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An Adaptive Spectrum Allocation Algorithm in Femtocell Networks Using Q-learning

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Abstract: An efficient spectrum allocation strategy is crucial to improving the spectrum utilization and Quality of Service (QoS) of users in femtocell networks. In this study, we formulate the downlink channel allocation problem in femtocell networks into a dynamic optimization problem. The formulation captures the stochastic nature of external packet arrivals as well as channel availability. Then, based on Q-learning techniques, we propose an Adaptive Spectrum Allocation Algorithm (ASAA), with a ε-greedy action exploration policy for the purposing of accelerating the rate of convergence. The algorithm can learn the statistics of both packet arriving processes and channel availability. In addition, it produces a near-optimal spectrum allocation strategy that aims at maximizing the system throughput. Simulation results demonstrate that the algorithm converges to a stationary spectrum allocation policy, which outperforms the classic Round Robin (RR) allocation policy.

Key words: Femtocell, spectrum allocation, q-learning, dynamic optimization

INTRODUCTION

With the rising popularity of mobile intelligent devices and growing requirement of indoor wireless data business, mobile operators are facing serious challenges of improving indoor wireless signal strength and coverage area. The traditional method to solve the above problem is to deploy more macro cells, however the design of network planning is the complexity and the deployment of the macro cell is expensive (Saunders *et al*., 2009).

Ubiquisys proposed a solution that deploy Femtocell Base Stations (FBS) in indoor (Brickhouse and Rappaport, 1996) to increase the indoor signal strength and coverage area. FBS is a low power wireless access point (Chandrasekhar *et al*., 2008), it can provide high quality indoor voice and data services for mobile phone or other mobile terminals. FBS can increase indoor wireless coverage and signal strength, provide good service quality for indoor high-speed data services, improve the network capacity and reduce the cost of macro cell (Calin *et al*., 2010). Femtocell has huge potential, but interference caused by spectrum reuse will seriously affect the cellular network throughput and its terminal user's service quality (Galindo-Serrano *et al*., 2010). Efficient spectrum allocation strategy can effectively reduce the interference and enhance throughput (Zhou and Yu, 2012).

At present, the study of spectrum allocation strategy in femtocell networks has made some preliminary results. Study (Galindo-Serrano *et al*., 2010) proposed a reinforcement learning method to solve the cognitive Spectrum allocation problem in cellular networks, shared knowledge of wireless environment between learners to speed the process of learning. However, this study focuses on the macro cell throughput while ignoring the QoS of femtocell. Study (He *et al*., 2010) defined the single user capacity maximization problem in femtocell network as a constrained integer programming problem and put forward a time efficiency resource allocation algorithm. It focus on the single user capacity maximization but ignore the multi-users' total capacity. Study (Lee *et al*., 2010) proposed a distributed channel selection method based on channel gain which can effectively reduce interference and enhance indoor capacity, but it did not consider the randomness of data arrive and time-varying of channel state. Study (Kim and Cho, 2009) mainly studied the centralized downlink wireless resource allocation problem in dense deployment femtocell network, however due to the randomness of FBS user deployment, centralized spectrum allocation needs huge cost.

Optimization theory is one of method widely used to solve resource allocation and task scheduling problem in the computer system and computer network. Compare to

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the static optimization theory,dynamic optimization theory could better describe the time-varying characteristics of system.

The objective of this study is to maximize the throughput of femtocell network and ensure the QoS of the terminal users, this study model the femtocell Downlink Spectrum Allocation (DSA) problem by using dynamic optimization theory, this model can describe the randomness of data arrival and the time-varying feature of channel status. Based on the above analysis, we proposes an algorithm named ASAA algorithm, whose distributed spectrum allocation strategy can maximize the overall throughput of femtocell network. Simulation result shows that the proposed algorithm is better than round robin allocation strategy.

The study is structured as follows: Section 2 summarizes the basic principles of Q-learning algorithm; Section 3 propose ASAA algorithm to solve the DSA problem; Section 4 design deployment simulation environment; Section 5 evaluate the proposed algorithm; Section 6, summarizes the full study, and point out the next step of work.

Q-LEARNING ALGORITHM RESEARCH

Q-Learning algorithm is a kind of reinforcement learning techniques, it regard learning process as a "testing-evaluation" process. Q-learning model can be defined as a quad $\{S, A, P_{S,S^1}, R(s, \alpha)\}$, where $S = \{s_1, s_2, \ldots, s_m\}$ is the all possible states set of agent, $A = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ is the actions set of the agent, $P_{s,s'}$ is transition probability of transit from state s to the state s′ after take action α, $R(s, \alpha)$ is the value function that defines the feedback which agent gained after take actions α when in the state s. The interaction between agent and environment is as follows:

- Agent perceive the environment and observe its current state $s_t \in S$
- Based on s_t, agent choose an action $\alpha_t \in A$
- Select an action based on α_t and $P_{s,s'}$ thus environmental changes to the new state $s_{t+1} \in S$ and receive a reward $r_t = R(s_t, \alpha_t)$
- Feedback the reward to the agent, then repeat the above process:

$$V^{\pi}(s) = E\left\{\sum_{t=0}^{\infty} \gamma^t r(s_t, \pi(s)) \mid s_0 = s\right\} \tag{1}$$

V (s) is the value function of the state s, which denotes the expected discounted reward over an infinite time. $0 \le \gamma \le 1$ is the discount factor. According to Eq. 2, the optimal value function can be written as:

$$V^*(s) = \max_{a \in A}\left(E\{r(s,a)\} + \gamma \sum_{s' \in S} P_{s,s'}(a) V^*(s')\right) \tag{2}$$

Q-learning is usually used to deal with situations where $P_{s,s'}$ is unknown. The ultimate goal of agent is to find an optimal strategy $\pi^*(s)$, which is the selected set of actions for state of $s_t\, \varepsilon S$ mean to maximize the expected discounted reward over infinite time. In order to achieve this goal, Q-value which defined the value of state-action pair is introduced. Q-value is defined as:

$$Q^*(s,a) = E\{r(s,a)\} + \gamma \sum_{s' \in S} P_{s,s'}(a) \max_{b \in A} Q^*(s', b) \tag{3}$$

from Eq. 3, the optimal value function can be expresses by:

$$V^*(s) = \max_{a \in A} Q^*(s,a)$$

Therefore, if Q-value of each state-action is known, we can be define the optimal strategy as $\pi^*(s) = \mathrm{argmax}_{\alpha \in A} Q^*(s, \alpha)$. The Q-learning algorithm finds $Q^*(s, \alpha)$ in recursive manner using update rule below:

$$Q(s,a) := (1-\alpha)Q(s,a) + \alpha\left(r(s,a) + \gamma \max_{b \in A} Q(s', b)\right) \tag{4}$$

where α is the learning rate. It was proved in that the iteration rules can converge to the optimal value under certain conditions. One of the conditions is every state-action of infinite can frequently visit. To meet this notion, this study uses ε-greedy algorithm which introduce a random number ε. At each step of learning process, use 1-ε probability random action ε-greedy1-ε and use ε probability random selection with this action.

MDP MODEL OF DSA PROBLEM

In two-tier femtocell network, FBS are randomly deployed by the user, and connect to the mobile operator's network by broadband means such as the existing residential digital subscriber lines, coaxial cable and fiber optic. Macrocell consists of a Macro Base Station (MBS) and several macro user (MMS, Macro Mobile Station). Each femtocell consists of a FBS and 2-4 femtocell users (FMS, Femto Mobile Station) (Claussen *et al*., 2008).

A typical two-tier femtocell network is illustrated in Fig. 1, each femtocell is deployed with a FBS, 2 FMS randomly deployed in FBS's coverage area. In this femtocell network, FBS allocate spectrum reso- urces to FMS in its coverage area. Indoor wireless propagation

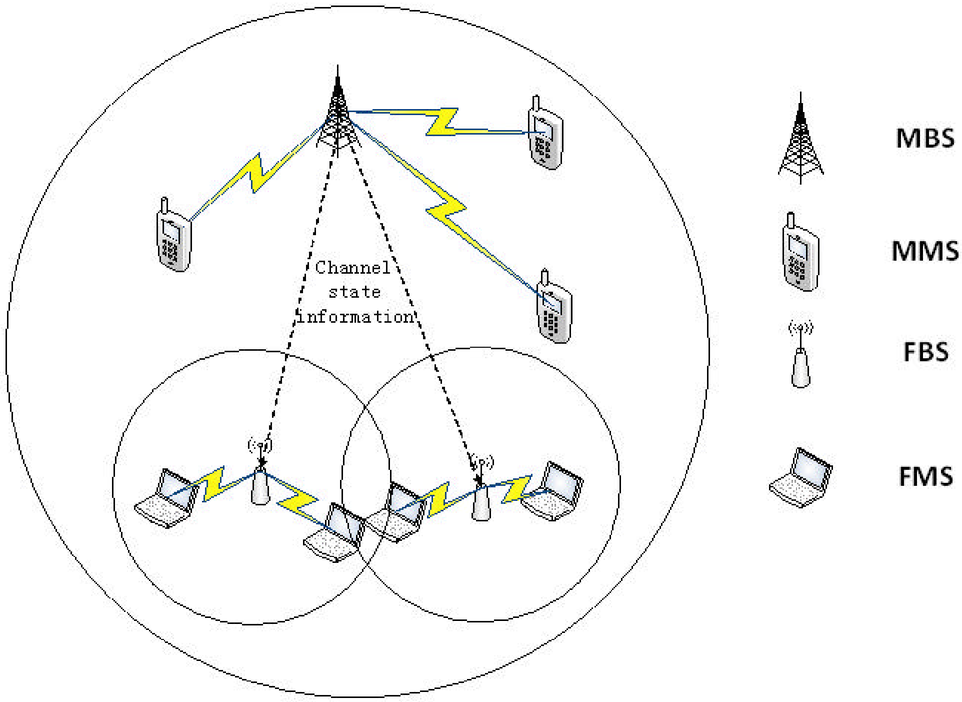

Fig. 1: Two-tier femtocell network

between FBS and FMS is characterized by Eq. 5 with the logarithm path loss model (Sundaresan and Rangarajan, 2009):

$$G(d) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + L_{pa} + L_{pe,} \tag{5}$$

In Eq. 5, d indicates the distance between FBS and FMS, PL (d_0) indicates free space propagation. d_0 indicates any reference distance. n indicates the path loss exponent. Free space propagation could be calculated as Eq. 6:

$$PL(d_0) = 20\log_{10}(d) + 20\log_{10}(f) - 27.55 \tag{6}$$

In Eq. 6, f indicates the channel's center frequency.

Based on the path loss model above, the channel gain between FBS and FMS could be indicated by:

$$g = 10^{\left(\frac{-G(d)}{10}\right)}$$

Consider the discrete time (t, t = {0, 1, 2, ...}) decision system, according to the current state of the system, FBS allocates channels to FMS at the start of each time slot , the collection of channel is indicated by J_a = {1, ..., j,..., J}, channe j's bandwidth is defined as B_j, j∈J. Assuming that the channel model is Additive White Gaussian Noise (AWGN) channel (Hussain *et al*., 2011), in t time slot, channel j∈J's capacity could be calculated as Eq. 7:

$$c_{tij} = B_j \log_2\left(1 + \frac{g_{tij}p_{tij}}{B_j N_0 + I_{tij}}\right) \tag{7}$$

In Eq. 7, B_j is the bandwidth of channel j, g_{tij} is FMS i's channel gain on channel j in t time slot.p_{tij} is FMS i's transmission power on channel j in t time slot. N_0 is the noise power spectral density. I_{tij} is the interference from the same frequency FMS i suffered on channel j.

Assumptions: (1) Inter-cell synchronization. Each femtocell are synchronized with neighbour femtocell and macrocell, (2) Spectrum access mode is closed mode (3) Coverage spectrum sharing mode. FBS allocate the authorized spectrum which are not occupied by MMS to FMS, (4) Channel listening mode. FMS collects and quantifies Channel State Information (CSI), such as channel gain and noise, then inform FBS the channel state information feedback through dedicated control channel.

ADAPTIVE SPECTRUM RESOURSE ALLOCATION USING Q-LEARING (ASAA)

In this model, Q-learning's agent, state, action and value function is defined as follows:

- **Agent:** FBS_i
- **State:** System state includs internal state s_{tj} and external variable W_t. Internal state s_{tj} characterize the occupancy of channel j in t time slot:

$$s_{tj} = \begin{cases} 0, & \text{idle} \\ 1, & \text{occupied by MMS} \\ 2 & \text{occupied by FMS} \end{cases}$$

$S_{tj} = 0$ indicates channel j is idle in t time slot; $S_{tj} = 1$ indicates channel j is occupied by MMS in t time slott; $S_{tj} = 2$ indicates channel j is occupied by FMS in t time slot t.

External variable $W_t = \{w_{t1},\ldots, w_{tj},\ldots, w_{tJ}\}$ is a 0-1 vector, indicates channel j is occupied by MMS or idle in slot t.

Action: System decision variable x_{tij} is a binary decision variable. $x_{tij} = 1$ indicates allocating channel j to FMS i in time slots t; $x_{tij} = 1$ indicates not allocating. Decision space shall satisfy the following constraints:

$$\begin{aligned} & s_{tj}\sum_{j\in J_t} x_{tij} \le 1, \forall i \in I_t \\ & \sum_{i\in I_t} x_{tij} \le 1, \forall j \in J_t \end{aligned} \tag{9}$$

Equation 9 indicates there could be up to one channel a single FMS could transmit on, Eq. 9 indicates there could be up to one FMS transmit on a channel at the same time slot, namely, FBS allocate a channel to a single FMS with non-empty queue (Chandra *et al*., 2008). J is the collection of all idle channel in t time slot. i is the collection of FMS that has a data transmission request in t time slot. q is defined as the queue length in the buffer of FMS i in time slot, q = 1 indicates there is a data transmission request.

Reward function: System gain function characterizes the throughput of femtocell in time slot, shown in Eq. 10:

$$R_t(s_t, x_t) = \sum_{i\in I_t}\sum_{j\in J_t} c_{tij} x_{tij} \Gamma \tag{10}$$

In Eq. 10, c_{tij} is the capacity of channel j which is allocated to FMS j in time slot t without interference, Γ is the fixed length of time slot, $X_t^{\pi}(S_t)$ characterizes the decision rules. The process of ASAA algorithm based on Q-learning is presented as follows:

ASAA algorithm

Input: ε, α, γ

Step 0. Initialization

0a. for all state S_t and decision $\alpha_t \in A_t$, initialize Q-table

0b. initialize S_0

Step 1. For t = 0, 1, 2, ... T do:

Step 1a. Apply ε-greedy algorithm to make decisions, select decision α_t randomly with a probability ϵ, apply Eq. 11 to make a decision with a probability $1-\varepsilon$:

$$a_t = \arg\max_{a\in A} Q(s_t, a_t) \tag{11}$$

Step 1b. Get the sample W_{t+1} and solve the next state $S_{t+1} = S^M(S_t, \alpha_t, W_{t+1})$

Step 1c. Apply Eq. 11 to update Q End for

Step 2. return to Q-table

Output: $Q_{t=1}{}^T$

In this algorithm, $\omega^n = (w_1, w_2, \ldots, w_t)$ is the samples generated by the external random variable in every time slot.

ASAA algorithm could learn statistical characte- ristics of external random variables such as packet arrival and channel availability autonomously, it apply greedy strategy to explore the behavior space, and accelerates the convergence rate. When the algorithm converges, it generate a near-optimal strategy of Spectrums allocation, which max -imizes the entire throughput of the femtocell.

PERFORMANCE EVALUATION

Simulation scienario: In the two-layer femtocell network, there are the femtocells named CF and RF in the macrocell coverage area. We can see the two femtocells as the two neighboring building femtocells, and each femtocell is deployed in the center. There are respectively two authorized FMSs which are defined as the $\omega^n = (w_1, w_2,\ldots, w_t)$. Coverage radius of each femtocell is the r = 40 m, R = 800 m.

The system bandwidth is 3.2 MHz, which is divided into six continuous but different-bandwidth channels J = {1, 2, ..., 6}. And each channel bandwidth is expressed as $B_{j,\, j\in J}$. Each channel that uses the center frequency is marked with its initial and end frequency (Wang and Moayeri, 1995). Femtocell network deployment and channel division are shown in Fig. 2.

The hardware emulation environment is required Intel (R) core (TM)2 Duo CPU E8400@3 GHz, memory 2.00 GB, windows7 32-bit operating system. The emulation software is Microsoft Visual Studio 2010 and programming language is C++.

It is assumed that each femtocell transmission power is 25 dbm and power allocation strategy that FBS allocates

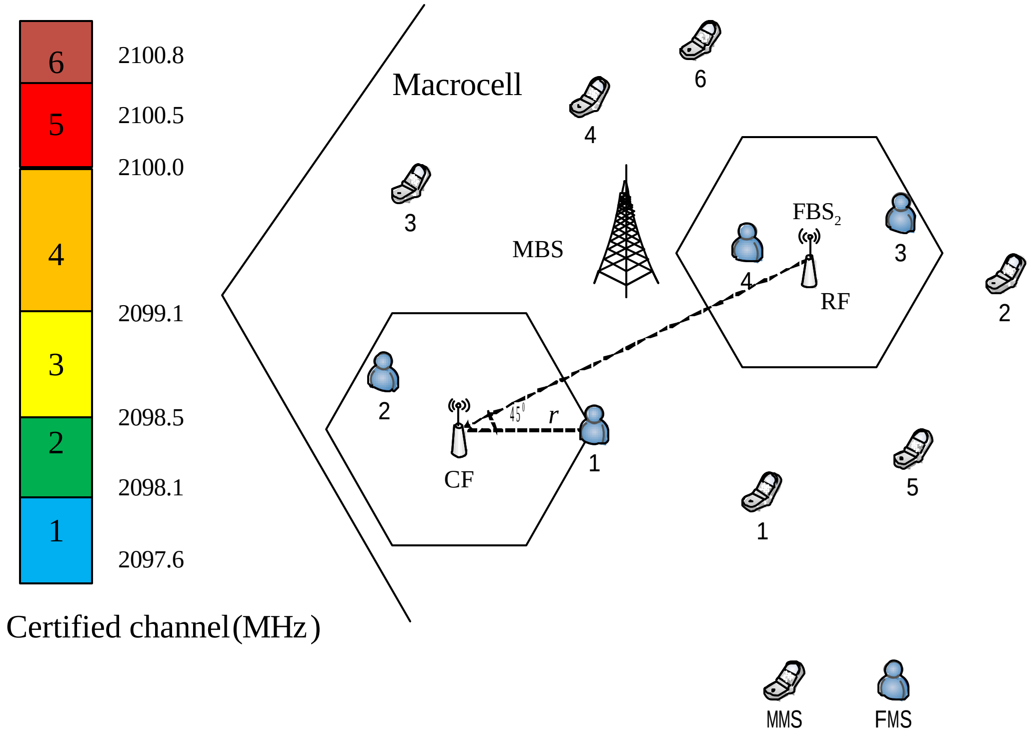

Fig. 2: Femtocell network deployment and channel division

Table 1: CF Path loss model parameters value

CF (FMS)	L_{pa}[dB]	L_{pe}[dB]	n	d [m]
1	3.9	N/A	$n_c = 2.1$	30.00
2	13.0			25.98
3	N/A	25.6	$n_{cr} = 3.4$	51.26
4				100.98

Table 2: RF path loss model parameters value

RF (FMS)	L_{pa} [dB]	L_{pe} [dB]	n	D (m)
1	N/A	25.6	$n_c = 3.1$	51.26
2				90.82
3	20.04	N/A	$n_r = 2.5$	25.98
4	7.0			15.00

power uniformly only for the FMS data request is designed (Xiang *et al*., 2013). The N_0 is –174dBm/Hz The interference information I_{tij} between the femtocell is unknown when an FBS allocates channel. An allocation strategy is obtained by the ASAA algorithm. Meanwhile, the actual interference I_{tij} can be calculated. The interference is calculated by Eq. 12:

$$I_{tij} = \sum_{r \in FBS_r} p_{trj} g_{trj} \quad (12)$$

In the Eq. 12, P_{tij} is the transmission power of the FMS r who uses the same channel j with the FMS i in the t time slot. i∈PF, r∈SF g_{trj} is the channel gain of the FMS r in the t time slot. The path loss model parameters of femtocell and SF are shown in the Table 1 and 2. n_c, n_r represents, respectively indoor path loss exponent of the femtocell and DF. n_{cr}, n_{rc} represents respectively path loss exponent between the femtocells. The distance of between FMS belonging to SF and the FBS belonging to femtocell is shown in Eq. 13:

$$d_r = \sqrt{D^2 + r^2 - 2rD\cos\theta} \quad (13)$$

The distance D between the femtocell and the SF is 65 m and the angle θ is:

$$\frac{\pi}{6}$$

In the Fig. 2, MMS channel occupancy is described with on-off procedure. On indicates that primary user m sends data over the channel j. However, off indicates that primary userm don't occupy channel. q_{mj} represents the probability of the on procedure occurrence. In the Fig. 2, the six channels are occupied respectively by the six authorized MMS users. And there is equation m = j. Namely, the m_{th} user occupies the j_{th} channel. The probabilities that MMS occupies channel j are represented below:

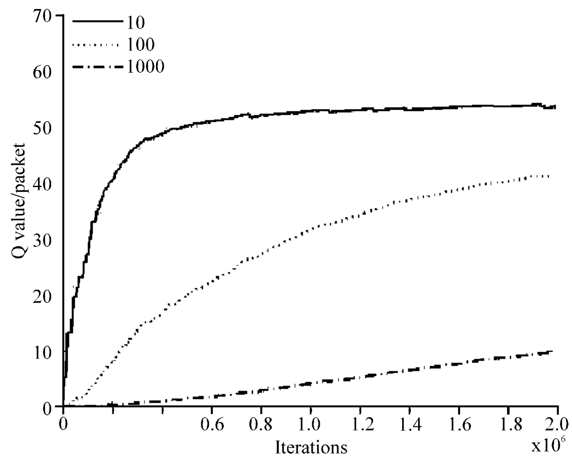

Fig. 3: Learning rate affects Q-learning algorithm convergence speed

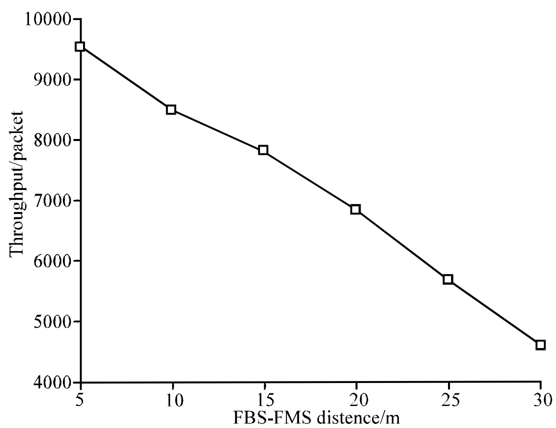

Fig. 4: Effect of distance between the FBS and FMS on the femtocell throughput

$$q_{mj} = (0.5, 0.6, 0.4, 0.3, 0.5, 0.1)$$

It is assumed that in the t time slot, FMS downlink data arrival corresponds to the Poisson distribution (Kim *et al*., 2010) and the average arrival rate λ_1~λ_4 is respectively equal to 5, 6, 5, 4 packets that each packet length is b = 512 bytes. The time slot length Γ is equal to 6 m. Femtocell buffer size can hold 15 data packets. Once the buffer is full , it will overflows. In the FBS buffer, queue length q_{ti} of FMS i is calculated by the Eq. 14:

$$\begin{cases} q_{0i} = k_{0i}, \\ q_{t+1,i} = q_{ti} - c'_{tij} x_{tij} + k_{t+1,i}. \end{cases} \quad (14)$$

c'_{tij} represents the rate that channel j serves the FMS i in the t time slot, Namely, actual capacity with interference. $k_{t+1,i}$ represents the data arrival queue length in the (t+1)Γ time.

NUMERICAL RESULTS

Simulation experiment on near-optimal Spectrum allocation strategy obtained after ASAA algorithm converges.

The input parameters of ASAA algorithm contain learning rate, exploring rate and time discount factor. The exploring rate is equal to ε = 0.2 Time discount factor is equal to γ = 0.9. The convergence speed is significantly affect by the size of the learning rate α In the Fig.3 , when there is an equation:

$$\alpha = \frac{1}{t/1000 + n}$$

different n values affect the Q-learning algorithm convergence speed. The vertical axis represents the Q values when status number is 0 and the decision number is 1 in the Q-table. In the Q-table, the status number is 2_6, in the range of 0-63. The decision number is $2^{6\times2}$, in the range of 0-4095.

It is shown in the Fig. 3 that when the:

$$\alpha = \frac{1}{t/1000 + 10}$$

the algorithm convergence speed is close to the fastest, and when the iterations reach to 4×10^5, the system is close to converge, the required time of 33 minutes. Because channel availability in the femtocell network only changes with the sudden use of macrocell users' the time scale about the flow changes is of hours. The proposed algorithm can be adapted to dynamic changes in the channel states in the femtocell network.

A steady and near-optimal spectrum allocation strategy π* is obtained after the algorithm converge. The system adopts strategy π* to execute 1000 time slots, to observe the effect of the distance between the FBS and the FMS and FSB buffer size on the femtocell throughput. Then judge the effectiveness of the strategy.

The Fig. 4 shows the effect of distance between the FBS and FMS on the femtocell throughput. When a FMS moves to the cell edge, Femtocell throughput declines faster. Because the cell edge FMS receives power down, and the interference becomes stronger from the neighboring femtocells, ultimately, femtocell downlink SNR is reduced. The results indicate that when the distance between FBS and FMS increases from 5 meters to 30 m, throughput declines up to 41.54%.

The Fig. 5 shows the effect of FBS buffer size on the femtocell throughput. When FBS buffer increases from 5 data packets to 20 data packets, femtocell throughput rapidly rises. But when FBS buffer is beyond 20 data packets, the throughput has no significant changes.

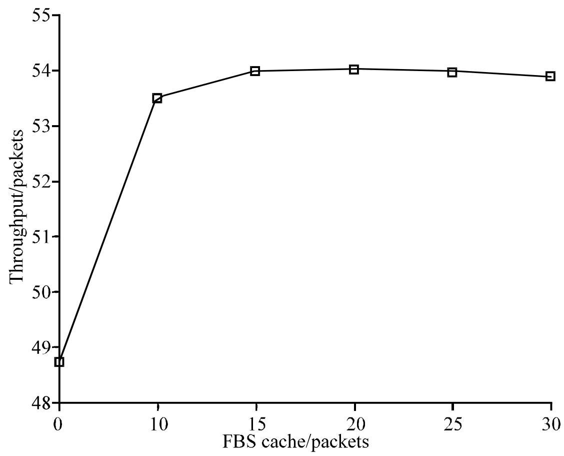

Fig. 5: Effect of FBS buffer size on the femtocell throughput

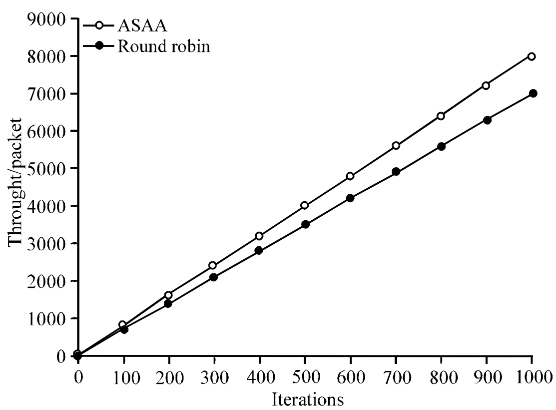

Fig. 6: Comparison of two algorithms objective function value

When the buffer is 20 packets, FMS data arrivals have been met, and the packet loss rate has decreased. The results show that When FBS buffer increases from 5 data packets to 30 data packets, throughput can be improved 10.88%.

Finally, compare the strategy derived from the ASAA algorithm with the classic round robin allocation strategy, the strategy efficiency can be Verified. The Fig. 6 indicates that there is a comparison on objective function of the two strategies. The results indicate that when iteration reach to 1000, the strategy derived from the ASAA algorithm is 26.12% higher than the classic round robin allocation strategy in the femtocell throughput. Obviously, the strategy provided in this article is better.

CONCLUSION

We study the cellular downlink link of Spectrum allocation problem, due to the data in the femtocell network reach is randomness and channel state time-varying characteristics, so we need to model use the basic theory of dynamic optimization . Because the system state transition probability is unknown,so we propose ASAA algorithm, and get near-optimal spectrum allocation policy of maximize the system throughput. This algorithm can self-learning external random variables of the statistical characteristics (such as packet arrival and channel availability). In addition, the exploration strategy in ASAA algorithm is effective to accelerate the convergence of the algorithm. The Simulation experiments shows that the algorithm can converge to a steady state eventually Spectrum allocation policy. Finally, compared with round robin allocation strategy, and prove the efficiency of the algorithm.

In the future work will focus on solving related follow-up questions. Research the related problem which is combinated LTE-A technology with OFDMA down link Spectrum allocation problem in femtocell network, and considering collaborative Q-learning methods to accelerate the algorithm convergence.

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