A Distributed Multiple Spectrum Pricing Scheme for Optimality Support in Multiaccess Systems

Yonghoon Choi, Khan Sohaib, Hoon Kim, Kapseok Chang, Sungyeol Kang, and Youngnam Han

Abstract: **This paper focuses on a distributed multiple spectrum pricing scheme to maximize system capacity in next generation multiaccess systems, where multimode user equipments (MUEs) can connect simultaneously to multiple base stations (BSs) with multiple radio access technologies (RATs). The multi-price based scheme provides a distributed decision making for an optimal solution where radio resource allocations are determined by each MUE, unlike most centralized mechanisms where BS controls the whole radio resource. By the proposed optimal solution, MUEs can decide their share of spectrum bands and power allocation according to the spectrum price of each RAT, and at the same time the multiaccess system can achieve maximized total throughput. Numerical analysis shows that the proposed scheme achieves the maximal capacity by distributed resource allocation for the multiaccess system.**

Index Terms: **Multiaccess system, optimization, radio resource management, spectrum management, spectrum price.**

I. INTRODUCTION

In future wireless networks, there will be numerous heterogeneous networks with multiple radio access technologies (RATs). These networks utilizing the multi-RATs are named multiaccess systems, and each RAT such as 3rd Generation Partnership Project Long Term Evolution (3GPP LTE), worldwide interoperability for microwave access (WiMAX), and wireless LAN (WLAN) is denoted as subsystem [1], [2]. In those multiaccess systems, spectrum management (SM) functions are required to make efficient use of radio and to extend spectrum utilization for sparse radio resources [3]. As one of SM methods, dynamic spectrum allocation (DSA) has taken a lot of attention as a promising technique for the efficient use of unused/underutilized spectrum resources. Similarly, in order to utilize radio resources efficiently, the multiaccess system will demand the optimal solution for maximizing system capacity and multiple spectrum prices (SPs) for reflecting each subsystem's property. In addition, it will be better that the system provides a distributed decision making for optimality, which reduces computational complexity of base station (BS) and gives a choice to MUEs because resource allocations are determined by each MUE, unlike most centralized mechanisms where BS controls whole radio resource with extensive signaling efforts. In this paper, the optimal multiple SPs to maximize system capacity is discussed. For the optimality, we formulate an optimization problem subject to spectrum bandwidth and power constraints and draw Karush-Kuhn-Tucker (KKT) conditions. More specifically, in a given multi-RAT multiaccess system, the usage of multi-pricing scheme managed in a distributed manner is analyzed.

Several interesting spectrum pricing concepts and centralized/distributed decision methods may be found in the literature. The way of putting an economic value on spectrum bands (SBs) is introduced in [4], [5]. After [5] providing the market-based approaches to SM, such as SP and auction, several pricing problems using a game theoretic model were developed [6], [7]. In [7], each of primary services aims to maximize its profit under quality of service (QoS) constraint. Likewise, [8] tries to find an optimal pricing strategy to maximize the profit using a queuing theory, where the primary user's applications are not queued whereas the secondary user's applications are queued. Some network types – 802.22 networks, wireless cellular networks employing code division multiple access (CDMA), and cognitive wireless mesh networks – are examined for spectrum pricing in [9]–[12]. Especially, [10] focuses on SM using a spectrum cleaning house which controls and provides time-bounded access to SB in a centralized manner. And [11] presents the distributed spectrum allocation problem using a universal SP in cognitive radio (CR) systems.

The main contribution of this paper is to demonstrate a multi-spectrum pricing solution for optimal spectrum allocation in multiaccess system. Moreover, unlike a centralized decision and universal spectrum pricing method, our proposed scheme provides distributed processing and multiple SPs to achieve the maximized system capacity in multiaccess system. The rest of the paper is organized as follows: Section II starts with some definitions and describes the system model. Section III goes through the problem formulation for multi-pricing and the description of distributed decision making in the proposed multi-spectrum pricing scheme. Simulation results are presented in Section IV, and finally Section V concludes the paper.

II. SYSTEM MODEL

As shown in Fig. 1, we are considering a multiaccess system consisting of three subsystems which are based on orthogonal frequency division multiple access (OFDMA) technology. This system has overlapped regions and we focus on the smallest area where a multimode user equipment (MUE) can access as many RATs as possible. It is assumed that an MUE may connect simultaneously to different BSs with heterogeneous RATs and can have multiple connections known as multi-homing ca-

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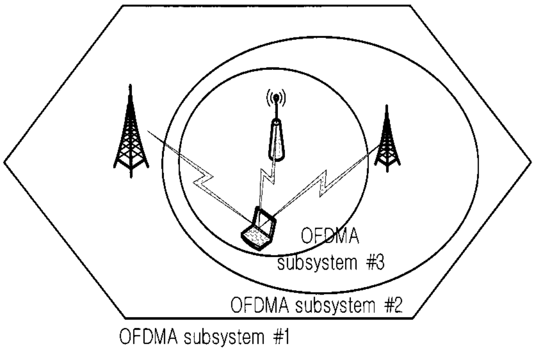

Fig. 1. An example of multiaccess system consisting of three subsystems.

pabilities. That is, MUEs have no significant interference among them and can adjust their radio operation parameters dynamically to make use of available SBs. In this way, it becomes possible to construct an intelligent multiaccess system with cognitive ability. Under this system, any MUE can access any subsystem which has its own spectrum price. Hence, for multi-spectrum pricing, some additional characteristics need to be taken into account.

- Each RAT (i.e., subsystem) of multiaccess system has its own SP, which is defined as the price to be eventually paid by the MUE for using the SB.
- The SP is determined by SM function of each RAT, according to the total requested amounts of SBs by all MUEs.
- In case that there are remaining SBs which are not allocated, SM function of each RAT can reduce the next step SP in order to induce MUEs to request more SBs in the next step.

III. MULTIPLE SPECTRUM PRICING AND DISTRIBUTED DECISION MAKING SCHEME

A. Multi-Spectrum Pricing for Optimal Resource Allocation

As illustrated in Fig. 1, we consider the OFDMA multiaccess system consisting of some OFDMA-based subsystems. Our objective is to find the multiple SPs of each subsystem for maximizing the system capacity, so we observe the optimal SB allocation value linked to each SP. In the multiaccess system, each MUE can obtain the SBs from some RATs for multiaccess and experience a different channel gain on each SB. For MUE i and RAT j, the channel transfer function and the total noise power spectral density are denoted as H_{ij} and N_{ij}, respectively. The channel gain-to-noise ratio for MUE i and RAT j can be indicated by

$$g_{ij} = \frac{|H_{ij}|^2}{N_{ij}}, i = 1, 2, \cdots, N, j = 1, 2, \cdots, M, \quad (1)$$

and it is assumed constant during SB allocation and each transmission time interval.[1] From Shannon capacity formula for a Gaussian channel, the data rate of MUE i can be defined as [13]

$$r_i = \sum_{j=1}^{M} x_{ij} \log\left(1 + \frac{g_{ij}p_{ij}}{x_{ij}}\right) \quad (2)$$

where x_{ij} is the allocated SB for MUE i from RAT j and p_{ij} is the transmission power of MUE i to RAT j. Here, x_{ij} can be regarded as the expectation for spectrum/rate (i.e., high speed and high quality) upon which MUEs will rely while requesting and allocating an SB.

In the multiaccess system as shown in Fig. 1, we can formulate a capacity maximization problem to obtain the multiple SPs (λ_j) of RAT j with respect to constraints in the MUE's transmit power and the RAT's available spectrum bandwidth as follows:

$$\max \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij} \log\left(1 + \frac{g_{ij}p_{ij}}{x_{ij}}\right), \quad (3)$$

$$\text{s.t.} \sum_{i=1}^{N} x_{ij} \leq X_j, \forall j, \quad (4)$$

$$\sum_{j=1}^{M} p_{ij} \leq P_i, \forall i, \quad (5)$$

$$x_{ij}, p_{ij} \geq 0. \quad (6)$$

In the above constraints, X_j is the total spectrum bandwidth of RAT j, and P_i is the maximum power constraint of MUE i. This problem formulation is the same as that in [14] except for choosing $X_j = 1$. Although mathematically it is the same model, the parameters of our work have different physical interpretations in the multiaccess system. In other words, both works start with the same mathematical model, but the subsequent focus is different. The focus of [14] is to consider a centralized resource allocation for OFDM systems. Whereas, in this work, our focus is to use the same model to analyze different RATs, consider multiple pricing, and motivate revenue, which was not considered in the other work. In addition, note that the objective function is concave with respect to $\{\mathbf{x}, \mathbf{p}\}$ [15], so the optimal value can be easily derived, where a local maximum is also a global maximum in our problem.

Not only to calculate the uplink resource optimality in spectrum and power allocation, but also to obtain the SP of each RAT, we should consider the Lagrangian of objective function and the KKT conditions as

$$\begin{aligned} L(x_{ij}, p_{ij}, \lambda_j, \mu_i) = & \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij} \log\left(1 + \frac{g_{ij}p_{ij}}{x_{ij}}\right) \\ & + \sum_{j=1}^{M} \lambda_j \left(X_j - \sum_{i=1}^{N} x_{ij}\right) \\ & + \sum_{i=1}^{N} \mu_i \left(P_i - \sum_{j=1}^{M} p_{ij}\right), \end{aligned} \quad (7)$$

$$\frac{\partial L}{\partial x_{ij}} = \log\left(1 + \frac{g_{ij}p_{ij}}{x_{ij}}\right) - \frac{g_{ij}p_{ij}}{x_{ij} + g_{ij}p_{ij}} - \lambda_j \leq 0, \quad (8)$$

$$\frac{\partial L}{\partial p_{ij}} = \frac{g_{ij}x_{ij}}{x_{ij} + g_{ij}p_{ij}} - \mu_i \leq 0, \quad (9)$$

[1] This work is interested in RAT-by-RAT based resource allocation, not carrier-by-carrier. Hence, it is assumed that H_{ij} is flat over spectrum and remains the same no matter in which SB x_{ij} lies [11].

$$x_{ij}\left(\log\left(1+\frac{g_{ij}p_{ij}}{x_{ij}}\right)-\frac{g_{ij}p_{ij}}{x_{ij}+g_{ij}p_{ij}}-\lambda_j\right)=0, \quad (10)$$

$$p_{ij}\left(\frac{g_{ij}x_{ij}}{x_{ij}+g_{ij}p_{ij}}-\mu_i\right)=0, \quad (11)$$

$$\lambda_j\left(X_j-\sum_{i=1}^{N}x_{ij}\right)=0, \quad (12)$$

$$\mu_i\left(P_i-\sum_{j=1}^{M}p_{ij}\right)=0 \quad (13)$$

where λ_j and μ_i are nonnegative Lagrangian multipliers, and particularly λ_j can be interpreted as SP linked to SB x_{ij}.

Using (9) and (11), we can obtain the spectrum and power relation

$$p_{ij}=x_{ij}\left(\frac{1}{\mu_i}-\frac{1}{g_{ij}}\right). \quad (14)$$

In this (14), to obtain the optimal x_{ij} and p_{ij} value, we have to know one of them. To obtain the optimal x_{ij} value firstly, one can use the well-known Newton's method [16] which can find successively better approximations to the roots of a real-valued function. In order to apply the Newton's method, $f(x_{ij}^{n})$ is assumed by

$$f(x_{ij}^{(n)})=\log\left(1+\frac{g_{ij}p_{ij}^{(n)}}{x_{ij}^{(n)}}\right)-\frac{g_{ij}p_{ij}^{(n)}}{x_{ij}^{(n)}+g_{ij}p_{ij}^{(n)}}-\lambda_j^{(n)} \quad (15)$$

where n represents the nth decision epoch. Then, simple algebra can derive the below formula for a better approximation value as

$$x_{ij}^{(n+1)}=x_{ij}^{(n)}-\frac{f(x_{ij}^{(n)})}{f'(x_{ij}^{(n)})}. \quad (16)$$

The process can be started with some arbitrary initial values x_{ij}^{0} and p_{ij}^{0} (i.e., positive values). With relatively short computations, one can obtain the better approximation of x_{ij} because (3) is concave and (15) is decreasing function of x_{ij} (see Theorem 1). After obtaining the x_{ij} value, the p_{ij} value can be taken using (14).

To obtain the SP of each RAT which maximizes the system capacity, we consider the Dual function as

$$D(\lambda,\mu)=\max_{x,p}L(x_{ij},p_{ij},\lambda_j,\mu_i). \quad (17)$$

For the next equation for SP adjustments rule, a subgradient-based search [17] is used and updated value can be given by

$$\lambda_j^{(n+1)}=\left[\lambda_j^{(n)}-\delta\frac{\partial D(\lambda^{(n)},\mu^{(n)})}{\partial\lambda_j}\right]^+ = \left[\lambda_j^{(n)}+\delta\left(\sum_{i=1}^{N}x_{ij}^{(n)}-X_j\right)\right]^+ \quad (18)$$

where $\delta>0$ is a constant step size, and $[z]^+$ represents the maximum element among z and 0. Likewise, we can also determine the μ_i value for the power allocation. Iteration stops when the SP converges or the maximum number of iterations allowed is reached. After iterative calculations, we can obtain the SP of each RAT for supporting the optimal spectrum allocation and maximizing the system capacity.

B. Characterizing the Spectrum Price

In order to elucidate the effect of the number of MUEs and RATs to SP, let us assume that

$$r_i=r(x_i,P_i,g_i)=\sum_{j=1}^{M}x_{ij}\log\left(1+\frac{g_{ij}p_{ij}}{x_{ij}}\right) \quad (19)$$

and then we obtain

$$\frac{\partial r_i}{\partial x_i}=\sum_{j=1}^{M}\left[\log\left(1+\frac{g_{ij}p_{ij}}{x_{ij}}\right)-\frac{g_{ij}p_{ij}}{x_{ij}+g_{ij}p_{ij}}\right] \quad (20)$$

where $x_i=[x_{i1},\cdots,x_{iM}]$, $P_i=[p_{i1},\cdots,p_{iM}]$, and $g_i=[g_{i1},\cdots,g_{iM}]$.

Theorem 1: $\partial r_i/\partial x_i$ is a decreasing function of x_i and is non-negative for all values of $[x_i,P_i]$ for fixed g_i.

Proof: One can deduce $\partial r_i/\partial x_i$ is decreasing in x_i from the fact that r_i is concave and $\partial^2 r_i/\partial x_i^2<0$. Since r_i is concave and increasing in $[x_i,P_i]$ for fixed g_i, it can be verified that r_i is concave and increasing in x_i for fixed P_i and g_i. Also, it is induced that $\partial r_i/\partial x_i$ is decreasing in x_i from concavity of r_i with respect to x_i. Therefore, it is concluded that $\partial r_i/\partial x_i\geq 0$ for all values of $[x_i,P_i]$ for fixed g_i. □

Theorem 2: The SP (λ_j) of each RAT j increases or maintains the same value as the number of MUEs increases in the multiaccess system.

Proof: Assume that RAT j is in equilibrium with N MUEs, which have been allocated for SB (x_{ij}), and MUE ($N+1$) joins in with $g_{(N+1)}$ and $P_{(N+1)}$. From (6), in the new equilibrium, the MUE ($N+1$) can acquire non-negative SB ($x_{(N+1)j}$). This will reduce the allocated SB or keep the same allocated SB for all other MUEs i ($1\leq i\leq N$). Because g_i and P_i is the same, this causes the SP (λ_j) of RAT j to go up or stay at the same value (from the Theorem 1 and (8) of KKT conditions). Therefore, a new MUE either increases or does not change the demand for SB and thus raises or maintains the SP. □

Theorem 3: $\partial r_i/\partial x_i$ is a strictly increasing function of P_i for fixed x_i and g_i.

Proof: In order to verify the above theorem, after substituting $z_i=g_iP_i/x_i$ in (20) for fixed x_i and g_i, one can obtain the following

$$\Theta(z_i)=\log(1+z_i)-\frac{z_i}{1+z_i} = \log(1+z_i)\left[1-\frac{z_i/(1+z_i)}{\log(1+z_i)}\right]. \quad (21)$$

Because $\log(1+z_i)$ is strictly increasing in z_i, it is a sufficient condition of $\Theta(z_i)$ to show that $F(z_i)=(1+z_i)\log(1+z_i)/z_i$ is strictly increasing in z_i. Taking the derivative of $F(z_i)$ demonstrates that $\Theta(z_i)$ is strictly increasing in z_i by using $z_i-\log(1+z_i)>0$ for all $z_i>0$. □

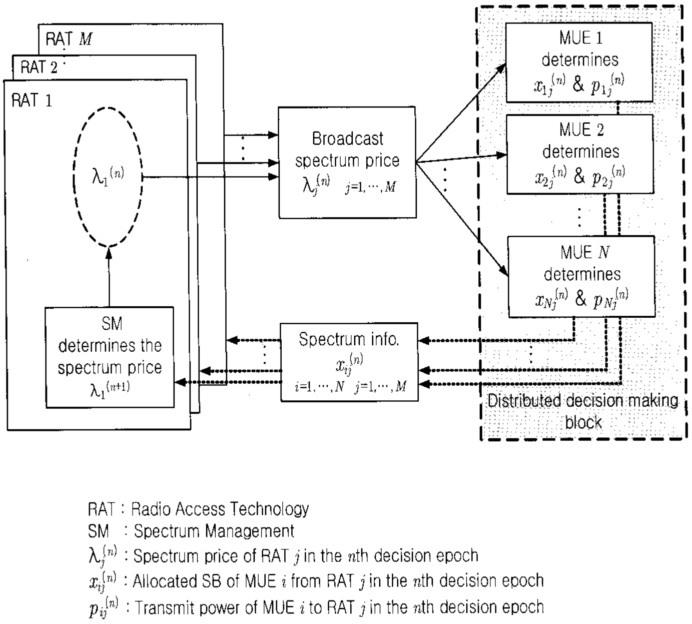

Fig. 2. Distributed multiple spectrum pricing scheme in multiaccess systems.

Theorem 4: An addition of another RAT either decreases the SP (λ_j) or keeps it unchanged.

Proof: Assume that the system is in equilibrium with M RATs and RAT $(M+1)$ joins in the system. If it offers no SB to any of the MUEs for all i $(1 \le i \le N)$, then no MUE engages itself to the RAT $(M+1)$ and the optimal solution (i.e., SP and SB) stays as same as before. As for MUE i, however, the new RAT provides a SB $x_{i(M+1)}$ from (6), then MUE i engages itself to RAT $(M+1)$ and adjusts its engaged power zero to $p_{i(M+1)}$. This will reduce the allocated transmission power p_{ij} for all other RATs j $(1 \le j \le M)$. Since g_i and x_i stay the same, this means that the SP (λ_j) of RAT j $(1 \le j \le M)$ goes down from the Theorem 3 and (8) of KKT conditions. □

Similar version of Theorems 2 and 4 is also observed in [11]. However, the difference between our claims and [11] is that we derive the multiple SPs and the downward SP (i.e., Theorem 4) when a new RAT is added in the multiaccess system. The reason is that our system model considers multiaccess in multi-RAT system which has its own total spectrum bandwidth (X_j), that is not limiting the available spectrum unlike in [11].

C. Proposed Scheme for Distributed Decision Making

Based on the above multi-spectrum pricing for optimal resource allocation, we have shown the applicability of a distributed decision making scheme as in Fig. 2. In this figure, the left part (i.e., RAT) plays a role of BS, the right part plays a role of MUE, and the middle part implies the information which is delivered through air interface. Also, the solid lines imply a flow of signal information from each RAT to MUEs, and the dotted lines represent feedback information from MUEs to each RAT. According to the signal/feedback information, each RAT and MUE ensures the side constraints (i.e., (4)–(6)) to be observed. In case when less SBs are available than requested, SM function of each RAT increases the SP by (18) to make MUEs require less. In addition, the reverse process can be applied. Through repetition, it results in an optimal solution.

The proposed multi-spectrum pricing scheme for distributed decision making is summarized as follows:

Algorithm : Distributed Multiple Spectrum Pricing

1: Initialize $x_{ij}^{(0)}$, $p_{ij}^{(0)}$, $\lambda_j^{(0)}$, and $\mu_i^{(0)}$.
2: At the n^{th} iteration, each RAT announces its own SP $\lambda_j^{(n)}$.
3: Each MUE determines a new $x_{ij}^{(n)}$ and $p_{ij}^{(n)}$ from broadcasted $\lambda_j^{(n)}$ by using (14)–(16) in the decision making block.
4: All MUEs feedback the $x_{ij}^{(n)}$ to each RAT.
5: **if** $\lambda_j^{(n)}$ is converged or n reaches the maximum number of iterations, **then**
6: Stop
7: **else**
8: SM function of each RAT determines the next step SP $\lambda_j^{(n+1)}$ from (18), and return to 2: with $n \leftarrow n+1$.
9: **end if**

Note that the allocation is determined not by a centralized mechanism (i.e., by RATs) but in a distributed manner (i.e., in MUEs) in order to maximize the total system capacity. This means that the proposed scheme gives a choice for MUEs to connect with multi-RAT and each MUE can determine its SB assignment considering each SP. In addition, by the assumption, if any RAT has available spectrum bandwidth which is not allocated, the SM function of each RAT has possibility to reduce the next step SP using (18) and induces MUEs to request more SBs in the next step. In this way, each RAT can manage its allocation by handling λ_j value.

Using the SP and information of SB allocation, one can determine the revenue of each RAT (Λ_j) as

$$\Lambda_j = \eta\lambda_j \sum_{i=1}^{N} x_{ij}, \quad \forall j \tag{22}$$

where η is a re-scalable weighting factor. Likewise, the cost each MUE should pay in order to connect the SB can be expressed as

$$\Gamma_i = \eta \sum_{j=1}^{M} \lambda_j x_{ij}, \quad \forall i. \tag{23}$$

Therefore, one can also think about the following relationship that the cost of all MUEs is equal to the revenue of RATs

$$\sum_{j=1}^{M} \Lambda_j = \sum_{i=1}^{N} \Gamma_i. \tag{24}$$

IV. NUMERICAL SIMULATIONS

A. Simulations Configuration

In order to prove the adaptibility and estimate the influence of distributed multi-spectrum pricing scheme, it is assumed that each RAT has the same initial SP at the beginning of a simulation. Table 1 shows parameters used in providing numerical results. It is admitted that multiaccess system has three RAT subsystems which are overlapping. The channel gain-to-noise ratio

Table 1. Simulation parameters and assumptions.

Parameters	Assumption
RAT 1	1.0 km
Radius of RAT 2	0.6 km
RAT 3	0.1 km
RAT 1	5 MHz
Spectrum bandwidth of RAT 2	10 MHz
RAT 3	20 MHz
MS's maximum power	20 mW
Antenna type	Omni-directional
Thermal noise	−174 dBm/Hz
Simulation step	1 sec
Initial spectrum price	2.2

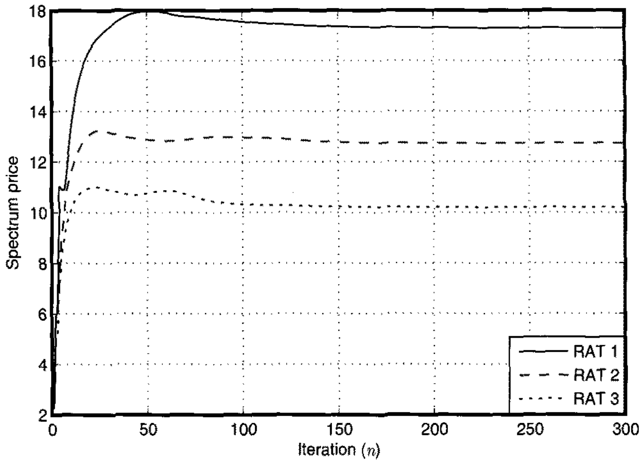

Fig. 3. An example of the converged spectrum price (when $N = 10$).

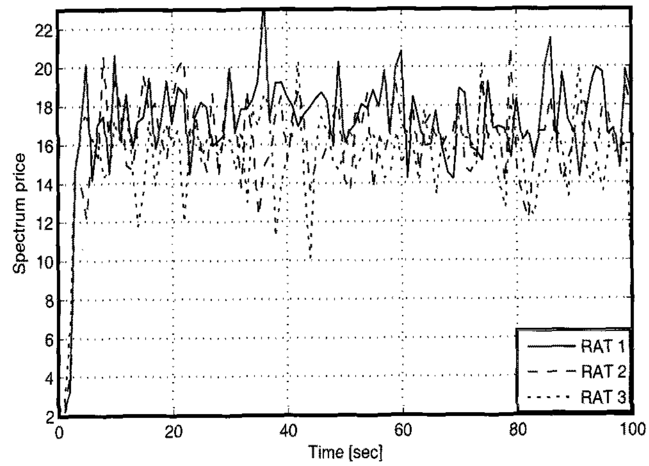

Fig. 4. Spectrum price versus time (when $N = 10$).

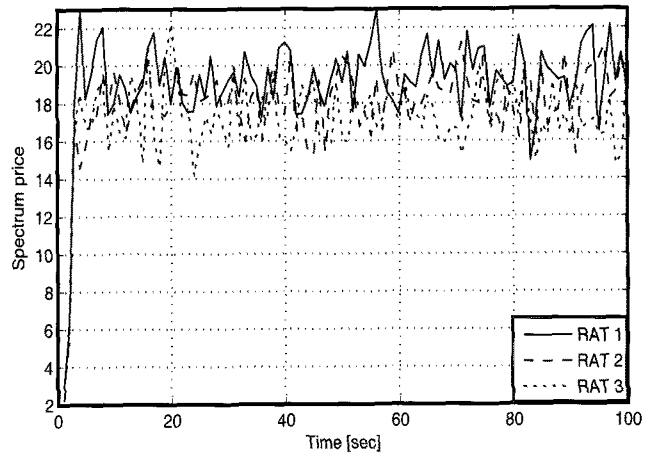

Fig. 5. Spectrum price versus time (when $N = 20$).

between each RAT and MUE is given as the product of path loss and shadowing including thermal noise. As a pathloss model, we used the modified Hata urban propagation model [18]:

$$\begin{cases} 122 + 38\log(d), & d \geq 0.05 \text{ km} \\ 122 + 38\log(0.05), & d < 0.05 \text{ km} \end{cases} \quad (25)$$

where d is the distance between RAT and MUE in kilometers. The shadowing component follows a lognormal distribution with the mean value of 0 dB and standard deviation of 8 dB. All MUEs are assumed to be generated at each simulation step and randomly distributed in RAT 3 region. This is intended for MUEs to be covered by all RATs because we are interested in the multiple connections MUEs can make.

B. Simulation Results

An intention of this simulation is to demonstrate the adaptability of the proposed multi-pricing scheme to multiaccess systems. A converged example of the proposed algorithm for optimality is shown in Fig. 3, where it is assumed that the number of MUEs is 10 and the maximum number of iterations is 300. Figs. 4 and 5 show the adaptability of multi-pricing and variation of SP when the number of MUEs is 10 and 20 respectively. In these figures, each point represents the optimal SP for maximizing system capacity when the channel condition of all MUEs is considered. Admitting that the SP of each RAT begins at the same value, each SP of RATs becomes different and varies on account of the optimal spectrum allocations which reflects channel conditions. Also, it is seen that the fluctuation of SP in Fig. 5 is smaller than that of Fig. 4 because the number of MUEs is doubled. This means that more MUEs request SBs in Fig. 5 and the variation of total allocated SBs of each RAT is small, because each SP is linked to the sum of allocated SB in (18). In addition, the average of SP in Fig. 5 is a little higher than that of Fig. 4 because of the increase in demand. This result is a good match with economic aspects (see Appendix).

In Fig. 6, we can also identify the average SP as per the number of MUEs, where RAT 3 having the largest spectrum bandwidth maintains low SP, comparing with RAT 1. This implies that more competition occurs in RAT 1 and less in RAT 3 under each fixed spectrum bandwidth. Also, RAT 1 having the smallest spectrum bandwidth has high price on average, comparing with RAT 3. Thus, the multi-pricing mechanism of Fig. 2 achieves the optimization-based distributed approach to multi-RAT environments, unlike a universal spectrum pricing method. An example of each RAT's revenue which is calculated by (22) is shown in Fig 7. In this figure, we can see that RAT 3 gains more revenues than RAT 1 because RAT 3, although its average price is cheaper

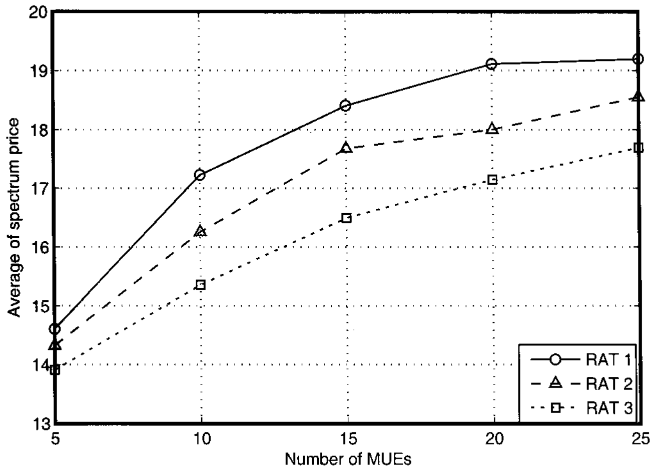

Fig. 6. Average of spectrum price versus number of MUEs.

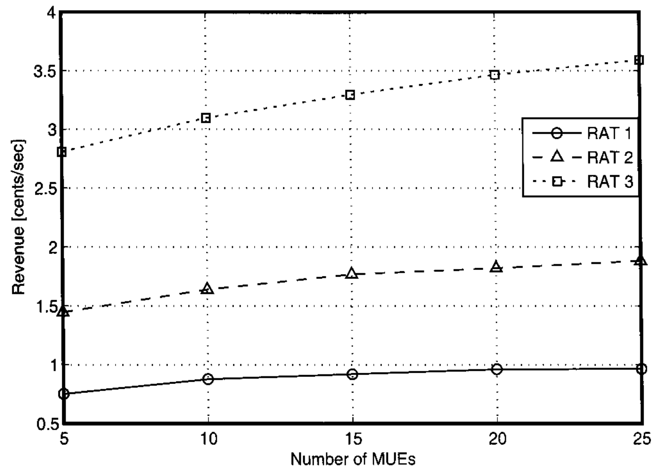

Fig. 7. An example of each RAT's revenue.

than RAT 1, has more spectrum bandwidth and distributes its SB more than RAT 1.

V. CONCLUSIONS

In this paper, we demonstrated the multiple spectrum pricing solution for maximizing system capacity in the multiaccess system, which was performed by a distributed manner. The results of numerical analysis and simulations validated the distributed feature of the proposed optimal multi-pricing scheme and its applicability for multiaccess systems. As a result, the proposed scheme can be considered as a viable solution to obtain more decentralized mobile networks because the computation for optimal solution could be executed not by a BS but by an MUE.

APPENDIX: VERTICAL SUPPLY CURVE

To understand the increase of SP in Fig. 6, one can refer to the economic aspects of supply and demand curve which is related to the SP and quantity as shown in Fig. 8. In general, total spectrum bandwidth of each RAT is fixed, so a supply curve is vertical according to the [19]: That is the spectrum quantity supplied is fixed, regardless of SP. No matter how much an MUE would be willing to pay for an additional SB, extra spectrum cannot be

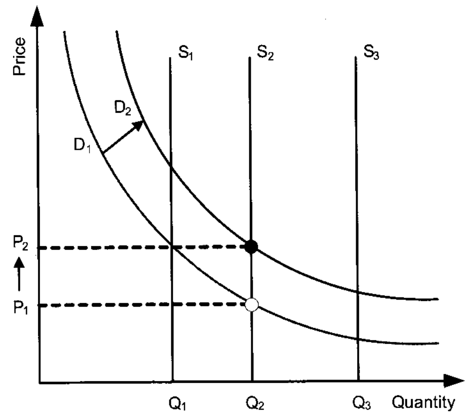

Fig. 8. An illustration of prices go up as an increase in demand.

created. Also, even if no MUE wanted all the spectrum, it would still exist. Spectrum therefore has a vertical supply curve, giving it zero elasticity (i.e., no matter how large the change is in price, supplied spectrum quantity will not change).

When the demand D_1 of MUE is in effect, the SP will be P_1. While an increase in demand D_2 is occurring, that is an increase of the number of MUEs, the SP will be P_2. Notice that at both values the spectrum quantity of each RAT stays the same. Since the supply is fixed, any shifts in demand will only affect the SP. Therefore, for systems with this vertical supply curve, the bigger the number of MUEs gets, the higher the SP reaches, because the number of MUEs means an increase in demand. Our simulation results are good match with the law of supply and demand in economics.

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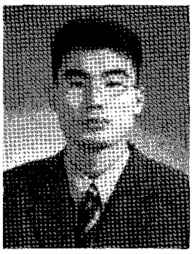

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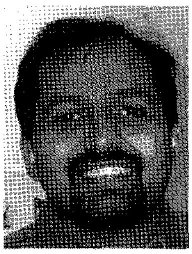

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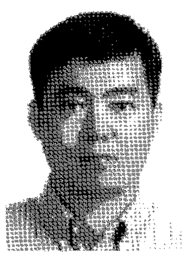

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