 2017ZX03001008), the Postdoctoral Research Plan of Jiangsu Province (Grant No. 1701167B), the Postdoctoral Science Foundation of China (Grant No. 2017M621795), the NUPTSF (Grant Nos. NY218007 and NY218026), and the NSF of Jiangsu Province (Grant No. BK20160900).

X. Liu et al. (Eds.): ChinaCom 2018, LNICST 262, pp. 438–447, 2019.
https://doi.org/10.1007/978-3-030-06161-6_43

So far, small cells and WiFi are the preferred candidates for data offloading and have attracted a lot of attention [1]. For data offloading through small cells, the work in [7] proposed a two-level offloading scheme that takes the network load and interference conditions into account in small cell networks, the work in [8] proposed a learning mechanism based fair auction scheme for data offloading in small cell networks, and the work in [9] proposed an optimal energy efficient offloading scheme based on the auction theory. For data offloading through WiFI, the work in [3] proposed a network-assisted user-centric WiFi offloading scheme in a heterogeneous network, the work in [6] analyzed the efficiency of the opportunistic and the delayed WiFi offloading schemes, and the work in [4] jointly considered the problem of base station (BS) switching, resource allocation and data offloading.

Meanwhile, the concept of cognitive radio (CR) has been proposed to address the conflict between spectrum scarcity and low spectrum utilization [2]. The CR allows the secondary users with no licensed spectrum band to access the spectrum band licensed to the primary users under the condition that the QoS of the primary users is guaranteed. By adopting the concept of CR, we propose to use third-party cognitive small cells with no licensed spectrum band to offload data traffic from macrocells with licensed spectrum band and at the same time gain transmission opportunities for cognitive small cells. The advantages of data offloading through third-party cognitive small cells are three fold: (1) There is no extra cost for building small cell infrastructures to support data offloading as these small cells are third-party; (2) The throughput of the macrocells can be improved as long as the QoS of data offloading is guaranteed by the cognitive small cells; (3) The third-party cognitive small cells can use the remaining resources from the macrocells to let their own users transmit information.

Therefore, this paper considers the data offloading scenario where a third-party cognitive small cell provides data offloading service to a macrocell. The transmission time is assumed to consist of two slots, where the first time slot is for macrocell user transmission and the second time slot is for small cell user transmission. The resource allocation problem for data offloading through such a third-party cognitive small cell is investigated. Particularly, we consider four scenarios, namely, successive interference cancellation (SIC) available at neither the macrocell BS (MBS) nor the small cell BS (SBS), SIC available at both the MBS and the SBS, SIC available at only the MBS, and SIC available at only the SBS. For all the four scenarios, we propose iterative optimization based data offloading schemes to maximize the sum rate of the small cell UEs (SUEs) subject to the required minimum sum rate of the macrocell UEs (MUEs). Simulation results are given to verify our proposed data offloading schemes.

2 System Model

This paper considers an uplink macrocell network with M MUEs served by a MBS, which is licensed with a narrow spectrum band for data communication. We assume that there is an uplink small cell network with K SUEs served by a SBS, which is in the coverage area of the MBS and is not licensed with any spectrum band for data communication. Since some MUEs may be near the SBS and far from the MBS, it is better to direct these MUEs to be served by the SBS. To reward the small cell network for data offloading, it can use the spectrum licensed to the macrocell network for its own purpose under the condition that the performance of the macrocell network is guaranteed.

We assume that all the channels are block-fading, i.e., the channel power gains are constant in each transmission block and change independently. The channel power gains from the MUE m to the MBS, from the SUE k to the SBS, and from the MUE m to the SBS are denoted by h_m^p, h_k^s and h_m^{ps}, respectively. The transmission time for each transmission block is denoted by T. We assume that the total transmission time is divided into two slots. The first time slot is for MUE data communication with time τ_1, while the second time slot is for SUE data communication with time τ_2. Thus, we have $\tau_1 + \tau_2 \leq T$. Let p_m^p and p_k^s denote the transmit powers of the MUE m and the SUE k, respectively. The transmit powers of the MUEs and the SUEs are restricted as $p_m^p \leq P_{max}^p$ and $p_k^s \leq P_{max}^s$, respectively for $m = 1, \ldots, M$, $k = 1, \ldots, K$. Let $\alpha_m \in \{0, 1\}$ and $\beta_m \in \{0, 1\}$ denote whether the MUE m is connected to the MBS and the SBS, respectively. Specifically, $\alpha_m = 1$ denotes that the MUE m is connected to the MBS and vice versa, while $\beta_m = 1$ denotes that the MUE m is connected to the SBS and vice versa. Since each MUE is assumed to be able to connect either the MBS or the SBS, we have $\alpha_m + \beta_m \leq 1$, for $m = 1, \ldots, M$.

In this paper, we assume that the performance of the macrocell network is guaranteed by satisfying the required minimum sum rate of the MUEs, given by $R_p(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \geq R_{min}$, where $R_p(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p)$ is the sum rate of the MUEs connected to the MBS, $R_{ps}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ is the sum rate of the MUEs offloaded to the SBS, $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_M]^T$, $\boldsymbol{\beta} = [\beta_1, \ldots, \beta_M]^T$, and $\boldsymbol{p}^p = [p_1^p, \ldots, p_M^p]^T$. Our aim is to maximize the sum rate at the SBS denoted by $R_s(\tau_2, \boldsymbol{p}^s)$, where $\boldsymbol{p}^s = [p_1^s, \ldots, p_K^s]^T$. The exact expression of the sum rate depends on whether SIC decoder is available at the MBS or the SBS. If SIC decoder is not available at the MBS, the sum rate of the MUEs connected to the MBS can be written as

$$R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) = \frac{\tau_1}{T} \sum_{m=1}^{M} \ln\left(1 + \frac{\alpha_m p_m^p h_m^p}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \alpha_{m'} p_{m'}^p h_{m'}^p}\right), \tag{1}$$

where σ^2 is the background noise power. If SIC decoder is not available at the SBS, the sum rate of the MUEs connected to the SBS and the sum rate of the SUEs can be written as

$$R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) = \frac{\tau_1}{T} \sum_{m=1}^{M} \ln\left(1 + \frac{\beta_m p_m^p h_m^{ps}}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \beta_{m'} p_{m'}^p h_{m'}^{ps}}\right), \tag{2}$$

and

$$R_s^{NSIC}(\tau_2, \boldsymbol{p}^s) = \frac{\tau_2}{T} \sum_{k=1}^{K} \ln\left(1 + \frac{p_k^s h_k^s}{\sigma^2 + \sum_{k'=1, k' \neq k}^{K} p_{k'}^s h_{k'}^s}\right), \tag{3}$$

respectively. If SIC decoder is available at the MBS and the SBS, the sum rate of the MUEs connected to the MBS, the sum rate of the MUEs connected to the SBS and the sum rate of the SUEs can be written respectively as

$$R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) = \frac{\tau_1}{T} \ln\left(1 + \frac{\sum_{m=1}^{M} \alpha_m p_m^p h_m^p}{\sigma^2}\right), \tag{4}$$

$$R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) = \frac{\tau_1}{T} \ln\left(1 + \frac{\sum_{m=1}^{M} \beta_m p_m^p h_m^{ps}}{\sigma^2}\right), \tag{5}$$

$$R_s^{SIC}(\tau_2, \boldsymbol{p}^s) = \frac{\tau_2}{T} \ln\left(1 + \frac{\sum_{k=1}^{K} p_k^s h_k^s}{\sigma^2}\right). \tag{6}$$

Depending on whether SIC decoder is available at the MBS or the SBS, we can study the resource allocation for data offloading in four cases.

3 Resource Allocation Schemes

3.1 Without SIC Decoders at the MBS and the SBS

In this subsection, we investigate the case when SIC decoders are not available at the MBS and the SBS. The optimization problem is formulated as

$$\max_{\tau_1,\tau_2,\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{p}^p,\boldsymbol{p}^s} R_s^{NSIC}(\tau_2, \boldsymbol{p}^s) \tag{7}$$

$$\text{s.t.}\ \tau_1 + \tau_2 \leq T, \tau_1 \geq 0, \tau_2 \geq 0, \tag{8}$$

$$\alpha_m \in \{0,1\}, \beta_m \in \{0,1\}, m = 1,\ldots,M, \tag{9}$$

$$\alpha_m + \beta_m \leq 1, m = 1,\ldots,M, \tag{10}$$

$$0 \leq p_m^p \leq P_{max}^p, m = 1,\ldots,M, \tag{11}$$

$$0 \leq p_k^s \leq P_{max}^s, k = 1,\ldots,K, \tag{12}$$

$$R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \geq R_{min}. \tag{13}$$

The problem in (7) is highly nonlinear and nonconvex. We solve the problem in (7) by optimizing τ_1, τ_2 with given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, optimizing $\boldsymbol{\alpha}, \boldsymbol{\beta}$ with given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, and optimizing $\boldsymbol{p}^p, \boldsymbol{p}^s$ with given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$.

With given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, we optimize τ_1, τ_2 by maximizing $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (8) and (13). It is easy to observe that a larger value of τ_2 can lead to a larger objective function value. Thus, according to the constraints (8) and (13), the optimal τ_2 is given by $\tau_2^* = T - \tau_1^*$, where the value of τ_1^* is achieved when the constraint (13) is satisfied at equality and is given by

$$\tau_1^* = R_{min} T \left(\sum_{m=1}^{M} \ln\left(1 + \frac{\alpha_m p_m^p h_m^p}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \alpha_{m'} p_{m'}^p h_{m'}^p}\right) \right.$$
$$\left. + \ln\left(1 + \frac{\beta_m p_m^p h_m^{ps}}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \beta_{m'} p_{m'}^p h_{m'}^{ps}}\right)\right)^{-1}. \tag{14}$$

With given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, we optimize $\boldsymbol{\alpha}, \boldsymbol{\beta}$ by maximizing $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (9), (10) and (13). It is observed that $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ does not depend on $\boldsymbol{\alpha}, \boldsymbol{\beta}$. Considering the fact that a smaller τ_1 leads to a higher $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$, we optimize $\boldsymbol{\alpha}, \boldsymbol{\beta}$ by maximizing $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ subject to the constraints (9) and (10). If the obtained $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ is smaller than R_{min}, then the original problem is infeasible. Since such problem is hard to be solved, we propose a heuristic scheme to solve it. The values of $\boldsymbol{\alpha}, \boldsymbol{\beta}$ are initialized as $\alpha_m = 0, \beta_m = 0$ for all $m = 1, \ldots, M$. Then, we sequentially set $\alpha_m = 1$ or $\beta_m = 1$ by selecting the one that provides higher value of $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$.

With given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$, we optimizing $\boldsymbol{p}^p, \boldsymbol{p}^s$ by maximizing $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (11), (12) and (13). Such problem can be solved by solving the following two subproblems as given by

$$\begin{aligned} &\max_{\boldsymbol{p}^s} R_s^{NSIC}(\tau_2, \boldsymbol{p}^s) \\ &\text{s.t. constraint (12)}, \end{aligned} \tag{15}$$

and

$$\begin{aligned} &\max_{\boldsymbol{p}^p} R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \\ &\text{s.t. constraint (11)}. \end{aligned} \tag{16}$$

If the obtained $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ from solving the problem in (16) is smaller than R_{min}, then the original problem is infeasible. We solve the problems in (15) and (16) by iteratively optimizing one variable with other variables being fixed. First, we solve the problem in (15). With given $p_1^s, \ldots, p_{k-1}^s, p_{k+1}^s, \ldots, p_K^s$, the variable p_k^s is optimized by solving the problem

$$\max_{0 \le p_k^s \le P_{max}^s} f_k(p_k^s), \tag{17}$$

where

$$\begin{aligned} f_k(p_k^s) = &\ln\left(1 + \frac{p_k^s h_k^s}{\sigma^2 + \sum_{l=1, l\neq k}^K p_l^s h_l^s}\right) \\ &+ \sum_{k'=1, k'\neq k}^K \ln\left(1 + \frac{p_{k'}^s h_{k'}^s}{\sigma^2 + \sum_{l=1, l\neq k'}^K p_l^s h_l^s}\right). \end{aligned} \tag{18}$$

The first derivative of $f_k(p_k^s)$ can be obtained as

$$\frac{df_k(p_k^s)}{dp_k^s} = \frac{h_k^s}{\sigma^2 + \sum_{l=1}^K p_l^s h_l^s}\left(1 - \sum_{k'=1, k'\neq k}^K \frac{p_{k'}^s h_{k'}^s}{\sigma^2 + \sum_{l=1, l\neq k'}^K p_l^s h_l^s}\right). \tag{19}$$

It is seen that the first part of the above expression is positive and the second part is a strictly increasing function of p_k^s. Thus, the solution to $\frac{df_k(p_k^s)}{dp_k^s} = 0$ is unique and is denoted by $p_k^s = x_k$. If $x_k \leq 0$, then $f_k(p_k^s)$ is a monotonically increasing function of p_k^s and the solution to the problem in (17) is thus $p_k^s = P_{max}^s$. If $x_k \geq P_{max}^s$, then $f_k(p_k^s)$ is a monotonically decreasing function of p_k^s and the solution to the problem in (17) is thus $p_k^s = 0$. If $0 < x_k < P_{max}^s$, then $f_k(p_k^s)$ first decreases as p_k^s increases and turns to increase when p_k^s is beyond x_k, and the solution to the problem in (17) is thus $p_k^s = 0$ if $f_k(0) > f_k(P_{max}^s)$ and is $p_k^s = P_{max}^s$ otherwise. The problem in (16) can be solved similarly as the problem in (15) and we omit here for brevity.

3.2 With SIC Decoders at the MBS and the SBS

In this subsection, we investigate the case when SIC decoders are available at both the MBS and the SBS. The optimization problem is formulated as

$$\max_{\tau_1,\tau_2,\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{p}^p,\boldsymbol{p}^s} R_s^{SIC}(\tau_2, \boldsymbol{p}^s) \tag{20}$$

$$\text{s.t. } R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \geq R_{min}. \tag{21}$$

$$\text{and constraints (8)}-\text{(12)}$$

Similar to the problem in (7), we solve the problem in (20) by optimizing τ_1, τ_2 with given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, optimizing $\boldsymbol{\alpha}, \boldsymbol{\beta}$ with given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, and optimizing $\boldsymbol{p}^p, \boldsymbol{p}^s$ with given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$.

With given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, the variables τ_1, τ_2 are optimized by maximizing $R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (8) and (21). The optimal τ_2 is easily obtained as $\tau_2^* = T - \tau_1^*$, where the value of τ_1^* can be obtained as

$$\tau_1^* = \frac{R_{min} T}{\ln\left(1 + \frac{\sum_{m=1}^{M} \alpha_m p_m^p h_m^p}{\sigma^2}\right) + \ln\left(1 + \frac{\sum_{m=1}^{M} \beta_m p_m^p h_m^{ps}}{\sigma^2}\right)}. \tag{22}$$

With given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, the variables $\boldsymbol{\alpha}, \boldsymbol{\beta}$ are optimized by maximizing $R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (9), (10) and (21). We solve the problem by maximizing $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ subject to the constraints (9) and (10). If the obtained $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ is smaller than R_{min}, then the problem is infeasible. Similar to Sect. 3.1, a heuristic scheme can be proposed to optimize $\boldsymbol{\alpha}, \boldsymbol{\beta}$ and we omit it here for brevity.

With given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$, the variables $\boldsymbol{p}^p, \boldsymbol{p}^s$ are optimized by maximizing $R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (11), (12) and (21). It is observed that the problem can be solved by solving the following two subproblems as given by

$$\max_{\boldsymbol{p}^s} R_s^{SIC}(\tau_2, \boldsymbol{p}^s) \tag{23}$$

$$\text{s.t. constraint (12)},$$

and

$$\max_{\boldsymbol{p}^p} R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \tag{24}$$

$$\text{s.t. constraint (11)}.$$

It is noted that the original problem is infeasible if the obtained $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ from solving the problem in (24) is smaller than R_{min}. It can be verified that the objective functions in (23) and (24) are increasing functions of $\boldsymbol{p}^s$ and $\boldsymbol{p}^p$, respectively. Thus, the optimal solutions to the problems in (23) and (24) are $p_k^s = P_{max}^s$ and $p_m^p = P_{max}^p$, for $m = 1, \ldots, M$, $k = 1, \ldots, K$.

3.3 With SIC Decoder at the MBS

In this subsection, we investigate the case when SIC decoder is available only at the MBS. The optimization problem is formulated as

$$\max_{\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s} R_s^{NSIC}(\tau_2, \boldsymbol{p}^s) \tag{25}$$

$$\text{s.t. } R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \geq R_{min}. \tag{26}$$

$$\text{and constraints (8)}-(12)$$

Similar to the problem in (7), we solve the problem in (25) by optimizing τ_1, τ_2 with given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, optimizing $\boldsymbol{\alpha}, \boldsymbol{\beta}$ with given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, and optimizing $\boldsymbol{p}^p, \boldsymbol{p}^s$ with given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$.

With given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, the optimal τ_2 can be obtained as $\tau_2^* = T - \tau_1^*$, where the value of τ_1^* is obtained by

$$\tau_1^* = \frac{R_{min} T}{\ln\left(1 + \frac{\sum_{m=1}^{M} \alpha_m p_m^p h_m^p}{\sigma^2}\right) + \sum_{m=1}^{M} \ln\left(1 + \frac{\beta_m p_m^p h_m^{ps}}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \beta_{m'} p_{m'}^p h_{m'}^{ps}}\right)}. \tag{27}$$

With given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, the variables $\boldsymbol{\alpha}, \boldsymbol{\beta}$ are optimized by maximizing $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (9), (10) and (26). We solve the problem by maximizing $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ subject to the constraints (9) and (10), and if the obtained $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ is smaller than R_{min}, then the problem is infeasible. Similar to Sect. 3.1, a heuristic scheme can be proposed to solve the problem and we omit it here for brevity.

With given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$, the variables $\boldsymbol{p}^p, \boldsymbol{p}^s$ are optimized by maximizing $R_s^{NSIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (11), (12) and (26). The problem can be solved by solving the following two subproblems as given by

$$\max_{\boldsymbol{p}^s} R_s^{NSIC}(\tau_2, \boldsymbol{p}^s) \tag{28}$$

$$\text{s.t. constraint (12)},$$

and

$$\max_{\boldsymbol{p}^p} R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \tag{29}$$

$$\text{s.t. constraint (11)}.$$

It is noted that the original problem is infeasible if the obtained $R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{NSIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ from solving the problem in (29) is smaller than R_{min}. Since

$R_p^{SIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p)$ is an increasing functions of $\boldsymbol{p}^p$. Thus, the optimal p_m^p is given as $p_m^p = P_{max}^p$ for $m \in \{m|\alpha_m = 1, m = 1, \ldots, M\}$. For the optimal $\{p_k^s\}$ of the problem in (28) and the optimal $\{p_m^p, m \in \{m|\beta_m = 1, m = 1, \ldots, M\}\}$ of the problem in (29), we iteratively optimize one variable with other variables being fixed similar to that in Sect. 3.1, which we omit here for brevity.

3.4 With SIC Decoder at the SBS

In this subsection, we investigate the case when SIC decoder is available only at the SBS. The optimization problem is formulated as

$$\max_{\tau_1,\tau_2,\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{p}^p,\boldsymbol{p}^s} R_s^{SIC}(\tau_2, \boldsymbol{p}^s) \tag{30}$$

$$\text{s.t. } R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \geq R_{min}. \tag{31}$$

$$\text{and constraints (8)}-\text{(12)}$$

Similar to the problem in (7), we solve the problem in (30) by optimizing τ_1, τ_2 with given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, optimizing $\boldsymbol{\alpha}, \boldsymbol{\beta}$ with given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, and optimizing $\boldsymbol{p}^p, \boldsymbol{p}^s$ with given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$.

With given $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{p}^p, \boldsymbol{p}^s$, the optimal τ_2 can be obtained as $\tau_2^* = T - \tau_1^*$, where the value of τ_1^* is obtained by

$$\tau_1^* = \frac{R_{min} T}{\sum_{m=1}^{M} \ln\left(1 + \frac{\alpha_m p_m^p h_m^p}{\sigma^2 + \sum_{m'=1, m' \neq m}^{M} \alpha_{m'} p_{m'}^p h_{m'}^p}\right) + \ln\left(1 + \frac{\sum_{m=1}^{M} \beta_m p_m^p h_m^{ps}}{\sigma^2}\right)}. \tag{32}$$

With given $\tau_1, \tau_2, \boldsymbol{p}^p, \boldsymbol{p}^s$, the variables $\boldsymbol{\alpha}, \boldsymbol{\beta}$ are optimized by maximizing $R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (9), (10) and (31). The problem is solved by maximizing $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ subject to the constraints (9) and (10), and if the obtained $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ is smaller than R_{min}, then the problem is infeasible. Similar to Sect. 3.1, a heuristic scheme can be proposed to solve the problem and we omit it here for brevity.

With given $\tau_1, \tau_2, \boldsymbol{\alpha}, \boldsymbol{\beta}$, the variables $\boldsymbol{p}^p, \boldsymbol{p}^s$ are optimized by maximizing $R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ subject to the constraints (11), (12) and (31). The problem can be solved by solving the following two subproblems as given by

$$\max_{\boldsymbol{p}^s} R_s^{SIC}(\tau_2, \boldsymbol{p}^s) \tag{33}$$

$$\text{s.t. constraint (12)},$$

and

$$\max_{\boldsymbol{p}^p} R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p) \tag{34}$$

$$\text{s.t. constraint (11)}.$$

Noted that the original problem is infeasible if the obtained $R_p^{NSIC}(\tau_1, \boldsymbol{\alpha}, \boldsymbol{p}^p) + R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ from solving the problem in (34) is smaller than R_{min}. Since

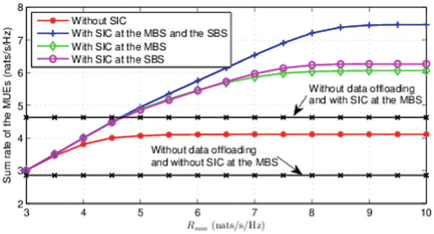

Fig. 1. Sum rate of the MUEs against R_{min}.

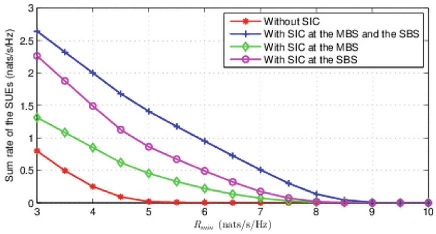

Fig. 2. Sum rate of the SUEs against R_{min}.

$R_s^{SIC}(\tau_2, \boldsymbol{p}^s)$ and $R_{ps}^{SIC}(\tau_1, \boldsymbol{\beta}, \boldsymbol{p}^p)$ are increasing functions of $\boldsymbol{p}^s$ and $\boldsymbol{p}^p$, respectively. Thus, the optimal p_k^s is given as $p_k^s = p_{max}^s$ and the optimal p_m^p is given as $p_m^p = P_{max}^p$ for $m \in \{m|\beta_m = 1, m = 1, \ldots, M\}$. For the optimal $\{p_m^p, m \in \{m|\alpha_m = 1, m = 1, \ldots, M\}\}$ of the problem in (34), we iteratively optimize one variable with other variables being fixed similar to that in Sect. 3.1, which we omit here for brevity.

4 Simulation Results

In this section, we verify the performance of the proposed data offloading schemes. The channels involved are assumed to follow Rayleigh fading with unit mean. In the following results, we set $\sigma^2 = 1$, $T = 1$, $M = 10$, $K = 10$, $P_{max}^p = 10\,\mathrm{W}$ and $P_{max}^s = 10\,\mathrm{W}$.

In Fig. 1, we illustrate the sum rate of the MUEs against the required minimum sum rate of the MUEs R_{min} for different data offloading schemes with or without SIC decoders at the MBS and/or the SBS. For the purpose of comparison, the results obtained from the schemes without data offloading are also given. It is observed that the proposed data offloading schemes can achieve the sum rate of the MUEs equal to R_{min} when R_{min} is not too high. When R_{min} is high, the achieved sum rates of the MUEs by the proposed schemes gradually saturate as R_{min} increases further. This is because that when R_{min} is high, the required minimum sum rate of the MUEs R_{min} will not be supported even if all the available time T is allocated for the MUE data communication with data offloading to the SBS. It is also observed that by choosing a proper large value of R_{min}, the proposed data offloading schemes can achieve much higher sum rate of the MUEs compared to the schemes without data offloading. In addition, it is observed that the sum rate of the MUEs achieved by the data offloading scheme with SIC at the SBS is higher than that achieved by the data offloading scheme with SIC at the MBS when R_{min} is high. This indicates that equipping a SIC decoder at the SBS is more beneficial for the MUEs compared to equipping a SIC decoder at the MBS. It is also observed that the sum rates of the MUEs achieved by the data offloading schemes with SIC at the MBS (or SBS) are always higher than that achieved by the data offloading schemes without SIC at the MBS (or SBS).

In Fig. 2, we illustrate the sum rate of the SUEs against the required minimum sum rate of the MUEs R_{min} for different data offloading schemes with or without SIC decoders at the MBS and/or the SBS. It is observed that the data offloading scheme without SIC achieves the lowest sum rate of the SUEs among the four data offloading schemes, while the data offloading scheme with SIC at the MBS and the SBS achieves the highest sum rate of the SUEs among the four data offloading schemes. It is also observed that the data offloading scheme with SIC at the SBS achieves higher sum rate of the SBS than that achieved by the data offloading scheme with SIC at the MBS. This indicates that equipping a SIC decoder at the SBS is more beneficial for the SUEs compared to equipping a SIC decoder at the MBS.

5 Conclusions

This paper investigates the mobile data offloading problem through a third-party cognitive small cell for a macrocell. By considering whether SIC is available at the MBS and/or the SBS, four scenarios are considered. For each scenario, iterative optimization based data offloading scheme is proposed. It is shown that the proposed data offloading schemes outperform the corresponding schemes without data offloading. It is also shown that equipping SIC at the SBS is more beneficial compared to equipping SIC at the MBS.

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