Chapter 3

Pricing

3.1 INTRODUCTION

This chapter deals with the procedure for devising the proposed dynamic pricing scheme. Initially, the term price is defined and later on some of the existing pricing schemes are reviewed from the literature. In this chapter, a novel approach is given for selecting a peer, which is based on our proposed dynamic pricing algorithm. Finally, the proposed dynamic pricing scheme is evaluated by the simulation model.

The p2pVoD system presents additional opportunities and challenges that are different from the traditional peer-to-peer file sharing mechanism. This challenge can be circumvented by deriving a utility function. The utility function is deported to each peer based on its availability of the video contents in its buffer, and its quality of transmission of streams. Wherein, the quality of streams depends on the characteristics of the streaming source (uplink bandwidth, availability etc.) and network paths (download bandwidth, loss rate, delay etc.). Now, the major challenge is to design a good peer selection strategy that offers a high quality streaming service. Therefore, an incentive mechanism is provisioned to all contributing peers, who can offer the quality streaming service to other peers. The peer that offers the quality streaming service is rewarded with a dividend (Habib and Chuang, 2004).

A price in terms of monetary cost is charged for each requesting peers (Prithwish and Little, 2000). The price charged to a requesting peer for the p2pVoD service is directly influenced by the user arrival rates and the overall availability of resources. Several pricing schemes are proposed in the peer-to-peer community for the p2pVoD services (Semret et al, 2000), (Lui et al, 2002), (Beverly and Molina, 2003), (Vishnumurthy et al, 2003), (Gupta and Somani, 2004), (Catalano and Ruffo, 2004), (Zou et al, 2005), (Huang and Zhao, 2009), (Chaudhary et al, 2010). In the next section, we will briefly introduce some of the existing pricing schemes, which are used for the streaming service from a profit maximization point of view.

3.2 PRICING SCHEMES

We have broadly identified four categories of the pricing scheme for the purpose of the study. They are altruism, cost model, game theory, and dynamic pricing scheme.
To have thoughtful insight of the pricing scheme, we have paraphrased each of the pricing schemes in the following subparagraphs.

In altruism pricing scheme, all contributing peers are completely altruistic in nature and contributes maximum resources to the p2pVoD system (Castro et al, 2003), (Chu et al, 2004). This leads to a socially optimal solution, and increases resource utilization of the p2pVoD system. In this scheme, a common price is fixed based on Oligopoly policy by the contributing peers before transmitting the video. The contributing peers earn its profit by devising a common fixed price for transmission of the video.

The cost model pricing scheme are characterized by the cost imposed on the contributing peer, which is a function of the experienced load and the resource availability (Chun et al, 2004), (Fabrikant et al, 2003). By considering the load imposed on each contributing peer, in addition to the distance and degree of connectivity to other peers, a social optimum price is calculated, which minimizes the sum of all costs in the network (Nicolas and Chuang, 2004). This social optimum price information is sent to all peers to adhere in its profit maximization scheme.

The objective of the game theory pricing scheme is to maximize the payoff for the contributing peers (Tao et al, 2005), (Ranganathan et al, 2003), (Wang and Li, 2003). The only concern in this scheme is that of contributing peer, which only maximizes its payoff without having any concern of other contributing peers in the network. Each contributing peer calculates a unique price based on the performance of its personal strategy and from the observations of the payoff played by other contributing peers. Then, the contributing peer decides whether to cooperate or restrain with the p2pVoD system. If it cooperates then this unique price is deployed to maximize its profit.

A dynamic pricing scheme defines a strategy that combines the pricing scheme and the production decisions under uncertain demand. In this scheme, the price changes over the time in response to the changes in the demand.

In this chapter, we propose a dynamic pricing scheme to maximize the profit for the contributing peers. In this scheme, we consider a highly stochastic environment of a p2pVoD system, in which demand for the movies are highly chaotic. The price is estimated independently for each of the contributing peer based on the revenue generated by storing the movies in its chaining buffer, and then calculating the transmission cost of the movies. A dynamic pricing algorithm is implemented herein
to strategically optimize the storage space, and to control the transmission rate, which maximizes the profit for the contributing peers. Further, the model is analyzed to obtain a utilization function and the decision variables. Finally, we derive an optimal policy that decides the values for the decision variables. In our case, the decision variables used are the optimal quantity of video blocks to be stored, and the stochastic demand for the movies. The outcome of the policy gives a best possible pricing scheme among other pricing schemes. Next, let us review some of the existing pricing schemes, which suits for our p2pVoD system.

3.2.1 RESOURCE PRICING SCHEME

Eger and Killat (2008) have proposed two different pricing schemes for the p2pVoD system, one uses explicit price information and other uses download rate as its price. In the first scheme, each peer pays a virtual price for using upload bandwidth at a remote peer. Each remote peer offers a price per unit of upload bandwidth. Furthermore, the price offered is relative to its upload capacity. Hence, this kind of scheme is known as resource pricing scheme. In this scheme, it is assumed that malicious users will not forge their price to obtain higher download rates. But this may not suit well for the p2pVoD system. Hence, a second scheme was proposed using implicit pricing known as signal reciprocal rate control. In this scheme, a peer uses its full upload bandwidth as a measurement for downloads from a remote peer. Thus, the total download rate is equal to the total upload rate of the peer. The disadvantage of both schemes is that the price is used to control the upload rates. It can be seen that any reduction of upload rate will decrease the download rate and its price. When the download maximizes its rate over the upload rate then it incurs additional cost to the receiving peer. Therefore, these schemes do not achieve a fair and efficient allocation of upload bandwidth contributed by the peers in the network. Our dynamic pricing scheme does not fully control the price over the upload and download bandwidth, but it controls the price over the demand that is dynamically generated by the movies. The advantage of our scheme is that it guarantees more earnings in terms of profit than the signal reciprocal rate control.

3.2.2 NOVEL PAYMENT INCENTIVE SCHEME

Guang and Jarvis (2008) have proposed a novel payment incentive based pricing scheme for streaming the media data in a peer-to-peer system. Here, the peer earns points by forwarding the media data to other peers. A first-price-action like procedure is used to select a good parent as the data supplier. Therefore, they have designed a
distributed algorithm to regulate peer competitions. The distributed algorithm defines the individual peer strategies by using the game theory perspective. As a result, only the affluent peers are able to choose the parents, whereas the indigent peers have relatively limited options for selecting a good parent. Therefore, there exist imputations among the peers, which lead the indigent peer to suffer from the starvation of resources. Note that, this scheme does not claim to solve the problem of resource starvation, because it ultimately depends on the aggregate amount of physical resources available in the network. In dynamic pricing scheme, all peers are equally and likely to earn the alike profits in the long run than the game-theory perspective.

3.2.3 QUASI LINEAR UTILITY FUNCTION
Golle et al (2001) has proposed a quasi linear utility function for the p2pVoD system, which maps on the variables for estimating the price. These variables are the amount of media data downloaded, disk space used, and the bandwidth. Furthermore, the peers are risk-neutral and peer’s utility for money is linear. This model is framed based on the game theory. The assumption made here is that peers are economically rational, i.e., they act to maximize their expected quality, given their beliefs about the strategy that other peers takes their knowledge about the way that their payoffs are calculated. This will actually surfeits many kinds of problem, because the peer directly controls their number of downloads and indirectly control their number of uploads. Depending on the nature and degree of peer’s risk aversion and their particular utility functions, they may prefer to reduce their own downloads to decrease their worst-case payments. This is not the case in the present dynamic pricing scheme, because the peer does not have any reservation towards the risk aversion, and follows a risk neutral policy. Actually, game theory approach cannot sustain the profit margin in a long run because of the peer’s risk aversion factor. One can inspect the peer’s risk aversion factor by providing a stable risk neutral policy in the utility function.

3.2.4 RANK BASED PEER SELECTION INCENTIVE MECHANISM
Habib and Chuang (2004) have proposed a rank based peer-selection incentive mechanism for peer-to-peer media streaming system. In this mechanism, a peer computes its score based on the resources contribution (i.e., bandwidth and storage) and the streaming cost. This score is mapped into a percentile rank, which orders the peers based on the quality of service that it offers to the users. Thus, a utility function based on the percentile rank is used to measure the revenue generated by the peers. A
peer earns more revenue as long as the resource contribution brings positive utility to its streaming session, otherwise none. The basic assumption in this mechanism is that all peers act as altruistic by nature. But in practice, it is otherwise. In the proposed dynamic pricing scheme a balance maintained between the amount of resource contribution of the peer and the utilization of the contributed resources of the peer. The peers do not directly depend on the percentile ranking to determine their utility function.

3.2.5 COST MODEL

Nicolas and Chuang (2004) have modeled the cost incurred by each participating peer in a peer-to-peer network. A cost model is proposed to gauge the potential disincentive for peers to collaborate with the peer-to-peer network. The cost imposed on a peer is characterized as a function of the experienced load and the peer connectivity. Also expresses the fringe benefits in collaborating with the peer-to-peer network in terms of price reduction. The easement of participation in peer-to-peer network is expressed in terms of latency reduction. If a peer forwards items to another peer, then benefits are calculated based on the order of ranking prices. But, the drawback is that each peer has to keep some state information about entire peer to peer network to operate decorously. This additional overhead incurs a cost for maintaining a neighborhoods’ table and for exchanging of information with all its neighboring peers. In the proposed dynamic pricing scheme, the overhead cost in exchanging the state information is partially reduced. The streaming server maintains the state information for the current demand of the movies. This state information is periodically broadcasted to the contributing peers for incorporation into the utility function.

3.2.6 STRATEGY PROOF RESOURCE ALLOCATION

Teo and Mihaiescu (2009) have investigated a design mechanism, and the computational economies to create a pricing scheme for strategy proof resource allocation. The pricing scheme is expressed in a virtual economy as a mechanism to provide incentives to the contributing peers. A virtual economy is a currency that provides the basis for a utilization function. The objective of this pricing mechanism is to choose winner determination peers and set a guidelines for the incentive. The winner determination is resolved by peers participating in exchange of media data, and the incentive for that set of exchange is facilitated by using a common currency. Overall, the pricing mechanism has achieved a better global efficiency. But, the
mechanism still lacks in scalability. Because in a highly dynamic peer-to-peer network with a decentralized pricing information, the main challenge to preserve the key properties of incentive compatibility still remains unresolved, and so is the multiple resource type allocation. But, one can resolve the scalability factor, which preserves the key properties of incentive compatibility.

3.2.7 ALTRUISM PRICING MODEL

Chu and Zhang (2004) have explicitly considered altruism pricing as a parameter for streaming applications in peer-to-peer network. The applications can tune this parameter to trade performance with fairness. An altruism policy is defined as the amount of actual bandwidth contribution and the services it receives in reciprocation. The level of altruism is defined as a single parameter $k$, where higher $k$ means a higher level of altruism. The simulation results demonstrated that a small level of altruism can significantly improve the overall performance of pricing. But it is not very much clear, whether 100% altruism can be achieved in a peer-to-peer system. In our dynamic pricing scheme, all contributing peers have certain quality of altruism behavior, and it achieves alike profit over the accumulated revenue earned. In our study, we found that the profit is depreciated in a long run for 100% altruism.

3.2.8 CORNET OLIGOPOLY GAME

Wang and Li (2003) have modeled the peer-to-peer system based on cornet oligopoly game with dynamic payoff functions, which incorporates system performance requirements. In this model, a payoff function is designed to optimally control the resources in every peer. This controller effectively adapts the user contributions to track the system dynamics, which in turn maximizes the total net gain. The incentive is calculated based on the contributing peers’ resources. A heuristic choice is assumed for the calculation of the marginal cost in the payoff function. However, in realistic peer-to-peer resource sharing applications, such an assumption may not reflect the true associated costs. In our dynamic pricing scheme, we found that, the utility function optimally controls the resources in every peer based on our dynamic pricing algorithm. The utility function also tracks the system dynamics in the stochastic environment, and maximizes the total profit gained.
3.3 DYNAMIC PRICING SCHEME

The dynamic pricing refers to the continuous fluctuation in the price value of the streaming services. The fluctuation results from the change in the supply and the demand for the movies in a p2pVoD environment. The fact is that when the supply is low and the demand is high then the price increases, while the supply is high and the demand is low then the price gradually decreases. Dynamic pricing affects how requesting peers negotiate with the contributing peers, where the price can change significantly during the negotiation process. However, it is important to note that, once the negotiation is completed then a contract is established between them, and the price is fixed for the remaining lifetime of the transmission. The establishment of a contract and setting a certain price only affects that contributing peer and that requesting peer. However, the price for the same streaming service is different for other requesting peers. Price is determined by a utility function, which depends on the number of parameters. Most of the parameters are the measures of the streaming service provided by the contributing peer. The primal parameters are the holding cost of the movie for storing the video blocks in its chaining buffer for a time period, and the transmission quality of the video blocks through its upload channels. A key parameter in this utility function is the degree of utilization of resources. Another key parameter that affects the price is that of base purchase cost of the movie. Based on these parameters, which forecasts the price, this section focuses the development of an algorithm for the dynamic pricing scheme.

In this section, we formulate a utility function that captures a range of parameters with a varying degree of complexity. These parameters define how much buffer space must be contributed by a peer, and how much capacity of upload bandwidth is required for the transmission of the video blocks to the requesting peer. We assume that the contributing peers are obedient and they do not change the underlying protocol behavior by circumventing the software.

The parameters are used to develop the utility function are described below. Let $N$ be the set of contributing peers in a cluster. For peer $i \in N$, let $F_i^b$ be the uplink bandwidth capacity and $R_i^b$ be the downlink bandwidth capacity. Both $F_i^b$ and $R_i^b$ represent the upper bound bandwidth that a contributing peer can potentially utilize respectively. These values are bounded by an accessing bandwidth of the peer $i$, and can be lowered by the competing Internet traffic. Note that, the capacity value for
these bounds can be estimated dynamically based on the Internet traffic measurements. Let $B_i$ be the maximum chaining buffer that the peer $i$ contributes to store the video blocks of the movie. Let $P_j$ be the base price of the $j^{th}$ movie. Herein, the price of the movie varies depending on its popularity $\theta$ and the type of the movie (action-oriented, suspense and drama) $K$. Note that, the type of movie is an important factor because of the bit rate. For action-oriented movie the bit rate is higher than the bit rate of drama movie. Thus price value follows a Pareto Distribution with a PDF of

$$g(P_j) = \frac{\theta K^\theta}{P_j^{\theta+1}} \quad (3.1)$$

Let $S_j$ be the number of video blocks for the $j^{th}$ movie. The cost of each video block of the $j^{th}$ movie is calculated as

$$C_j = \frac{g(P_j)}{S_j} \quad (3.2)$$

Therefore, the base cost of the $j^{th}$ movie is $C_j^M = \sum_{i=1}^{S_j} C_i$. Let $C_j^{initial}$ be the initial cost of the storage space, and the value is $C_j^{initial} = C_x \sum S_x$; where $C_x$ be the initial cost of the video blocks and $S_x$ be the initial number of video blocks, and $x$ is the number of video blocks. The meaning of summation symbol herein represents just a set of video blocks without any specific range, and henceforth the same meaning is retained in the subsequent equations thereon. Let $C_j^{residual}$ be the remaining cost to store the latter quantities of the video blocks, and the value is

$$C_j^{residual} = C_j \sum (S_j - S_x) \quad (3.3)$$

Therefore, the offered price to store the $j^{th}$ movie by the peer $i$ is given by

$$C_j^{offer} = C_j^{initial} + C_j^{residual} \quad (3.4)$$

Let $C_{B_i}^U$ be the cost of the uplink bandwidth, and the value is

$$C_{B_i}^U = f(F_i^b) = \alpha e^{-\alpha R_i^b}$$

where $\alpha$ is the average uplink bandwidth needed for the transmission.

Let $C_{B_i}^D$ be the cost of the downlink bandwidth and the value is

$$C_{B_i}^D = f(R_i^b) = \beta e^{-\beta R_i^b}$$

where $\beta$ is the average downlink bandwidth needed for the reception.

Let $IC$ be the initial setup cost to store the preliminary parts of the video blocks. Initial setup cost is the sum of the base cost, initial storage cost with its transmission.
cost of the video, and the offered price. The value of the initial setup cost is given by

\[
IC = C_i^M + C_i^D \sum S_x + C_i^{offer}
\]  

(3.5)

Let \( HC \) be the holding cost for storing the video blocks in the chaining buffer space \( B_i \) of the peer \( i \) over a period of time \( T \), and is expressed as

\[
HC = \int_0^T g(P_s, t) S^+ \, dt
\]  

(3.6)

where \( S^+ \) is the optimal quantity of the video blocks that is stored in the chaining buffer space \( B_i \) of the contributing peer \( i \). The value of optimal quantity is derived later in this section. \( g(P_s) \) is a function defined for the base price of the movie. The function follows a Pareto distribution with popularity \( \theta \), and the type of the movie \( K \). The value of \( P_s \) changes over a period of time based on the stochastic demand generated for the \( j \)th movie.

Let \( CC \) be the chaining cost for the transmission of video blocks from the contributing peer \( i \) to the requested peer over a period of time \( T \) and it is expressed as

\[
CC = \int_0^T \omega(C_{B_i}^U, t) dt
\]  

(3.7)

where \( \omega(C_{B_i}^U, t) = \frac{(C_{B_i}^U - C_{B_i}^{UL})}{(C_{B_i}^{UL} - C_{B_i}^{LL})} \) is the uniform distribution with \( C_{B_i}^{UL} \) and \( C_{B_i}^{LL} \) as the cost of the upper bandwidth limit and lower bandwidth limit respectively.

Let \( WC \) be the wastage cost for the dissipated storage of video blocks in the chaining buffer. These video blocks are neither transmitted to any other peers nor have any demands in the cluster. It only superfluously increases the holding cost and impacts directly in minimizing the earned profit of the contributing peer. The wastage cost is expressed

\[
WC = \int_0^T HC \cdot z(t) \, dt
\]  

(3.8)

where \( z(t) \) is a Weibull instantaneous deterioration rate function for the video blocks stocked and it is defined as \( z(t) = \gamma \delta t^{\delta-1} \), where \( \gamma \) is the scaling factor and \( \delta \) is the shaping parameter, \( \delta \geq 1 \) and \( \gamma > 1 \).

The utility function is quantized by using the parameters of holding cost of Equation 3.6, initial setup cost of Equation 3.5, chaining cost of Equation 3.7 and salvage cost of Equation 3.8, which is expressed as follows
Next, we make a detailed analysis of the utility function to obtain a cost function that maximizes the profit on the optimal quantity of stocked video blocks $S^+$ under stochastic demand $D$.

### 3.4 ANALYSIS OF THE UTILITY FUNCTION

The decision on the value of $S^+$ depends on the probability distribution of current demand for the movies. Now, from the statistical point of view, we need to minimize the expected value of the sum of the cost incurred. The amount of video blocks transmitted is given by

$$
U_i(t) = \int_0^T g(P_s, t) S^+ dt - \left\{ C_j^M + C_B^D \sum S_x + c_{offer} \right\} - \int_0^T \omega(C_{BI}, t) dt
- \int_T HC \cdot z(t) dt (3.9)
$$

where $D$ is the stochastic demand for the number of video blocks in the video chain, and $S^+$ is the video blocks stocked in the chaining buffer of peer $i$. Hence, the cost incurred for $D$ and $S^+$ is expressed as

$$
C(D, S^+) = \int_0^T g(P_s, t) S^+ dt - \left\{ C_j^M + C_B^D \sum S_x + c_{offer} \right\}
- \int_0^T \omega(C_{BI}, t) dt \cdot \max\{0, (D - S^+)\}
- \int_T HC \cdot z(t) dt \cdot \max\{0, (S^+ - D)\} (3.11)
$$

Here, the demand $D$ is a random variable with an exponential distribution having a PDF of $\phi(\xi) = e^{-\xi/\lambda}$, with a mean demand $\lambda$, and CDF of $\Phi(a) = \int_0^a \phi(\xi) \, d\xi$. Therefore, the expected cost $C(S^+)$ is expressed as

$$
C(S^+) = E[C(D, S^+)] = \int_0^\infty C(\xi, S^+) \phi(\xi) \, d\xi
= \int_0^T g(P_s, t) S^+ dt - \left\{ C_j^M + C_B^D \sum S_x + c_{offer} \right\}
- \int_0^T \omega(C_{BI}, t) dt \cdot \max\{0, (\xi - S^+)\} \phi(\xi) \, d\xi
$$
\[-\int_{0}^{T} \int_{t}^{T} HC \cdot z(t) dt . \max\{0, (S^+ - \xi)\} \phi(\xi) \delta \xi\]  
\[ (3.12) \]

It is necessary to find the value of \( S^+ \), which minimizes the overall cost of the utilization. Therefore, we derive an optimal policy to find the value of \( S^+ \).

### 3.5 DERIVATION OF THE OPTIMAL POLICY

Let \( p_1^s \) and \( p_2^s \) be the two different empirical prices defined for the storage of the movie in the contributing peer. We define a function \( h(\xi, S^+) \) to analyze these prices depending on the current demand \( \xi \) and stocked quantity of video blocks \( S^+ \).

\[
h(\xi, S^+) = \begin{cases} 
p_1^s (S^+ - \xi) & \text{if } S^+ > \xi 
p_2^s (\xi - S^+) & \text{if } S^+ \leq \xi \end{cases} \]
\[ (3.13) \]

and let \( H(S^+) \) be the expected quantity of video blocks to be stored.

\[
H(S^+) = \int_{0}^{\infty} h(\xi, S^+) \phi(\xi) \delta \xi + p_s S^+ 
= p_1^s \int_{0}^{\infty} (S^+ - \xi) \phi(\xi) \delta \xi + p_2^s \int_{\xi}^{\infty} (\xi - S^+) \phi(\xi) \delta \xi + p_s S^+
\]

Taking the derivative of \( H(S^+) \) w. r. t \( S^+ \) and equating to zero gives,

\[
\frac{dH(S^+)}{dS^+} = p_1^s \int_{0}^{S^+} \phi(\xi) \delta \xi - p_2^s \int_{S^+}^{\infty} \phi(\xi) \delta \xi + p_s = 0
\]

\[
p_1^s \Phi(S^+) - p_2^s (1 - (\Phi(S^+)) + p_s = 0
\]

\[
\Phi(S^+) = \frac{p_2^s - p_s}{p_1^s + p_2^s}
\]

Here, the stocked quantity of video blocks \( S^+ \) is a random variable with an exponential distribution having a CDF

\[
\Phi(S^+) = \int_{0}^{S^+} e^{-s^+} = 1 - e^{-s^+}
\]

\[ 1 - e^{-s^+} = \frac{p_2^s - p_s}{p_1^s + p_2^s} \]

Solving this expression results in

\[
S^+ = \frac{1}{\lambda} \ln \left(\frac{p_s + p_1^s}{p_1^s + p_2^s}\right)
\]
\[ (3.15) \]

The value of \( S^+ \) is the optimal quantity of video blocks to maximize the profit.
We devise a dynamic pricing algorithm that maximizes the generation of profit by using the utility function. This algorithm is executed only in contributing peers to estimate a best offered price to the requesting peers.

Algorithm 3.1: DYNAMIC PRICING ALGORITHM

Start:
wait(RP)
obtain $F_i^b$ and $R_i^b$
calculate $C_{u_i}^b$, $C_{d_i}^b$, $g(P)$, $C_j$ and $C_j^M$
compute $C_j^{offer} = C_j^{initial} + C_j^{residual}$
compute $IC = C_j^M + C_{Bi} \sum S_x + C_j^{offer}$
obtain $B_i$
if $B_i < \sum S_j$ then
reject RP
goto Stop:
else
acquire $D_j$
estimate $S_j^+$
calculate $HC$ and $CC$
estimate $P$
R: send $P$ to RP
response = wait(T)
If response == “Accepted” then
while ($S_j^+$) transmit $S_j^+$ to RP
   calculate and accumulate $UF$
else
reject RP
goto Start:
$P = wait(T')$
if ($P == new RP$) goto step R:
if (periodicReview() == true and checkSalvage() == true)
calculate $WC$
reduce $UF$
remove $S_j^+$ from $B_i$
Stop:

The description of the dynamic pricing algorithm is as follows: A contributing peer $i$ ($CP$) will wait during its uptime for a new request from the requesting peer ($RP$) in the cluster. Each time a new request is accepted from $RP$, the $CP$ will obtain the status of its current uplink and downlink bandwidth capacity ($F_i^b$ and $R_i^b$). The parameter
values are calculated using the formulae as discussed in the previous section. First, the cost of uplink and downlink bandwidth ($C_{B_i}^U$ and $C_{B_i}^D$) are calculated. Second, the base price $g(P_j)$ of the $j^{th}$ movie is calculated based on Pareto distribution knowing the current popularity and the type of the movie. The cost for the beginning of the video blocks ($C_j$) of the $j^{th}$ movie is calculated. Then, the cost of subsequent video blocks ($C_j^M$) of the movie is calculated. Based on the above value, the CP will calculate the offered storage cost $C_j^{offer}$ and the initial setup cost $IC$. The CP will check its available chaining buffer capacity for storing the video blocks of the $j^{th}$ movie. If it does not have sufficient chaining buffer space then the request is abruptly rejected and further no more new requests will be accepted. If the chaining buffer capacity satisfies the current storage requirement for the $j^{th}$ movie then the current demand $D_j$ for the $j^{th}$ movie is acquired from the streaming server. Based on the value of $D_j$, the optimal number of video blocks are estimated in $S_j^+$. To this estimated number of video blocks, the price ($P_1^j, P_2^j, P_3^j$) is chosen on par with the current demand $D_j$ based on the analysis made in the previous section. The chosen price is used as an estimation to calculate the holding cost ($HC$) for the storage, and the chaining cost ($CC$) for the transmission. Now, the CP will calculate the best price $P$ based on the utility function $U_i(t)$. The value of $P$ is sent to RP. The CP waits for a period of $T$ unit of time to receive the response from RP. The RP sends a response as either acceptable of the offered price or rejection towards the offered price. If the response received is “Accepted” then the optimal quantity of video blocks $S_j^+$ are transmitted to RP. Note that, the transmission mechanism is dealt in detail under Chapter 7. While transmitting the video blocks to RP, the CP increases its utility factor $UF$ to gain the profit. Else if the received response is “Rejected” then the request is cancelled, and the current course of action is terminated. Concurrently, the CP waits for $T'$ unit of time until a new request arrives from different RP for the same $j^{th}$ movie. During this period, if a new request arrives for the $j^{th}$ movie then the value of $P$ is sent to the new RP, and the procedure from there on is repeated. Periodically, a review is made for the salvaged video blocks in the chaining buffer. If such kind of video blocks are found in the chaining buffer (which is neither used in the transmission for a longer time nor has any demand in the cluster) then the salvage cost $WC$ is calculated for storing the desecrated video blocks over a period of holding time. The utility factor $UF$ is
decreased accordingly and loss is estimated for the CP. Finally, all the desecrated video blocks are removed from the chaining buffer space. This algorithm is executed repeatedly for a period of CP uptime or until the CP is terminated abruptly. Now, we apply our dynamic pricing algorithm in the simulation model and evaluate the performance as well as scrutinize the appropriateness of our scheme.

3.7 SIMULATION

In this simulation, we run the following pricing schemes to calculate the performance of the utilization factor. The pricing schemes used herein are Game Theory Perspective, Altruism Approach, Cost Model, and our Dynamic Pricing Scheme. The utilization factor of our scheme is measured based on the proposed dynamic pricing algorithm. The utilization factor for all other schemes is measured as the ratio of download rate and upload rate of the video blocks that are transmitted between the peers. The utilization factor of all schemes includes the following parameters; the price of the movie, both download and upload cost of the bandwidth, storage cost, offered cost, salvage cost, and transmission cost. In a cluster of peers, the probability of choosing a scheme is equally and likely. Each peer that contributes to the p2pVoD system maximizes its profit based on the chosen scheme. For a better evaluation, we have considered four equal number of group of peers in which each group applies only one scheme to evaluate the performance of the utilization factor. Note that, all groups belong to the same cluster in this simulation.

The first group of peers applies a game theory perspective scheme, within the group; each peer creates a strategy and calculates the payoff table. This payoff table is distributed among the peers in the group. Then, the peer uses a strategy and the payoff of other peers to maximize its profit based on Min-Max criterion. To maximize the profit, each peer offers a price for transmitting the video blocks in the video chain to the requested peer. Then, the requested peer will select a contributing peer that offers the best price among all the peers in the group for receiving the necessary video blocks to its buffer.

The second group of peers applies an altruism approach; in which each contributing peer in a group shares information about its maximum available resources to all other peers in that group. Based on this information and the current demand of the movie an oligopoly decision is made to fix a common price for all contributing peers to transmit the video blocks in the video chain. Now, the requested
peer selects a contributing peer in this group that gives maximum resource for the transmission of the video blocks to its chaining buffer.

The third group of peers applies cost model scheme to maximize the profit, in this scheme a price is fixed by the streaming server for storing and transmitting of the video blocks in the video chain. Here, the streaming server evaluates a standard cost benefit procedure to fix a price by aggregating the overall available resources. The price fixed by the streaming server should be agreed by all contributing peers in that group. The requested peer selects a contributing peer that has maximum resource for reception of video blocks to its chaining buffer.

The fourth group of peers applies our dynamic pricing scheme; a price for transmission is calculated based on the demand generated for the movie and available stock of video blocks in the contributing peer. Based on our dynamic pricing algorithm, each peer in the group calculates its profit maximization, and offers a price to the requested peer. Then, the requested peer selects a contributing peer in this group that offers the best price for the reception of video blocks to its chaining buffer.

The simulation was executed for several trials using the simulation parameters from Table 1.1, and the result shown is an average of all trials carried out in all five clusters. The utilization factors are compared among all pricing schemes to measure overall performance of the p2pVoD system. Figure 3.1 shows the comparison of

![Comparison of Utilization Factor of all Pricing Schemes.](image)

Figure 3.1: Comparison of Utilization Factor of all Pricing Schemes.
utilization factor of all the pricing schemes. In this graph, it can be observed that in altruism approach scheme, initial utilization of the resources are higher due to the behavior of the altruism and later on the utilization decreases rapidly over the time due to exhaust of available resources for the new coming requests. In cost model scheme, the utilization of resources is linear even over the period of time, because of the fixed allocation of resources to the requesting peer. The game theory perspective scheme shows a peculiar behavior in the utilization of the resources. Initially, the utilization factor shows some reasonable utility of the resources. Later on, as the time progresses, speculations occur among the peers to play the best strategy, which drastically reduces the utilization of their own resources. In this figure, it can also be observed that over a period of time the game theory perspective scheme converges with the altruism method. Our proposed dynamic pricing scheme does a fairer resource allocation than all other schemes because the resource allocation is directly influenced by the stochastic demand of the movie and the number of available video blocks in its chaining buffer. In case of fluctuation in the demand, the utilization factor is also affected. Therefore, the utility factor varies accordingly. In this graph it can also be observed that when there is a high demand for the movies then the

Figure 3.2: Utilization Factor of Dynamic Pricing Scheme.
utilization factor is also high with respect to the demand of the movie generated in the cluster. It can also be observed from the graph that there is steep drop in the utility factor for dynamic pricing scheme. The utility factor increases to gain profit for transmitting the video blocks otherwise decreases to loss. The loss is because of the video blocks stored in the peers’ chaining buffer is neither requested by any peers nor has any current demand in the cluster. Initially, there will be a high demand for the videos, so the utility factor is higher. As the time progresses, there will be decrease in the demand, so the utility factor is lower. The steep drop in the utility factor is due to the periodic review of the utilization function. This function is executed periodically as long as the peer is available for chaining. Due to this periodicity, there is a steep drop in the utility factor for dynamic pricing scheme.

Now, we further extend the demand constraint used in our dynamic pricing algorithm for better understanding. Figure 3.2 shows a 3D graph for the utilization factor under the stochastic demand generated over the period of time. It can be observed from the graph that where there is low demand the utilization of resources is drastically reduced. As the demand increases in a highly stochastic environment of the cluster, the utilization factor also increases with time.

Finally, if the demand is high in the cluster then the graph shows more than 80% of the resources are utilized very effectively. In our dynamic pricing scheme, the low demand condition restricts the effectiveness of the algorithm. Therefore, a threshold is defined in the progress of the resource utilization. If the utilization factor falls below the threshold, the method of dynamic pricing scheme is switched to the standard cost model scheme. In this way, a balance is obtained to earn more profit in case of low demand environment. Actually, in the simulation, we have observed that the frequency of the demand is always high for the popular movies. This is because most of requests made by the peers are only for the highly popular movies than the least popular movies. Hence, the switching between the dynamic pricing scheme and the cost model scheme is minimal. Therefore, our dynamic pricing scheme fairs better than the other schemes in utilizing the resources effectively.

Now, we will compare the utilization factor based on the bandwidth and storage utilization respectively. Figure 3.3 shows the average bandwidth utilization in the peers. In altruism approach, the consumption of bandwidth is definitely high due to the altruism behavior. This does not mean that video blocks are effectively transmitted to the peers in the video chain. The cause of the high bandwidth
utilization can be due to the overflow of video blocks on the destination peers. Here, the overflow of video blocks means, buffering more than the required number of video blocks needed for the player to playback the movie. However, one advantage of buffering greater number of video blocks in the peers is that the performance of the VCR operations increases. In the cost model, the utilization of bandwidth is less than the altruism method. The utilization is linear over a period of time, and hence there is a smooth transmission of the video blocks to the destination peers in the chain.

In game theory perspective, the bandwidth consumption varies according to the strategies laid by the peers. It can be observed from the graph that there is no regularity in transmission of video blocks in the video chain. But, this method utilizes the bandwidth effectively and conserves most of it for the new requesting peers. By our dynamic pricing scheme, the pattern of bandwidth utilization is similar to that of game theory perspective. Eventually, our dynamic pricing scheme also conserves the remaining bandwidth more efficiently than other schemes. Finally, there is a smooth transmission of video blocks in the video chain to the destination peers, which effectively meets the current demand of the video blocks.

Figure 3.4 depicts the utilization of storage space in the peers. It can be observed that both altruism approach and cost model scheme utilizes maximum
storage spaces initially, and later on converges with the game theory perspective and the dynamic pricing scheme.

![Figure 3.4 Comparison of Storage Consumption by different Pricing Schemes.](image)

The game theory perspective scheme maintains a steady utilization of its storage for a short duration. Subsequently it decreases the utilization factor rapidly to save the storage space for the new peers in the future. Thereby, the game theory perspective scheme can increase its profit by frequently changing its strategies in long run. In our dynamic pricing scheme, initially only a few video blocks occupy the storage space in the peers, and at later stages due to the demand generated in the cluster, the utilization of the storage space is increased linearly with respect to time. Finally, it converges at a point similar all other schemes. From the graph, it can be observed that all schemes converge to a nearer point on a long run of the video chain. This fact indicates that all schemes are effectively serving the peers in the video chain. Out of all schemes used, our dynamic pricing scheme does not exploit the storage space. It actually balances the equilibrium between the storage space and the current demand. Figure 3.5 shows the average profit earned by peers for transmitting the video blocks to other peers. Our dynamic pricing scheme earns greater profit when compared to any other schemes. The cost model scheme earns a stable profit over a long period of time. In game theory perspective scheme the profit level varies according to the strategy played. The profit level is almost constant over a period of time. The altruism
approach earns a huge profit in the beginning of the transmission of the video blocks and holds this profit for a while. But, unfortunately as the time progresses there is a decline in its profit level which stumbles into losses for a long duration of time.

Figure 3.5 Comparison of Profit Earned.

Figure 3.6 Comparison of Loss Occurred.
Therefore, our dynamic pricing scheme has an edge in terms of profit earning over other schemes.

Figure 3.6 shows the losses that occurred over the period of time. The loss is directly related to the video blocks that are of no use, and it is still stored in the peers after the expired period. Such storage of the video blocks will only increase the salvage cost. It can be observed from the graph that dynamic pricing scheme shows a least loss over a period of time than other schemes. Therefore, our dynamic pricing scheme is the best scheme that can be deployed in all peers to earn more profit. It is also very much suitable for a highly stochastic demanding environment.

Further, to get an insight of our dynamic pricing scheme that was described in Section 3.3, we need to find the optimal value of $S^+$ which will minimize the overall cost occurred and will maximize the profit to be earned. The decision variable $S^+$ depends on the value of holding cost and on the probability distribution of the demand generated for the movies in the cluster. In this case, we have considered exponential distribution to measure the stochastic demand and calculated the expected cost that can occur for the value of $S^+$. We have defined two different empirical pricing ($P^1_S$ and $P^2_S$) strategies for the storage of video blocks in the peers, depending upon the stochastic demand and the stocked quantity of video blocks in the peer.

![Dynamic Pricing Decision](image)

Figure: 3.7 Convergence of Pricing Strategies.
As we had discussed in Section 3.3, we obtained $S^+$, which is an optimal number of video blocks that should to be stored in the peer, and the maximal profit will be earned by using the best price $P_2^*$. When the demand is high and the available size of chaining buffer is small, the pricing strategy $P_1^s$ is used. If the demand is low and the available size of chaining buffer is large, the pricing strategy $P_2^s$ is used. Over the long run of the algorithm, it can be observed from Figure 3.7 that all pricing strategies converge to the same point. Later on, the price from the converged point onwards is same for maximizing the profit. By using our dynamic pricing scheme, average bandwidth utilization in peers are between 30% and 50% as depicted in Figure 3.8, and average holding storage utilization are between 30% and 60% as depicted in Figure 3.9. These results substantiate that in a highly stochastic environment, the dynamic pricing scheme can be espoused by all peers.

Figure 3.8: Average Bandwidth Utilization in Peers.
3.8 SUMMARY

This chapter introduced a novel dynamic pricing scheme for selection of the contributing peers in our p2pVoD system. The objective of this scheme is to maximize the profit earned by the contributing peer by using its resources. For this purpose, we have devised an efficient dynamic pricing algorithm to calculate the utilization factor. Initially, we have extensively studied the existing pricing schemes such as altruism approach, cost model, game perspective for better understanding of the problem. Subsequently, we proposed a framework to develop an effective dynamic pricing scheme to earn more profit. The outcome of the proposal brings out an optimal quantity of video blocks required to store in the contributing peer’s chaining buffer under a highly stochastic demanding environment. Finally, we have evaluated the performance of the proposed dynamic pricing scheme by using the simulation model. The simulation results show that our proposed dynamic pricing scheme fairs better in all aspects of trials when compared to other schemes. Further, our pricing scheme can be improved by incorporating game theory perspective to earn maximum profit in the future. In the next chapter, we investigate the security issues related to the videos that are stocked in peers.