Revenue Maximizing Game and its Extension for Multicell Wireless Access Networks

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***Abstract*—As the number of wireless service providers increases, competition among them is becoming stronger in wireless access networks. On the other hand, users actively change their behaviors toward the networks to get more network resources such as service time, bandwidth, capacity, etc. That is, each user will actively choose a cell or a network that offers the largest amount of resources with the lowest cost. In these environments, service providers have to consider not only technical factors but also economical factors such as revenue and user price. By controlling the pricing policy, a service provider can recruit or refuse users that are trying to associate with.**

In this paper, we first model the resource purchasing and pricing game scheme that takes not only revenue of a service provider but also user satisfaction into account. Assuming selfish behaviors, solution is derived using game theoretic approach. The solution produces the integrated purchasing and pricing scheme that shows cell breathing effect. We extend the model to multicell environments where a user has freedom to choose its service provider. As a user actively changes its weight of the utility function and chooses a cell to associate with, overall performance can be improved. We demonstrate the effect of load balancing with the pricing policy, and the performance improvement compared to a conventional method of association via simulation.

I. Introduction

With a remarkable proliferation of wireless services and an exponential growth in the number of wireless devices, high data rate communication is one of the goals in future wireless networks. Since bandwidth or capacity that each individual user demands is gradually increasing, more APs (Access Points) or BSs (Base Stations)[1] are required to be installed to overcome the shortage of wireless resources. For this reason, there is a possibility of having several different service providers that establish APs in a fixed region. Femtocells, which work like cellular BSs or WLAN APs except for covering a small area, are such emerging example of multiple provider environments. Since each service provider will behave in a selfish manner to increase utilization of its limited wireless resources, competition among the service providers will be a new paradigm of future wireless networks to come [3]–[5].

This research was supported by the Ministry of Knowledge Economy, Korea, under the Information Technology Research Center support program supervised by the Institute of Information Technology Advancement. (grant number IITA-2009-C1090-0902-0006)

[1]In this paper, we use the terms AP, BS, and provider interchangeably.

On the other hand, since the wireless communication technology is significantly advanced compared to the past and it evolves continually, in near future, a mobile device will be able to associate with different types of networks simultaneously or change the network service provider while receiving services. It is called churning which refers to the migration of a user from one service provider to another [4], [6]. If a user is not satisfied with the currently associated network, he or she will switch to another network that provides more bandwidth or capacity. The churning explicitly incurs competition among users in a hot spot region, and implicitly induces competition among network service providers.

In such future environments, more complicated network models incorporating both technical and economical factors are needed. The technical factors can be throughput and quality of service (QoS), and the economical factors can be revenue of each service provider, cost that each user pays for the service, and reputation. There needs to be an integrated framework or model to reflect there technical and economical aspects of the network to further analyze future network environments.

Game theory is a mathematical tool developed to understand competitive situations where rational and selfish decision makers act based on their own interests. It is a good tool for researchers to adopt to model interaction among service providers and among users in competitive environments as presented in [7]–[10].

In this paper, we first formulate a game in a single cell environment. Resource of a service provider is time and each user purchases a fraction of time from the service provider to maximize his own utility. Knowing the action of each user, a service provider can determine its pricing policy that maximizes its own revenue. With the game theoretic modeling and approach, we derive a unique solution and express it in a closed form. The solution maximizes the total utility of all users as well as the revenue of the service provider at the same time.

Based on the solution derived from the game, we formulate a cell-site selection scheme that helps to maximize the sum of the utility of each user when each user first selects a cell to associate with. Briefly speaking, a user associates with a service provider that would be expected to offer a largest amount of resources with a good cost. To meet QoS requirements of each user, we propose a way in which each user actively behave. Each user involved changes the weighting factor of the utility function to get more resource at an increased cost in a given situation. It is beneficial for a user to modify the weight because otherwise he will not be able to get the desired QoS. For a service provider, it is also beneficial otherwise the user will switch to another service provider due to the lack of resources.

With simulations, we show that the pricing game has an intrinsic nature of cell breathing and association control. This effect leads to load balancing characteristic in multicell environments. We also show that our proposed association scheme that considers both technical and economic factors works well. Compared to a scheme that uses a conventional association method based on the pricing game, our proposed association scheme outperforms in the game situation that we are interested in.

The remainder of the paper is organized as follows. In Section II, we model the interaction of a service provider and users in a single cell using the Stackelberg game, and then transform the game into a convex optimization problem and derive its solution. In Section III, we extent the result of the single cell game to a multicell environment, and model active behaviors of users to preserve their QoS requirements. In Section IV, we present simulation results and show that our game theoretic cell-site selection works well compared to the conventional non-game theoretic one. Finally, we conclude the paper in Section V

II. Resource Purchasing and Pricing Game

In this section, we apply the Stackelberg game to model the interaction between a service provider and users [1]. After that, the game is transformed to a convex optimization problem and its solution is derived in a closed form expression.

A. Stackelberg Game

The Stackelberg game is an example of an extensive form game. It basically models two companies in the market that are trying to decide the amounts of production of goods sequentially. The game is played in two stages. At stage one, the leader company decides the amount of production q_1. Then at stage two, watching q_1, the following company decides the amount of production q_2. The range of q_1 and q_2 is from 0 to ∞. Fig. 1 shows an example of the Stackelberg game.

After the two companies decide their amounts of production, company i gets payoff π_i as follows.

$$\begin{aligned}\pi_1 &= P(q_1+q_2)\cdot q_1 - C_1(q_1)\\ \pi_2 &= P(q_1+q_2)\cdot q_2 - C_2(q_2),\end{aligned} \tag{1}$$

where $P(\cdot)$ is the market price (i.e., demand) function that depends on the total amount of goods in the market, and $C_i(\cdot)$ is the producing cost function for company i which is a function of the amount of production. We assume that the market price function $P(\cdot)$ is non-increasing[2] and that producing cost function $C_i(\cdot)$ is non-decreasing.

[2]More goods in a market, lower price due to law of demand and supply.

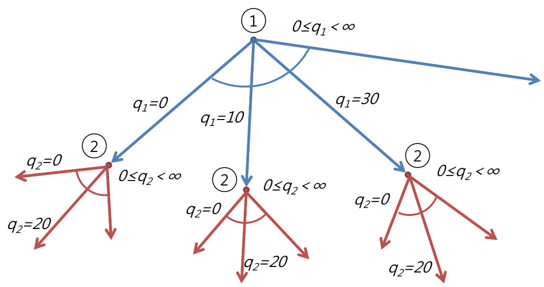


Fig. 1. An example of the Stackelberg leader and follower game. The number one and two denote leader and follower, respectively. The payoffs of the two players are not shown.

In this game, the solution (i.e., subgame perfect equilibrium) is achieved with the backward induction technique. With the backward induction, player 1 can anticipate player 2's action if he decides q_1. That is, to maximize his own profit, player 1 chooses q_1 with the consideration of q_2 which is a function of q_1.

B. User Utility Function and Service Provider Revenue

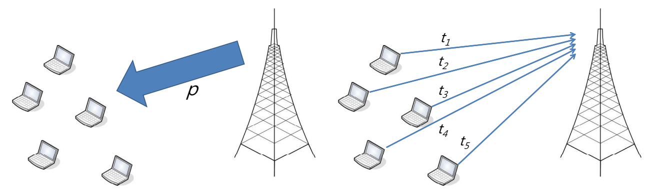
The utility function of a user in the network can be defined in various manners. Motivated by [7], we use the following utility function that needs to be maximized through time purchasing.

$$u_i(w_i, r_i, t_i, p) = w_i \cdot \log(1 + r_i \cdot t_i) - p \cdot t_i, \qquad 0 \le t_i \le 1, \tag{2}$$

where w_i is a weight for user i, r_i is a feasible transmission rate that depends on the channel condition of user i, $t_i$is a fraction of the time that user i purchases from the service provider, and p is the price per unit time that the provider announces.

Assume all the users have the same weight. Without the cost of purchasing time and the term '1' in the log function, the utility function is identical to that used in proportional fair (PF) scheduling [11]. In our utility function, subtracting the cost incurred by purchasing time is intuitive while the '1' in the log function is not. If the '1' in the log function does not exist, the users in the network are forced to purchase a nonzero amount of time since its utility is $-\infty$ when $t_i = 0$. In this case, users do not have any negotiation power over the provider. The provider can set the price arbitrarily large, and the user must accept and follow the price not to get the utility of '$-\infty$'. So, the '1' in the log function enables users in the network to negotiate the price through the amount of time to purchase with the provider. Thus, it helps to obtain a meaningful solution in the Stackelberg game. The weight w_i of user i reflects user i's willingness to purchase a fraction of time at the cost of price. Higher the weight, more time a user is willing to purchase with higher price.

On the other hand, a service provider wants to maximize its own revenue. Since a service provider sells its time resource at a fixed price per unit time, the revenue is the sold time multiplied by the price. The provider has a total time of one



(a) AP announces price per unit time.
(b) Each user purchases a fraction of time from the AP.

Fig. 2. The procedures for the single cell game. After the provider announces the price per unit time using the beacon or pilot, each user purchases a fraction of time to maximize his own utility.

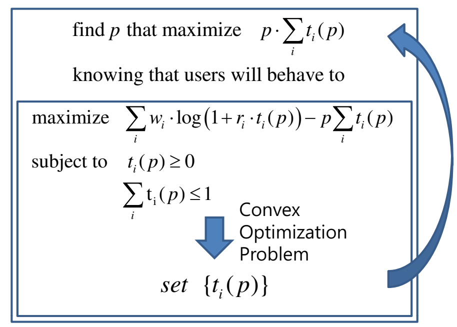


Fig. 3. The overall problem structure. The provider anticipates actions of users for a specific value of price p and chooses a price that maximizes its revenue.

in each game and sells a fraction of the time to each user according to the demand. We then have the revenue of the provider as

$$\text{revenue}(p) = p \cdot \sum_i t_i. \tag{3}$$

In the game model, a user purchases a fraction of the time to maximize his own utility when given the price, and the provider decides the price to maximize its own revenue. It can be modeled by the Stackelberg game where the leader is a provider deciding the price and the follower is users that purchase time resource with a given price.

C. Pricing Game and Convex Optimization

In Fig. 2, the pricing game procedures are presented. We assume that a feasible transmission rate of user i, r_i, is commonly known to the provider and user i. After hearing the beacon or pilot, each user can measure the channel condition and get a feasible transmission rate through the adaptive modulation and coding mechanism. The provider knows the set $\{r_i\}$ for all users after receiving the channel feedback from each user. We assume that the provider and users have the common knowledge of the set $\{w_i\}$, which is made available through the feedback.

The fraction of time each user i purchases can be obtained by solving the following optimization problem:

$$\begin{aligned} (\mathbf{O}) \quad \max \quad & u_i(w_i, r_i, t_i, p), \\ \text{subject to} \quad & 0 \leq t_i \leq 1. \end{aligned}$$

The constraint indicates that time fraction lies between 0 and 1. Since w_i and r_i are larger than 0, it is easy to show that the objective function is strictly concave.

From the assumption that w_i and r_i for all i are common knowledge, the provider can anticipate the action of each user when the provider decides the price. Thus, from the viewpoint of the provider, the behaviors of users are obtained by summing up each.

$$\begin{aligned} (\mathbf{P}) \quad \max \quad & \sum_i u_i(w_i, r_i, t_i, p) \\ \text{subject to} \quad & t_i \geq 0, \\ & \sum_i t_i \leq 1. \end{aligned}$$

The game is now transformed into a convex optimization problem [2]. Its solution enables the provider to decide the price to maximize the revenue. The overall problem structure, presented in Fig. 3 shows two-tier optimization structure, which captures backward induction technique to derive equilibrium of the Stackelberg game. The solution of the optimization problem is therefore the equilibrium(i.e., subgame perfect equilibrium) of the game. Through a technique to solve the convex optimization problem, we can obtain the solution[3] p and t_i of the game as

$$p = \frac{\sum_i w_i}{1 + \sum_i \frac{1}{r_i}} \tag{4}$$

and

$$t_i = \begin{cases} \frac{w_i}{p} - \frac{1}{r_i} & \text{if } r_i \geq \frac{p}{w_i} \\ 0 & \text{if } r_i < \frac{p}{w_i} \end{cases} \tag{5}$$

When a user senses a channel supporting a high feasible transmission rate, the amount of time to purchase gets larger and it is more likely to satisfy the threshold condition. This coincides with an intuition that a player with good condition has higher probability to win in a game. Since the price is determined by feasible rates and weights of all users, a user gets a small amount of resources if many users are competing in the game or they are with better channel conditions.

From the provider's perspective, more users means higher price due to the summation term of weights. With more users competing, the provider has more negotiation power over users, resulting in higher price. By changing the pricing policy, the provider controls the amount of resources each user purchases when the network gets crowded while gaining more revenue.

Obviously a user gets more resource if he gets a higher weight. Since the weight can be self modifiable, if a user increases his own weight, then his optimum time gets longer. But it also induces price increment by the provider. Thus, self increment of the weight of a user means that he is

[3]The detailed procedures are omitted due to page limit.

willing to purchase more resource at the increased cost. For a different user utility function that satisfies the concavity characteristic and conditions for the game theoretic approach, it is straightforward to modify the result of this paper.

III. Multicell Extension with QoS requirement

In this section we extend the result of the single cell game approach to multicell environments. the user actively changes the provider or modifies the weight for the utility function to meet the QoS requirement. In this paper, we assume that the QoS requirement of each user is minimum throughput.

A. Cell-Site Selection

In each cell, the game is played independently, so a user must consider the game information of each cell when he decides to join. Based on the result of the single cell game, a user can calculate the expected throughput of each cell when he joins. For that reason, let provider a in the network broadcast price p_a and W_a $(= \sum_{i \text{ in } a} w_i)$, the sum of the weights of the users the provider is currently dealing with. The information is contained in the beacon signal or other broadcast messages that the provider periodically broadcasts to advertise its existence.

After hearing all the information, a user selects a cell that provides the highest throughput. Then the user sends an association request message and waits for admission. While calculating the expected throughput, the user must consider the price increment incurred by his joining. The price after new user j joins provider a is

$$p'_a = \frac{W_a + w_j}{1 + \sum_{(i \text{ in } a)} \frac{1}{r_i} + \frac{1}{r_j}}, \tag{6}$$

where users with index i indicates user i already in the cell and W_a is $\sum_{(i \text{ in } a)} w_i$. Then we have the expected throughput for user j associating with cell a as

$$\text{Throughput}_{a,j} = \begin{cases} \frac{w_j \cdot r_j}{p'_a} - 1 & \text{if } r_j \geq \frac{p'_a}{w_j} \\ 0 & \text{if } r_j < \frac{p'_a}{w_j}. \end{cases} \tag{7}$$

After calculating the expected throughput of each cell, the user selects the best one and joins it. Choosing a cell with the highest throughput implies that the user selects a game field that he can expect to play most efficiently.

B. Increasing the Weighting Factor

If the highest expected throughput when a user selects a cell to join is less than the user's QoS requirement, the user modifies his own weight of the utility function to achieve the QoS requirement. That is, the user informs the provider of his willingness to get more resource at the increased cost at the time of association. Clearly, the first derivative of the expected throughput (7) with respect to w_j is always larger than 0. This means that increasing the weight always brings more throughput. The minimum weight for user j to achieve QoS satisfaction is expressed as follows

$$\bar{w_j} = \frac{(Q_j + 1) \cdot W_a}{r_j \cdot \left(1 + \sum_i \frac{1}{r_i}\right) - Q_j}, \tag{8}$$

where Q_j is the QoS requirement of user j. With $\bar{w_j}$, user j is able to obtain required QoS at the minimum price increment.

While receiving the service from a provider, a user's optimum amount of time to purchase can vary. This is because the price of the provider can change due to variation of communication environments. For instance, there can be joining and leaving of users, and changes of feasible transmission rates of users. In these cases, violation of QoS requirement can happen. A different thing from the weight setting for user joining is that only the weight increment influences the price since the weight before modification is already counted in the calculation of the price. We obtain the throughput of user j already in cell a as

$$\text{Throughput}_{j,a} = \frac{w_j \cdot r_j}{W_a} \cdot \left(1 + \sum_i \frac{1}{r_i}\right) - 1. \tag{9}$$

This throughput function is concave since its second derivative with respect to w_j is always negative. So, increasing the weight of the utility function of a user increases the throughput. The minimum weight when a user is already associated is expressed as follows

$$\hat{w_j} = \frac{(Q_j + 1) \cdot W_{a-j}}{r_j \cdot \left(1 + \sum_i \frac{1}{r_i}\right) - Q_j - 1},$$

where W_{a-j} is the summation of weights of all user in cell a except for the weight for user j. To get satisfaction with the minimum price increment, user j must increase the weight up to $\hat{w_j}$.

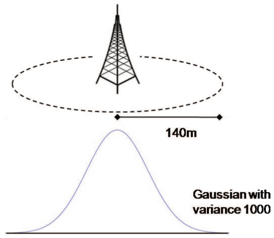
C. User Churning

Because of the advance of access technologies, user devices become smarter. Thus in near future, a user will have freedom to change the provider while receiving some service. In this game scenario, a user periodically listens to broadcasting messages of all providers near by. With all the game information, if it is found to be beneficial for a user to move from the current provider to another, the user changes it. Again the metric is throughput. When the expected throughput of any candidate provider is greater than the current receiving throughput, the user disassociates with the current provider and joins the candidate one with a new weight of the utility function to meet his QoS requirement.

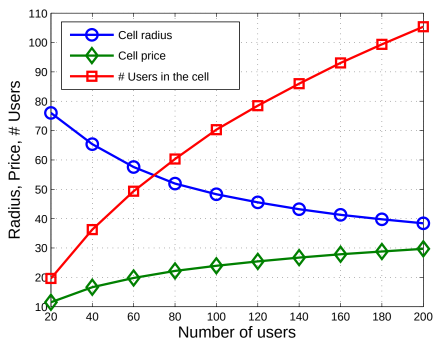
IV. Performance Evaluation

In this section, we see how the proposed game works and show the effects of cell breathing and load balancing. We also show how association and active behaviors to achieve QoS satisfaction, such as churning and weight modification, affect network performance.

We use a simulator which is written in C++ programming. We assume that the received SNR of a user depends only on the distance from a provider and the user with the path loss exponent is 2. The channel bandwidth of 11Mhz is used and the maximum transmission range is set to 100m. The Shannon capacity is used in calculation of throughput. The game is



(a) Single cell environments



(b) Price, Radius, Number of users admitted in a single cell versus Number of users

Fig. 4. Single cell scenario.

played in the time slot based. So a time slot is considered as a single game. Each simulation is performed for 1,000 time slots and the results are averaged over 100 repeated simulations. Also we assumed that each node has random on/off time which follows exponential distribution with the averages of 10 and 5 slots for on-time and off-time, respectively.

A. Cell Breathing and Load Balancing

Fig. 4 shows a single cell scenario. In Fig. 4(a), users are positioned in the cell (i.e., provider) of 140 meter coverage, following Gaussian random distribution with variance $1000m^2$.[4] With the number of total users in the network, the price that the provider announces increases following the result of the pricing game. After knowing the announced price, only a portion of the total users join the provider according to the channel condition. The joining users are those with relatively good channels while users with relatively bad channels disassociate with the provider. As a result, cell radius decreases with the price as shown in the Fig. 4(b). This shows the cell breathing characteristic of the pricing game.

When there are two cells sharing a portion of their service area as shown in Fig. 5(a), the effects of cell breathing and load balancing characteristic of the game are clearly shown. With respect to cell 1, users are placed with Gaussian random distribution while cell 2 has 5 fixed users. With the number of users around cell 1, the price of cell 1 increases as shown in Fig. 5(b), because of the strong competitions among users to purchase resources from the provider 1. As a result, only users with relatively good channels survive, and accordingly the radius of the cell 1 decreases. Some of the users that do not survive in cell 1 switch to cell 2 because competition in cell 2 is weaker due to less number of users in it. As a consequence, the radius of cell 2 increases. The pricing game has the cell breathing characteristic through the control of the number of users in the cell with the price that the provider announces. This aspect of the game leads to load balancing effect.

[4]Since we have set the maximum transmission range to 100m, users that are 100m away from the AP are unable to associate with.

B. Association, Churning, and Weight Modification

To see the effects of association and QoS aware behavior such as weight modification and churning, the grid topology where the distance between two neighboring providers is 100m is used. Users are distributed with respect to one provider. Each user generates a Poisson traffic, and its on/off time is exponentially distributed. So, when a user starts to generate a traffic, it scans the networks with the association scheme and participates in the game already existing. When the user stops generating the traffic, it simply disassociate with the provider.

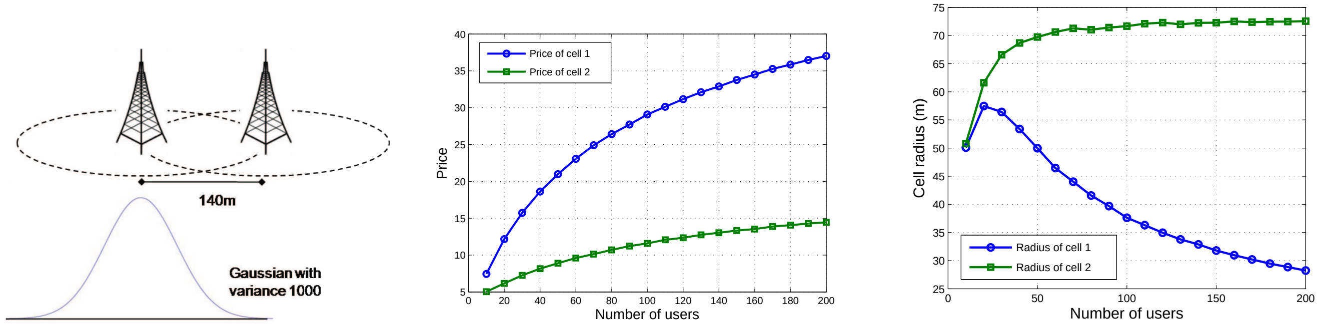
It can be seen in Fig. 6(a), the network-wide throughput performance mainly depend on the association scheme. Although churning and weigh modification are allowed, the network throughput does not improve. This is because each user has exponentially distributed on/off time. When users frequently associate and disassociate, the association scheme mainly affects throughput performance. With the number of users, the throughput gap between the association schemes gets smaller. It is due to the fact that when the network is saturated, there are quite a few users utilizing the good channels in close proximity to a provider.

Price-aware association is also beneficial to the service providers. In Fig. 6(b), the price-aware association scheme dramatically improves the revenue of the service providers. This is due to the load balancing effect. Compared to the conventional association scheme, the price-aware association distributes users evenly throughout the network. So users that might not be able to purchase resources from a hot-spot provider can easily associate with a relatively free provider. This improves the total network revenue. Also when the number of users increases, the network revenue increases without a bound. This is because competition among users gets strong since the provider's capacity is limited. Combined with the throughput results, when the network gets crowded, users should pay more although there is no more throughput gain.

QoS behavior dramatically improves QoS violation performance as shown in Fig. 6(c). The price-aware association can also improve QoS violation performance by distributing users throughout the entire network well. However, self QoS behavior improves the performance further by allowing individual user's movement for QoS preservation.

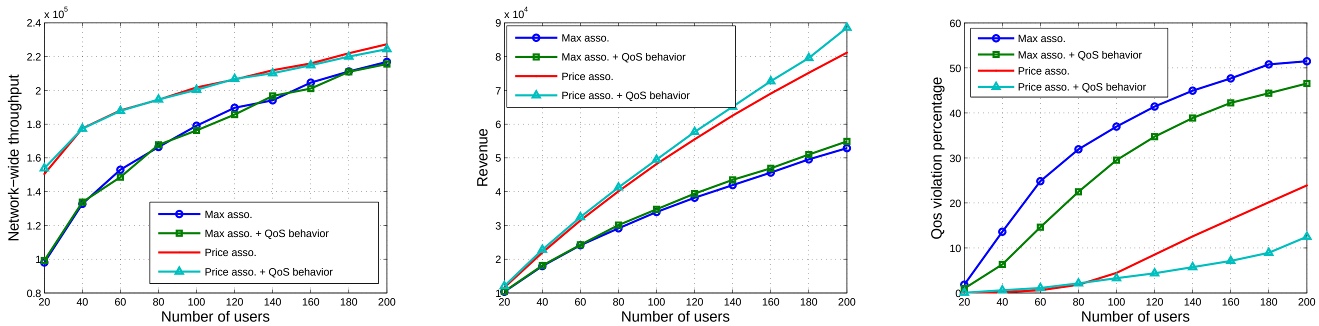
V. Conclusion

In this paper, we modeled network resource allocation with Stackelberg game model. Time resource is considered for allocation between a provider and users in a single cell first. In



(a) Two cell environments (b) Price of the two cells (c) Radius of the two cells

Fig. 5. Two cell scenario.



(a) Network wide throughput (b) Network wide provider revenue (c) Percentage of user QoS violation

Fig. 6. Network performance versus Number of users.

the considered scenario, each user tries to maximize his own utility that is proposed to count the transmission rate, price, and time resource together. Knowing all user information, each provider sets the price per unit time to maximize his own revenue. Then we extended the result of the single cell game to the multicell game scenario where multiple providers are available for each user to associate with. To preserve QoS requirement, each user is enabled to have active movement by weight modification and game-aware churning.

Through simulations we showed that the proposed game has the advantage of cell breathing and load balancing with the aid of pricing. We also showed that when network resources are allocated to users through the game, game aware association, which is price-aware association in this paper, and active behavior of each user to preserve QoS requirement improve network performance.

Although churning can give users more negotiation power over providers that can bring price down or more resource, we leave this aspect as a future work to formulate a game between providers or a negotiation between a provider and users.

References

[1] R. B. Myerson, *Game Theory - Analysis of Conflict*, Harvard University, 1991.

[2] S. Boyd and L. Vandenberghe, *Convex Optimization*, Cambridge University Press, 2004.

[3] D. Charilas, O. Markaki, and E. Tragos, "A Theoretical Scheme for Applying Game Theory and Network Selection Mechanisms in Access Admission Control," in Proc. *IEEE ISWPC*, Santorinim, Greece, May 2008.

[4] H. Lin, M. Chatterjee, S. K. Das, and K. Basu,"ARC: An Integrated Admission and Rate Control Framework for Competitive Wireless CDMA Date Networks Using Noncooperative Games," *IEEE Transaction on Mobile Computing*, vol. 4, no. 3, pp. 243-257, May 2008.

[5] A. N. Rouskas, A. A. Kikilis, and S. S. Ratsiatos, " Admission Control and Pricing in Competitive Wireless Networks Based on non-cooperative Game Theory," in Proc. *IEEE WCNC*, Las Vegas, USA, Apr. 2006.

[6] D. Noyato and E. Hossian, "Modeling User Churning Behavior in Wireless Networks Using Evolutionary Game Theory," in Proc. *IEEE WCNC*, Las Vegas, USA, Mar. 2008.

[7] T. Basar and R. Srikant, "Revenue-Maximizing Pricing and Capacity Expansion in a Many-Users Regime," in Proc. *IEEE INFOCOM*, New York, USA, Jun. 2002.

[8] J. Joutsensalo, A. Viinikainen, T. Hamalainen, and J. Siltanen, "Bandwidth Allocation, Bit Rate and Pricing," in Proc. *IEEE ICC*, Seoul, Korea, May 2005.

[9] S. Sengupta, M. Chatterjee, and S. Ganguly, "An Eoconomic Framework for Spectrum Allocation and Service Pricing with Competitive Wireless Service Providers," in Proc. *IEEE DySPAN*, Dublin, Ireland, Apr. 2007.

[10] D. Niyato, E. Hossain, and L. Le, "Competitive Spectrum Sharing and Pricing in Cognitive Wireless Mesh Networks," in Proc. *IEEE WCNC*, Las Vegas, USA, Mar. 2008.

[11] F. P. Kelly, "Charging and Rate Control for Elastic Traffic," *European Transactions on Telecommunications*, vol. 8, pp. 33-37, 1997.