Resource Allocation and Pricing Mechanisms for Wireless Multimedia Service: Auction and Bargaining Models

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General wireless network services such as multimedia streaming services require effective models to cost efficiently or fairly distribute limited resources to users in different network environments. The network manager should make decisions related to effective utilization and fair allocation of limited resources, and appropriate guarantee of service quality. In this paper, we introduce a comparative method to help the network manager using resource allocation and pricing mechanisms for wireless multimedia services by considering user qualities of service and service provider profits. To that end, two well-known models of game theory: auction and bargaining are adapted. In particular, progressive second price auction and Kalai-Smorodinsky bargaining solution are analyzed with regard to user cost and utility and service provider profit. While the network manager utilize the result of comparisons, it may be possible to make rational decision of selecting resource allocation and pricing mechanism by considering the status of network.

Keywords: Auction Model, Bargaining Model, Pricing Mechanism, Resource Allocation, Wireless Multimedia Service

1. Introduction

Great advances in wireless network technologies such as GSM, PHS, WCDMA and WLAN have enabled us to access the network from anywhere at any time and have considerably increased the number of users and the variety of network services. Consequently, network services such as wireless multimedia services require additional resources to provide fast and stable service while accounting for quality issues such as delay sensitivity, bandwidth-intensity, and loss-tolerance [1].

Since network resources are often limited regardless of the type of mobile wireless link infrastructure [2], effective utilization of limited resources and an appropriate guarantee of service quality are critical issues in wireless networks.

Especially, in a wireless network, it is assumed that users compete for network resources such as bandwidth, channel, and transmission power. Such network environments require fair resource allocation and efficient rational pricing mechanisms. In the standpoint of the network manager, it is rational management strategy to make more profit by utilizing limited resources. However, in order to keep the service continuity and make user satisfaction degree high, the network manager should present the stable quality of service and guarantee that all resources are fairly allocated to all users.

However, since these two strategies are mutually exclusive, it is nearly impossible to apply them to a wireless network at the same time. Therefore, the network manager should make decision that which resource allocation strategy is more profitable based on the network circumstance such as competition degree on resource.

Generally, fairness and rationality are critical and difficult issues in microeconomics. If the user preferences and the physical environments differ, the harmonization of users with their contents becomes more difficult. In the case of wireless multimedia service, users often access the network with different types of devices, including cell phones, smart phones, personal digital assistants, and laptops, under different environmental circumstances (e.g., distance to the base station or access point). Moreover, users generally have differing service quality preferences (e.g., user tolerance for network delay and sensitivity to network cost) according to the types of multimedia contents and services[3].

For the effective resource allocation, game-theoretic mechanisms are developed in order to transmit video in real-time over a shared WLAN infrastructure using Vickrey-Clarke-Groves (VCG) mechanism [4] and to prevent the tasks from behaving strategically and manipulating the available system resources using proportional-share mechanism [5]. In addition, van der Schaar and Shankar suggested a new paradigm that allows users to interact through the exchange of information and the distribution of resources [1].

In this paper, to help the network manager make rational decision, we present the result of comparative experiments using resource allocation and pricing mechanisms for wireless multimedia services by considering user quality of service and service provider profit. To deal with the issues of user fairness and utility, we adopted two well-known models of game theory: auction and bargaining. Fundamental differences exist between the two models in that auctions discriminate between users based on bid prices, and bargaining models guarantee fairness among users. Nevertheless, the models share the common purpose of distributing limited goods or resources to users who have different preferences in different environment. In the case of wireless multimedia service, service providers must consider the allocation of limited resources to users in order to maximize profit. Providers should also consider the quality of services and the utilities of users to maintain overall system quality.

Published in Journal of Internet Technology, Vol. 14, No. 7, Dec 2013, pp. 1093-1103.

Auction and bargaining models can be utilized to address those issues in wireless multimedia service.

We compared and analyzed auction and bargaining models for use as resource allocation and pricing mechanisms in wireless multimedia services. The progressive second price (PSP) auction was adopted for the multimedia resource auction, and Kalai-Smorodinsky bargaining solutions (KSBS) models was chosen to address the different requirements of multimedia content. We investigated the differences of the total service provider profit and the average user utility-cost ratio between the two models. With the result of comparisons, the more effective resource allocation and pricing mechanism can be determined based on the competition degree on the resource.

The remainder of this paper is organized as follows. In Section 2, prior studies related to resource allocation using game theory are compared and analyzed. The basic assumptions and system models are described in Section 3. Resource allocation frameworks using PSP auction and KSBS and the utility function as the criteria for resource allocation are formalized in Section 4. In Section 5, we present experimental results of the comparison of PSP auction and KSBS. We finally conclude the paper with some contributions and limitations in Section 6.

2. Game-Theory for Multimedia Service

Game theory, a formal study of conflict and cooperation, has been applied extensively in telecommunication for the last decade. The reason for the popularity of game theory in communication networks is that it deals primarily with distributed strategy optimization in situations in which selfish individual users make their own decisions instead of being controlled by a central authority [6].

An auction is one of the most useful tools in economics as it provides a mechanism for determining the value of a commodity that has an undetermined or variable price. Most auctions are designed with the goal of more efficiently allocating limited goods or resources [7]. By framing the network resource management problem as an auction or as a general game theory problem, the service provider is no longer the sole determinant of how resources are allocated among users. Individual users now have incentive to actively participate in the resource negotiating process because they can influence their resource allocations through their bids [2].

For example, auction-based mechanisms are used to address the spectrum sharing problem subject to interference temperature constraints [8] and dynamic spectrum sharing problem for cognitive radio networks [9]. The second price auction mechanism was proposed for channel allocation in the wireless network [10] and for the variable-sized shares of a resource [11]. These mechanisms also assumed complete knowledge of opponents' bid profiles, asynchronously submitted bidding, and the same learning rule in order to study the equilibrium and convergence properties of the PSP auction. However, Mastronarde and van der Schaar pointed out that these assumptions are not appropriate for a multimedia resource allocation scenario [2]. They investigated different levels of centralized coordination in the auction game and introduced learning rules that require an agent to acquire different levels of information from the service provider about its heterogeneous opponents at the edge of the content delivery network (CDN).

Another famous game theory tool for resource allocation is the bargaining game and its solutions. The concept of Nash Bargaining Solution (NBS) is a well-known bargaining solution which can be utilized to assign limited capacity, control network flow, design network structure [12-14], and improve network efficiency [15-18]. NBS is characterized using the four axioms of 1) Pareto optimality, 2) scale invariance, 3) independence of linear transformation, and 4) symmetry [19]. The third axiom is often criticized since it does not consider users' differential receptive capacities. Accordingly, the notion of proportional fairness was introduced in [19] to allocate resources based on user requirements. In terms of proportional fairness, KSBS was often compared with NBS because KSBS applies individual monotonicity instead of independence of linear transformation. Park and van der Schaar analyzed optimality conditions for both solutions and the differences of proportional fairness between the NBS and the KSBS [16].

Few studies have compared auction and bargaining models for use as multimedia resource allocation mechanisms including analysis of the effects of pricing mechanisms. In particular, although it is common to consider pricing in an auction-based mechanism, the existing works related to the bargaining solution rarely considered cost factors for multimedia service users. In the present study, we compared the characteristics of two resource allocation mechanisms for wireless multimedia service in dramatically variable circumstances.

3. Bid-based Multimedia Service Model

In this research, the multimedia service environment in a wireless network is assumed as follows:

-There are n users who request a different multimedia service to the server through different multimedia devices.

-There is a single service provider who controls the process of resource allocation and pricing.

-The multimedia device has an agent that submits a bid $s_i(q_i,p_i)$, composed of the amount of resources q_i and the unit price p_i.

-A server transmits the results of resource allocation, which are the amount of allocated resources, $a_i(s)$, and the total cost paid by user i, $c_i(s)$.

Since the service provider has limited resources Q and users have a certain budget b_i, the optimal solution should meet the following three feasibility conditions, where d_i represents the minimum requirements for user i to retain the multimedia service.

$$\sum_{i=1}^{n} a_i\left(s\right) \le Q \qquad (1)$$

$$c_i(s) \le b_i \quad (2)$$

$$d_i \le a_i(s) \le q_i \quad (3)$$

The notations used in the proposed resource allocation models are summarized in Table 1.

Table 1. Notations and short descriptions

Notation	Description
n	The number of users in the network
Q	The maximum amount of service provider resources
$s=(s_1, \ldots, s_n)$	Bid profile of all users
$s_i(q_i,p_i)$,	User i's bid with quantity q_i and price p_i
q_i	Amount of resource needed by user i, $d_i \le q_i \le Q$
p_i	Bid price of user i
$a_i(s)$	Amount of resources allocated to user i
$c_i(s)$	Total cost that user i should pay for the allocated resources
d_i	The minimum requirement of user i
X_i	Utility of user i
X_i^{MAX}	The maximum achievable utility of user i
π_i	Utility function of user i
α_i	Bargaining power of user i, $\sum_{i=1}^{n} \alpha_i = 1$
b_i	Available budget of user i

4. Resource Allocation Frameworks

In this section, some basic assumptions and criterion for the resource allocation and pricing mechanisms are presented in details. First of all, the user utility functions are defined, which are utilized as the criteria for allocating resources and comparing the performance of both mechanisms.

4.1 User utility function

Several utility functions such as distortion rate models have been proposed to quantify service qualities of users in multimedia services [20, 21]. For the distortion rate model in [22], the distortion of the sequence that is measured using the mean squared error (MSE) is well suited for the average rate-distortion behavior of state-of-the-art video coders [23]. The utility function is the major criteria for resource allocation in both PSP auction and KSBS models in our research. The user utility function can be interpreted as the Quality of Service (QoS). Here, the definition of peak signal-to-noise ratio (PSNR) design is based on the distortion-rate (D-R) model in [22] and is adopted as the utility function without considering the logarithm or constant multiplication of the PSNR.

$$X_i = \pi_i(s) = QoS_i(a_i(s)) = \frac{\kappa_i(a_i(s)-d_i)}{D_{0i}(a_i(s)-d_i)+\omega_i} \quad (4)$$

, where κ_i and ω_i are positive and D_{0i} is a nonnegative parameter of the D-R model, and all of these variables are dependent on video sequence characteristics; spatial and temporal resolutions, and delay.

4.2 PSP auction model

The PSP auction has been proposed as an efficient mechanism for allocation of variable-sized shares of a resource among multiple users [9]. The PSP rule generalizes Vickrey ("second price") auctions [22] for non-divisible objects. In this paper, we adopt the simplified PSP auction-based mechanism to allocate resources to multiple users [15]. In a bid profile, $s=(s_1,\ldots,s_n)$, a user bid s_i means that user i wants to purchase a quantity q_i at the unit price p_i. The auctioneer adopts an auction rule A to respond to an allocation $A(s)=(a(s), c(s))$, where $a_i(s)$ and $c_i(s)$ are the quantity allocated to and the total cost paid by user i, respectively. The PSP allocation rule is:

$$Q(p_i, s_{-i}) = \left[Q - \sum_{k\ne i: p_k > p_i} a_k(s)\right]^+ \quad (5)$$

$$a_i(s) = \min\left(q_i, \frac{q_i}{\sum_{k: p_k = p_i} q_k} Q(p_i, s_{-i})\right) \quad (6)$$

$$c_i(s) = \sum_{j\ne i} p_j \left[a_j(0; s_{-i}) - a(s_i; s_{-i})\right] \quad (7)$$

Equations (5) to (7) represent that the resource Q will be allocated to higher price bidders prior to lower price bidders. Term $Q(p_i, s_{-i})$ denotes the quantity remaining after complete allocation to users who bid higher prices than user i. The variable in (6), $a_i(s)$ follows the revised allocation rule proposed in [24]. If the remaining quantity $Q(p_i, s_{-i})$ is sufficient, q_i can be allocated to user i; otherwise, the remaining resource will be allocated to user i and the users who bid the same as user i. Then, if the remaining one is short to the users with the same bid price, it will be shared proportionally to their requested resource amounts. And, if not, the remainder will be again allocated to the users who bid lower prices than user i.

This rule is computationally simple $O(n^2)$ and can thus be used in real-time dynamic auctioning. It has been shown that, if the assumption for the valuation function of user, $\theta_i(q_i)$, holds, then there exists a consistent and truthful ε-Nash equilibrium s^* for any bid fee $\varepsilon>0$ [15]. The assumptions for the valuation function are as follows:

-- $\theta_i(0)=0$

-- θ_i is differentiable

-- $\theta_i' \ge 0$, non-increasing and continuous

--$\exists \gamma_i > 0, \forall z > 0, \theta_i'(z) > 0$

$\Rightarrow \forall \eta < z, \theta_i'(z) \le \theta_i'(\eta) - \gamma_i(z-\eta)$

The truthful bid price is equal to the marginal valuation according to (8) [15]

$$p_i = \theta_i'(q_i) \quad (8)$$

where the user utility function can be interpreted as the valuation function because the following characteristics of the QoS satisfy the all assumptions for the valuation function.

$$\frac{\partial}{\partial a_i} QoS(a_i(s)) > 0, \ \frac{\partial^2}{\partial a_i^2} QoS_i(a_i(s)) < 0 \quad (9)$$

The first derivate of QoS is positive and the second one is negative as described in (9). Thus, all of the assumptions for the valuation function in [9] which guarantee the existence of an equilibrium are satisfied.

4.3 Bid-based bargaining model

Several bargaining solutions with different properties considering optimality and fairness can be found in existing research on resource management [23, 25]. KSBS guarantees that the utility of a user will decrease proportionally to the user's maximum achievable utility [19]. This proportional decrease of utility can be interpreted as the service satisfaction, δ, as defined in (10).

$$\delta = \frac{X_1}{\alpha_1 X_1^{MAX}} = \cdots = \frac{X_n}{\alpha_n X_n^{MAX}} \tag{10}$$

This equation can be solved by substituting utility X_i into the bargaining condition $\sum_{i=1}^{n} \pi_i^{-1}(X_i) \le Q$ and it generally requires an nth degree polynomial. Hence, efficient and simple numerical methods like the bisection method can be utilized [26]. Because the upper bound Q and the lower bound d_i of the resource allocation are already known, the bisection method can be easily applied. In addition, the method requires $\lceil \log_2 ((u-l)/\varepsilon) \rceil$ iterations [16]. It can be said that identifying the optimal resource allocation plan with KSBS involves the determination of the maximum value of δ, which results in a rate of utility drop in (11).

$$\delta^* = \max\left(\delta = \frac{X_1}{\alpha_1 X_1^{MAX}} = \cdots = \frac{X_n}{\alpha_n X_n^{MAX}} \right) \tag{11}$$

Considering (11) and the bisection method, it is possible to easily obtain the optimal resource allocation plan with the reversed utility function:

$$a_i(s) = \pi_i^{-1}(X_i^*) = \pi_i^{-1}\left(\delta^* \cdot \alpha_i \cdot X_i^{MAX}\right) \tag{12}$$

Here, the maximum achievable utility (X_i^{MAX}) and the user bargaining power (α_i) should be defined to determine the optimal bargaining solution.

The generalized KSBS is obtained at the intersection between the feasible solution set and the line L defined in (13), where α_i is the bargain power of user i.

$$L = \left\{ X \,\middle|\, \frac{X_1}{\alpha_1 X_1^{MAX}} = \cdots = \frac{X_n}{\alpha_n X_n^{MAX}} \right\}$$

$$\text{such that } \sum_{i=1}^{n} \alpha_i = 1,\ X_i > 0,\ \alpha_i \ge 0 \text{ for } \forall i \in N. \tag{13}$$

As described in Sections IV.A and IV.B, the utility function is a continuous and increasing function that does not have a maximum value. In a typical situation, the amount of requested user resources is determined based on the multimedia content and network circumstances, and the allocation amount is limited to the resource amount of which the user requested. Thus, the maximum achievable utility is obtained according to the bid quantity, $X_i^{MAX} = X_i(q_i)$.

In the PSP auction model, a user who submits a higher price has an unconditional priority to the remaining resources. However, bidder i's bid price should only determine whether bidder i wins or loses the auction; it does not guarantee any particular amount of resources, but determines the rank among bidders. In the case of KSBS, adjustment of bargaining power is the only way to differentiate the service level or amount of allocated resources [16, 19] and this adjustment directly determines the allocation of the resources. We propose a method which adheres to this fundamental discriminating role of the bargaining power and the ranking of bid prices in a PSP auction. The user i's bargaining power can be determined according to the following equation, which satisfies $\sum_{i=1}^{n} \alpha_i = 1$.

$$\alpha_i = \frac{1}{nk+1}\left(k + \frac{p_i}{\sum_j p_j} \right) \tag{14}$$

In this equation, a network manager can adjust gaps between users by varying factor k. By using this method, appropriate discrimination based on differences in bid prices is guaranteed.

4.4 Total network manager profit

From the standpoint of the network manager, total profit is the most important metric for evaluating performance based on resource allocation and is calculated by summing all user costs. In the PSP auction model, the cost of user i is considered to be the sum of the cost that other users would pay in user i's absence. Thus, the total cost for a certain user, $c_i(s)$, is determined by the bidding strategies of the other bidders as follows.

$$c_i(s) = \sum_{j \ne i} p_j \left[a_j(0; s_{-i}) - a_j(s_i; s_{-i}) \right] \tag{15}$$

To maintain consistency in the profit function of the network manager, (15) is applied to the user cost function for the KSBS model as well as PSP auction. By applying the same cost approach to both models, we can evaluate the impacts of each resource allocation framework.

5. Experimental Comparison of Pricing in Auction and Bargaining Models

In this section, we present a comparison of resource allocation and pricing in two models based on numerical experiments. Since auction and bargaining models have different pricing mechanisms, they cannot be directly compared. Nevertheless, multimedia service providers should consider the allocation of limited resources to only some profitable users (e.g., auction) or to all users in the network (e.g., bargaining). Although auction and bargaining models represent extremes of resource allocation, it must be meaningful to identify how their strategies affect the total network profit ($TP = \sum c_i(s)$) and the user utility-cost ratio ($r = X_i / c_i(s)$).

5.1 Design of experiment

To enhance the understanding of the differences between the two pricing mechanisms, PSP auction and KSBS, two cases will be utilized. One is a four user case with a simple bidding profile, and the other is a generalized case with more users and complicated bid profiles. In this subsection, we provide detailed information about the two cases and the experimental environment. All assumptions and parameters for the experiments are chosen to characterize and simplify the circumstances of streaming the practical video sequences on the WiMAX network.

5.1.1 Case1: Four user case

In this small numerical experiment, we assume that four users (n=4) request video bit-streams from a server whose resource capacity Q is 250Kbps. The user utility function parameters and bid profile of four users are summarized in Table 2.

Table 2. Experimental parameters of the four user case

Fixed Parameters		User Parameters				
Para.	Value	Para.	User1	User2	User3	User 4
Q	250	κ_i	5.0	5.0	5.0	5.0
n	4	D_{0i}	0.10	0.12	0.11	0.13
b_i	∞, $\forall i$	ω_i	5.0	5.3	5.2	4.7
d_i	0.0, $\forall i$	q_i	700	600	400	100
		p_i	0.00444	0.00443	0.01074	0.07501

The bid profile contains the bid strategy of each user s_i (q_i, p_i), where q_i is the bit-stream rate required by user i. With these parameters and bid quantities, the truthful bid price pi of each user is determined using the marginal valuation described in (10).

Because the first derivative of the user utility function shows an exponential decrease in the bidding quantity, User 4 submits the highest truthful bid price among the users even though his/her bidding quantity is the smallest. The utility functions of four users are depicted in Figure 1

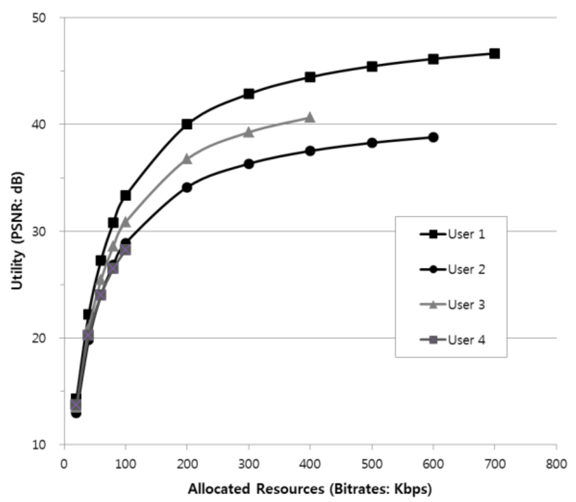

Figure. 1 Utility function of all users

5.1.2 Case 2: Generalized case

In this section, we present a design of experiments that extend the resource (Q=56,000kbps) and diversify the user bid quantities to identify the general characteristics and differences of the users. To simplify the problem without loss of generality, it has been assumed that all users have an unlimited budget and their minimum requirements are zero. The parameters for constructing a user utility function, D_{0i}, κ_i and ω_i, are randomly selected in the corresponding sets as described in Table 3.

Table 3. Experimental parameters in the generalized case

Fixed Parameters		Random Parameters	
Q	56,000	D_0	$D_{0i} \in \{d \mid d = 0.1 + 0.005 \cdot k,\ k = 0,1,...,9\}$
b_i	∞, $\forall i$	κ	$\kappa_i \in \{\kappa \mid \kappa = 5.0 + 0.5 \cdot k,\ k = 0,1,...,9\}$
d_i	0.0, $\forall i$	ω	$\omega_i \in \{\omega \mid \omega = 5.0 + 0.5 \cdot k,\ k = 0,1,...,9\}$

A new parameter, the competition degree ζ, is considered in the generalized case. The status of the network is dynamically changed because the total amount of resources requested from users varies considerably over time. Thus, we examine and compare the results of resource allocation based on different resource allocation and pricing mechanisms as the availability of resources and level of competition among users are changed. A competition degree is defined as the ratio between total requested resources and maximum network capacity. And, it is utilized as the index to represent the competition degree, which varies from 1.0 to 15.0. To remove the impact of randomness and to determine the general characteristics, each experiment was repeated 50 times at a certain competition degree.

5.2 Comparison of Truthful Bid Price Auction and Bargaining Models

5.2.1 *Experiment 1-1*: Four user case

Based on the bid profiles of four users in Table 3, resource allocation for a PSP auction was determined, and the results were summarized in Table 4

Table 4. Results of PSP auction with truthful bid prices

	User 1	User 2	User 3	User 4	Total
$a_i(s)$	0.00	0.00	150.00	100.00	250.00
$c_i(s)$	0.00	0.00	0.67	1.07	1.74
X_i	0.00	0.00	34.56	28.25	62.81

The resource allocation results of KSBS were summarized in Table 5. To compare the resource allocation results of two models, we used the same truthful bid prices as PSP auction. The important difference between PSP auction and KSBS is in the number of users who received resources.

Table 5. Results of KSBS with truthful bid prices

	User 1	User 2	User 3	User 4	Total
$a_i(s)$	56.06	49.29	55.19	89.46	250.00
$c_i(s)$	1.10	1.06	0.97	0.60	3.74
X_i	26.43	21.98	24.48	27.39	100.28

While resources are allocated to all of users in KSBS, only two users who submitted high bid prices receive resources in PSP auction. As shown in Table 3, User 4 submits the highest bid price because his/her bid quantity is smaller than those of the other users. The highest bid price of User 4 increases the bargaining power of the user to be greatest among the users. Therefore, the amounts of resources allocated to the other users were bounded by bargaining power of User 4 due to the characteristics of (11) and (15). If the bargaining power is concentrated on a certain user, the rest of users have to share the remainder of bargaining power. Thus, the utilities of others which are obtained by (16) are under of control of the quality drop of User 4.

$$\frac{X_i}{X_i^{MAX}} = \frac{\alpha_i}{\alpha_4}\frac{X_4}{X_4^{MAX}}, i \in \{1,2,3\} \quad (16)$$

And in KSBS, the limited resources are allocated to all users to guarantee the equal quality drop to all users. Then, different from PSP auction, users who have relatively small bid price also have some cost because there are differences of allocated resources when one of them would not participate in the resource allocation game. Therefore, the total amount of profit in KSBS is greater than that in PSP auction. As a result, though the total profit of the network in KSBS (*TPB*=3.74) is greater than that in the PSP auction (*TPA*=1.74), the average user utility in KSBS ($\sum X_i/n$=100.28/4=25.07) is smaller than that in the PSP auction ($\sum X_i/2$=62.81/2=31.4). Note that the average utility-cost ratio of the PSP auction (*rA*=39.07) is greater than that of KSBS (*rB*=28.84). Therefore, the preferred resource allocation framework of the network manager or users cannot be determined.

5.2.2 *Experiment 1-2*: Generalized case

Based on the results of *Experiment 1-1*, we cannot say which resource allocation among the two models is more effective in general situations because it has few users and considers a certain bid profile. Thus, we compare the results of resource allocation in the generalized case. Unlike the results of *Experiment 1-1*, Figure 2 shows that the network manager and users prefer different resource allocation mechanisms as the competition degree increases. Let us compare total profits of the network manager in two models in Figure 2 (a). In KSBS, the total profit of the network manager radically decreases at low level competition degrees and then stabilizes at a certain level. In the case of a PSP auction model, however, total profit continuously increases. Thus, above a certain competition degree ($\zeta > 10.3$), the PSP auction produces a greater profit. On the other hand, with respect to average utility-cost ratios in Figure 2 (b), up to a certain competition degree (ζ < 3.3), the PSP auction produces a larger ratio value than does KSBS. After this point, the opposite result is obtained.

These results are due to the difference in the resource allocation rules between PSP auction and KSBS. PSP auction focuses on users who submit relatively higher bid prices and allocates resources to users accordingly, so that users are divided into two groups, those who receive resources and those who do not. As a result, as the competition degree increases, more users become unsuccessful in the PSP auction. However, the KSBS model guarantees a certain level of utility to all users based on their bargaining powers. Thus, if all resources of a network manager are allocated to all users, the total profit is not greatly changed even though the competition degree increases.

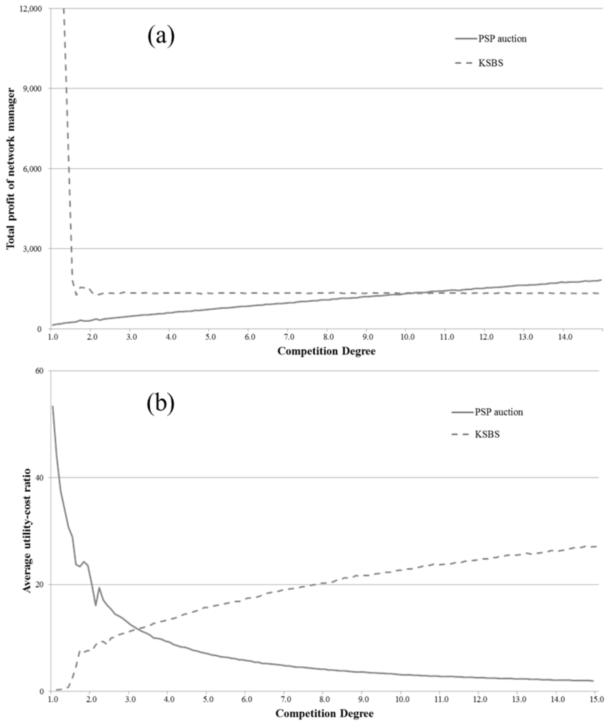

Figure 2. Comparison resource allocation results: (a) Total profit of network manager, (b) Average utility-cost ratio

5.3 Comparison with the singular pricing policy bargaining

In the *Experiment 1-1* and *1-2*, it was assumed that the unit price of a resource was determined by users, not by the network manager. In this section, we examine the results of resource allocation when the network manager applies a singular pricing policy to the bargaining model. To do that, we first derive the unit price of the bargaining model that guarantees an equivalent profit for the network manager to a given auction model. For convenience, we present a method for determining the price of the bargaining model as the following equation.

$$p^B = \frac{\sum_i c_i^A}{Q}, i \in N \quad (17)$$

The equation guarantees that the total profit ($pB \times Q$) of the bargaining model is equal to the total user cost ($\sum c_i A$) in the auction. In this bargaining model, all users are assumed to have identical unit prices and bargaining powers.

5.3.1 *Experiment 2-1*: Four user case

In this experiment, we compare the results of KSBS with those of PSP auction when using truthful bid prices. Using (18), we find that the unit price of the KSBS model is 0.0044, so that the total profit of the network manager is the same in the two models (TPA=TPB=1.74). The resource allocation in this situation is summarized in Table 6.

Table 6. Results of KSBS with a singular unit price

	User 1	User 2	User 3	User 4	Total
$a_i(s)$	79.27	69.66	67.35	33.72	250.00
$c_i(s)$	0.55	0.49	0.47	0.23	1.74
X_i	30.66	25.50	26.71	18.56	101.43

Let us compare the results in Table 6 with the results of PSP auction in Table 5. The total utility in KSBS ($\sum X_i$=101.43) is greater than that in PSP auction ($\sum X_i$=62.81). These results are due to the characteristics of the utility function.

As shown in Figure 1, because the marginal utility is diminishing, if a user receives relatively small amount of resources comparing with the maximum requirement, the utility can be greatly changed with the even small changes in resource allocation. In the aspect of the average utility-cost ratio, KSBS with a singular unit price shows greater value (rB=61.33) than the PSP auction does (rA=39.07). Thus, if the network manager applies KSBS with a singular unit price, users will be more satisfied with the resource allocation than they will be when using the PSP auction model.

5.3.2 *Experiment 2-2*: Generalized case

The same approach for determining the unit price as that in *Experiment 2-1* is applied to the generalized case. Figure 3 shows the overall result of resource allocation based on using KSBS with a singular unit price. The results of resource allocation can be interpreted as in *Experiment 1-2*. When guaranteeing the same total profit, the utility-cost ratio in KSBS with a singular unit price is greater than that in the PSP auction over the all range of competition degree. The average difference of the average utility-cost ratio between two models is 20.78.

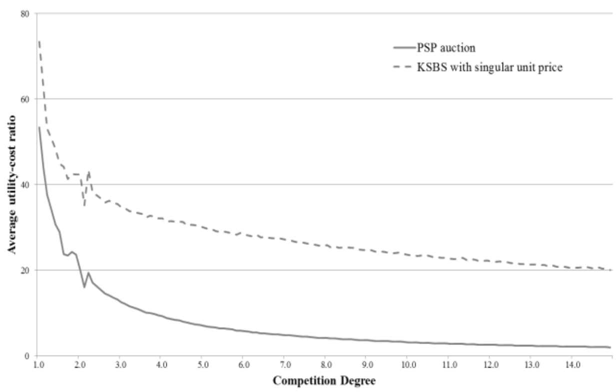

Figure. 3 Resource allocation results of KSBS with a singular unit price and PSP auction

When, all users have equal bargaining power, the amounts of resources allocated to users are determined in proportion of the maximum requirement as found in (12). And then, the amount of allocated resource and average utility of all users dramatically decreases as the competition degree grows up because the marginal utility function decreases. On the other hand, the cost of users does not decrease as much as the utility does. Thus, different from the result of *Experiment 1-2*, the average utility-cost ratio keeps decreasing as the competition degree increases.

In PSP auction, because the number of users who have zero-utility increases as the competition degree grows up, the average utility-cost ratio shows lower value than KSBS with the singular unit price. Thus, resource allocation using KSBS is more attractive to users if the singular pricing policy can be applied by the network manager.

5.4 Implication

First of all, from the results of *Experiments 2-1* and *2-2*, if the network manager can apply the singular unit pricing policy, it can be said that KSBS is more advantageous resource allocation mechanism than PSP auction. Otherwise, based on the results of *Experiments 1-1* and *1-2*, which compare PSP auction and KSBS, we are not able to determine which method is more advantageous to both the network manager and users. As depicted in Figure 4, different results can be obtained by varying the competition degree range.

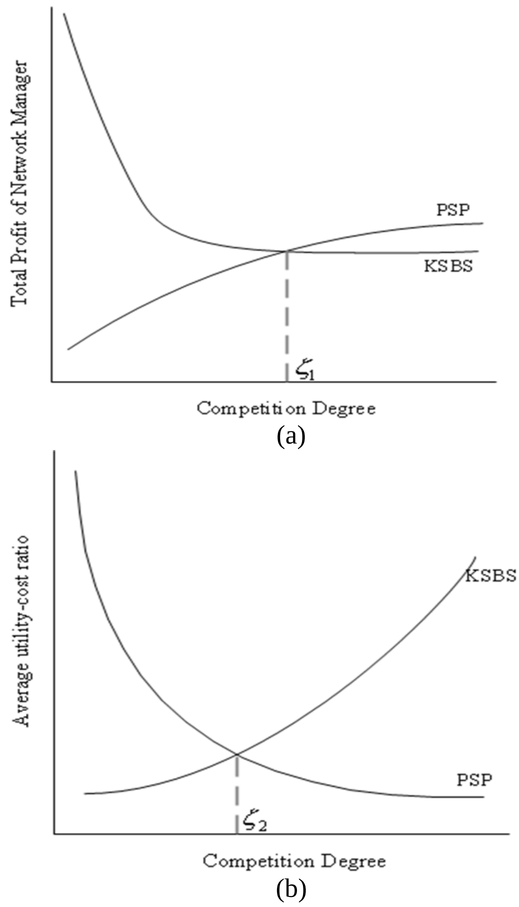

Figure. 4 Resource allocation mechanisms based on competition degree

As summarized in Table 7, we can find that there is a certain range of competition degrees between ζ_1 and ζ_2, in which the preferred resource allocation mechanism can be identified.

TABLE 7. Profitable mechanism based on the competition degree range

Range	*if* $\zeta_2 \le \zeta_1$			*if* $\zeta_1 \le \zeta_2$		
	$(1.0, \zeta_2)$	$[\zeta_2, \zeta_1)$	$[\zeta_1, \infty]$	$(1.0, \zeta_1)$	$[\zeta_1, \zeta_2)$	$[\zeta_2, \infty]$
Network manager	KSBS	KSBS	PSP	KSBS	PSP	PSP
Users	PSP	KSBS	KSBS	PSP	PSP	KSBS
Conclusion	-	KSBS	-	-	PSP	-

However, outside of that range, a new criterion is necessary to compare two mechanisms. An integrated performance metric $Pf(x)$ was devised by integrating the average utility-cost ratio of users and the total profit of the network manager as follows:

$$Pf\left(x\right)=\frac{1}{n}\left(\sum_{i=1}^{n}\frac{X_i\left(x\right)}{c_i\left(x\right)}\right)+\tau\sum_{i=1}^{n}c_i\left(x\right) \tag{18}$$

In (18), x refers to the resource allocation result. And, the parameter τ plays two important roles; it adjusts scales between the average ratio and the total profit and it also represents the market power of the network manager. Thus, the network manager should determine the proper value of τ by simultaneously considering the market structure and the user characteristics. For example, if the value of τ is 0.001, PSP auction is more advantageous until the competition degree is less than 3.2 as depicted in Figure 5.

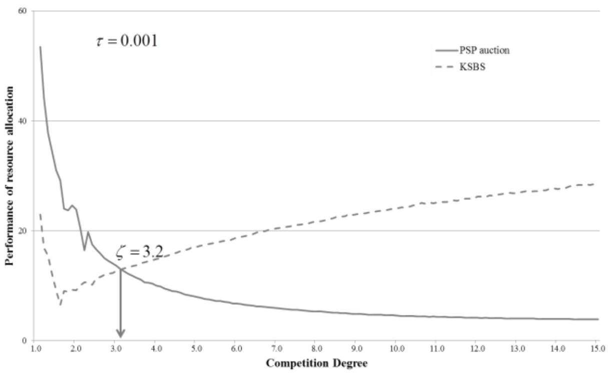

Figure. 5 Performance evaluation of resource allocation results

To identify the best resource allocation and pricing mechanisms, the network manager should consider his/her own relationship with users and the structures of the market and users.

6. Conclusions

Wireless network services such as multimedia streaming services require effective models for effectively and fairly distributing a limited resource to users in different network environments.

In this paper, we introduced resource allocation and pricing mechanisms for wireless multimedia services by considering the quality of user service and the profits of service providers. To address the issues, we compared two well-known models of game theory: auction and bargaining. In particular, PSP auction and KSBS are analyzed with regard to the user utility and the service provider profit via numerical experiments.

From the overall results of experiments, the network manager can decide which resource allocation framework and pricing mechanism are adequate for the network based on the network characteristics. For example, the PSP auction model enhances the level of service to premium users who are willing to pay higher usage fees. However, the bargaining model using KSBS with truthful bid prices or KSBS with a singular unit price are useful when the overall fairness is more important or when more users should be satisfied. This research will be helpful for service providers who deliberate resource allocation mechanisms in terms of service quantities and profits for wireless network services.

Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No.2013R1A2A2A03014718).

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Published in Journal of Internet Technology, Vol. 14, No. 7, Dec 2013, pp. 1093-1103.