Macrocell Resource Adaptation for Improved Femtocell Deployment and Interference Management

Ahmed Ahmedin, Ahmed R. Elsherif, and Xin Liu
University of California, Davis, California 95616
{ahmedin, arelsherif, liu}@ucdavis.edu

J. Hämäläinen, and R. Wichman
Aalto University, Finland
{jyri.hamalainen, risto.wichman}@tkk.fi

***Abstract*—This paper[1] studies the spectrum sharing of femtocell base station (FBS) and macrocell base station (MBS) in a heterogeneous network setting. We allow femtocell users (FUEs) to re-use the resource blocks of certain macrocell users (MUEs) who are categorized as outdoor users. We study the design tradeoff between MUE spectral diversity and the need to accommodate femtocells by intelligently determining when an MUE should be allowed to change resource allocation. Modeling the wireless channel state as a Markov chain, we formulate the decision as a Markov decision process (MDP). In the case of homogeneous channels environment, we reduce the MDP complexity, which enables the MBS to form the optimal decision matrix by solving only two equations. Our closed form expressions reveal the quantitative relationship among system parameters. Hence, we obtain an easy policy for the optimal channel switching. Our scheme is also robust to the uncertainties in the Markov models.**

I. Introduction and Background

One recent focus on heterogeneous networking centers on the deployment of femtocells by cellular users to improve indoor coverage and data rate in homes or small offices where traditional macrocell coverages are unsatisfactory. Given operator-approved FBSs, subscribers may set up their own femtocells under contract and registration. The distributed nature of femtocell deployment can reduce the cost of cell coverage planning and easily adapt to the potentially time-varying need of special user groups or special events. From the network operator's point of view, femtocells offload the macrocell traffic load which helps improve macrocell's throughput and coverage. In addition to the improved signal quality and data rates, FBS can also use low transmission power to reduce interference to nearby stations. The low signal power improves frequency reuse, and increases the number of users in the same area for spectrum sharing. FBSs typically use generic broadband connections such as DSL or Data Over Cable Service Interface Specification (DOCSIS) as backhaul links to connect with the cellular backbones for better control and operation.

Despite many clear advantages, the distributed nature of femto-cell deployment also poses a number of new challenges. Foremost among them are problems arising from the distributed resource allocation and uncoordinated spectrum sharing between femtocell and macrocell users. The main focus of this work is to mitigate mutual interference due to the spectrum sharing by FUE and MUE. In particular, this paper focuses on adapting the physical resource block (PRB) of the MUEs in time-frequency or spatial-frequency domain such that interference from the FBS in downlink transmission on MUEs can be contained and managed in a controlled manner.

There have been some recent works on femtocell interference mitigation. Power control can reduce the interference in areas with strong coverage from the MBS [2]-[4]. In [5], an adaptive power control is shown to decrease the transmission power of the femtocell in order to maximize frame utilization. A centralized and distributed adaptive FBS power calibration algorithm is introduced in [6] by using feedbacks to adapt FBS transmission power under a supervision. Authors in [7] study the case when the FUEs form a subset of the MBS user group. Beamforming techniques can also mitigate femtocell interference in MIMO systems, as considered in [8]. Limiting spectrum sharing by only reusing outdoor MUE resource blocks is discussed in [9]. This should further reduce the impact FBS interference. The authors consider probabilistic assignment of PRBs to FUEs by reassigning outdoor MUE's PRBs with higher access probability.

In this paper, we consider a scenario in which the FBS utilizes a delayed PRBs assignment information from the MBS received through the Internet backhaul or during MBS downlink. The FBS would assign the PRBs occupied by outdoor MUEs to the FUE after following the MBS assignment information. In an overloaded system, FBS has to reuse PRBs assigned to some MUEs. The strategy is to let FUEs follow certain outdoor MUEs by reusing their PRB. In this scenario, if the outdoor MUEs receive PRB assignment that are long term (as in semi-persistent allocation) [11], it should be easier for FUEs to follow and coexist. However, slower PRB re-allocation means that these MUEs tend to benefit less from spectral diversity. On the other hand, faster PRB re-assignment may lead to better MUE diversity, but the FBS interference can become more severe to some nearby MUEs. In other words, the outdated PRBs assignment information at FBS diminishes its ability to shadow outdoor MUE PRBs.

Our design objective is to maximize the expected weighted

[1]This material is based on works supported by the National Science Foundation under Grants 0917251, 1147930 and gifts from Fujitsu Inc.

sum throughput from both the MUE and the FUE in the downlink. We consider each PRB cluster as a physical layer channel whose state transition is Markovian. We then formulate the PRB cluster (channel) reassignment decision as a Markovian decision process (MDP) of finite horizon. We will show that when the MBS has to choose between homogeneous channels (PRB clusters), the MUE reassignment decision matrix is optimally obtained by solving only two equations, which is a large reduction to the MDP complexity. Our scheme maximizes the total expected future reward which balances the performance of MUEs and FUEs. The proposed approach has many advantages over the other existing schemes. It increases the spectrum utilization due to the reuse of the same outdoor PRBs. Our scheme also allows the network to keep the balance between the MUE diversity and the FBS access. Using the existing network feedback signals allows the FBS to access the network without being aggressive to the indoor MUEs and with no signaling overhead.

The rest of the paper is organized as follows: In Section II, we describe the system model for the problem of MUE resource re-allocation problem. We elaborate the optimization objective and the proposed MDP approach in Section III. In Section IV, we prove the closed form solution for homogeneous multiple channels and discuss the complexity reduction. In Section V, we present the simulation results with comparative results from greedy algorithm in which MUE only maximizes its own reward regardless the FBS. Our numerical results also show the robustness of our scheme to uncertainties in channel state transition probabilities.

II. System Model

We consider a heterogeneous network environment where a macrocell base-station (MBS) covers both indoor and outdoor users whereas an overlaying FBS serves some of the indoor users through channel (PRB) reuse as shown in Figure 1. We focus only on the downlink direction in this paper, although uplink issues are similar. We assume that FBS has a backhaul link to connect with the cellular core networks as in [10] and can receive MBS allocation information (known as the Downlink Control Information (DCI) in LTE). This DCI signal is delayed such that it is impossible for the FBS to perfectly synchronize with MBS allocation and assign only outdoor PRBs to FBS.

Still, the FBS can use the DCI along with its overheard MUE feedback information (ACK/NAK) to estimate and classify the allocation of various PRBs. We consider three types of PRBs: *unoccupied, outdoor, and indoor.* If the FBS is able to overhear a strong ACK/NAK signal from the MUE, then this MUE will be marked as an indoor user. Otherwise, it is outdoor. The FBS picks unoccupied PRBs to allocate to its FUEs first. However, in a congested network, there will not be enough PRBs unoccupied, then the FBS picks the PRBs from any of the outdoor users randomly and reassigns its PRBs to an FUE, as illustrated in Figure 2. The FBS learns the allocated PRBs from the DCI. However, this information

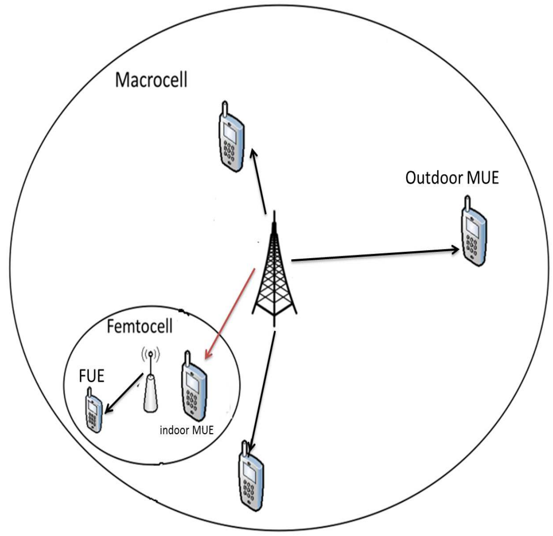

Fig. 1: Chasing the shadow scheme description.

comes with a delay D on the order of milliseconds due to the Internet latency. As a result, the received DCI information may be outdated. Suppose the MBS maintains M channels that can be swapped to this MUE for diversity gain. As the MUE downlink PRBs vary, the received DCI by the FBS may be outdated. When the MBS swaps the PRB cluster assignment of the followed MUE with another MUE, the FBS does not immediately follow. The original MUE channel may be swapped to an indoor MUE with a certain probability q, which can be estimated based on the number of users connected to the MBS and their activities. As the FBS continues to transmit on the "swapped PRB cluster", it may cause interference with the indoor MUE with probability q. Thus, it is clear that the longer the MUE can hold on to its PRBs, the easier it is for the FBS to follow and not to cause potential interference to an indoor MUE.

Unlike the traditional cognitive radio networks, interfering heterogeneous FBS and MBS are mostly run by the same network operator or co-operative network operators. A collaborative resource allocation presents overall advantages, particularly by the "more pro-active" MBS in re-assignment PRB clusters to outdoor MUEs. In particular, there will be a reward for the FBS if it is able to follow the outdoor MUE correctly. On the other hand, FBS may cause a penalty C_0 if it ends up using the PRB channel of an indoor MUE owing to the outdated DCI. That is to say, $C = q \cdot C_0$ is the average penalty when accounting for probability that the evacuated PRB channel is given to an indoor MUE where C_0 is proportional to D.

We assume that we have M total MUE downlink channels (PRB clusters). Each channel i has N states and its state change follows a Markov chain model with transition probability matrix P_i. We consider one generic MBS and one generic FBS. We assume the MBS is able to know the state of each channel using the CQI sent by the MUE. In the case of

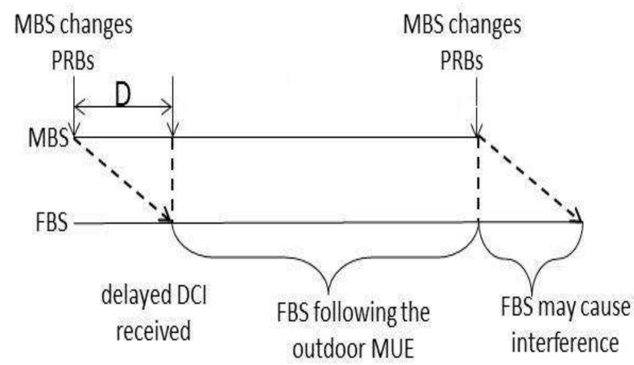

Fig. 2: Chasing the shadow scheme description.

$N = 2$, the channel gain is alternating between a high value (good state) and a low value (bad state). We define γ_k^i as the signal to noise ration (SNR) of the channel i in state k and $\gamma^i(n)$ as the SNR of channel i at time n. The MBS has to decide either to keep the MUE in the same channel or move it into a new one based on the MUE diversity gain, FBS reward, and cost.

III. Problem Formulation

We study the scheme in two cases **(a)** case of heterogeneous channels, and will be studied in this section, and **(b)** homogeneous channels where the channel charachteristics are identical for all PRBs. Homogeneous channels can be considered a special case and will be discussed in the next section. In our study, the MBS decides between moving the outdoor MUE to another channel or staying in the same channel. The FBS only acquires outdated DCI from the MBS. The decision for the MUE to seek a new channel or stay in the same channel can be optimized by seeking maximum expected return for its decisions in an MDP formulation.

A. Optimum Policy

Our design objective is to make the MBS decision to maximize the expected total reward, which is a weighted sum of MUE and FUE performance. The problem can be formulated as an MDP. To define the MDP we need the following notations. Let $S(n)$ be the state vector at time n, which contains the SNR values of all channel gains at time n including the current channel occupied by the MUE. This vector is defined as

$$S(n) = \begin{pmatrix} \gamma^1(n) \\ \gamma^2(n) \\ \cdots \\ \gamma^M(n) \\ \mathbb{C}(n) \end{pmatrix}, \tag{1}$$

where we define $\mathbb{C}(n) \in A$ as the current channel at time n, where $A = \{1, 2, \cdots, M\}$ is the set of possible channels that MUE can use including the currently occupied one. Hence $S_\ell \in S$ is one of the possible states, where S is the set of $M \times N^M$ states for the system.

We define $V(n|S_\ell, \mathbb{C}(n) = i)$ as the accumulated reward from time n till a finite horizon T when the MUE is occupying channel i, while the system state is S_ℓ. Our goal is to maximize $V(1|S_\ell, i)$ based on the observation of channel state S_ℓ at time $n = 1$. Eq. (2) describes the future reward expression in our system.

$$V(n|S_\ell, \mathbb{C}(n) = i) = \max_j (a_i(n), \{b_j(n)\}_{j \neq i}). \tag{2}$$

The first argument, $a_i(n)$, is the accumulated reward when MBS chooses to keep the channel. The FBS gets a reward R, the FBS rate, and MUE has the same rate as the previous time slot. Hence $a_i(n)$ is defined as:

$$\begin{aligned} a_i(n) = w \log(1 + \gamma^i(n)) + (1 - w)R + \\ \lambda \mathbb{E}_{S(n+1)}(V(n+1|S(n+1), \mathbb{C}(n+1) = i)), \end{aligned} \tag{3}$$

where $\mathbb{E}$ denotes expectation over the different states. The second one, $b_j(n)$, is the set of rewards when the MUE channel is changed to channel j, since there is a cost C and the MUE has a new rate due to the change of the channel.

$$\begin{aligned} b_j(n) = w \log(1 + \gamma^j(n)) + (1 - w)C + \\ \lambda \mathbb{E}_{S(n+1)}(V(n+1|S(n+1), \mathbb{C}(n+1) = j)). \end{aligned} \tag{4}$$

The future reward is weighted by λ, where $\lambda \leq 1$. The weight w represents the importance of the MUE relative to the FBS. Hence, the fairness between the FUE and the MUE can be adjusted by the parameter w which can be set by the MBS. In other words, increasing w gives more priority to the MUE over the FUE. The expectation in the future reward term is with respect to the channel gains S. This MDP problem can be solved using backward induction and the problem complexity is $O(T \times N^M \times M)$.

B. Greedy Policy

We compare our policy with the greedy policy where the MBS maximizes the MUE diversity gain regardless the FBS. Greedy policy is exactly the same as optimal policy when $w = 1$ and $\lambda = 0$. The decision policy can be obtained by solving the following equation

$$\max_{1 \leq j \leq M} (\log(1 + \gamma^j(n))). \tag{5}$$

IV. MDP Complexity Reduction

The MDP complexity depends on the number of available channels and the time horizon. In this section we prove that the MDP problem (generally can be executed as a table-look-up algorithm) can be reduced to solving couple of equations in the case of homogeneous channel without any performance degradation.

A. Reduction for 2 Homogeneous Channels

We consider two homogeneous channels where the transition probabilities and the channel gains for each state are the same for all channels, then the channel index i can be removed to simplify notations. We assume that each channel has 2 channel states with self transition probabilities p_1 and p_2 and gains γ_1 and γ_2. Due to the nature of the homogeneous channel and for the simplicity of notations, we redefine the state at time n as S(n)=[current channel state, other channel state]. In other words, S_1 is when both channels are in good state, S_2 is when the current channel is good and the other is bad, S_3 is the opposite, and S_4 is when both bad.

Lemma 1: Channel switching could only happen in S_3.
The proof is in the appendix. The intuition behind is clear, the MBS does not need to switch the channel if the current channel is good because the other channel is either worse or the same, where switching introduces only a cost. Similarly, if both channels are in bad states, the MBS decides to stay on the same channel.

The following theorem can be used to complete the decision matrix for S_3 without solving the backward induction.

Theorem 1: If the following conditions are satisfied

1)
$$(1-w)(1-\lambda(p_1+p_2-1))(R-C) < -w\Gamma, \quad (6)$$
where $\Gamma = \log(1+\gamma_2) - \log(1+\gamma_1)$
2) There exists K such that
$$K = \min\left\{k : \frac{w\Gamma\lambda^{k+1}(p_1+p_2-1)^{k+1}-1}{p_1+p_2-2}\Gamma < (1-w)(R-C)\right\}, \quad (7)$$

then, channel switching happens in S_3 for stage 1 to $T-K$ otherwise, the optimal decision is to stay in the current channel.

Proof 1: At stage T, the necessary and sufficient condition to switch channel in S3 is

$$R + w\log(1+\gamma_2) < C + w\log(1+\gamma_1). \quad (8)$$

Suppose the decision at time $T-K+1$ is to NOT move, the necessary and sufficient condition to move at $T-K$ can be obtained as follows:
For all $n > T-K$

$$\begin{aligned} V(n|S_1) = V(n|S_2) = V_g(n). \\ V(n|S_3) = V(n|S_4) = V_b(n). \end{aligned} \quad (9)$$

Hence, the recursion can be written as

$$\begin{aligned} V_g(n) =& (1-w)R + w\log(1+\gamma_1) + \lambda(p_1V_g(n+1) + (1-p_1)V_b(n+1)) \\ V_b(n) =& (1-w)R + w\log(1+\gamma_2) + \lambda(p_2V_b(n+1) + (1-p_2)V_g(n+1)) \end{aligned}$$

The condition to move at stage $T-K$ is

$$\begin{aligned} &\lambda(p_1+p_2-1)(V_b(T-K+1|S_3) - V_g(T-K+1)) + \\ &(1-w)(R-C) + w\Gamma \underset{\text{move}}{\overset{\text{stay}}{\gtrless}} 0. \end{aligned} \quad (10)$$

Hence the first movement moment, K, is the minimum k that satisfies the inequality

$$w\frac{\lambda^{k+1}(p_1+p_2-1)^{k+1}-1}{p_1+p_2-2}\Gamma < (1-w)(R-C). \quad (11)$$

If the decision at $T-K$ is to move, then the decision at $n = 1, \cdots T-K-1$ is to move if and only if

$$\begin{aligned} &w\log(1+\gamma_1) + (1-w)C + \lambda\mathbb{E}(V(n+1|S_2)) > \\ &w\log(1+\gamma_2) + (1-w)R + \lambda\mathbb{E}(V(n+1|S_3)), \end{aligned} \quad (12)$$

where

$$\begin{aligned} \mathbb{E}(V(n+1|S_2)) &= p_1(1-p_2)V(n+1|S_1) + p_1p_2V(n+1|S_2) \\ &+ (1-p_1)(1-p_2)V(n+1|S_3) + (1-p_1)p_2V(n+1|S_4). \\ \mathbb{E}(V(n+1|S_3)) &= p_1(1-p_2)V(n+1|S_1) + p_1p_2V(n+1|S_3) \\ &+ (1-p_1)(1-p_2)V(n+1|S_2) + (1-p_1)p_2V(n+1|S_4). \end{aligned}$$

By subtracting the two arguments, the threshold is given as

$$\begin{aligned} &(1-w)(R-C) + w(\log(1+\gamma_2) - \log(1+\gamma_1)) + \\ &\lambda(p_1+p_2-1)(V(n+1|S_3) - V(n+1|S_2)) \underset{\text{move}}{\overset{\text{stay}}{\gtrless}} 0. \end{aligned} \quad (13)$$

Assuming that the decision at stage $n+1$ is to move, then the decision will be also to move for all stages from 1 to n if and only if Eq. (6) is satisfied.
This means that the base station can solve Eq. (7) and obtain the optimum value of K which corresponds to the first moving time, and then apply the condition at Eq. (6). If this condition is satisfied, then the decision is always to move till stage 1. That is to say, the complexity is reduced and the MBS can form the decision matrix by solving only 2 equations instead of solving the whole backward induction steps. Hence, the MBS can follow an easy optimum policy instead of forming a complex lookup table.

B. Generalizing for Multiple Homogeneous Channels

When channels are homogeneous, we can reduce the number of states from $M \times 2^M$ to $2M$. By the nature of the homogeneous channel, the states that have the same current channel and the same number of good and bad channels are redundant. For instance, when $M = 3$, the states [G B G] and [G G B] are equivalent and one of them can be removed. Specifically, let S_k, $k = 1, 2, \cdots M$, represents that the current channel is good, and in addition there are $M-k$ good channels and k bad channels. On the other hand, S_k, $k = M+1, M+2, \cdots 2M$, represents the current channel is bad and there are $2M-k$ good channels and $k-M$ bad channels. Again, it is clear that when the current channel is good, the decision is always to stay regardless the state of any of the other channels. Switching will happen only when the MUE is currently on the bad channel and one or more of the other channels are in a good state. In states S_k, $k \geq M+1$, the MBS decides either to stay in the same bad channel or move to one of the other good channels.

$$V(n|S_j) = \max \begin{cases} w\log(1+\gamma_2) + (1-w)R + \lambda\mathbb{E}(V(n+1|S_j)) \\ w\log(1+\gamma_1) + (1-w)C + \lambda\mathbb{E}(V(n+1|S_k)) \end{cases} \quad (14)$$

Following the same argument of Eq. (9) to obtain the first moving moment, the values of the rewards for all the channels that are currently in good state are the same and equal to $V_g(n)$ for all $n > T - K$. Similarly, the ones that are currently on a bad channel have equal rewards, $V_b(n)$.

$$\begin{aligned} V(n|S_1) = \cdots = V(n|S_M) = V_g(n). \\ V(n|S_{M+1}) = \cdots = V(n|S_{2M}) = V_b(n). \end{aligned} \quad (15)$$

By subtracting the two arguments, we obtain the same results as Eq. (10) which is the same recursion, hence, the same closed form solution obtained in Theorem 1.

V. Simulation Results

In this section we evaluate the performance of our scheme. In our simulations we have finite horizon $T = 2000$. We also have $R = 1$ and $C = -2$. The performance shown in the simulations is normalized over the total number of channels, states, and the time horizon. We conducted the simulations in two cases. The first one assumes that the transition probabilities are known and the second assumes that they are estimated with errors to study the robustness of our scheme. All simulations are conducted for one femtocell that follows one of three outdoor users. Each user has a two state channel.

A. Perfect Transition Probabilities

We assume that the transition probabilities of all the channels are known. We draw the total MDP reward, FBS reward, and the MUE rate for the optimal MDP scheme versus the greedy algorithm. As shown in Figure 3, as the weight increases, the gap between the greedy scheme and ours decreases because of the increasing emphasis on MUE. In the case of small weights, we emphasize the FBS over the MUE. Hence, the policy is to always stay and the FBS reward equals to R. The values of self transition probabilities are 0.8, 0.85, and 0.9.

In Figure 4, all the channels have 2 states with different γ_1^i and γ_2^i values. We plot the different rewards versus the ratio γ_2^i/γ_1^i, which we assume in this setup to be the same for all i. We call this ratio L. As shown in the figure, as L increases, the optimum MDP and FBS reward increases. As the ratio becomes closer to 1, the greedy policy becomes closer to the optimal. The explanation is that the gain value of the best channel is better than all other channels even in their good states.

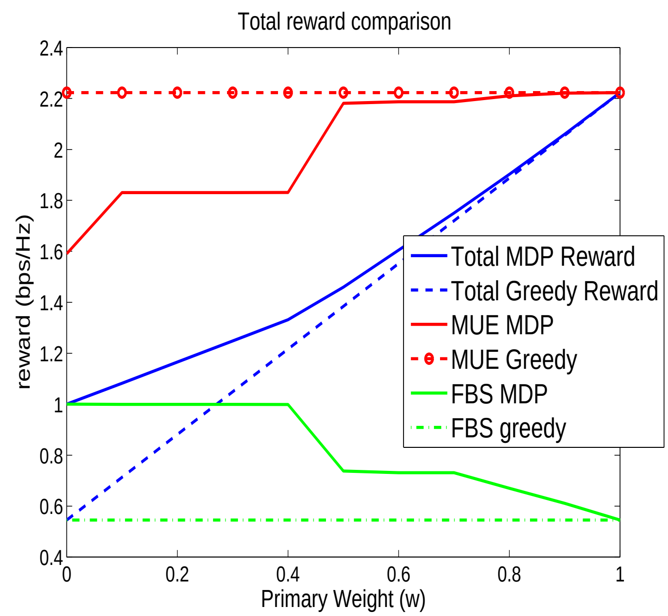

Fig. 3: Greedy versus our optimal scheme.

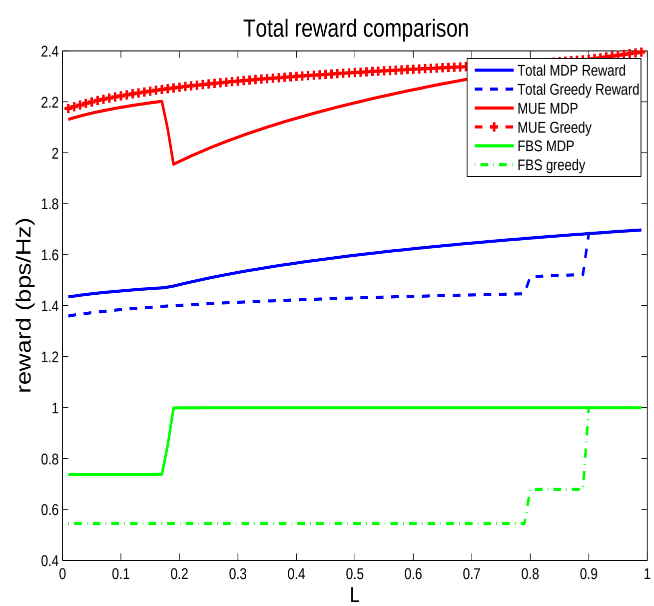

Fig. 4: Greedy versus our optimal scheme for different SNR ratios.

B. Channel Uncertainty

In this subsection, we show the robustness of our scheme when estimation errors exist in the transition probabilities. In Figure 5, the total reward, MUE rate, and FBS reward are plotted by applying the optimal scheme, however using the estimated transition probabilities instead of the real ones. In our simulations, $R = 3$, $C = -2$, and the maximum error between the true transition probabilities and the estimated one is 0.3. As shown in the figure when the weight is small or large, the rewards are as the optimal ones because the impact of transition probabilities is not significant. At the small weights, the policy is always to stay regardless the transition probabilities. Similarly, at large weights the policy is a greedy policy that will maximize the current MUE rate. The maximum loss in the total reward is about 20%. In summary, the scheme

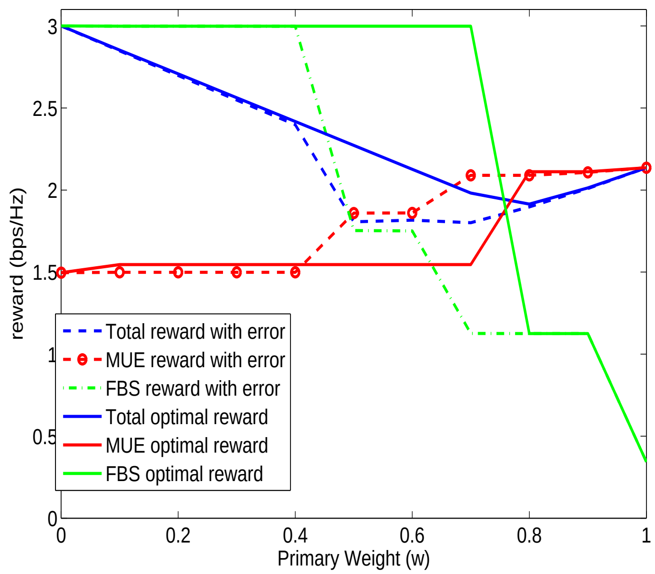

Fig. 5: Robustness of the MDP scheme.

is robust to estimation errors.

VI. Conclusion

In this paper we introduce a novel MUE resource allocation scheme to decrease the interference between the FBS and indoor MUEs. We use the fact that FBS is using the DSL as its backhaul and is part of the same network as the MBS. Hence, FBS and MBS can communicate to exchange the resource allocation information. However, this information could be delayed so FBS may introduce interference on the indoor users. Thus, the MBS optimize the tradeoff between MUE diversity and FBS access chances. We formulate the problem as an MDP and compared our optimal scheme with the greedy algorithm. We have significantly reduced the MDP complexity in the case of homogeneous channels. We also have done simulations to show the robustness of our scheme. There are open problems that can be addressed in the future work, such as the case of multiple MUEs and FBSs and testing the proposed schemes in the scenario of interfering FBSs. Another issue is to derive the conditions for the greedy algorithm to be optimal. Also, the impact of the number of channels on both MUE and FBS rates should be studied.

Appendix

Lemma 1 can be proven as follows:

Proof 2:

$$V(n|S_1) = \max \begin{cases} w\log(1+\gamma_1) + (1-w)R + \lambda\mathbb{E}(V(n+1|S_1)) \\ w\log(1+\gamma_1) + (1-w)C + \lambda\mathbb{E}(V(n+1|S_1)) \end{cases} \quad (16)$$

Hence $a_1(n|S_1) > b_2(n|S_1)$, where

$$\mathbb{E}(V(n+1|S_1)) = p_1^2 V(n+1|S_1) + p_1(1-p_1)V(n+1|S_2) + (1-p_1)p_1 V(n+1|S_3) + (1-p_1)^2 V(n+1|S_4).$$

Similarly we can prove the same for S_4. Repeating the same steps for S_2,

$$V(n|S_2) = \max \begin{cases} w\log(1+\gamma_1) + (1-w)R + \lambda\mathbb{E}(V(n+1|S_2)) \\ w\log(1+\gamma_2)) + (1-w)C + \lambda\mathbb{E}(V(n+1|S_3)) \end{cases} \quad (17)$$

By subtracting the 2 arguments, the threshold is

$$(1-w)(R-C) + w(\log(1+\gamma_1) - \log(1+\gamma_2)) + (p_1+p_2-1)(V(n+1|S_2) - V(n+1|S_3)) \underset{\text{move}}{\overset{\text{stay}}{\gtrless}} 0,$$

which is always positive for slowly varying channel, i.e., p_1 and p_2 are greater than 0.5 and it is clear that $V(n|S_2) > V(n|S_3)$ for all n. Hence the decision will always be to stay.

Acknowledgment

The authors would like to thank Professor Zhi Ding for his help to improve the quality of the paper.

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