Issues in Bandwidth Pricing using Software Agents

Bijendra Vishal, Prashant *
Computer Science & Engineering
Indian Institute of Technology Kanpur, INDIA - 208016
{bijendra, prash}@cse.iitk.ac.in

Abstract

Agent mediated bandwidth market, like any other market, is one where buying and selling of a commodity takes place. The item of interest is bandwidth and trading is done by adaptive, software agents, called pricebots and shopbots. In this work, a simple market model for bandwidth market is proposed, which differs from the normal market, in that it has a constant supply of its commodity. Moreover, bandwidth is non-storable and the corresponding market is highly sensitive to fluctuations in demand and supply status. Two different market strategies are considered, one where the buyer can choose any seller for transaction and second, where the buyer only looks for the seller with the optimum price to maximize his profit. A mathematical model is constructed for market analysis and the effect of two different pricing strategies is extensively studied via simulations in a variety of market scenarios.

1 Introduction

Agent mediated e-commerce is an active area of research these days, especially with the exponential growth of the Internet. Agents differ from the traditional software, in that they are semi autonomous and personalized. They are usually entrusted with a fixed goal to satisfy in a fixed set of environment. Agents have the ability to communicate with other agents(peers) present in the same environment. These agents can be used in expert brokering task such as network selection, connection negotiation and bandwidth trading.

The information economies group at IBM([1, 2]) have studied the dynamics of *shopbots*, agents employed by the buyers to purchase goods on the internet, and *pricebots*, agents employed by the sellers to do pricing of a commodity for sale. Dynamic pricing using pricebots has also been studied by Joan Morris([6, 7]) at MIT Media lab using the learning curve approach to do online pricing of goods.

Shopbots are agents that automatically search the Internet for goods and/or services on behalf of consumers. For example, www.acses.com compares the price and expected delivery times of books offered for sale online, while www.jango.com and webmarket.junglee.com can offer everything from apparel to gourmet groceries. On the other hand, pricebots are automated agents that employ price-setting algorithms in an attempt to maximize profits. A primitive example of a pricebot is available at books.com, an online bookseller. When a prospective buyer expresses interest in a given book, books.com automatically queries amazon.com, Borders.com and Barnesand Noble.com to determine the price that is offered at these sites and then undercuts by 1% the lowest of the three quoted prices.

Agent mediated bandwidth market is one where pricebots and shopbots participate in selling and buying of bandwidth. Bandwidth as a commodity for sale differs from the normal commodity, in it's aggregate

*This work has been done as a B.Tech Project under the guidance of Dr Dheeraj Sanghi, CSE, IIT Kanpur supply being fixed over a period of time, contrary to the normal commodities whose supply can be controlled by the firms. Bandwidth is non-storable in the sense that unused capacity from yesterday has no value today. Inventories act to smooth variations in supply and demand. When no inventories exist, prices can jump if supply or demand change suddenly. Prices can also change suddenly when the perception or expectation of supply or demand status suddenly changes. Bandwidth is non-storable so price jumps and spikes (in both directions) are to be expected.

Deregulation of the telecommunications industry, advances in transmission and routing technologies, and the increasing demand for network capacity by a large number of service providers and end-users are the main factors changing the way bandwidth is bought and sold today. The development of an open and efficient market leading to optimal allocation of network resources, reduced search costs, price transparency, and the development of instruments for risk management is an exciting prospect.

The issue of bandwidth pricing concerns itself with the parameter used to measure the consumption by the end user, and hence to price bandwidth. Among the various parameters seen in real life situations are bandwidth link and the connection time. In this paper, a homogeneous market with respect to the type of bandwidth connection has been studied and we have concentrated on pricing based on connection time, by taking as inputs the start and end time for which the request for bandwidth is made.

Olov Schelen in her PhD thesis[5] has explored the possibilities of resource reservation on the internet to ensure *Quality of Service(QoS)*. In such a scenario agents can effectively be utilized to price the services offered in real time, and to maximize the profit in a competitive environment.

This paper is organized as follows. Section 2 constructs the economic model for the bandwidth market and explains why it is different from previously studied models. The two pricing strategies are discussed in Section 3 while simulation results obtained by varying the market parameters are presented in Section 4. Finally, Section 5 is the concluding section, in which we discuss the feasibility of the model and approach taken in the paper to analyzing real life bandwidth markets and highlight the possible future work in the area.

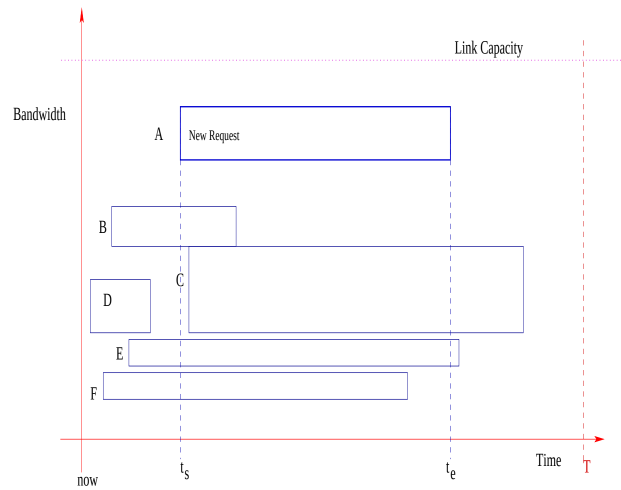

Figure 1: Bandwidth Reservation

2 Market Model

The Market model we have considered is derived from the market model proposed by A Grewald and Jeffrey O. Kephart in ([3]). This model has B buyers and S sellers. In this paper, we are looking from the perspective of the sellers and the objective is to maximize their profit. Typically, $S \ll B$. Each seller has a fixed amount of bandwidth to sell. This is the seller's link capacity L (refer to Fig 1). The implication of fixed link capacity for each seller is that we are considering a market which is homogeneous with respect to the bandwidth connection the sellers have to offer. A seller agent receives a request from the buyer agent for reservation of bandwidth $b\,(\leq L)$ starting from time t_s to time t_e. Fig 1 is a snapshot of the admitted flows in the time/bandwidth diagram. In this figure A is the new request that has arrived, while $B \ldots F$ has been allocated earlier. The new request is granted if the sum the new flow and the aggregate of flows from t_s and t_e do not exceed the total link capacity L. Moreover, the profit of the seller accrues both to the fraction of bandwidth requested by the consumer together with the connection time. Hence, pricing of bandwidth based solely upon the type of connection is not taken into account.

There are two kinds of buyers: *Any seller* (Type A) These type of buyers randomly approach any seller for transaction, irrespective of price offered and purchases the commodity if the price charged by that seller is less than the buyer's valuation. *Bargain hunter* (Type B) which checks price with all the sellers, determines the seller with the lowest price and purchases the good if that lowest price is less than the buyer's valuation. (This type of buyer responds to those who typically relies on shopbots for their interaction with the sellers). Fraction w_a of buyers employ the *any seller* strategy, while w_b behaves as bargain hunters, with $w_a + w_b = 1$. Each buyer agent generates request at some rate ρ_b and each seller reconsiders (and potentially resets) it's price p_s at random times, with rate ρ_s. Every buyer has a valuation V_b. For buyers of type B valuation is a function of the maximum amount he is willing to pay $P_{b,max}$ and the amount of bandwidth bw he is willing to buy. So a buyer agents transacts with a seller agent only if it's valuation is more than the price offered by the seller agent.

A seller s's expected profit per unit time π_s is a function of the price vector $\overrightarrow{P}$, as follows: $\pi_s(p) = p_s D_s\left(\overrightarrow{P}\right)$, where $D_s\left(\overrightarrow{P}\right)$ is the rate of demand for the good for seller s. This rate of demand is determined by the overall buyer rate of demand, the likelihood of the buyers selecting seller s as their potential seller, and the likelihood that seller s's price p_s does not exceed the buyer's valuation V_b.

For the purpose of simulations and analysis we have slightly simplified this generalized model. Here each seller does reservation for same time interval τ and have the same link capacity L. Further each seller sells bandwidth in fixed quantum, i.e of fixed time length τ_0 and fixed capacity b_0. Thus the total amount each is capable of selling in each time interval τ is

$$M = \frac{L\tau}{\tau_0 b_0}$$

Thus each request will be characterized by it's valuation. It is assumed that for all buyers the maximum valuation is V. For the buyers of type B. the valuation is distributed from V_{min} to V. Thus the buyer population is described by a cumulative distribution function $G(p)$, i.e. $G(p)$ is the probability that a randomly selected buyer has valuation $\leq p$. Further the total number of request in the market in the time interval τ is

$$R = \sum_{s=0}^{S} \rho_s$$

So the aggregate demand in the market expected at price p is

$$AD = w_a R + w_b R\left(1 - G(p)\right)$$

and the aggregate supply is

$$AS = MS$$

For the linear distribution function the curves are shown in Figure 2.

These assumptions may seem to oversimplify the model, but the generalized model will have the distribution function $T(t)$ and $B(b)$ to describe the request pattern in terms of the time interval of reservation and the amount of bandwidth requested. In that case the values τ_0 and b_0 can be replaced by the expected value of these distribution function. Thus the simplifying assumption does not oversimplify the generalized model.

In our case since there is no cost of production, the buyer's turnover is synonymous with his profit, and has been used interchangeably in this paper .

3 Pricing Strategies

We have considered two pricing strategies described in [2]. These pricing strategies require high level of information about the buyer characteristics and buyer demand pattern.

- Myopically Optimal Profit Maximizers(MYPM) This strategy typically reflects the strategy followed by myopic sellers in any market, whereby they try to undercut their rivals seller's quoted prices by a slight margin resulting in having

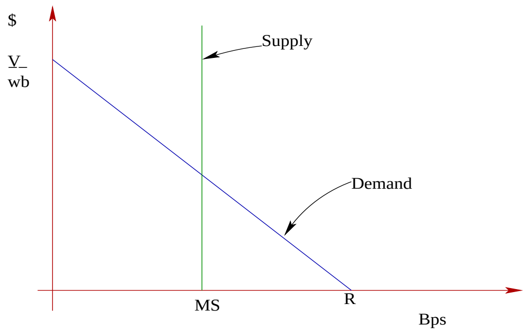

Figure 2: Demand and Supply Curve

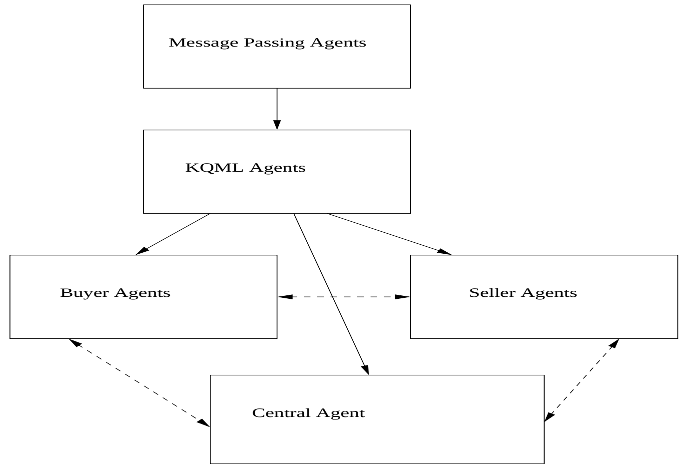

Figure 3: Class Diagram for Agents

higher profits. At the instant when any random seller reconsiders his price, he has a complete knowledge of the prices and corresponding profits of all the sellers. In our market model, having kept trace of the status of others, the chosen seller exhaustively searches for the optimum price $p*$ in the market which if chosen would maximize his profit in the next turn.

- Game Theoretic Nash Followers(GTNF) In this strategy, the sellers set their mindset as participants in a game. The seller agents considers setting their price as a strategy in a game theory. Having known all the information about the market, the sellers are able to map the price vector to the profit vector. The mapping strictly depends upon the topology of the market and hence forms the core in deciding the way in which the market behaves to the prevailing conditions of price and profit.Moreover, the price to profit mapping can be used to calculate the pure/mixed strategy Nash equilibrium. The price are generated using the probability density function corresponding to the Nash Equilibrium. In this context Nash Equilibrium is a condition, or a price vector at which every one maximizes it's cumulative profit, and have no tendency to deviate from this price. Details of Nash Equilibrium can be found in [4].

4 Simulations and Results

Any market is characterized by three main parameters, the *Aggregate Demand* in the market, The *Aggregate Supply* of goods in the market, and the current *price* of the commodity. The later being determined by the former two, which in turn acts as a feedback to cause variation the demand and the supply. The price in the market also determines the profit of the sellers involved. In the simulation results that follows we have studied the variation in the price and profit levels of the sellers as the factors determining the demand and the supply change, and also tried to come up with possible explanation for such behavior of the economy.

4.1 Test Bed

Simulation is carried out using a test-bed capable of simulating an environment where autonomous agents can interact and pass messages to other agents. This testbed was an extension of the simulator developed earlier by Amit Manjhi[10]. The agents exchange and interpret strings in *Knowledge Query Manipulation Language: KQML* format, which is the standard set by IETF.

Figure 3 gives a high level view of the organiza-

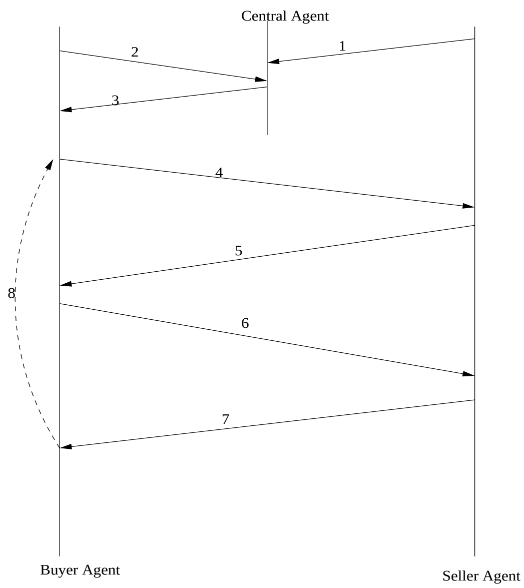

Figure 4: Interaction Diagram For different agent

tion of the test bed. The test bed has a layered architecture. The bottom most layer consist of simple message-passing agents, which is capable of sending and receiving string messages over the TCP/IP network. This layer takes care of all the network related aspect of the test-bed. The next layer built upon the message passing layer is the KQML Layer. The KQML agents are responsible for parsing and interpreting the messages encoded in KQML. A typical string in KQML can be:

```
:sender{A}
:receiver{B}
:performative{SEND}
```

This layer gives the agents, the ability to interact with any other agents on the network, who are capable of interpreting KQML strings. There are three kinds of autonomous agents inheriting from the KQML-Agents. The buyer agent, the seller agents and the central agent. The central agents are responsible for keeping track of the sellers currently registered in the market. This is to facilitate any king of accounting thats is needed for simulation purposes and it also provides a way for the buyer agent to query on the number of sellers currently available. The Buyer agents are responsible for sending bids or requests to the seller agents. The seller agents are responsible for processing of these bids. Their main job however is to monitor the market condition: the current demand pattern in the market, the number of sellers present in the market and the price of all the competitive sellers. Using these parameters as input the seller agents does online pricing of it's commodity. Figure 4 shows the sequence of steps in order that takes place for a typical transaction to carry out.

To carry out simulation the sequence of steps that needs to be carried out are as follows: First the global parameters, governing the overall simulation are written in a configuration file. Thus a configuration file will have entries like, the period for which the simulation needs to be carried out, the time interval of each bid sequence, the number of buyers and sellers in the market, the distribution of the buyer population, their valuation function and also the kind of strategies that the sellers needs to be followed. For the simulation purposes we have considered the parameters listed in TABLE I. The simulation is carried for some large number of turns. In each turn a seller is randomly selected and is allowed to reset it's price at the beginning of the turn. In each turn approximately R request is generated and interaction is carried out between the buyer and the seller agents resulting in possible transaction. For monitoring purpose a seller is randomly selected at the start of the simulation and his profit and price value is traced.

This testbed is coded in JAVA and can be used for simulating any market scenario in general, on any platform/OS supporting Java Runtime Environment [11].

4.2 MYPM strategy

The results in this subsection corresponds to the case when all the sellers follows the first strategy.

4.2.1 Demand change

Here we have monitored the changes in the price and profit level at the demand side of the market change.

Table 1: The List of parameters.

Number of Sellers S	64
Capacity M	200
Maximum Valuation V	100.0
$G(p)$	$\frac{p}{V}$
w_a, w_b	0.3, 0.7
P_{min}	20.0

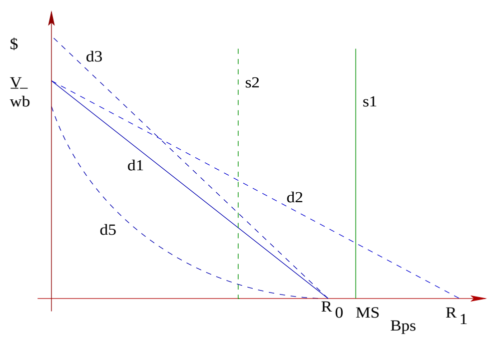

Figure 5: Changes in the Demand Curve

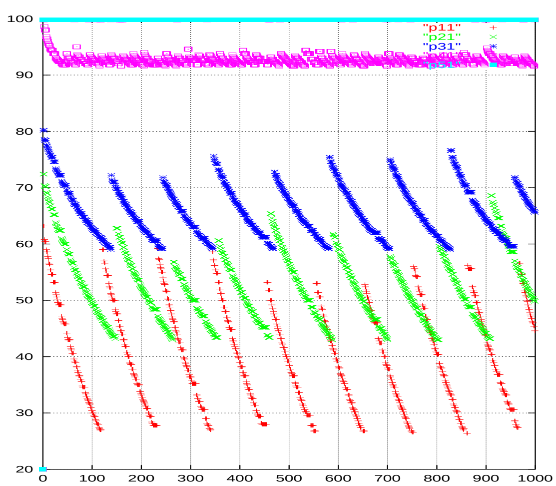

Figure 6: price Variation with time

The most important factor affecting the demand is the total number of request generated in the time interval τ, i.e. R. Figure 6 shows the variation of price when R changes. Each of the cyclic curves in this figure correspond to the price at that time for a fixed value of R. The bottommost curve is for low value of R, followed by curves corresponding to increasing value of R. It is observed that when the value of R is less than MS, the price follows a cyclical pattern. In economic terms, when the maximum possible demand (demand at 0 price) is less than the aggregate supply in the market ($M \times S$), each of the sellers continuously adjusts it's price to sell most of the available resources, well before the time for the current turn τ, ends. However as the demand increases, the cyclical price wars tends to stabilize. Now each seller is able to sell most of their inventories. It is also observed that there is an increase in the average level of price, as the value of R changes. This is evident from the continuous upward shift in the cyclical price curves with increase in R. This happens because of the fact that as more number of request are available in the market, so the number of request having valuation on the higher side also increase. This gives the opportunity to the seller agents to charge more, or in other words maintain the price at a higher level. The demand curve $d2$ in Figure 5 shows the new the demand curve resulting from the change in the value of R.

Figure 7 shows the corresponding profit variation. The increase in the profit level with the increase in the value of R is justified as sellers are able to extract more from the market as explained earlier.

Demand curve also determined by the characteristics of the buyer population, namely the value of w_a, w_b, the maximum valuation of buyers V, and their distribution function $G(p)$. Figure 8 shows the change the price and profit level with the change in the buyer characteristics like change in the values of w_a and w_b, and change in maximum valuation of any buyer V. It is observed that as the value of V increases the average level of price shifts up. This happens because the range of price for the sellers to search and set, increases, besides the number of sellers having valuation placed on the high side also increases. The increase in the average price levels

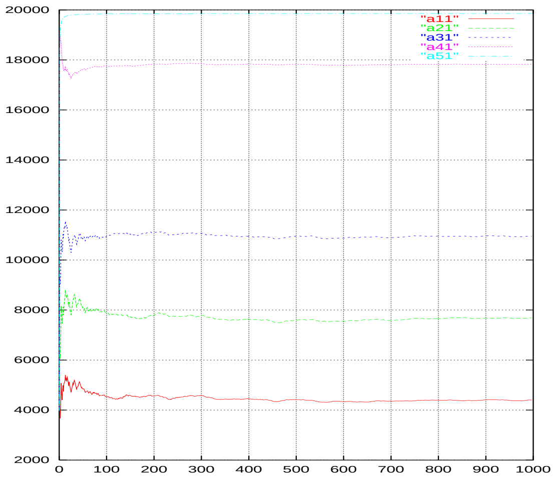

Figure 7: corresponding profit variation

are also reflected in the increase in the average profit earned by the sellers (refer to Figure 9). The corresponding change in the nature of the demand curve is shown in curve d3 of figure 5. The effect of change in the value of w_a/w_b is shown in the middle curve. It is observed that as w_a increases the variation in the price decreases and the average level of price shifts up. This is shown by the reduction in the frequency of the cyclical variation of price. The main reason for such a behavior of the economy is the fact that with in increase in the value of w_a, the number of buyers with maximum possible valuation is large, so the sellers are able to make profit even by keeping price high, besides no much variation in price is needed, as the fraction of the population having varying valuation also reduces. The corresponding increase in the profit change can be seen in figure 9.

4.2.2 Supply Change

The supply function is determined by the number of sellers(S) and their individual capacity(M). In the short run this supply remains fixed, hence a vertical supply curve in Figure 2. As the number of seller changes in the market the supply curve shifts parallel to the left or right. The corresponding change in

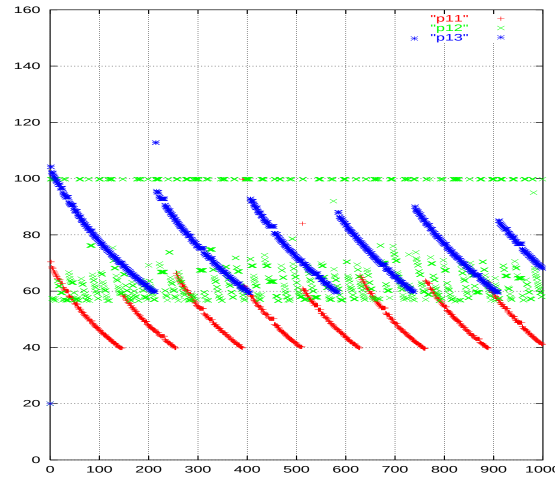

Figure 8: Price Variation

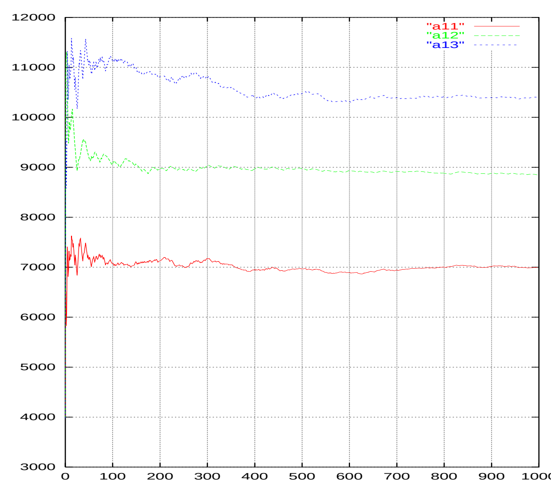

Figure 9: Corresponding profit variation

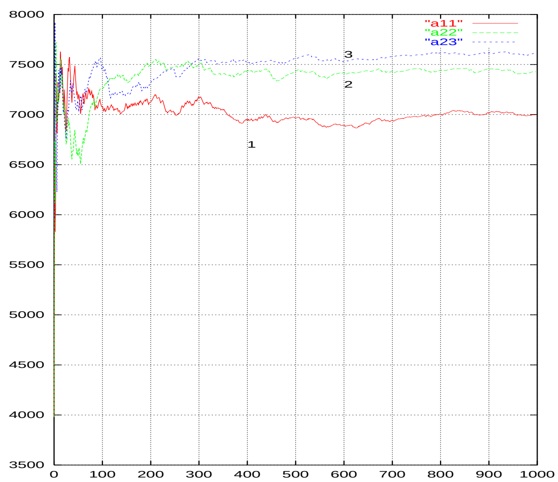

Figure 10: Profit Variation

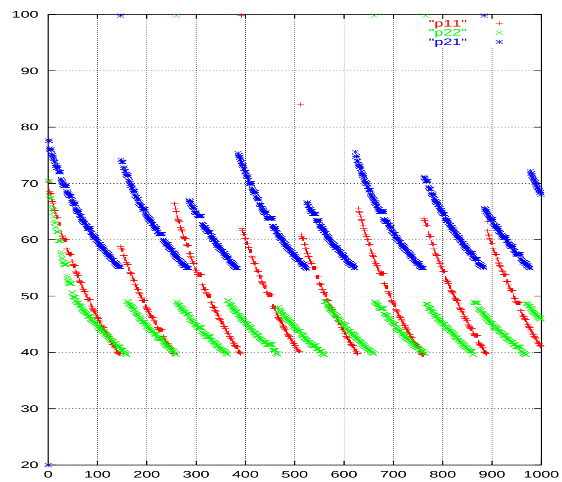

Figure 11: Prie Variation

the price is shown in figure 10. It is observed that average price level rises. This case is similar to the increase in the value of R and can be explained in the same way. In the context of supply, it is also interesting to observe the case when some sellers starts charging monopolistic prices. In such situation, if k sellers join to charge their own fixed price p^*, then at $p = p^*$ their overall profit should be maximized. The value of p at which the profit $p(1 - \frac{p}{v})R$ is maximum is $\frac{V}{2} = 50.0$. Other variation of monopolistic pricing can be found in [8]. Curve p22 in figure 11, shows the modified price variations of the sellers following *MYPM* strategy. In this case 20% of the total seller population started charging fixed price i.e $V/2 = 50.0$, while other following the same strategy, exhibits cyclic price variation, with maximum being equal to 50.0. However the average profit of both the group rises. The curve 2 in figure 10 corresponds to the average profit made by sellers following *MYPM* strategy, while curve 3 corresponds to the monopolist sellers. In this case the average profit of monopolist may be more, but in general, as more and more sellers join the monopolist group, their average profit may actually fall.

4.3 GTNF strategy

The sellers following this strategy has the probability density function, in accordance with which the price in the market is generated. Figure 12 shows one such cumulative distribution curve obtained for the parameters listed in table 1. The value of curve $G(p)$ ant any price p gives the probability that if a random seller X is selected, then the price of X is less than p. For the purpose of simulation we have used standard algorithm like *LIAP, PoluEnum, QRE, QREgrid* to compute the mixed and pure strategy Nash equilibrium. Details of these algorithms can be found at the website [9]. Most of these algorithm are very much compute intensive and requires a high information setting, to come up with a probability distribution function that approximates the Nash-equilibrium distribution function.

For this class of strategies we have done a similar kind of analysis to get an insight into the market economy. The cumulative distribution curves in figure 13 shows the effect of the variation of R. It is observed that for lower values of R (less than MS), the curve is essentially flat (curve 1 in figure 13). This implies that there is more or less equal probability of setting the price over all the price range possible. This is similar to the observation for the earlier strategy. As the value of R increases, the probability distribution curve becomes steeper and shifts to the right. The increase in the steepness of these curves implies that probability of the price being set is more at points where steepness increases. This kind of behavior happens because with increase in the R value, the sellers have more incentive to set price higher, to gain more profit.

This result also takes care of the expected distribution function when the supply side is changed, as explained in an earlier section.

The distribution curves in figure 14 corresponds to the case when the nature of the buyer population is changed. It is observed that when the value of w_a is close to 0, the distribution curves are steep and are toward the left or lower part of the price range. This implies the overall price in the market is going to be low. This is expected because, low w_a means high w_b, i.e there is a large population which is going to scan though all the price and select the minimum possible, hence there is a tendency to keep the price lower. On the contrary as w_a increases, the fraction of the population which is going to choose the sellers randomly, and have high valuation increases. So there is a tendency to keep the price as high as possible. This is shown by a steep distribution towards the left.

Figure 15 shows the comparison between the expected profit value if mixed strategy Nash equilibrium value is followed and if first strategy is followed. Curve 2 is the expected value of profit, and curve 1 is the profit obtained if $MYPM$ strategy is followed. It is clear that following Nash distribution gives a better outcome to all the sellers.

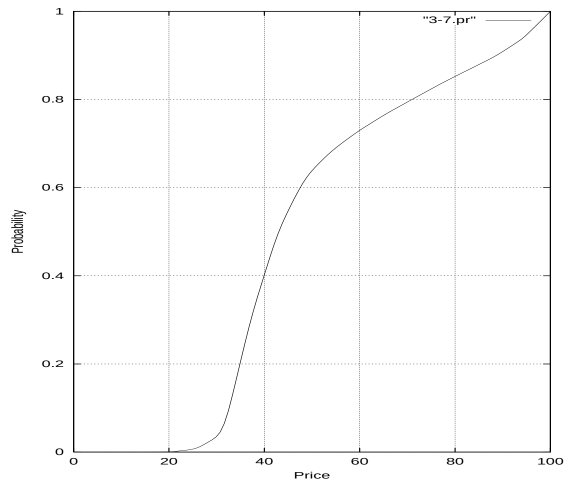

Figure 12: Probability density function with Nash Equilibrium

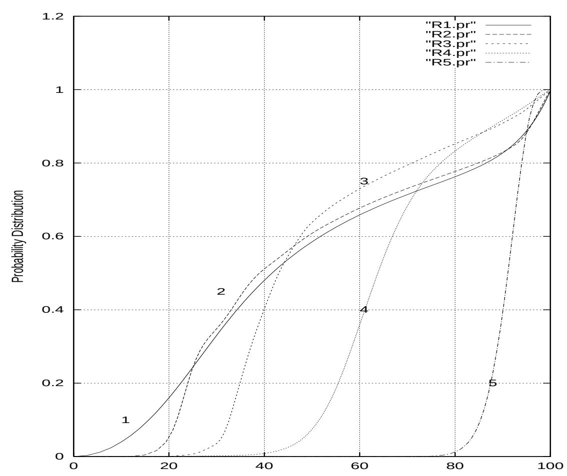

Figure 13: Probability Distribution Variation with price

5 Conclusion

In this paper we have examined the various situations that may arise when seller agents are entrusted with the task of selling and buying a commodity like bandwidth. We have seen the effect of the same on the market price and individual profit of each agents. We have studied two different pricing mechanism, one of which belongs to greedy class of algorithm, and may

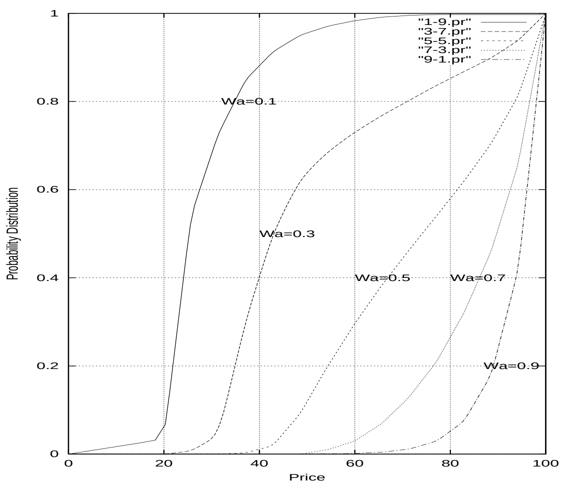

Figure 14: Probability Distribution Variation with price

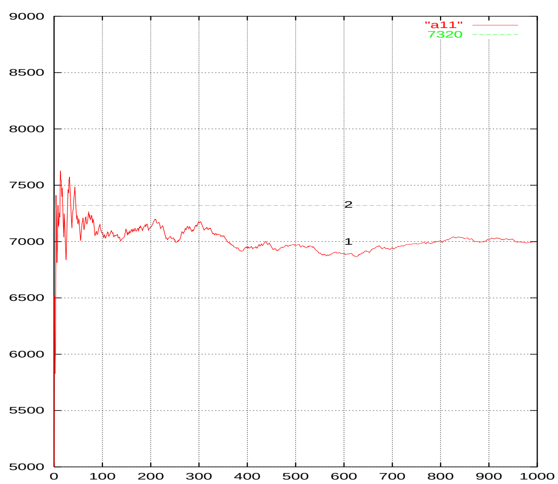

Figure 15: Probability density function with Nash Equilibrium

not give optimal result in the long run, but is not compute intensive. The other algorithm was based on game theories of NASH, and may give optimal solution(maximum profit), but it is highly compute intensive and may not be suitable in real life. Simulations carried out on both these algorithm have shown that an increase in the demand of the commodity, or an increase in the willingness to pay more for the commodity leads to a corresponding increase in the market price, and in the situation where demand is less, there is large variation in the price, or in economic terms, there are cyclical price wars, because of perfect competition among the sellers. We have thus analyzed by means of simulation both the demand and the supply aspect of the market.

This line of research ultimately aims to come up with agents that can interact with the world in a more realistic way. So one of the future work could be developing strategies for low information setting, which is generally the case in real life. In this paper we have considered inly the situation corresponding to perfect competition, which again may not always be the case in real world. There are collusions and uncertainties in the market, which needs to be taken care of during the actual pricing.

References

[1] Jeffrey O. Kephart, J E Hanson, and A R Grewald, *Dynamic Pricing by Software Agents*, Computer Networks, 2000.

[2] A Grewald and Jeffrey O. Kephart, *Probabilistic Pricebots* , Fifth International Conference on Autonomous Agents, Montreal, May 2001.

[3] A Grewald and Jeffrey O. Kephart, *Shopbots and Pricebots* , IJCAI-1999.

[4] J. Nash, *Non Cooperative Games.*, Annals of Mathematics, 54:286-295, 1951.

[5] Olov Schelen, *Quality of Service in the Internet* Ph.D Thesis. Lulea University of Technology, Sweden, August 1998.

[6] Joan Morris, *A Simulation-based Approach to Dynamic Pricing.* Masters Thesis, MIT Media Lab, May 2001.

[7] Joan Morris, P.Maes, and A Grewald, *Learning Curve: Analysis of an Agent Pricing Strategy under Varying conditions* Proceedings of the 2001 International Conference on Arteficial Intelligence(IC-AI-2001), Las Vegas, NV, June 2001.

[8] Eric Maskin and John Riley, *Monopoly with Incomplete Information* Rand. Journal of Economics, Volume-15, Number 2, Issue Summer 1984, pages: pp. 171-196.

[9] *http://www.hss.caltech.edu/gambit*

[10] Amit Manjhi, *Trading Agents* B.Tech Project, IIT Kanpur, India, May 2001.

[11] *www.sun.com/java*