Dynamic Price Discovering Models for Differentiated Wireless Services

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***Abstract*—Heterogeneous subscriber base with wide range of wireless services makes the wireless service market more challenging for a service provider (SP). This challenge is related to the revenue model of the SP, where pricing policy plays a central role. The pricing policy should be such that an SP will recover the investment while keeping the desired level of customer satisfaction. An ideal pricing policy should be less complex and be able to price the service close to the worth, a subscriber attached to it. This calls for dynamic price discovering models for differentiated wireless service. In this paper, we have proposed auction based price discovering models like uniform pricing auction and discriminatory pricing auction for dynamic pricing of differentiated wireless services. We have compared their performances with flat-pricing scheme for differentiated wireless services, which is quite popular in the wireless domain. Simulation results show that auction based models have a potential to replace the traditional flat pricing models.**

***Keywords*- Differentiated wireless service pricing, Price iscovery models, auctions, flat pricing.**

I. INTRODUCTION

The rapid proliferation of the wireless network has given rise to wide range of applications to a large subscriber base. Each of these applications has unique needs in terms of network resources. In addition to that each subscriber attaches different worth to each of these applications. This heterogeneity in application and in the subscriber base makes the wireless service market more complex and challenging to wireless service providers. This challenge is mainly associated with allocation of constrained resources to a set of subscribers who need it most and charge them an amount close to the worth they derive from the service. This is where economics of the wireless network gains significance.

The economics of the wireless network though very similar to that of a wired one differs in one aspect i.e., the wireless networks are constrained by the limited spectrum allotted to them by the regulators. This hinders the scalability of wireless networks as opposed to wired counterparts. The service providers manage this scarcity by a judicious allocation of the spectrum to its users. A revenue model paradigm can effectively be used to manage this problem. Consequently the service providers use pricing as a tool to resolve this constraint on the bandwidth.

A traditional approach to pricing network services is to have a flat-rate pricing scheme (the consumers pay a fixed fee for an unlimited access to the network) for the consumers. An extension of this approach is to have flat pricing with differentiated customer base. However this is fraught with its unique set of problems. A prominent issue is the excessive usage of the network by those who avail of this pricing scheme. This denies the genuine users an access to the network when they need it. To counter this problem, the service providers are adding capacity to the extent of over provisioning capacity [1] as much as possible. However, this does not obviate the need for putting normative control on network resource usage. An effective network pricing mechanism is a potent tool for usage control while maximizing revenues at the same time.

In this paper, we have adopted two different auction based dynamic price discovering models for differentiated wireless services in a cellular network and compared it with the traditional flat pricing model in terms of call blocking probability and revenue earned. We consider two of the popular auction mechanisms- uniform pricing and discriminatory pricing auction and compare their effectiveness with respect to the flat-pricing scheme.

Through simulation study, we observe that uniform pricing auction yields higher revenue than discriminatory pricing auction when aggressive price index is more than 8%, and both the auction models yield better revenue when compared with flat pricing policy.

The rest of the paper is organized as follows. In section II, we present a brief overview of previous works on pricing in both wired and wireless networks. In section III, we briefly introduce the basics of pricing models that are made of use in this work. We provide the mathematical formulation for the revenue generation in section IV. The simulation model and the interpretation of the results are presented in section V. Conclusions are drawn in the last section.

II. Survey of Previous Works

Various pricing techniques have been suggested in the literature for wired networks. Each approach tackles the problem from different perspectives- consumer surplus, social benefit, Pareto optimality, etc. Some of the notable pricing schemes are the Smart Market [2], the Paris Metro Pricing [3], the Progressive Second Pricing [4], and the Priority pricing scheme [5]. Each performs differently when revenue generated by the model is considered as a parameter for evaluating the effectiveness of a pricing mechanism.

The Smart Market model [2] views the inter-connected network as a marketplace in which various services are offered to the users and they get to select from these services. Given a service supply curve, the demand across various users is aggregated in terms of their bids for the packets. These demand and supply curves yield the price which all the users are charged. These users pay at most their bid, and the equilibrium price is the bid of the marginal user. The concept of incentive compatibility ensures that the users come up with their true bids. The revenues in the model give an idea about the optimal investment in the capacity expansion. Another benefit of this scheme is that the winner's curse is avoided. But, although various implementation schemes have been suggested [2], the model involves an overhead in collecting the bid from users and using the same for revenue calculation and user profile.

The Paris Metro Pricing scheme [3] is borrowed from the ticket pricing mechanism followed in the metro system in Paris. In this pricing scheme different service classes (or compartments) have different prices associated with them. Extending this logic to the pricing of networks this scheme forces the user to choose the channel over which his packet should travel and the price he would pay for it. The system is self-regulating in the sense that the users themselves partition themselves into the classes, and move to another class, if they find that the present class is too congested, or the same service can be obtained from the other class at a lower unit price.

While the smart market scheme takes the one-dimensional bid in terms of price, the Progressive Second Pricing [4] takes the concept further by including two dimensions in the bid – the bid rate, and the bid quantity. Once it is decided which users get the service based on their bids, a price is set as the bid rate of the lowest bidder. However, the price of the lowest bidder is set based on the bid rates of the opponents who were denied service because of the last bidder. But the requirement of a large number of players and complexity involved in bidding on routes, rather than on links, are the disadvantages of this scheme.

The priority pricing scheme [5] highlights the role of pricing policies in multiple service class networks. It suggests that some forms of graduated prices are required in order for any multi-class service discipline to have the desired effect. For some users the performance penalty received for requesting a less than optimal service class is offset by the reduced price of the service. For the other users the monetary penalty incurred by using the more expensive higher quality service classes is offset by the improved performance they receive. Thus prices allow the service provider to spread the benefits of multiple service classes around to all users rather than just allowing these benefits to remain exclusively with users who are performance sensitive.

On the other hand, the existing studies on pricing wireless network services [8]-[15] can be again broadly classified in two categories, namely static (S) pricing and dynamic (D) pricing. Again each of these subcategories is having sub-classes of differentiated (D) service (variable), and non-differentiated (ND) service (flat). For instance, in [8], authors have proposed a "dynamic non-differentiated pricing strategy" (DNDPS), which is a simple and straightforward technique and work on real-time basis. It monitors the congestion in the network. If congestion in the network exceeds a threshold value then the price will be changed to regulate the demand following an exponential demand function [8].

The study [10] falls under "static differentiated pricing strategy" (SDPS). In this study, the author analyzed a communication network with heterogeneous customers and used priority queuing as a way to differentiate them. The study assumed that the customers join the network as long as their utility (which is a function of the queuing delay) is larger than the price of the service. The specific situation considered is having two types of users namely delay-sensitive ('voice'), and delay-tolerant ('data'). Two models developed, based on queuing theory, and game theory, try to determine the price to maximize the service provider's profit.

The study in [5] falls under DNDPS. Here, authors investigated the role of pricing as an additional dimension of the call admission control process in order to efficiently and effectively control the use of wireless network resource. The study proposed an integrated pricing and call admission control scheme where the price is adjusted dynamically based on the current network conditions in order to alleviate the problem of congestion. The integrated approach implicitly implements a distributed user-based prioritization mechanism by providing negative incentives according to the current network conditions and therefore shaping the aggregate traffic in the network.

The study in [12] falls under SDPS, where authors considered resource allocation and pricing for the downlink of a wireless network with a time-slotted system or a CDMA system. The main feature of this model is that the channel quality varies across the users. A pricing scheme is used for the allocation of radio resources. The authors have shown that to maximize revenue in such a system, the base station should allocate resources in a discriminatory manner, where different users are charged different prices based on their channel quality.

The study in [13] falls under SDPS. In this study, authors provided a game theoretic approach for maximizing the utility of a carrier in a competitive market. Authors proposed a utility function based on a non-cooperative game which considers the probabilities of users leaving the network. In this study, there are three classes of users in a CDMA system. The users get differentiated services based on the price they are willing to pay. The game theoretic approach allocates resources both during service admission and burst admission. The utility function considered is from the service provider's point of view.

The study in [14] falls under DNDPS. Here, the authors have considered dynamic pricing strategies for connection oriented wireless service. The authors have modeled the user demand and the call duration as functions of price. The study has used Markovian techniques to represent the system evolution to devise an optimal linear pricing scheme.

The paper [15], however, has considered the dynamic differentiated pricing strategy (DDPS). They have assumed that a provider differentiates subscribers into different QoS levels on the basis of QoS parameters. The provider varies the price of a call from the subscribers of a QoS level in discrete steps within an allowable range to regulate the demand from the subscriber base.

The paper [16], considered dynamic pricing for non-differentiated wireless services. In this paper, authors have used auction based model for pricing wireless services.

But, to the best of our knowledge, no work has been done to apply dynamic price discovery models to price differentiated wireless network services till date.

III. Basics of Pricing Modles

An *auction* is the process of buying and selling goods with a setting of asymmetric information on the intended price of buying or selling. In economic theory, an auction is a method for determining the value of a commodity that has an undetermined or variable price. In some cases, there is a minimum or reserve price; if the bidding does not reach the minimum, there is no sale. Traditional auctions involve single seller and many buyers. The buyers compete among themselves to procure the goods of their choice by placing a bid, which they feel most appropriate. Today there many auction models which are many variant of the traditional one. Two of these variants, adopted by us in this paper are discussed below.

Uniform pricing auction [6]: This auction mechanism is based on uniform pricing scheme. Once the bids are collected in the time interval Δt, the stop out bid is decided at which the aggregate demand exhausts the available resource. This clearing price is then charged to all the bids selected. To explain this mechanism let us consider a simple example. Suppose we have resources to support 3 calls and 5 requests are made (i.e., 5 bids arrive in contention for these resources). Let the bids have values \$1, \$2, \$3, \$4 and \$5. Since only three calls can be supported, first three bids are selected in terms of price of the bids. The bid price of the clearing bid becomes the uniform price to be charged for everyone. Hence, the selected bids would be \$3, \$4 and \$5 bids and each would be charged at the uniform rate of \$3 each. The uniform pricing auction eliminates winner's curse [6]. The individual bid price depends on the aggressive price index of the bidder.

Discriminatory Pricing Auction [6]: In this auction mechanism, a discriminatory pricing scheme is followed. Let us again consider the previous example to explain this concept. Here, a discriminating monopolist's pricing policy is followed for allocating the resources to the highest bidder until all the resources are exhausted. This implies that the three bids selected would be the top three bids of \$5, \$4 and \$3 and each would be charged according to the price quoted in his bid.

The other popular pricing model in wireless service domain is *flat pricing* model. It is a static pricing model. In the flat pricing mechanism, there is no concept of bid here. The call requests, which arrive first, will be allocated the available resource and will be charged at a pre-determined flat rate according to the class of services for the usage of these resources.

IV. Revenue Generation

Let us consider the revenue that would be generated by the different pricing schemes. We consider the presence of a single service provider that provides service to the users. The users are differentiated in terms of K quality of service (QoS) levels. Here, QoS is defined by call admission probability (Let us assume that the admission probability for QoS level k be ε_k). We concentrate on a cell being served by a base station having a finite spectrum. It can be noted that due to the absence of multiple service providers, no inter-provider competition is considered.

We consider a sequence of N calls, where $N = \sum_{k=1}^{K} n_k$ from a K QoS levels arriving at the base station in a time interval Δt. All the calls are identical and they require the same amount of resources. The bid price of each call from QoS level k per unit time is denoted by the vector P^k where

$$P^k = \left\{ p_{1t}^k, p_{2t}^k, \ldots\ldots, p_{n_k t}^k \right\} \tag{1}$$

Let there be resources for M users available at the base station. Hence, at any point in time a maximum of M calls can be served simultaneously by the base station. Thus, there can be two broad scenarios depending on the relative values of M and N.

Scenario 1 : $M > N$

In this case, the number of channels available is more than the request load, and hence the resource is under utilized. Therefore, all the calls are serviced while satisfying the requirement of all QoS levels. However, depending on the auction mechanism, the revenue will differ. For discriminatory pricing auction, the pricing vector reduces to

$$P^k = \{p^k_{jt}\}, \text{ where } 1 \le j \le n_k \quad (2)$$

However, since uniform pricing auction eliminates the winner's curse, the price set for all users is identical to the lowest bid. Let this lowest bid among first n_k bids be p^k_{min}. Hence, the vector P will have identical element and hence

$$P^k = \{p^k_{min}\} \text{ where } 1 \le j \le n_k \quad (3)$$

Let the duration of the calls indicated in equation (2) and (3) be given by $T^k = \{t^k_{jt}\}$, where $1 \le j \le n_k$.

Thus for both the auction schemes, the revenue generated, R, is given by

$$R = \sum_{k=1}^{K} P^k \bullet \{T^k\}^{-1} \quad (4)$$

It can be noted that the revenue obtained by this vector multiplication gives the revenue when the admission decisions are made. The instantaneous revenue will vary based on the bids placed and the duration of the respective calls.

Scenario 2: $M < N$

In this case, the number of users, N from all QoS level requesting to establish call exceeds the capacity, M, of the base station. In this scenario one of the following conditions may occur.

Condition-1

The capacity of base station M is more than capacity M_0, required meeting the requirement of all QoS levels. Therefore, the base station must employ first a call admission mechanism to admit first M_0 calls and followed by another call admission mechanism for admitting remaining $(M-M_0)$ calls.

The first M_0 calls needs to be admitted taking m^k_0 calls from k^{th} QoS level such that $\frac{m^k_0}{n_k} = \varepsilon_k$ (this is true for $\forall k$).

Let the price vector for first m^k_0 calls from k^{th} QoS levels (in the descending order of price) be

$$P^k_0 = \{p^k_{1t}, p^k_{2t}, ..., p^k_{m^k_0 t}\} \quad (5)$$

The price vector in (5) is applicable for discriminatory pricing. However for uniform pricing the price charged to each of the first m^k_0 will be p^k_{min}. Hence the price vector will be

$$P_0{}^k = \{p^k_{min}\} \text{ where } 1 \le j \le m^k_0 \quad (6)$$

Let the duration of the calls indicated in equation (5) and (6) be given by $T^k_0 = \{t^k_{jt}\}$, where $1 \le j \le m^k_0$

Then the revenue earned from M_0 calls can be obtained as follows

$$R_0 = \sum_{k=1}^{K} P^k_0 \bullet \{T_0{}^k\}^{-1} \quad (7)$$

The remaining resource $(M-M_0)$ can be allocated calls with highest bids across QoS levels. Let the price vector for the residual bids with first $(M-M_0)$ elements be

$$P^R = \{p^R_{1t}, p^R_{2t}, ..., p^R_{(M-M_0)t}\} \quad (8)$$

The price vector in (8) is applicable for discriminatory pricing. However for uniform pricing the price charged to each of the first $(M-M_0)$ will be p^R_{min}. Hence the price vector will be

$$P^R = \{p^R_{min}\} \text{ where } 1 \le j \le (M-M_0) \quad (9)$$

let the duration of the calls indicated in equation (8) and (9) be given by $T^R = \{t^R_{jt}\}$, where $1 \le j \le (M-M_0)$

Thus total revenue can be obtained as:

$$R = \sum_{k=1}^{K} P^k_0 \bullet \{T_0{}^k\}^{-1} + P^R \bullet \{T^R\}^{-1} \quad (10)$$

Condition-2

In case the base station has resources M such that $M<M_0$, then call requests from higher level of QoS will be supported first. Let us assume that with the available resources request from first K′ QoS levels are supported.

Let the price vectors for m^k_0 calls from k^{th} QoS level such that $\frac{m^k_0}{n_k} = \varepsilon_k$ (in the descending order of price) be

$$P^k_0 = \{p^k_{1t}, p^k_{2t}, ..., p^k_{m^k_0 t}\} \quad (11)$$

However, equation (9) gives the price vector for discriminatory pricing auction. For uniform pricing auction, the price set for all users is identical to the lowest bid. Let this lowest bid among first m^k_0 bids be p^k_{min}. Hence, the vector P will have identical element and hence

$$P^k = \{p^k_{min}\} \text{ where } 1 \le j \le m^k_0 \quad (12)$$

Let the duration of the calls indicated in equation (11) and (12) be given by $T^k_0 = \{t^k_{jt}\}$, where $1 \le j \le m^k_0$

The total revenue in this case is derived as

$$R = \sum_{k=1}^{K'} P^k_0 \bullet \{T_0{}^k\}^{-1} \quad (13)$$

V. Simulation Model and Results

We have conducted extensive simulation experiments to obtain the revenue for each of the pricing schemes. In our experiment we have used three categories viz. gold, silver, and bronze, of customers, differentiated w.r.t. service level agreement (SLA) for quality of service (QoS). The methods used to simulate are indicated in Fig. 1. In 2G deployment, these policies shall be implemented at the mobile switching center (MSC).

We focus our attention on a finite time interval of Δt. The results obtained, i.e., revenue generated and call blocking probability, are for this interval. Since, the simulation interval was taken to be sufficiently large, we can say that the results are steady-state values. Incoming calls are generated following a Poisson distribution with a

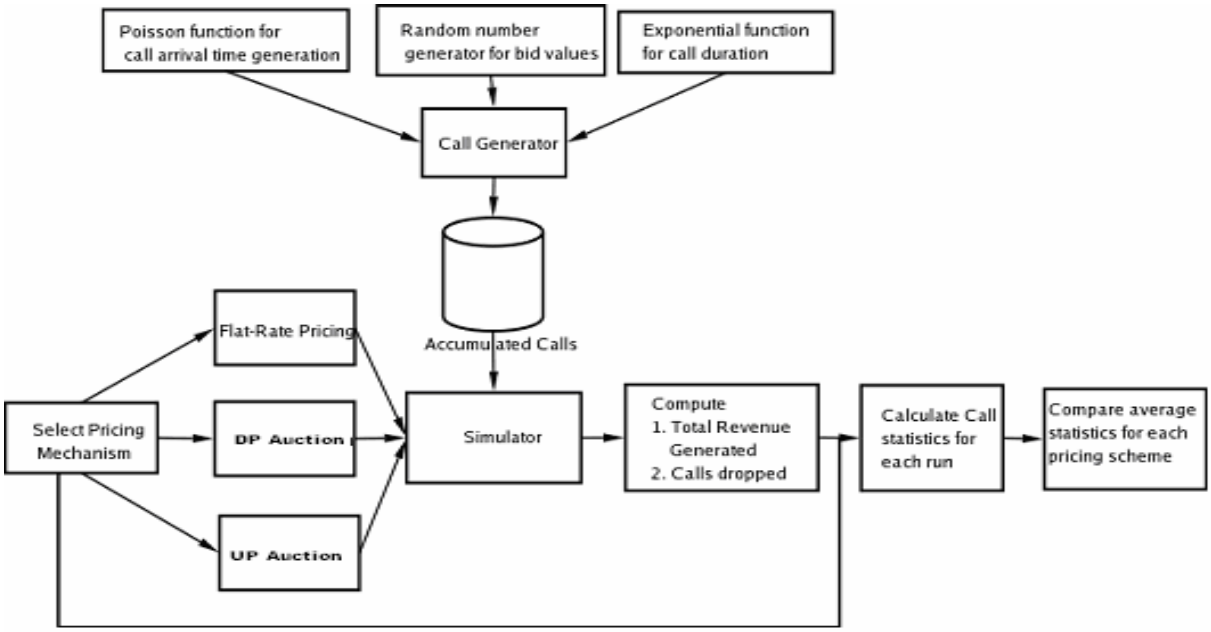


Figure 1. Flow Chart for indication simulation steps.

mean λ. The duration of a call is generated following an Exponential distribution with a mean μ. After each simulation period, we noted the cumulative revenue and call drops for each pricing strategies. The simulation has been conducted for varying λ and Δ*t*. Results thus obtained are presented in Figures 2 to 5.

Fig. 2 shows the variation of the ratio of revenue earned by the auction based models and revenue earned by the flat pricing model. From the plot it is seen that the ratio is increasing for both the auction models. This can be explained as follows. With the increase of call arrival rate in a call accumulation period, there will be more options left with the system for a certain number calls admission and on an average system gets better options in terms of price. We have used an aggression coefficient [7] equal to 5% for the uniform pricing model. In the simulation we have used a price range for bid generation with lower bound less than the flat price. Thus, when the arrival rate is low then the stop out bid price in uniform pricing auction is less than the flat price. This explains the fact of having ratio 0.94 for λ =2 (Fig. 2).

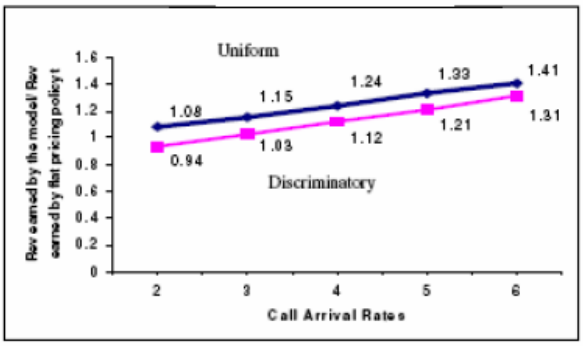


Figure 2. Revenue earned w.r.t. flat pricing model

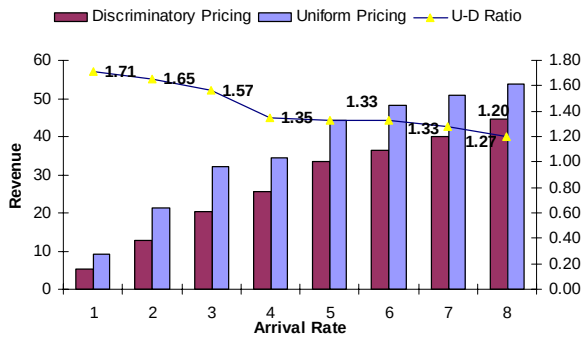
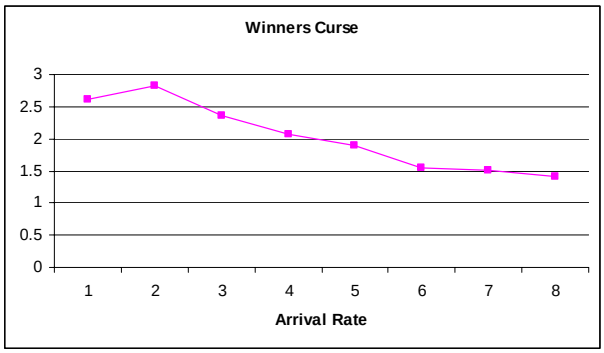


Figure 3. Variation of revenue earned ratio with call arrival rate

Figure 3 depicts the variation of the ratio of revenue earned by uniform pricing auction and revenue earned by discriminatory pricing auction with call arrival rate. We have assumed an aggression factor [7] of 40% (i.e. average bid price for uniform pricing is 40% higher than the average bid price of discriminatory pricing) for the uniform pricing scheme. In this setting we have found that the overall revenue earned is higher for uniform pricing scheme. As the number of call arrivals per unit time increases, the ratio of revenue in uniform pricing to the revenue in discriminatory pricing decreases. In the practical scenario, this is due to the fact that as the number of bidders increases, market discovery of the true intrinsic value of the object is better and hence, price discovery is more optimal. Hence, for both uniform and discriminatory pricing schemes, the bid values are nearer to the optimal value of the object being auctioned.

Figure 4 shows the variation of winner's curse with call arrival rate. Winner's curse for a discriminatory pricing scheme has been calculated as a ratio of the maximum bid value to the average bid value in that auction mechanism. From the figure it is seen that, the winner's curse, on an average decreases as the arrival rate

increases. With higher arrival rate, the number of bidders for resource increases and as a result the bid value goes up. Hence, the average bid value of the auction is closer to the maximum bid value. This makes the winner curse is not very prominent. In the practical scenario, this can be compared to the fact that as the number of bidder increases, market discovery of the true intrinsic value of the object is better and hence, price discovery is more optimal.



Fihure 4: Wiiner's curse for discriminatory pricing auction with call arrival rate

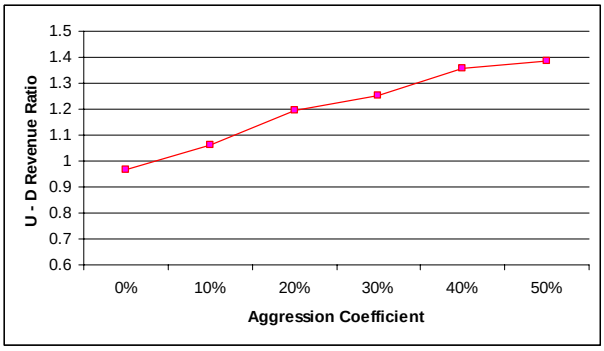


Figure 5: Variation of ratio of revenue in uniform pricing scheme and discriminator pricing scheme with agression coefficient

Figure 5 shows the variation of the ratio of revenue earned by uniform pricing mechanism and discriminatory pricing mechanism with the aggression coefficient. As the aggression coefficient increases, the ratio of uniform to discriminatory (U-D) revenues increases. This is due to the fact that with more aggression coefficient, the bid values in the uniform pricing mechanism are higher and hence the revenues earned by uniform pricing scheme is higher than that in the discriminatory pricing auction scheme. Due to this the U-D revenue ratio increases with increasing aggression coefficient. From the figure it is found when the aggression coefficient is more than 8% then the revenue earned by the uniform pricing scheme exceeds the revenue earned by discriminatory pricing.

VI. Conclusions

In this paper, we have used two auction based dynamic pricing discovery models namely uniform pricing auction and discriminatory pricing auction for wireless network services. We have found that for differentiated services if the aggression coefficient for uniform pricing auction exceeds 8% then uniform pricing auction performs better than discriminatory pricing auction. However, both the auction based model out perform the flat pricing model when the load on the network is high.

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