Power Adaption in Heterogeneous Network with Varying Gain

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***Abstract*—Femto Access Points (FAP) has encouraged mobile operators to install them due to their great benefits. Nevertheless, these FAP may cause great interference, which require technique for mitigation find the optimal power levels. Q-learning is a common technique that been widely used for similar problems. In the literature, most of the work has been on the downlink interference, however, we focus on the uplink interference in this paper. We conduct several experiments to show that the the choice of the power level plays a significant role in the total capacity of the network. This has the potential to enable networks to act in an improved manner. Results from the simulation can be used to configure any realistic network model.**

Keywords.* *femtocell; Q-learning; Interference mititgation; reinforcement learning.

I. INTRODUCTION

Interference is one of the great challenge mobile operators face when building Heterogeneous Network. Femto access points (FAP) are new devices which are used to improve coverage although they cause interference to the maroc base stations (MBS)[1]. These FBS or femtocell can improve the capacity and allow mobile users to receive signals where signals are weak or does not even exist. Depending on the cells interfering in the network, two main types of interference are observed. For example, in two-tier femtocell network architecture, a network with one macrocell and at least one femtocell, we can have a co-tier interference or/and a cross-tier interference. Co-tier interference is the interaction between femtocells . Usually when there is a cluster of femtocells, there exist a co-tier interference between them. On the other hand, cross-tier interference describes the interaction between the macro cell or base station and a femtocell or /and a femto base station. The transmitter agent and the receivers determine the type of interference and transmission mode observed in a heterogeneous network. For example, if a femtocell user equipment (FUE) is transmitting a signal and a femto base station (not associated with the femtocell user) is also active, the femto base station will suffer an uplink co-tier interference. In summary, the possible interference in such a heterogeneous network are enumerated below.

1. The femtocell base station may suffer from an uplink co-tier interference from another femtocell user equipment
2. The femtocell base station may also suffer from an uplink cross-tier interference from a macro cell user equipment (MUE)
3. The macrocell base station may also suffer from an uplink cross-tier interference from a femto cell user equipment
4. The femtocell user equipment may suffer a cross-tier downlink interference from a macrocell base station
5. The macrocell user equipment may suffer a downlink cross-tier interference from a femto cell base station
6. The femtocell user equipment may suffer a co-tier downlink interference from a femtocell base station

The co-tier or co-channel interference problem is a traditional problem in wireless network. Although it has been investigated intensively in traditional cellular network, in heterogeneous network (HetNet), we face the same problem with new scenarios and challenges. In the HetNet, we have multiple mobile users in the different tiers described previously. In this scenario, some users have priority over other users. For example, the macro user equipments are given priority access to the network compared to the femto user equipments. Orthogonal

scheduling is performed separately by the macro base stations and each FAP, so the mobile users associated with the same FAP or MBS will surely not interfere with each other. But due to high density of FAPs and FUEs, it is very likely that multiple FUEs, each associated with a different FAP, are using the same sub-channel in a nearby area, potentially causing a co-tier uplink interference. Also in HetNet, FAP and MBS are using the same spectrum. Therefore, if a MUE is nearby in the same area of FAPs, co-tier and cross-tier interferences will happen together. This case is common in an office building scenario. The problem with this setting is that there might be a state of instability in the peer transmission levels and destructive interference in the network which affects the signal to noise transmission level of the users in the network. Hence, solving the power equilibrium problem in this kind of scenario is crucial. To address this problem, there are several approaches that have been proposed in the literature.

II. RELATED WORK

In managing the interference, one common approach is to allow the agents—femtocells and macrocells—learn from the dynamic environment created by the coexistence of both cells. By learning from their environment, these devices can adjust their parameters such as power transmission level to satisfy the quality of service of their respective users. In literature, one common tool that has been used widely to achieve this learning is a reinforcement learning technique called Q-learning [2]. An advantage of Q-learning is that it does not need any prior information on the state of the environment. This means that we do not need to be concerned about the number of femtocells in the system or their spatial locations. Furthermore, the learning can be independently performed by each of the agents or it could be cooperative learning [3] where, for instance the femtocells share their information with each other. The actions taken by any agent in this setting affects the state or environment and also affects the learning process. One merit of Q-learning is that the agents can take actions while still learning from the actions of other agents. This learning leads to network acting in an improved manner [4]. This improved performance of the network and the easiness of the algorithm motivates us to adopt Q-learning in this work. Details of this learning algorithm will be discussed in the following section.

III. Q-Learning

In this section, the concept of Q-learning (QL) is presented. QL is one of the reinforcement learning (RL) algorithms. RL is a machine learning (ML) algorithm where an agent learns from a dynamic environment through trial-and-error interactions. In QL, an agent can find the optimal decision policies through interaction with the environment. These interactions can be modelled as a Markov Decision Process (MDP) [5],[6].

The Q learning model can be defined as a tuple (S, A, $P_{s,s'}$, R(s, a)) where S = (s_1, s_2, ..., s_n) is a finite set of environment states the agent can enter, A = (a_1, a_2, ..., a_m) is a finite set of actions the agent may choose, $P_{s,s'}$ (a) is the state transition probability function from state s to the new state s' after taking action a, and R(s, a) is the reward function that determines the reward for the agent when performing action a in state s. In a system of more than one agent, the agents may decide to share their actions with other agents or may not. A very thorough description of how many agents may interact or learn has been reported by [7]. Emphasis is on the learning goal of the interacting agents.

The objective of each agent is to find an optimal policy π^*(s), which tells the agent the optimal action to choose in each state $s_t \in$ S in order to maximize the the total expected discounted reward. The expected discounted reward over infinite time given the policy π and initial state s can be written as:

$$Q(s,a) = E\left\{\sum_{t=0}^{\infty}\gamma^t R(s_t, \pi(s_t), s_{t+1})|s_0 = s\right\} \quad (1)$$

where $\gamma \in [0,1)$ is called the discount factor which determines the significance of future rewards. If γ = 0, the agent will ignore all future rewards. If γ = 0.9, the agent will put emphasis on future rewards. In QL, Q(s, a) is called the Q value. When the agent selects action a according to the optimal policy π^*(s), then the Q value (expected discounted reward) is maximized. The optimal Q value Q^*(s,a) to find the optimal policy π^*(s) is defined as:

$$Q^*(s,a) = E\{R(s,a)\} + \gamma \sum_{s' \in S} P_{s,s'}(a) max_{b\in A} Q^*(s',b) \quad (2)$$

where Q^*(s',b) is the optimal Q value from the the next state s' after choosing the next action b. QL process finds Q^*(s, a) in a recursive manner by using the following update rule:

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max_{b\in A} Q(s', b) - Q(s, a)] \quad (3)$$

where α is the learning rate which determine how much the new information will override the old information. It was proved that the update rule in Equation (3) converges to the optimal Q-value under certain conditions [2][8]. One of the conditions is that the agent has to try all the possible actions and visit all the possible states infinitely. To achieve this condition, the ε greedy exploration is introduced in the Q-learning algorithm.That is, in each iteration, the agent chooses a random action with probability $\varepsilon \in (0,1)$ and chooses the greedy action that will maximize the Q-value with probability 1−ε .

Related works that have used Q-learning to address interference problems and resource allocation in HetNET include [9],[10],[11]. The main idea in these works is to model the femto network as a multi-agent system where the femto user equipments are the agents. Depending on the context, these agents are in charge of managing the resources to be allocated to their femto base stations. The interaction between the agents and the surrounding environment leads to a learning of an optimal policy to solve the interference problem. The vast majority of the literature on Q-learning proposes algorithms that attempt to solve the power control problem, while showing improved performance in terms of convergence of the capacity, e.g. as in [10],[11]. The role of the choice of the reward function and how it can greatly affect the performance of the Q-learning algorithm was presented by [12]. The authors showed how the distance between the interacting agents and the total number of agents in the network can affect the capacity and the SINR. In addition, they affirmed the learning algorithm as an efficient tool for resource allocation and management in femtocell networks. Another significant work by [3] was aimed at solving the power control problem with Q-learning to manage the interference caused by the femtocells on the macrocells in the downlink. The authors showed that, using Q-learning, the femtocells can either learn independently or cooperatively, i.e. they share their "Q-table", in order to enhance their performance.

The number of related work described above and the opportunity to adopt the powerful Q-learning tool for resource allocation in a HetNET motivates us to explore the role of this algorithm to manage and control the uplink interference in a two-tier network. In the next section, we set up the system model which depicts the various agents and the associated interference patterns.

IV. SYSTEM MODEL

Figure 1 illustrates the system model we shall be investigating. The system consists of one macro base stations (MBS) underlaid with N_f Femto access points (FAPs). The marco user equipment (MUE) is randomly located in the coverage area of the MBS, while the femto user equipment (FUEs) are randomly located in their associated FAPs. Orthogonal scheduling is assumed in every FAP, so only one FUE is allowed to transmit in a single time slot to avoid interference within a femtocell.

According to our model, there is only one active FUE in each femtocell at every given time slot. Hence, we are only interested in the interference caused by the neighbouring active FUE and the neighbouring active MUE at the designated FAP. In this system, we consider the uplink co-tier and cross-tier interferences between femtocell and macrocell contrary to the downlink interference studied by [9]. In addition, we also analyze the power control problem in a single sub-channel OFDMA in this system. To simplify our study, we assume all the MUE and FUEs are on the same sub-channel and have the same amount of available resource blocks (RB), which allows to increase the spectral efficiency per area through spatial frequency re-use [3][9]. In our model, the length of the RB is the length of the power transmission levels. The performance of our system is analyzed using the common parameter of signal interference noise ratio (SINR) and capacity (C). Although there are other measures of importance in characterizing a mobile network of femtocells and macrocells such as the total throughput, our choice of estimating the SINR and C follows from recent studies such as the references described previously.

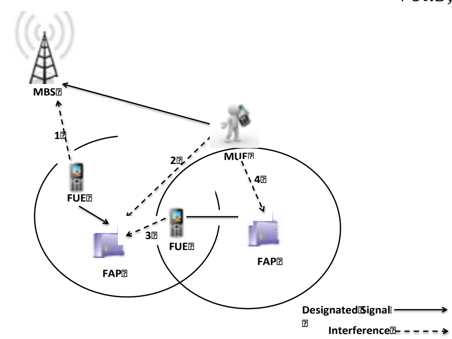

Figure 1. System Model

The throughput quantifies the volume of traffic in the network and this amount continues to increase steadily as technology advances. On the other hand, the capacity describes the maximum amount of signal strength the user equipments receives. Our study will be focused on the capacity and not the throughput which will be a subject of future research. The objective of the network service providers is to increase the capacity of the MUEs and FUEs. The SINR and the capacity are as defined in related literature such as [12], [9], and [11]

V. SIMULATION SCENARIO & PARAMETERS

The wireless network we consider consist of one macrocell underlaid with two femtocells. Each of the cells has an associated macro user and femtousers respectively. The channel gain between the transmitter i and receiver j depends on the distance between the transmitter and receiver. This is modeled as $g_{ij} = d^{-k}$, where d_{ij} is the physical distance between the ij transmitter i and receiver j and k is the path-loss exponent. In our simulations, we choose k = 4 just like [12]. In our network, we are interested in studying the uplink interference from the femtouser to the macro user and the interference between the two femtousers. Therefore, the signal to interference noise ratio of one FUE depends on the strength of the interference from the nearby MUE and the nearby FUE. Furthermore only one FUE is allowed to cause interference at the MUE while the MUE can cause interference at both FUEs because of the infinite range of possible distances between the transmitters and receivers, even in such a simplified network model, we tried several values for d in a bid to attain specific deterministic values for each pair of d_{ij}. Nevertheless, we initialized our simulations by setting $d_{ij} = 1$ to verify the usability of the simulation algorithm. The effect of this distance value will be explored in another related experiment.

The Q-learning aspect of our simulation considers two main factors - the reward function and the thresholds that were

chosen adaptively. simulation. Computation of the SINR followed the conventional approach in literature, so we set the noise power $\sigma^2 = 0.1$ in line with [12]. In addition, the learning rate α = 0.5 and the discounted factor used in the Q-learning algorithm is set to 0.9. Finally, the simulation is implemented in MATLAB on a desktop.

In this section, we repeated the several of experiments, however, we altered the distances for each of the agents which is different than our work in [15] where we set the distance to be the same. Therefore, for the FUEs and MUEs, we fixed their distances from their respective base stations to d = 100. This ensures they have a constant gain from their dedicated base stations. On the other hand, their locations from the interfering stations was set at d = 10. So, this changes the problem slightly from [15] where d = 1 in all cases. After performing 1000 iterations, and invoking Q-learning in the process, the observed results are shown in Figures 4.4, 4.5 and 4.6

Setting the threshold parameters as (γ_T = 2), we performed 1000 Q-learning iterations where at each iteration, the agents choose a random action corresponding to one of the transmission power levels in the range 2dB, 4dB, 18dB. The number of iterations was chosen as a reliable statistic for the Q-learning simulation and it is similar in the related literature.

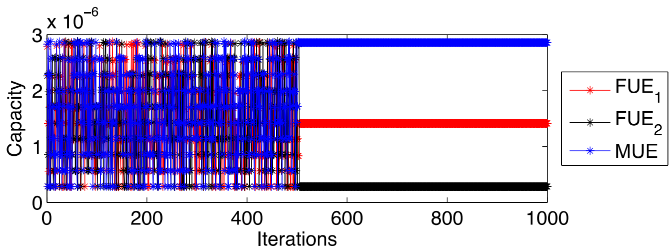

Figure 2. Macrocell and femtocells' capacity as a function of iterations. Independent Q-learning with agents at different distances from base stations

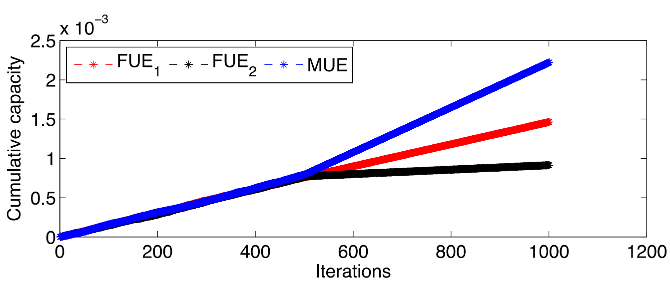

Figure 3. Cumulative capacity at the base stations as a function of iterations. Agents at different distances from base stations

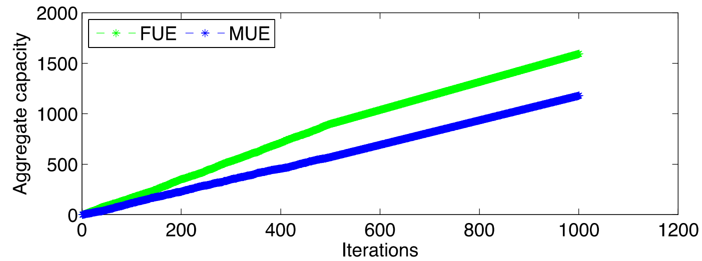

Figure 4. Total capacity of the FUEs and the MUE in the network as a function of iterations using independent Q-learning of agents at different distances from base station

In this experiments, our first observation was the drop in magnitude of the capacity. This decrease is related to the distance, hence the varying path loss in the network between the femtocells and macrocells. Further, the capacity of the macrocell after half of the iterations is still higher than the femtocells. Then, we observe reversal in the role of the two FUEs - the FUE experiencing both cross-tier and co-tier interference subsequently has a higher capacity than the one experiencing only a cross-tier interference. Perhaps, this is related to the change in the distance between the two FUEs. We also noticed that we no longer see the convergence between the FUE_2 and the MUE we saw previously. There is a distinct difference in the convergence of the cumulative capacities for all the agents. These observations shows the robustness of the Q-learning algorithm as a tool to efficiently allocate resources when the positions of the agents can be controlled. A cooperative learning between the agents might be a way to improve the network ability to manage the interference more efficiently.

VII. CONCLUSION

By means of numerical simulations and results, we have evaluated the performance of Q- learning algorithm. Our system comprising of one macrocell and two femtocells can be extended to multiple macrocells and femtocells. We showed how convergence can be attained using the Q-learning algorithm. We also illustrated how we can achieve a high quality-of- service for the macro user equipment while dealing with the uplink co-tier interference from the femtouser(s). The power levels which the macrouser and femtousers can choose also be varied in the network. We have shown the prove that the agents can find the optimal power level after several iterations.

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