An Auction-Based Pareto-Optimal Strategy for Dynamic and Fair Allotment of Resources in Wireless Mobile Networks

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***Abstract*—Ongoing advances in sophisticated mobile computing technologies and wireless communications have propelled substantial research work toward designing and implementing a new breed of mobile communications systems. One of the fundamental design objectives of such systems is to ensure complete roaming ability for the mobile users. In addition, upon handoff events, the mobile users also require to be able to perform renegotiations pertaining to their required quality-of-service (QoS) requirements with the concerned system. In this paper, we envision a fair and dynamic auction-based QoS negotiation scheme to deal with this issue. The envisioned scheme provides the mobile users with the flexibility to dynamically negotiate or renegotiate their preferred service levels with the corresponding service provider. The proposed technique has three crucial design objectives: First, it ensures a high level of fairness among the competing mobile users (each with a specific budget). Second, it ensures efficient utilization of the available network resources. Finally, its auction-based mechanism aims at maximizing the revenue of the service provider. A mathematical analysis is provided to demonstrate that, when the three design goals are taken into account, the resource allocation function that the proposed scheme provides represents a Pareto-optimal solution. The effectiveness of the proposed scheme is also verified through extensive simulations.**

***Index Terms*—Auction-based resource allocation, dynamic SLS negotiation, fairness, mobile network, Nash game theory, quality of service (QoS).**

I. Introduction

ALONG with the recent and ongoing advances in mobile networking, the trend in the telecommunications industry of the 21st century is toward the development of efficient mobile communications systems. In these systems, a plethora of bandwidth-intensive and real-time services, such as multimedia web browsing, video- and news-on-demand, and mobile office systems, is expected to be delivered to a potential number of mobile users while supporting their full mobility anywhere, anytime. A serious challenge to service mobility is the provision of efficient and continuous quality of service (QoS), as the services are essentially QoS constrained and delivered to a large number of users roaming over unevenly loaded wireless networks.

For QoS provisioning in Internet Protocol networks, the Internet Engineering Task Force (IETF) has proposed various frameworks. Differentiated Services (DiffServ), Integrated Services (IntServ) with Resource reservation Protocol (RSVP), and Multiprotocol Label Switching (MPLS) with Constraint-based Label Distribution Protocol (CR-LDP) are notable examples. Among these architectures, DiffServ is the most scalable and has thus been considered for implementation in different projects, such as the 3rd Generation Partnership Project (3GPP). Most of these architectures are specifically designed for wired networks and are inapplicable, in their current versions, to wireless mobile networks. Indeed, current QoS architectures are based on centralized and highly static service-level agreement (SLA) mechanisms, where SLAs are usually agreed on, verbally or in writing, by both a client and the service provider when the client signs up for a service. The service level remains static throughout the contract period and is only manually changeable after an explicit request from the end user. The contractual duration of such SLAs is in a large time scale, which is typically on the order of months or years.

Given the mobility of users, heterogeneity in wireless technologies, and diversity of user terminals, applying static SLA approaches to wireless mobile users may result in unfavorable performance. Indeed, due to user mobility, mobile users freely and often frequently change their points of attachment to the network, which is an operation referred to as handoff. Upon a handoff occurrence, the amount of resources available at the new point of attachment may be different from that at the old point of attachment. This disparity in resource availability can be due to differences in traffic load or due to the use of different wireless access technologies. Assigning a constant level of service to a mobile end user, all the time during its contract period, may lead to unfair service toward the user. In fact, upon a handoff event, it is likely that a user is offered a service level that is higher than what it can be actually provided by the network or is bearable by the user's device. In such an overbooking scenario, the customer will be unfairly charged for a service level that he/she cannot fully utilize. In case of multiple users from different traffic classes, this unfairness

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issue becomes more aggravated as the service provider is not able to fulfill its QoS commitments to all its customers.

As a remedy to this issue, a dynamic negotiation of SLA in a small time scale is of utmost importance. This dynamic negotiation of SLA should propose to mobile users only what they are seeking for or what is allowable by the current network conditions. This should be beneficial for both users and service providers. From the customer's perspective, a dynamic negotiation of service level is beneficial as users will be charged for only what they have actually requested or indeed used. At the service provider side, the system scalability can be improved as savings in the network resources become possible and more users can then be served. It should be stressed that the focus of this research work is on the case of elastic users. Via an appropriate adjustment of the requirements of elastic users to network conditions, savings in network resources can be used to satisfy the needs of inelastic users. Unless otherwise stated, we do thus consider the case of only elastic mobile users throughout this paper. Generally speaking, QoS provisioning consists of two major operations: 1) dynamic service level negotiation or management and 2) resource allocation. The former addresses the issue of QoS continuity when end users roam over different wireless networks, whereas the latter refers to the operation of enforcing the negotiated and agreed QoS terms. In this respect, the authors have recently proposed a scalable and prompt mechanism for dynamic service level specification (SLS) negotiation in next-generation wireless mobile networks [1], [2]. A detailed survey on other SLS negotiation mechanisms is available in [3].

In any communication system, the usefulness of dynamic SLS negotiation mechanisms hinges on an efficient resource allocation strategy. In resource allocation, a service provider finds optimal allocations of network resources to meet the service contract between a client and the service provider. A fundamental characteristic of wireless mobile environments is that demands for network resources are time varying (due to mobility of users). In such environments, the resource allocation should thus be dynamic and adaptive to changes in network conditions. Indeed, when the network is about to get congested, a service provider can offer some privileges to subscribers that accept to downgrade their current service levels. Similarly, if sufficient network resources become available, the service provider can encourage subscribers to join high service levels for better QoS. For this purpose, it is essential to develop a pricing scheme that prioritizes competition for resources among users, i.e., a strategy that allows mobile users to bid for network resources based on the competitiveness of their associated budgets.

In this paper, an auction-based admission-control and resource-allocation policy is proposed. When demand exceeds supply (due to the arrival of new subscribers to a wireless network), the service provider runs an auction to determine the set of users that will be served and the corresponding service level of each user. During the resource allocation operation, three major design goals are considered: 1) insurance of high fairness among competing users; 2) efficient utilization of network resources; and 3) guarantee of the highest profit for the service provider. Indeed, when a population of users, each with a particular budget, is competing for scarce wireless network resources, the proposed scheme attempts to find the best resource allocation strategy that makes maximum use of the network resources without overbooking them, yields the highest revenue for the service provider, and achieves the highest fairness among the competing users.

This paper is organized in the following fashion: Section II highlights the relevance of this work to the state-of-art of dynamic SLS negotiation and auction-based resource allocation techniques. Section III describes the envisioned network architecture and states the resource allocation problem via a simple example. Section IV formulates the problem and analyzes the proposed auction-based resource allocation policy. The section also provides a mathematical model of the proposed solution. Section V evaluates the proposed scheme via a number of computer simulations. This paper concludes in Section VI.

II. Related Work

To achieve higher network utilization in wireless environments, most of the research work conducted over the years relied on optimally allocating the available resources. However, they lack the provision to instruct the users to free the unused resources, particularly when the excessive demands result in scarce resources. Furthermore, these work invariably adopted pricing models, which naively assume that the prices remain fixed during the course of the contract period. Since many users may be highly mobile in a mobile network, the network resources greatly vary with time. As a consequence, these naive models fail to fairly reflect the continuously changing price of the concerned network resources. To deal with this issue, the work proposed in [4] uses network elements to calculate the monetary values of network resources (e.g., bandwidth cost) in terms of a function of the local supply and demand and consistently notifies the current market value of the respective resource to the brokers. By contacting the brokers, the end users can then purchase the required resources from them. This provision is also not without its shortcomings: First, it fails to motivate the users to compete with one another. Second, when the competition among the users become significantly high, service degradation becomes inevitable. For resolving these issues, the concept of auction-based resource allocation schemes has evolved, whereby the users may bid against one another to obtain sufficient network resources. For instance, in [5], a proportional share-based resource allocation framework is introduced. In this framework, users get resources reserved in proportion to their predefined weight. The work in [6] introduces another proportional share-based resource allocation system. The system is built in a distributed fashion, having auctioneers distributed and managing only local resources. In [7], Semret *et al.* envisioned a bandwidth broker for every subnetwork that carries out auctions to assign bandwidth among contending users according to their offered prices. On the other hand, a flexible auction-based pricing method, which was envisioned by Malewicz *et al.* [8], expresses the bandwidth-unit price offered by a user as a temporal function to prevent clients from frequently renegotiating their service requirements. This provides the brokers with more flexibility to make their resource allocation decisions. However, the majority of such auction-based resource allocation schemes attempt to maximize the data throughput and thus ignore fairness issues involving the competing clients.

In the existing research work, different concepts of fairness have been adopted. For example, the max-min fairness in assigning bandwidth, which was envisaged in [9], allocates resources to the most resource-deprived clients while utilizing well the wireless network resources. On the other hand, Sun *et al.* [10] presented a game-theory-based scheme to enable the concerned service providers to maximize their respective revenues and to also ensure that each user may maximize his/her utilities. In this particular approach, by employing the second price auction mechanism, the users are able to bid for a wireless channel.

Radio spectrum-sharing and trading concepts have evolved over the years with a prime objective in mind, i.e., to maximize the revenue of the owner of the spectrum. At the same time, researchers have attempted to enhance the quality of satisfaction as perceived by the cognitive radio users. Klemperer *et al.* [11] introduced a market-equilibrium-based spectrum-trading scheme where they used spectrum demand and supply of various grades of users. Due to the stochastic nature of the spectrum supply, a distributed and adaptive learning method was employed. Klemperer *et al.* demonstrated that the application of this economic theory can, indeed, lead to spectrum-market equilibrium if the demand and supply of the radio spectrum are estimated *a priori*. This work was followed by the evolution of the double auction mechanism to maximize revenues for TV broadcasters and wireless regional area network (WRAN) service providers who purchase and sell TV bands [12]. This idea addresses the issues originating from the tough competition among the multiple WRAN service providers and attempts to adjust the service price charged to the WRAN clients. The double auction mechanism consists of spectrum-bidding and service-pricing schemes. In addition, a noncooperative game-theory-based approach was developed for effectively determining the number of TV bands and the service price of a provider.

Belzarena *et al.* [13] investigated the problem of assigning network capacity via periodic auctions. By assuming that the resources allocated in a specific auction are reserved for a user for the entire duration of the connection, they provided a distributed solution that treats this problem as a Markov decision process (MDP). Accordingly, they designed a series of receding horizon approximations to solve the formulated MDP problem. Their envisioned mechanism achieves near-optimal solutions via convex optimizations and scales well in various network topologies.

III. Problem Formulation

This section attempts to illustrate some issues and challenges associated with resource allocation in wireless mobile networks. Before delving into that, we first outline the key components of the envisioned architecture.

The components of the architecture are schematically shown in Fig. 1. The figure portrays the coverage area of a number of access points forming different domains, which are potentially administrated by different network operators (NOs). Each domain is administrated by a global service negotiation manager (GSNM) and an authentication, authorization, and accounting (AAA) server [2]. While our analysis can be easily extended to the case of multiple NOs, our focus in this paper is on resource allocation in a single domain. The AAA server is used to verify whether mobile users are entitled to access their requested services, whereas the GSNM server carries out the service level negotiation procedure using our previously proposed dynamic QoS negotiation mechanism [1], [2]. It also operates as a resource broker. Indeed, upon receiving a service initiation or renegotiation request from a mobile user, the GSNM uses information about outstanding requests (e.g., budgetary constraints of users) and resource availability to accept or reject requests, and downgrade or upgrade others. As it might take a user awhile to discover the true value of a service (which can be discovered after a series of unsuccessful biddings) and hence affect the handoff delay, the location of GSNMs in domains should be decided in a way that the mechanisms for allocating resources are fast and reliable, as well as being scalable and easy to adapt to the changing needs of users[1]. In case of the evolved packet system [14], which defines future mobile communications systems, the GSNM can be a function of the policy control and charging function (PCRF) node. In current 3GPP specifications, a single PCRF node could be in charge of the entire mobile operator network. However, along with the trend toward decentralized mobile operator networks, small-scale PCRF nodes could be locally deployed. In either case, a GSNM would be in charge of one mobile operator domain. It could be part of the PCRF node or an independent node collocated with PCRF. PCRFs are usually designed in a robust way to handle tens of thousands of requests per second. All of these requests are about NO policies, admission control (including accepting or rejecting bearer establishment requests), QoS setup, and charging. While we are unable to identify ways to quantify the running time that could be required by our algorithm per request, it is expected to be on the order of microseconds, if not shorter, mainly if the proposed scheme is implemented as part of the PCRF node, on top of the existing QoS control mechanisms of PCRF. At the GSNM server, different service levels are available. The GSNM server sets a minimum price and a maximum price for each service level (as a function of the offered QoS metric). Admittedly, determining such prices is not an easy task, particularly if one of the goals of the service provider is to maximize revenues. Indeed, when the minimum price is lower than it should be, users request higher services, and

[1]In current 3GPP specifications [14], several operations are involved in the connection setup and handoff procedures. Some of these operations pertain to authentication, security, ciphering, admission control, QoS setup (including QoS negotiations), etc. They involve different nodes such as PCRF, mobility management entity, packet data network gateway, serving GW, home subscriber server, etc. Despite all of these different operations, 3GPP mobile networks are still capable of maintaining a control plane latency of 50 ms (i.e., in case of long-term evolution advanced), which is largely shorter than the International Telecommunication Union-Telecommunication (ITU) requirements (i.e., 100ms). The QoS negotiations proposed in this paper are thus expected not to have a major impact on ITU requirements in terms of the control plane latency.

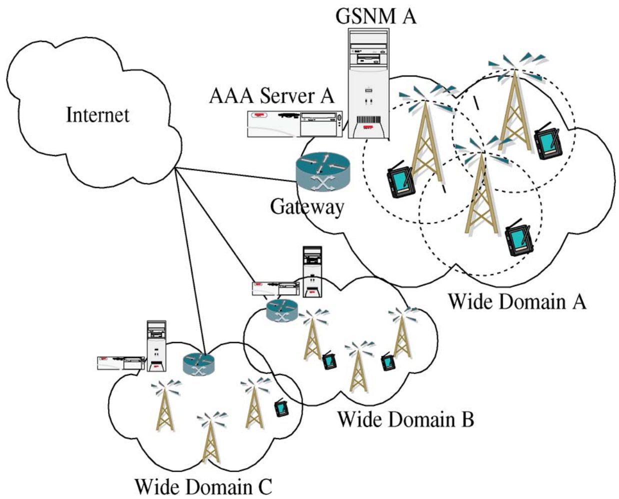

Fig. 1. Key components of the envisioned QoS architecture.

this results in congestion. On the contrary, when the minimum price is high, few requests will be made to the service. Both cases would affect the obtained revenues. The impact of setting high maximum prices is similar. While the setting of prices deserves further investigation and study, it is outside the scope of this paper. However, given the fact that network resources are highly time varying in wireless mobile networks, we suggest that the prices should reflect the varying market value of the network resources by taking into account the current channel quality conditions. This shall yield maximum system efficiency and shall render the proposed scheme more flexible and fairer. Indeed, to sustain a certain level of QoS, the maximum and minimum prices of a particular service level should not be constant but rather changeable during the entire communication course as a function of the channel quality conditions. A user subscribed to a given service level will be charged for a price from within the corresponding minimum and maximum prices. It is assumed that each user possesses an initial amount of money. In this paper, money is used to differentiate the QoS given to users. It can be, however, replaced by any unit that can evaluate the satisfaction of users (e.g., institutional hierarchy).

The mechanisms by which GSNMs admit or turn down requests, or allocate resources for users follow our proposed resource allocation strategy, as will be explained later. The GSNM allows users to compete for the wireless network resources. Naturally, users are interested in getting higher service levels for the most reasonable price. On the other hand, the GSNM is interested in maximizing its revenue. This gives rise to an auction where users are given responsibility to determine their service levels. It should be noted that, unlike traditional auction algorithms, the auction considered in this research has a finite number of objects (service levels), and the cost of each service level is bounded by a minimum value and a maximum value.

In economic theory, there is a wide variety of algorithms for auctioning. Notable examples are the all-pay auction, first-price auction, and second-price (or Vickrey) auction algorithms. In the all-pay auction algorithm, bidders independently submit single bids for an object. The object is sold to the bidder who makes the highest bid. However, the other bidders still have to pay their bid, despite their failure in winning the auction. In the first-price auction algorithm, the object is given to the bidder with the highest bid. Losers do not have to pay. In the second-price auction algorithm, the winner is intuitively the bidder with the highest bid. The object is however sold for a price equal to the second highest bid. In [10], the second-price algorithm is used for resource allocation in wireless networks. It is demonstrated that it yields good allocation of network resources, not to mention intrinsic incentive compatibility.

TABLE I
SIMPLE SERVICE LEVEL PRICING SCENARIO

Service level	Bandwidth (kbps)	Min. Price	Max. Price
L_1	25	1	3
L_2	50	4	6
L_3	75	7	9
L_4	100	10	12

In the remainder of this section, we demonstrate via a simple example that the application of current auction algorithms still fail in guaranteeing the best use of network resources, thus maximizing the revenue of a NO while fairly satisfying the expectations of users. Instead, we propose an auction algorithm that (when necessary) considers downgrading the service level requested by the winning bidder, should that yield better network performance and higher competitive fairness.

To illustrate the idea with more clarity, we consider the following scenario: We consider the case of a single GSNM with two subscribers A and B, each with an initial budget worth 7.5 and 8 money unit, respectively. We assume that the maximum bandwidth that can be served by the GSNM domain is 100 kb/s. It should be stressed that the focus of our envisioned resource allocation strategy is bandwidth, specifically the maximum guaranteed bit rate (i.e., using the terminology of 3GPP specifications [14]).

We consider the case when GSNM provides four service levels, as indicated in Table I. The minimum and maximum prices (in money units) of each service level are listed in the table. For the sake of simplicity, we ignore the variations of channel conditions and assume that the prices remain constant.

In this scenario, both mobile users can afford service level L_3. They can, thus, compete against each other for this service. We adopt a pricing scheme that has the following feature: If a mobile user, with an initial budget that makes it eligible for service level L_i, gets his/her request downgraded to service level L_j $(j < i)$, the user will be charged for the maximum price of service level j. This will make the user have the highest bid on service level L_j (on top of the other users competing for service level L_j) and will prevent the user from experiencing further downgrades in his/her requested service level. Let S_{jk} denote the resource allocation strategy where mobile users A and B are allocated service levels L_j and L_k, respectively (when $j = 0$, request is rejected). Given the fact that user A bids an amount of money that is smaller than what user B bids, the latter should always be allocated a service that is higher or similar to that of user A $(j \leq k)$. Table II lists all possible resource allocation strategies, along with the total required bandwidth, the total revenue, and fairness in the

TABLE II
FAIRNESS INDEX VALUE, TOTAL REQUIRED BANDWIDTH, AND TOTAL REVENUE IN A NUMBER OF RESOURCE ALLOCATION STRATEGIES

Strategy	Required Bw (kbps)	Revenue (money unit)	U(A)	U(B)	Fairness
S_{01}	25	3	0	2.778	0.5
S_{02}	50	6	0	5.556	0.5
S_{03}	75	8	0	6.250	0.5
S_{11}	50	6	2.778	2.778	1
S_{12}	75	9	2.778	5.556	0.9
S_{13}	100	11	2.778	9.375	0.772
S_{22}	100	12	5.556	5.556	1
S_{23}	125	14	5.556	9.375	0.94
S_{33}	150	15.5	10	9.375	0.999

users' satisfaction. The satisfaction of a user C $(C \in \{A, B\})$ is computed as follows:

$$U(C) = \frac{bw_i}{bw_k} \cdot \frac{bw_i}{\alpha_{C.i}} \tag{1}$$

where i and k denote the index of the allocated service level and the requested service level, respectively. bw_i and bw_k denote the bandwidth provided by service levels L_i and L_k, respectively. $\alpha_{C.i}$ is the actual price user C paid to subscribe to service level L_i per time unit (i.e., monetary unit per time unit). The rationale behind such a definition of the satisfaction metric is twofold: first, to reflect how much a user gets his/her initially requested service level downgraded and, second, to indicate the bandwidth unit price at which the user paid for the service. Similar in spirit to Jain's index [15], the fairness index is computed as follows:

$$F = \frac{(U(A) + U(B))^2}{2 \cdot (U(A)^2 + U(B)^2)}. \tag{2}$$

The fairness index ranges from 0 to 1. Low values of the fairness index represent poor fairness among the competing users.

In the preceding scenario, the two strategies S_{23} and S_{33} cannot take place as the total required bandwidth exceeds the available network resources, i.e., 100 kb/s. There are two strategies that make full utilization of the network resources, i.e., S_{22} and S_{13}. By applying a simple auction mechanism that merely allocates resources to the winning bidder and does not incorporate fairness (an equally important metric), the GSNM may allocate service level L_3 to user B as it makes the highest bid. To make full use of the network, user A will then be allocated service level L_1. This strategy S_{13} will lead to a revenue of 11 money unit and a fairness index equal to 0.772. However, by having an auction mechanism that can downgrade the service level of user B (winner when traditional auction algorithms are in use) to L_2 and allocating the same service level to user A, the network achieves its best performance, and the NO gets the maximum revenue. At the same time, the overall system fairness improves.

From the aforementioned example, it can be deduced that the use of traditional auction algorithms may favor users that make the highest bid and allocate to them their requested service levels. However, this comes at the cost of reduced revenue and poorer fairness. A new auction-based resource allocation algorithm that takes into account system fairness and maximizes revenue and network utilization is required. In the next section, we formulate the studied problem and analytically demonstrate the uniqueness of the strategy provided by our envisioned auction-based resource allocation scheme.

IV. ENVISIONED AUCTION-BASED RESOURCE ALLOCATION SCHEME

For the sake of simplicity, we consider a single domain governed by a single GSNM as in Fig. 1. As previously stated, in resource allocation, our focus is on bandwidth. The available bandwidth of the network is denoted as Bw. At a certain point in time, we assume that N mobile users are competing for the network bandwidth, each with an initial budget B_i $(i \in [1, N])$ and a call duration worth θ_i time unit. The unit of the initial budget is defined as money unit per time unit. Without loss of generality, we assume that $(B_1 \leq B_2 \ldots \leq B_N)$. It should be noted that parameters such as B_i and θ_i $(i \in [1; N])$ decide the incentive compatibility of the system. Indeed, generally speaking, a system is said to be incentive compatible if its participants truthfully reveal any private information to be used by the system for taking a decision. In the proposed scheme, the private information that are revealed to the GSNM are the budget and service-length parameters. Should they be truthfully revealed, the system would be thus said incentive compatible.

The GSNM is assumed to serve M service levels, L_j $(j \in [1, M])$. A user subscribing to service level L_k is allocated a portion of the bandwidth equal to Bw_k. Without loss of generality, we assume that the higher the index of a service level is, the higher its offered bandwidth is, i.e.,

$$j \leq l \Leftrightarrow Bw_j \leq Bw_l. \tag{3}$$

Each service level L_j has lower and upper bound prices $P_{j.min}$ and $P_{j.max}$, respectively. It should be recalled that price-fixed models do not fairly and efficiently reflect the varying market value of the network. We, therefore, attempt to reflect the channel conditions (e.g., available bandwidth) in the service pricing. For simplicity, we assume that the prices of each service level are set proportionally to their offered bandwidth as follows[2]:

$$\frac{Bw_j}{P_{j.max}} = cst_1 \quad \forall j[1, M] \tag{4}$$

$$\frac{Bw_j}{P_{j.min}} = cst_2 \quad \forall j[1, M]. \tag{5}$$

[2]It should be noted that the assumption that bandwidth price linearly increases may not always hold. In particular, for the high end of the service range, prices tend to dramatically increase. For example, an increase from 25 to 50 kb/s may correspond to a twice increase in price, whereas an increase from 150 to 300 kb/s may correspond to a quadruple increase in price. However, for the sake of simplicity, we consider a linear increase of price versus bandwidth. It should be noted that such assumption shall not impact the fundamental observations made about our proposed scheme.

Without loss of generality, we also assume that

$$P_{1.min} < P_{1.max} \leq P_{2.min} < \cdots < P_{M.min} < P_{M.max}. \tag{6}$$

Denoting by x_j the number of subscribers to service level L_j, we do have the following admission policy that assures that the network bandwidth is not overbooked:

$$\sum_{j=1}^{M} x_j \leq N \tag{7}$$

$$\sum_{j=1}^{M} Bw_j \cdot x_j \leq Bw. \tag{8}$$

Let $\alpha_{i.j}$ be the price that user i actually pays for service level L_j. The following expresses money constraints:

$$P_{j.min} \leq \alpha_{i.j} \leq P_{j.max} \tag{9}$$

$$\alpha_{i.j} \leq B_i. \tag{10}$$

Basically, a user i can compete with other users for any service level L_j, provided that $(P_{j.min} \leq B_i)$.

If, due to lack of network resources or tough competition, a user i, which is eligible for service level L_j, gets his/her requested service level downgraded to a service level L_k $(k \leq j)$, the user will be charged for the maximum price of L_k, i.e., $P_{k.max}$. The rationale behind adopting this pricing scheme lies beneath the fact that this will make the user have the highest bid on service level L_k (on top of the other users competing for L_k) and will prevent the user from experiencing further downgrades in his/her requested service level.

It should be noted that this pricing scheme also assists in dynamically changing the price per network resources as a result of changes in network demand, and that is for a set of competing users. Indeed, we assume that, at a certain point in time, N mobile users are competing for the network bandwidth, each with an initial budget B_j. A user i is subscribing to a service level L_k and is allocated a portion of the bandwidth equal to Bw_k^i. When network resources become insufficient, e.g., due to the arrival of one or more users, the following downgrade policy is applied by the GSNM. Effectively, from the set of mobile users that are competing for the network bandwidth, the one with the minimum value of B_i/Bw_k^i is first downgraded to a lower service level L_j $(j < k)$; the user will then be charged for the maximum price of service level L_j. If the network resources are still not enough to cover all users' demands, the user with the second lowest value of B_i/Bw_k^i is next downgraded, and so on. In case of the arrival of multiple new users all at the same time or nearly the same time, the GSNM may also consider downgrading the service level of a set of existing users with a value of B_i/Bw_k^i lower than a certain threshold (e.g., depending on the number of newly arriving users), all in one bulk.

From the user perspective, a user i is naturally always interested in subscribing to the highest possible service level for the most reasonable price. From the system perspective, it is desirable to maximize the revenue. In our auction strategy, we want to provide a fair system that makes best use of the network resources, fairly satisfies the requests of all users, and maximizes the service revenue. This can be translated into the following equations:

$$Minimize\left(N - \sum_{j=1}^{M} x_j\right) \tag{11}$$

$$Minimize\left(Bw - \sum_{j=1}^{M} Bw_j \cdot x_j\right) \tag{12}$$

$$Maximize\left(\sum_{i=1}^{N} \theta_i \sum_{j=1}^{M} \alpha_{i.j}^*\right) \tag{13}$$

where

$$\alpha_{i.j}^* = \begin{cases} \alpha_{i.j}, & \text{if user } i \text{ subscribes to } L_j \\ 0, & \text{otherwise} \end{cases}. \tag{14}$$

Note that, in (13), the call duration of each user is used. This is for the purpose of guaranteeing high revenue in the long run. Furthermore, while (11) attempts to increase the scalability of the system by satisfying as many requests as possible, it does not guarantee fair service to all competing users. To reflect system fairness, we consider the use of users' satisfaction metric, as defined here. Let user i request subscription to service level L_j, whereas it is allocated service level L_k. The satisfaction of user i is measured as follows:

$$U(i) = \frac{bw_k}{bw_j} \cdot \frac{bw_k}{\alpha_{i.k}}. \tag{15}$$

Similar in spirit to Jain's index [15], the fairness index is computed as follows:

$$F = \frac{\left(\sum_{i=1}^{N} U(i)\right)^2}{N \cdot \left(\sum_{i=1}^{N} U(i)^2\right)}. \tag{16}$$

To guarantee fairness, the objectives of our resource allocation strategy become

$$Maximize(F) \tag{17}$$

$$Maximize\left(\sum_{j=1}^{M} Bw_j \cdot x_j\right) \tag{18}$$

$$Maximize\left(\sum_{i=1}^{N} \theta_i \sum_{j=1}^{M} \alpha_{i.j}^*\right) \tag{19}$$

subject to

$$0 \leq F \leq 1 \tag{20}$$

$$0 \leq \sum_{j=1}^{M} Bw_j \cdot x_j \leq Bw. \tag{21}$$

It should be stressed that the proposed auction scheme is different from traditional auction algorithms. Indeed, in the proposed scheme, there is no real winner. When there is abundant bandwidth, users bidding for a given service level can all be assigned the same service level, even if they bid different amounts of money. Intuitively, the priority goes first to the bidders with the highest bid. At the same time, users can all have their requested service levels downgraded to help enhance the overall system fairness, its performance, and its revenue, as previously discussed. Additionally, if a bidder gets his/her requested service level, it will be charged for the bid it made. However, if it gets a lower service level, the user will be charged for the maximum price of the allocated service level. In case of a tie (when all bidders bid the same amount of money for a particular service level), the winners are chosen among the equal bidders with equal probability.

Resource allocation in the envisioned architecture can be seen as a set of mixed strategies for finite noncooperative games between the mobile users. In the theory of noncooperative games, this is known as the Nash game. In the remainder of this section, we analytically demonstrate that, when the three constraints, i.e., network utilization, fairness, and revenue, are taken into consideration, our proposed resource allocation scheme provides a Pareto-optimal solution, i.e., a unique Nash equilibrium.

First, we demonstrate that the resource allocation in case of N $(3 \leq N)$ users can be simplified to the case of two users.

Lemma 1: If the proposed scheme can provide a unique and optimal solution in the case of two users, it can do the same for N $(3 \leq N)$ users.

Proof: The proof of this lemma can be done in a recursive manner with respect to N. Let Bw denote the total available bandwidth that can be allocated to all the users. From the condition of the lemma, an optimal and unique allocation can be found for $N = 2$. Let us assume that the lemma holds for up to the case of $(N-1)$ users, we prove that there is an optimal allocation in case of N users. For $(N-1)$ users, each with an initial budget B_i, from the assumption that there is an optimal strategy, $S^*_{N-1}(Bw, \{B_1, B_2 \cdots, B_{N-1}\})$, where the Bw bandwidth of the network is optimally allocated. Now, let us assume that the Nth user has an initial budget of B_N and is eligible for service levels L_k or lower. For the N users, there are thus a finite number $(= k)$ of strategies for bandwidth allocations, i.e.,

$$S^j_N = \left\{S^*_{N-1}\left(Bw - Bw_j, (B_1, B_2 \cdots, B_{N-1})\right), Bw_j\right\}$$

where $(j \in [1, k])$.

Considering the $(N-1)$ users as a single user that has an initial budget worth $(\sum_{i=1}^{N-1} B_i)$ and requests a service level that provides a bandwidth equal to $(Bw - Bw_j)$, and using the condition of Lemma 1, an optimal and unique resource allocation strategy can be found for the $(N-1)$ users and the Nth user separately, e.g., S^m_N. Again, using the recursive assumption, an optimal and unique allocation of the $(Bw - Bw_m)$ bandwidth can be found for the $(N-1)$ users. ◊

Lemma 2: The proposed scheme can provide a unique solution (Pareto optimal) when two users are competing for the network resources.

Proof: We consider two users A and B, each with an initial budget equal to B_1 and B_2, respectively. They are eligible to service levels L_k and L_l, respectively. Without loss of generality, we assume $(B_1 \leq B_2)$. Assuming that the service levels are ordered according to their index, L_l should be thus higher than L_k; $(k \leq l)$. Let Bw again denote the total available bandwidth that can be allocated to the two users.

1) Case 1 $(Bw_k + Bw_l \leq Bw)$: In this case, users are simply allocated the service levels L_k and L_l that they are eligible for.
2) Case 2 $(Bw_k + Bw_l > Bw)$: In this case, the two users will be assigned two service levels L_x and L_y subject to $(x \leq y)$, $(x \leq k)$, and $(y \leq l)$. Here, two situations can be envisioned.
   a) $x < k$ and $y < l$: In this case, the prices that users A and B will pay are $P_{x.max}$ and $P_{y.max}$, respectively. To ensure high fairness, both users should exhibit almost the same satisfaction, i.e.,

$$\frac{U(A)}{U(B)} = (1 \pm \epsilon)$$
$$\Leftrightarrow \frac{Bw_x}{Bw_k} \cdot \frac{Bw_x}{P_{x.max}} = (1 \pm \epsilon)\frac{Bw_y}{Bw_l} \cdot \frac{Bw_y}{P_{y.max}} \quad (22)$$

where ϵ is negligible $(0 \leq \epsilon \ll 1)$. From (4), we obtain

$$Bw_x = (1 \pm \epsilon) \cdot \frac{Bw_k}{Bw_l} \cdot Bw_y. \quad (23)$$

From maximizing the utilization of the network resources, we obtain

$$Bw_x + Bw_y = Bw$$
$$\Rightarrow Bw_y = \left(1 + (1 \pm \epsilon) \cdot \frac{Bw_k}{Bw_l}\right)^{-1} Bw. \quad (24)$$

In this way, x and y are the index of the service levels whose bandwidths are the closest to the values that can be obtained from (23) and (24). It should be noted that, since the price of service levels is proportional to the allocated bandwidth, the total revenue of the whole system can be maximized by maximizing the utilization of the network resources. It should be observed that, from (24), Bw_y is unique. From (23), the value of Bw_x is also unique. It should also be remarked that a movement from the obtained allocation to a different allocation by modifying the values of Bw_y or Bw_x will affect the link utilization, even if we guarantee high fairness, and vice versa. This shall make one user better off, whereas the other user will be made worse off. This indicates the Pareto optimality of the obtained solution when the three objectives are taken into account. To conclude, the values of x and y represent a unique and optimal solution for both users A and B that satisfies the three objectives of our proposed scheme.

b) $(x = k)$ or $(y = l)$: The values of x and y can be derived in the same manner as in the previous case. The only change will be in the price that will be paid by the users (e.g., in case of $(x = k)$, $\alpha_{A.k} = B_1$ and $\alpha_{B.y} = P_{y.max}$). $\diamondsuit$

Using both Lemmas 1 and 2, we conclude that, when the constraints on the system fairness, system revenue, and network utilization are taken into account, our proposed scheme provides a Pareto-optimal resource allocation strategy to all competing users.

V. Performance Evaluation

While the performance of our proposed resource allocation mechanism can be evaluated considering the case of a large number of users and a general pricing scheme, for the sake of simplicity, we first consider the example provided in Section III with two users (1 and 2) and a simple pricing scheme, as shown in Table I. We only vary the initial budgets of the two users (B_1 and B_2).

As previously discussed, in traditional auction-based resource allocation schemes, the user that makes the highest bid is allocated his/her requested service level. Other users get their requested service level downgraded if there is not much available bandwidth to satisfy their requests. In our proposed scheme, for the sake of a better fairness among competing users and higher revenue, even the user with the highest bid can get his/her requested service level downgraded. In the remainder of this section, we compare the performance of the proposed scheme against that of any traditional auction-based resource allocation mechanism. It should be noted that, given the available 100-kb/s bandwidth in the considered example, our proposed scheme and traditional auction-based schemes will exhibit the same performance if the two users issue requests for service level L_2 or lower (Table I). We, therefore, consider the case when at least one end user has an initial budget that makes it eligible for service level L_3 and beyond. Indeed, we consider the four following scenarios where the two users have initial budgets (B_1, B_2) equal to (5,8), (7.5,8), (7.5, 11), and (11, 11), respectively. According to Table I, in the four considered scenarios, the two users are eligible for service levels (L_2, L_3), (L_3, L_3), (L_3, L_4), and (L_4, L_4), respectively.

Fig. 2 plots the value of fairness index in case of both the proposed and traditional auction-based resource allocation schemes for the four considered scenarios. Results in terms of link utilization are omitted as in all considered scenarios, both schemes achieve 100% link utilization. As for the provider revenue, the proposed scheme always achieves the highest revenue $(= 12)$, compared with the traditional auction-based resource allocation scheme $(= 11)$. From Fig. 2, we observe that the proposed scheme achieves the highest fairness. This is intuitively attributable to the features of our proposed scheme that downgrades the service level of even users with the highest bid if that yields better fairness among users and higher revenue for the service provider.

We further evaluate the performance of the envisioned auction-based approach by taking into account the mobility of users. For this purpose, a simple simulation topology, as shown in Fig. 3, is considered for this evaluation. We conduct simulations based on a network simulator (NS-2) [16] using a mobility model, whereby the arrival times of new users to the wireless domain and their service times follow two exponential distributions with means λ and μ, respectively. The rest of the simulation parameters are listed in Table III. The proposed resource allocation scheme is executed over every time slot Δ_t. Fig. 4 shows the impact of Δ_t on the fairness of resource allocation among the considered users. The results clearly exhibit better performance of the proposed scheme, in contrast with the highest bid method. For higher service durations, the fairness is reduced since the users request for resources over longer time periods. From these results, it may be observed that the fairness is reduced with the increment of Δ_t. This is attributable to the fact that the users do not frequently downgrade their services.

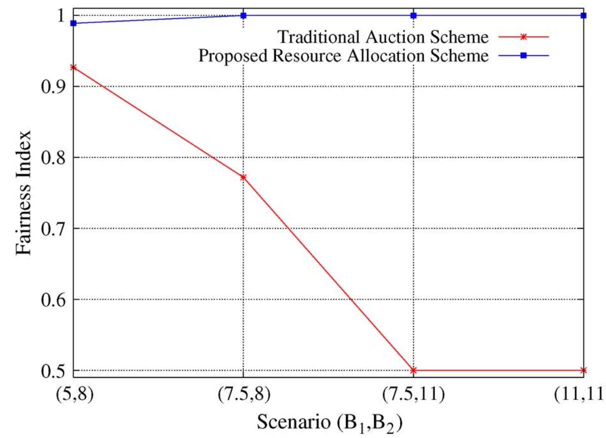

Fig. 2. Fairness index values in case of the proposed scheme and traditional auction-based resource allocation schemes for different scenarios with varying initial budgets of users.

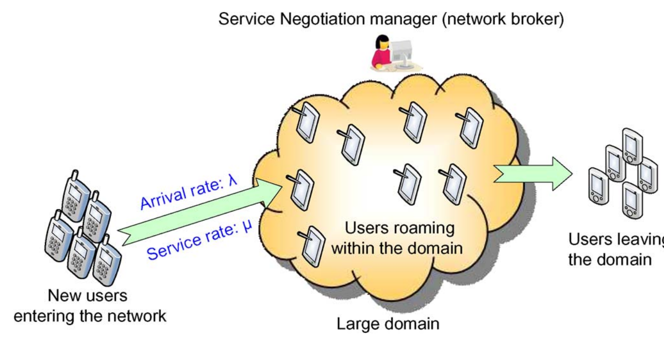

Fig. 3. Considered simulation topology with mobility.

TABLE III
SIMULATION PARAMETERS

Simulation parameter	Value
Total network bandwidth, BW	3Mbps
Number of service levels, M	4 or 7
Bandwidth of each service S_k, i.e., BW_k	64Kbps, 128Kbps, 192Kbps, 256Kbps
Price of each service S_k, i.e., $\{P_{k.min} : P_{k.max}\}$	L_1: 1\$: 3\$ /h L_2: 4\$: 6\$ /h L_3: 7\$: 9\$ /h L_4: 10\$: 12\$ /h
Initial budget of each user	Randomly selected from within {1\$: 12\$}

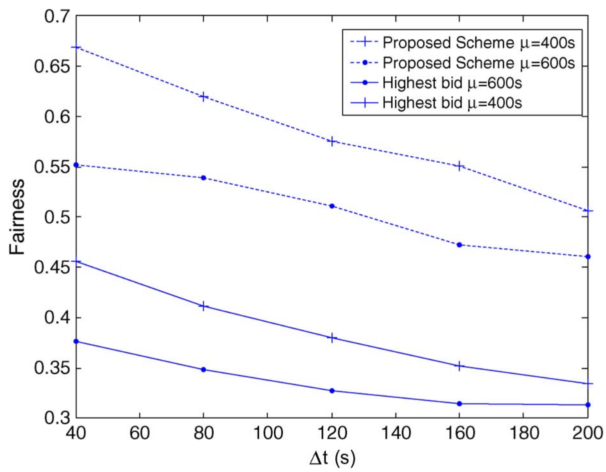

Fig. 4. Fairness index values in case of the proposed auction-based scheme and the highest bid resource allocation scheme for two service times and various time slots.

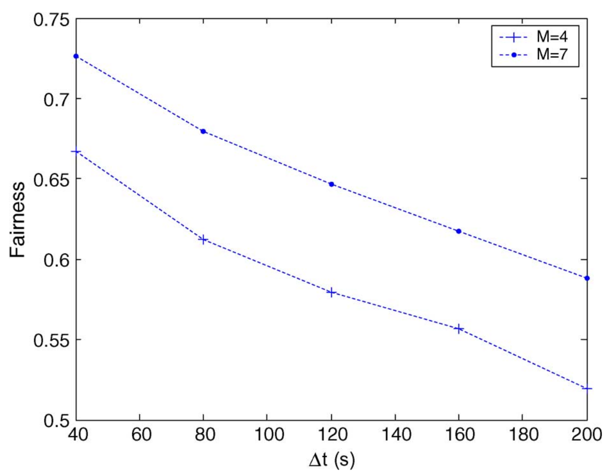

Fig. 5. Fairness index values for various time slots under the proposed scheme in case the number of service class M is either four or seven.

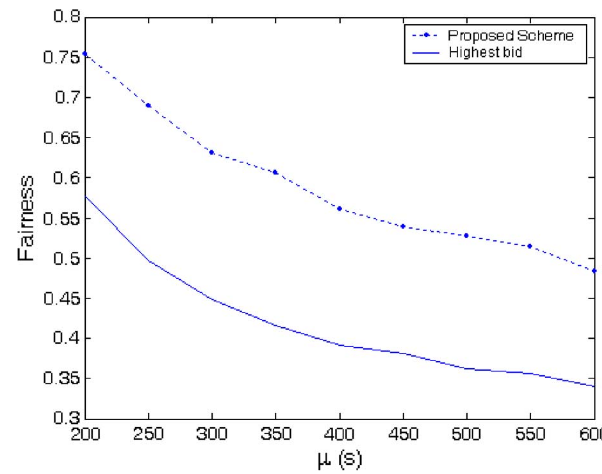

Fig. 6. Fairness index values in case of the proposed auction-based scheme and the highest bid resource allocation scheme for various service times.

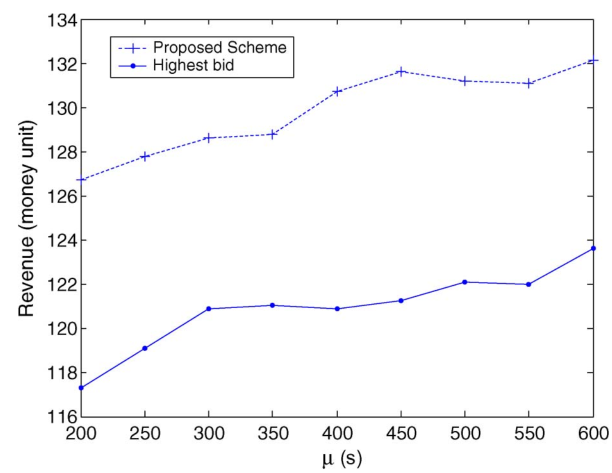

Fig. 7. Revenues earned by the service provider in case of the proposed auction-based scheme and the highest bid resource allocation scheme for various service times.

To investigate the impact of the number of service classes on the envisioned scheme, we conduct further simulations. To be consistent with the previous simulation setting, the total network bandwidth BW is set to 3 Mb/s throughout these particular experiments. The number of service classes, which is denoted by M, is increased to seven (instead of only four). The service classes offered are {64, 96, 128, 160, 192, 224, and 256 kb/s}. Accordingly, the price ranges of the classes are readjusted. The initial budget of each user is randomly selected from one to 12 money unit (i.e., $). Fig. 5 shows the influence of the increase in M on the fairness of the proposed scheme for various values of Δ_t. The higher value of M improves the fairness among contending users due to the more varied choices that the users can make. However, the fairness still reduces with the increasing values of Δ_t because of the infrequent service downgrades conducted by the clients.

By intuition, service duration μ is also bound to significantly influence fairness. To investigate this issue, λ and Δ_t values are set to 10s and 100s, respectively, in the simulations. The fairness achieved by the proposed method and that achieved by the highest bid method are plotted against different values of μ in Fig. 6. The fairness substantially degrades in both schemes as the service time increases. However, there is a tradeoff between this loss of fairness and the service revenue. The impact of μ on the service provider's revenue is shown in Fig. 7. The results suggest that the revenues increase when the users are served for longer periods of time. Moreover, both Figs. 6 and 7 demonstrate the superior performance of the proposed scheme in contrast with the conventional highest bid approach in terms of fairness and obtained revenues for a given service time.

Finally, we investigate the effect of increasing numbers of user requests to access the service. Figs. 8 and 9 plot the fairness and revenue, respectively, along with the average number of considered users. The number of users is varied from 10 to 27 without any specific purpose in mind and without any loss of generality. Although the fairness achieved by the proposed approach gradually decreases (as shown in Fig. 8), when the demand for the service becomes higher, the level of fairness remains significantly high (0.83), in contrast with the highest bid method (0.51) for the highest number of users (i.e., 27). Furthermore, in the proposed method, the revenue continues to substantially increase for the higher number of customers,

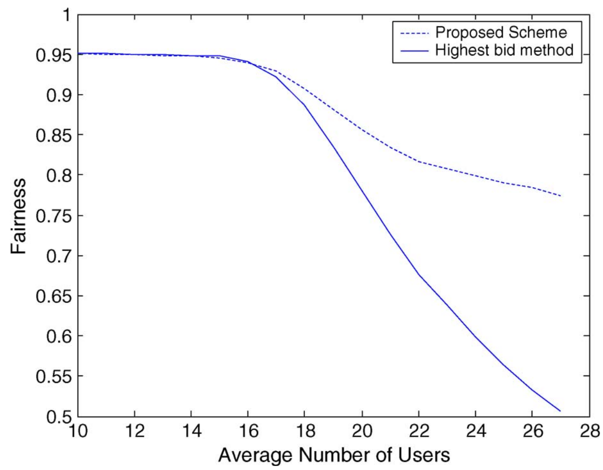

Fig. 8. Fairness index values in case of the proposed auction-based scheme and the highest bid resource allocation scheme for different numbers of users.

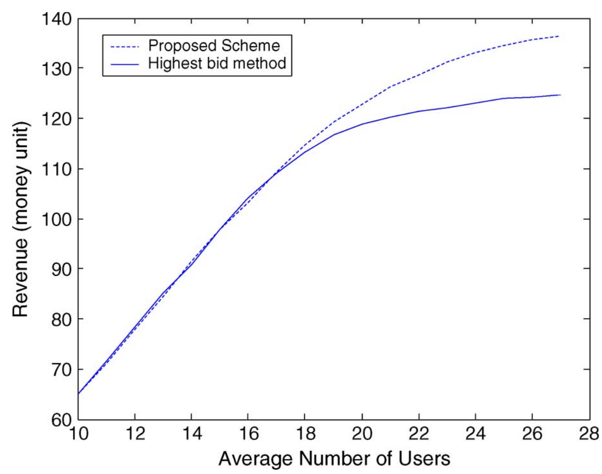

Fig. 9. Revenues earned by the service provider in case of the proposed auction-based scheme and the highest bid resource allocation scheme for different numbers of users.

as shown in Fig. 9. Compared to a mere $60 revenue for only ten users, the envisioned scheme enables the service provider to make more than a 100% profit when the number of users is doubled. For the maximum number of users (i.e., 27), the revenue earned by the provider is more than $135 in the proposed approach in contrast with $121 in case of the highest bid method.

VI. Conclusion

This paper has presented an analysis of the intricate relationship, which exists between the end users and the service providers. This paper has focused on ensuring a number of important issues, i.e., fairness among the users, optimal utilization of the available network resources, and maximization of the revenues of the concerned service providers. Since these design goals are intertwined, we designed an auction-based dynamic resource allocation approach to take into careful consideration each of these aspects. The envisioned scheme considers the deployment of a number of service classes. The service provider presents the clients with the price range of each service class and then executes a mathematical optimization model for determining the appropriate clients that are to be serviced. We have adopted the Nash game theory, i.e., a set of mixed strategies for finite noncooperative games between the mobile users, to allocate the resources in a dynamic fashion, whereby the service level of a particular user may be downgraded to fairly serve all the users. The analysis demonstrates that the envisioned resource allocation model converges to a Pareto-optimal solution, i.e., it reaches the "Nash equilibrium," provided that all the three design goals are taken into account. The mathematical analysis has been validated through computer simulations that exhibit encouraging performance of the proposed approach in contrast with its conventional counterpart. In addition, even when the number of users significantly increases, the proposed scheme has been able to maintain substantially high fairness while ensuring that the providers receive high revenues.

References

[1] T. Taleb, A. Nafaa, L. Murphy, K. Hashimoto, N. Kato, and Y. Nemoto, "Towards efficient service-level QoS provisioning in large-scale 802.11-based networks," *IEEE Netw.*, vol. 21, no. 5, pp. 42–48, Sep. 2007.

[2] J. C. Fernandez, T. Taleb, M. Guizani, and N. Kato, "Bandwidth aggregation-aware dynamic QoS negotiation for real-time video applications in next-generation wireless networks," *IEEE Trans. Multimedia*, vol. 11, no. 6, pp. 1082–1093, Oct. 2009.

[3] V. Sarangan and J. C. Chen, "Comparative Study of Protocols for Dynamic Service Negotiation in Next Generation Internet," *IEEE Commun. Mag.*, vol. 44, no. 3, pp. 151–156, Mar. 2006.

[4] E. Fulp, D. Reininger, M. Ott, and D. S. Reeves, "Paying for QoS: An optimal distributed algorithm for pricing network resources," in *Proc. IWQOS*, Napa Valley, CA, May 1998, pp. 75–84.

[5] I. Stoica, H. Abdel-Wahab, and K. Jeffay, "On the duality between resource reservation and proportional share resource allocation," in *Proc. SPIE—Multimedia Computing Network*, 1997, pp. 207–214.

[6] K. Lai, L. Rasmusson, E. Adar, L. Zhang, and B. A. Huberman, "Tycoon: An implementation of a distributed, market-based resource allocation system," *J. Multiagent Grid Syst.*, vol. 1, no. 3, pp. 169–182, Aug. 2005.

[7] N. Semret, R. F. Liao, A. T. Campbell, and A. A. Lazar, "Pricing, provisioning and peering: Dynamic markets for differentiated internet services and implications for network interconnections," *IEEE J. Sel. Areas Commun.*, vol. 18, no. 12, pp. 2499–2513, Dec. 2000.

[8] G. Malewicz and A. Shvartsman, "An auction-based flexible pricing scheme for renegotiated QoS connections and its evaluation," in *Proc. 7th IEEE MASCOTS*, Oct. 1999, pp. 244–251.

[9] L. Tassiulas and S. Sarkar, "Maxmin fair scheduling in wireless networks," in *Proc. IEEE INFOCOM*, New York, Jun. 2002, pp. 763–772.

[10] J. Sun, E. Modiano, and L. Zheng, "Wireless channel allocation using an auction algorithm," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 5, pp. 1085–1096, May 2006.

[11] D. Niyato and E. Hossain, "Spectrum trading in cognitive radio networks: A market-equilibrium-based approach," *IEEE Wireless Commun.*, vol. 15, no. 6, pp. 71–80, Dec. 2008.

[12] D. Niyato, E. Hossain, and Z. Han, "Dynamic spectrum access in IEEE 802.22-based cognitive wireless networks: A game theoretic model for competitive spectrum bidding and pricing," *IEEE Wireless Commun.*, vol. 16, no. 2, pp. 16–23, Apr. 2009.

[13] P. Belzarena, A. Ferragut, and F. Paganini, "Network bandwidth allocation via distributed auctions with time reservations," in *Proc. INFOCOM Mini Conf.*, 2009, pp. 2816–2820.

[14] "General Packet Radio Service (GPRS) enhancements for Evolved Universal Terrestrial Radio Access Network (E-UTRAN) access," 3GPP, Sophia-Antipolis, France, TS 23.401, Mar. 2011.

[15] D. Chiu and R. Jain, "Analysis of the increase and decrease algorithms for congestion avoidance in computer networks," *Comput. Netw. ISDN Syst.*, vol. 17, no. 1, pp. 1–14, Jun. 1989.

[16] Network Simulator - NS-2. [Online]. Available: http://www.isi.edu/nsnam/ns/

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