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Decentralized Learning Algorithm for LTE and Femtocells Networks

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ABSTRACT: Femtocells aim to improve the cellular network coverage and capacity. However, new conception challenges are posed by deploying the femtocells randomly on the cellular network. One of the major issues is the interferences caused by the cross-tier transmissions between femtocell and macrocell which both work on the same spectrum.

Among all the access control mechanisms, hybrid access seems to be the promising choice, since the femtocell opens a part of its resources for macro users while reserving the residual part to its own users.

We propose a hybrid access control mechanism, where the macrocell remunerates a refunding amount to femtocells depending on their contribution to macro user's data transmission.

The aim of this work is to study the environment concurrence between the femtocells with a decentralized manner by using the learning algorithm LRI.

Some simulations have been conducted and the results show that the utilities of both, femtocell and macrocell, are significantly improved exploiting the hybrid access mechanism.

I. INTRODUCTION

Mobile Ad Hoc Networks (MANETs) The access control mechanisms of the femtocell can be classified in three categories: open access that all resource is open to public use, closed access that only authorized femtocell users could get access, and hybrid access that some of the resource remains reserved while the residual part is open. As both closed and open access have their own pros and cons, hybrid access is proposed to exploit the benefit of the two yet overcome their shortcomings. From this point of view, it is a reasonable option that the macro cells providers turn to femtocells providers and ask them to open some of their resources for macro users. However, too successfully leverage hybrid access is challenging because the femto providers are selfish, unwilling to share their femto facilities and spectrum resource with macro users without any reward, the macro providers have to offer an incentive mechanism to ensure the FHs that their contribution is not fruitless.

The paper is organized as follows: First, we describe the system model in section II. The refunding framework to adopt the hybrid access by the Femtocells is proposed in section III. In section IV, we use the learning algorithm LRI to analyse the refunding framework. Some numerical results are then presented in section V in order to validate the theoretical results and demonstrate the desirable performance of the LRI algorithm. The last section summarizes our work.

II. SYSTEM MODEL

In this section, we describe the system model to study the utility, including network architecture and basic parameters. Figure 1 depicts a two-tier macro-femto network, consisting of a macro BS (Base Station), which is owned by WSP, and three femto BSs, which are possessed by FHs.

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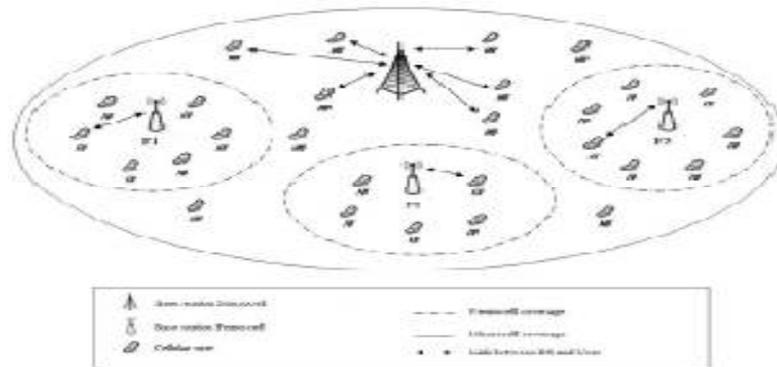


Figure 1: Macrocell-femtocell Network.

Time division multiple access (TDMA) strategy is utilized for data transmission. Data transmission is divided into frames, which are further divided into time slots. FHi(Femtocell Holder) is in charge of distributing time slots to users who are transmitting through Fi (i femto- cells).

Each frame consists of two parts, namely transmission period reserved for femto users and transmission period open to passer-by macro users.

Assume that FHi plans to open a fraction of α_i in each frame to macro users and transmission time for macro user $MU_{i,j}$ (j macro users from 1 to $K_{m,i}$) is $\gamma_{i,j}$ satisfying $\sum_{j=1}^{K_{m,i}} \beta_{i,j} = 1 - \alpha_i$.

The rest fraction $(1 - \alpha_i)$ is dedicated to femto users transmission. Femto user $FU_{i,j}$ (j femto users from 1 to K) gets β , is satisfied $\sum_{j=1}^{K_{f,i}} \beta_{i,j} = 1 - \alpha_i$.

We presume that macro BS and femto BSs operate on different frequencies and do not interfere. Users of the same femtocell adopt TDMA for data transmission, causing no interference for each other. Different femto BSs may reuse the same spectrum and we assume that the femto-femto interference received by Fi is only determined by the density of femto BSs, denoted by I_i (K).

The received Signal to Interference Ratio SINR (Signal Interference Noise ratio) is expressed as [1]:

$$\eta_i = \frac{P_i}{N_o + I_i(K)} S_d^{-n} |h^2|$$

Where:

- P_i is the transmission power of Fi.
- N_0 is the Gaussian noise.
- S_d is the log-normal shadowing component.
- n is the path fading exponent.
- $|h|$ the Rayleigh distributed fading magnitude.

Therefore, we can obtain the aggregated transmission rate of femto and macro users who are served by femto BSs respectively by multiplying the transmission time and channel capacity[1].

$$R_{f,i} = (1 - \alpha_i) C_{f,i} \quad (2)$$

$$R_{m,i} = (\alpha_i) C_{m,i} \quad (3)$$

Where:

$$C_{f,i} = \log(1 + \eta_{f,i}) \quad (4)$$

$$C_{m,i} = \log(1 + \eta_{m,i}) \quad (5)$$



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In this section, we propose a utility refunding frame-work within which WSP (Wireless Service Provider) hopes to motivate FHs to adopt hybrid access through refunding. By utilizing femto resource, WSP is able to expand its network capacity and increase user satisfaction.

We assume that WSP puts forward a total sum of m refunding amount, which is further distributed among FHs who open their BS to macro users. As different FHs allow macro users to transmit for different fraction of time α_i , it is reasonable to split the refunds in the way that the FH who contributes the most time achieves highest refunds and who contributes the least achieves lowest.

The main The refunds obtained by each FH can be derived as the total amount of refunds multiplies the ratio of individual open time to the sum of open time of all femtoBSs[1].

$$m_i = m \frac{\alpha_i}{\sum_{j=1}^k \alpha_j} \quad (6)$$

2.1. Utility Function of WSP:

The utility function of WSP is defined as the benefit from reduced user churn rate minus the refunds given to FHs.[1].

$$U_{WSP} = \omega_m(1 - C) - m \quad (7)$$

Where:

- c is the churn rate of macro users.
- ω_m is the equivalent revenue when c decreases by one percent.

Poor QoS (Quality Of Service) causes user dissatisfaction, ending up in user switching WSP for better cover-age. If femto BSs are leveraged to increase the capacity of macro BS, WSP is able to provide better QoS, thereby more macro users are willing to stay with the WSP.

The churn rate can be expressed as:

$$c = \frac{1}{1 + \exp^{-a(b-\lambda)}} \quad (8)$$

Where:

- a represents the users sensitivity towards QoS increment.
- b is the reserved traffic demands of macro users.
- λ is the achievable data rate for macro users. It can be derived as :

$$\lambda = \sum_{i=1}^k R_{m,i} + \lambda_0 \quad (9)$$

In which λ_0 is the capacity of macro BS?

2.2. Utility Function of FH:

The utility function of FHI consists of two aspects: the transmission rate that femto users have attained and the refunds gained from WSP by opening part of transmission time to macro users. As femto users mostly demand data service from femto BSs, the more capacity they can achieve, the more satisfied they will be. So we assume that the utility of FHs is linearly increasing with the transmission rate of femto users[1].

$$u_{f,i} = \omega_f R_{f,i} + m_i \quad (10)$$

Where w_f denotes equivalent revenue the FH receives on one unit transmission rate for femto users.

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III. LEARNING ALGORITHM IMPLEMENTATION ON FEMTOCELLS

The system is modeled as a Markov decision process (MDP).

Definition: A Markov decision process is a quadruple $\{S, A, r, t\}$ composed of a state set S , an action set A containing the available actions in the system, a reward function r and a state transition probability function t .

The interaction between the agents and its environment, shown in Figure 2, can be summarized as follows[2]:

- 1) Agents observe the state S_t of environment and make actions at based on the current observed S_t at the time t .
- 2) State transits to the next state S_{t+1} due to the execution of the selected action a_t , and agents get costs c_t when executing action a_t in state S_t .
- 3) Time t transits to $t + 1$, and then repeat steps 1 and 2.



Figure 2: Interaction between agent and environment.

The first Lr-i (linear reward inaction) is a learning algorithm that aims to reward the chosen actions by the agent. The learning algorithm calculates the selected action probabilities for the next step $t + 1$ depending on the reward r and the present probabilities at moment t [3-7].

The update of the algorithm is given by:

$$P_i^{(t+1)} = p_i^{(t)} + lr_i^{(t)}(1 - p_i^{(t)}) \text{ if } a_i \text{ is selected}$$

$$P_i^{(t+1)} = p_i^{(t)} - lr_i^{(t)} p_i^{(t)} \text{ else} \quad (11)$$

With $P_i^{(t)}$ the selected action probability for the action I and $r_i^{(t)}$ the received reward at moment t . The learning parameter $0 < \lambda < 1$ controls the size of the update, and thus the speed of learning.

- 1) In order to compute the optimal refunding m , WSP should periodically collect information about the entire network of both macrocell and femtocell, possibly with the help of FHs.
- 2) Each femto BS periodically collects information about the channel condition of femto users it support and macro users within its coverage, Then, they piggyback the gathered information of channel condition $\eta_{f,i}, \eta_{m,i}$ on the data frame to WSP through the broadband line.
- 3) With the information from FHs, WSP is able to compute $C_{f,i}, C_{m,i}$ according to: $C_{f,i} = \log(1 + \eta_{f,i})$ and $C_{m,i} = \log(1 + \eta_{m,i})$
- 4) WSP piggybacks the aggregated data rate $\sum_{j=1}^K$ on the data frame to FHs through the broadband line. With the actions to choose (Access control mechanism):
 $a_1 = 1$ is the closed access
 $a_2 = 2$ is the open access
 $a_3 = 3$ is the hybrid access
- 5) FHs choose the access control mechanism. If $K_{f,i} < K_{f,i,max}$, FH*i* selects closed access and simply rejects access request from any macro users when its users reach the maximum number.
- 6) We suppose that FH*i* chooses the action $a_1 = 1$ (closed access) or $a_2 = 2$ (open access) \rightarrow the reward $r_i^{(t)} = 0$ that is the response of FH*i* is unfavorable \rightarrow inaction (the algorithm LRI probabilities remain unchangeable), return to 5. WSP don't give any reward in the case where FH*i* chooses the closed or open access, thus $m_i = 0$.
- 7) FHs who have chosen hybrid access decide the fraction of transmission time that will be open for macro users.



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8) WSP first checks whether conditions are satisfied. If not, it is unprofitable for WSP to run refunding policy, thus $m = 0$. If conditions are satisfied, WSP computes the best refunding amount m , which yields highest utility for itself.
9) WSP broadcasts the refunding amount m to FHs.
The proposed algorithm is described in Algorithm 1.

IV. PERFORMANCE ANALYSIS AND NUMERICAL

In order to evaluate the learning algorithm LRI performance implemented on femtocell, we provide some numerical results.

In our simulation setting, we have one macrocell and three femtocells, each one of them chooses its action independently, the learning parameter $\lambda = 0.5$, the femto maximum number $K_{fmax} = 0.5$ is fixed to 15. Simulation data shows that for hybrid access, the probabilities update stop when the action probability $U(a_3(t))$ reaches the value 1 where the convergence is obtained, the algorithm converges slowly within 439 iterations, indeed the time to reach the convergence depends on the learning parameters, a slight change in the parameter value λ affects the convergence speed, generally, the small values of λ tally with slower convergence rate, and vice versa. The figure 3 shows as well that the femtocell utility increases by adopting the hybrid access.

Algorithm 1 Decentralized Learning Algorithm for LTE Femto Cells.

System: MBS=1

Agent: FBS_i, $\forall i \in 1, \dots, K$

State: $S_i = (k_{mi}, k_{fi})$

Action: $a_i \forall i \in (1, 2, 3)$

$a_1 = \text{closed access,}$

$a_2 = \text{open access,}$

$a_3 = \text{hybrid access,}$

Reward: $r_{ai} = m_i = m \frac{\alpha_i}{\sum_{j=1}^k \alpha_j}$

Data: $K_{mi}, k_{fi}, \lambda, K_{imax}$

$u_{a1}^t = 0.3, u_{a2}^t = 0.2, u_{a3}^t = 0.5$

Choose an action a_i randomly (exploration step)

if $K_{mi} \neq 0$ **and** $K_{fi} = K_{fimax}$ **then**

Choose $a_1 = 1$

$u_{a1}^t = 0.3$

$r_{ai} = m_i = 0$

Update $u_{ai}^{(t+)} = u_{ai}^{(t)} + \lambda r_{ai}^{(t)} (1 - u_{ai}^{(t)})$

else

if $K_{mi} = 0$ **then**

Choose $a_2 = 2$

$u_{a1}^t = 0.2$

$r_{ai} = m_i$

Update $u_{ai}^{(t+)} = u_{ai}^{(t)} + \lambda r_{ai}^{(t)} (1 - u_{ai}^{(t)})$

else

if $K_{mi} \neq 0$ **and** $K_{fi} < K_{fimax}$ **then**

Choose $a_3 = 3$

$u_{a1}^t = 0.5$

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Give α_i
Calcul m_i

Receive immediate reward $r_{ai}^t = m_i$

Update $u_{ai}^{(t+)} = u_{ai}^{(t)} + \lambda r_{ai}^{(t)} (1 - u_{ai}^{(t)})$

end if
end if
end if

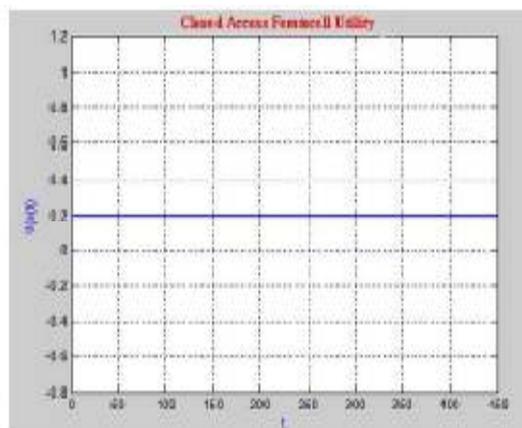
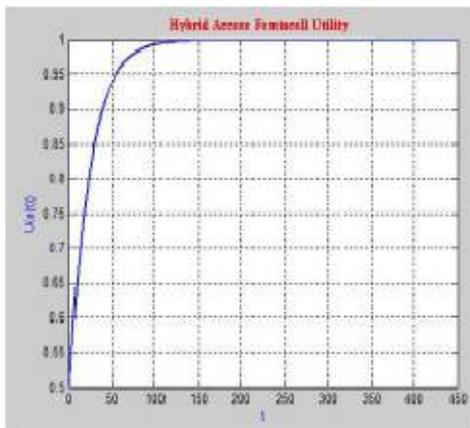


Figure 3: Femtocell utility in hybrid access. **Figure 4:** Femtocell utility in closed access.

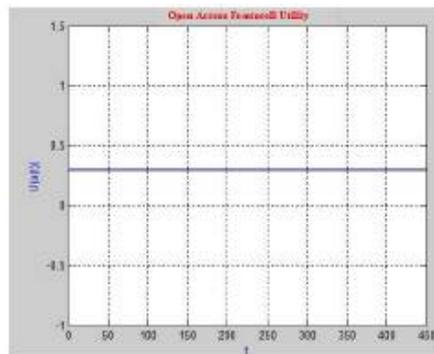


Figure 5: Femtocell utility in open access.

The figures 4 and 5 show that both closed and open access utilities remain constant the whole time because WSP didn't give any reward in these cases.

The figure 6 shows that the algorithm converges quickly for higher values of a_i , by increasing the open time value to 0, 7 the algorithm converges within 123 iterations.

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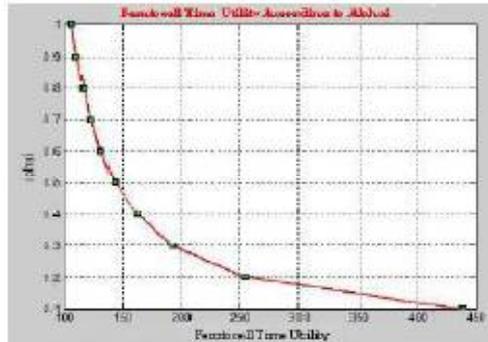


Figure 6: Time utilities versus different values of alpha.

When the femtocell contributes with more open time, it obtains a better refunding and thus considerable utility gain.

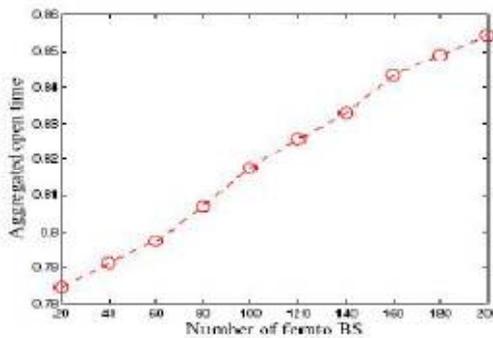


Figure 7: Aggregated open time versus the number of femto BS. versus

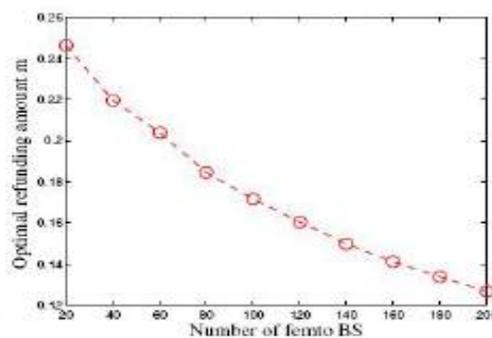


Figure 8: Optimal refunding amount m the number of femto BS.

Those nodes the figure 7 shows that the aggregated open time keeps rising along with the number of femto BS. Therefore, it is greatly beneficial for WSP to carry out the refunding policy.

The figure 8 shows that the refunding amount m abates when the number of the femto BS increases. As the refunds slightly decreases, the open time of each femto BS also declines.

V. CONCLUSION

Small hop In this paper, the authors proposed a refunding frame-work to adopt the hybrid access, in which WSP remunerates a refunding amount to FHs to their contribution to macro cellular users data rate. They modeled the problem by using the LRI learning algorithm, and the provided numerical results have illustrated that both WSP and FHs can achieve considerable utility gain under the refunding framework where the algorithm convergence is obtained.

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