A Revenue-Rewarding Scheme of Providing Incentive for Cooperative Proxy Caching for Media Streaming Systems

ALAN T. S. IP and JOHN C. S. LUI
The Chinese University of Hong Kong
and
JIANGCHUAN LIU
Simon Fraser University, Canada

Network entities cooperating together can improve system performance of media streaming. In this paper, we address the "*incentive issue*" of a cooperative proxy caching system and how to motivate each proxy to provide cache space to the system. To encourage proxies to participate, we propose a "*revenue-rewarding scheme*" to credit the cooperative proxies according to the resources they contribute. A *game-theoretic model* is used to analyze the interactions among proxies under the revenue-rewarding scheme. We propose two cooperative game settings that lead to optimal situations. In particular, (1) We propose a distributed incentive framework for peers to participate in resource contribution for media streaming; (2) Proxies are encouraged to cooperate under the revenue-rewarding scheme; (3) Profit and social welfare are maximized in these cooperative games; and (4) Cost-effective resource allocation is achieved in these cooperative games. Large scale simulation is carried out to validate and verify the merits of our proposed incentive schemes.

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1. INTRODUCTION

Cooperative networks, in particular P2P or overlay networks, have caught much attention in recent years. In such systems, network entities collaborate with each others by sharing their own resource, such as storage, bandwidth or computational power, to form a resource pool, and this aggregated re-

Authors' addresses: A. T. S. Ip and J. C. S. Lui, Department of Computer Science and Engineering, The Chinese University of Hong Kong, Shatin, N. T., Hong Kong; email: alanip@gmail.com; cslui@cse.cuhk.edu.hk; J. Liu, Computer Science Department, Simon Fraser University, Vancouver, BC, Canada; email: jcliu@cs.sfu.ca

source pool helps to improve the system performance. Many applications have been deployed, such as distributed file sharing systems [Kazaa] [BitTorrent], collaborative web caching, P2P streaming [Zhang et al. 2005], distributed computing, etc. It is generally agreed that the cooperative network performs significantly better than the traditional client-server model in supporting large amount of users. In short, it provides an inexpensive platform for application that requires scalability, efficiency and robustness.

However, most cooperative systems assume that peers are "voluntary" to contribute. In fact, this assumption is not realistic. The autonomous peers are selfish in nature, and without concrete incentive, there is no motivation to contribute resources, by which they incur service degradation or suffer from cost. A study in Gnutella file sharing system [Adar and Huberman 2000] suggested that over 70% of users share little or no content. The large-scale deployment of the cooperative systems are obstructed by the free-riding problem, and motivating the users to cooperate is critical to the success of such systems.

To increase the involvement of peers, participation incentive mechanisms [Lui et al. 2002] have to be used to effectively encourage the users' collaboration in the network [Ranganathan et al. 2003]. Different approaches have been proposed in the literature. Better quality of service is given to the peers who contribute to the network, while free-riders are discriminated against. However, effective resource allocation that differentiates the contributors in a highly dynamic network is complicated. Others suggested using the reputation based system, where reputations of the participating peers are accumulated so as to reflect their contribution. The major issues here are how to quantify the user's contribution, how to provide a secure and trusted reputation system to prevent fake reputation (and it is difficult to achieve without a centralized authority). Furthermore, whitewashing is possible for the malicious user by pretending to be another user.

Another approach is to setup a contribution-rewarding mechanism to credit the peers cooperating in the system. The reward may come from the overall revenue of the cooperative network, by means of service pricing or cost reduction. The simplest way to achieve this goal is to grant a fixed credit to a peer whenever it participates. Such a scheme can be implemented easily, but it is unfair to the peer who contribute more resource. One can also reward the peers in proportional to the resources they contributed. This scheme not only achieves proportional fairness, but also encourages peers to supply sufficient amount of resource. By rewarding appropriately, sufficient amount of resources are supplied by the peers, and the efficiency of the overall system can be improved.

In this article, we propose a "*revenue-rewarding mechanism*" to encourage participants to supply caches in a cooperative proxy caching system for media streaming. Ip et al. [2005, 2007] showed that proxies "*cooperating*" together can significantly reduce the aggregated transmission cost in delivering the video streams, and it is worthwhile to setup the cooperative system. However, the authors did not address the incentive issue. It is important to point out that our revenue-rewarding scheme works complementary with the cooperative network in encouraging participation from the proxies. In fact, our analysis has suggested that it is profitable to setup an incentive-based cooperative system for media streaming [Hefeeda et al. 2003].

Our work follows the contribution reward-based incentive approach to reward the contributors by the partial revenue obtained from the cooperative system. We focus on how peers' contributions are influenced by the revenue-rewarding scheme. we propose a *game theoretic model* is used to analyze the interaction between proxies under different resource allocation games. We show that in the noncooperative environment, the proxies selfishly optimize its own utility. As a result, the optimal aggregated benefit received by the network nodes may not be guaranteed. We further propose two "*cooperative resource allocation games*" that lead to two different optimal situations. We examine the performance of the scheme in terms of profit maximization and utility maximization. By evaluating the net profit and the social welfare received by the network entities, we demonstrate that the proposed game settings

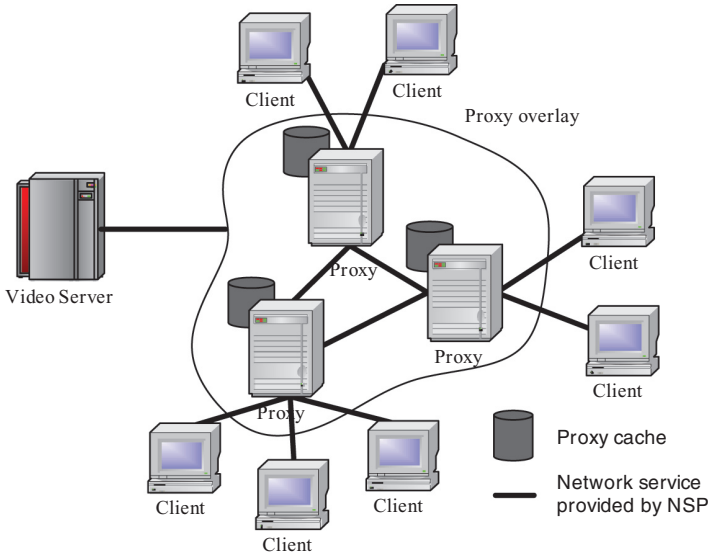


Fig. 1. The architecture of the cooperative proxy caching system.

motivate different entities in the network to cooperate. In addition, two system-wide objectives, net profit and social welfare, are achieved. Also, the resulting resource allocation is cost-effective as only the proxies with low-cost participate in the system. Our contributions are summarized as following: (1) We propose a distributed incentive framework for peers to participate in resource contribution for media streaming. (2) Proxies are encouraged to cooperate under the revenue-rewarding scheme. (3) Net profit and social welfare are maximized in the cooperative games. (4) Cost-effective resource allocation is achieved in the cooperative games.

The article is organized as follows: Section 2 gives an overview of the system, and presents the mathematical formulation. Section 3 describes the revenue-rewarding scheme applied in the three resource allocation games: Non-cooperative game, Profit maximizing game and Utility maximizing game. The performance of these games are evaluated in Section 4. Section 5 reviews the related work. Finally, Section 6 concludes.

2. SYSTEM MODEL

In this section, we present the overall system architecture and then we will present our mathematical formulation.

2.1 Overview of System Architecture

Figure 1 illustrates a cooperative proxy caching system for multimedia streaming. It consists of a logical video server, a number of proxies and their clients, and a network service provider (**NSP**). The NSP provides solely the network connection service to the entities in the network. The client requests for videos, which are streamed from the far-located server to the client through the intermediate proxies. It is assumed that the intermediate proxies are setup by the clients of the NSP, such as Internet Service Provider (ISP) which provides Internet service to the end users. The proxy is similar to the peer in the cooperative network in the sense that it represents an autonomous entity, which has its own freedom in making decision so as to optimize its performance. Thus, the proxies are treated like peers in some cooperative streaming system [Ip et al. 2005].

The proxies are capable of caching the video stream passing through them. However, they are different from mirror server as they cache only part of the video. Each video is divided into equal-sized segments for caching, and whether a segment is being cached in the proxy is determined by the cache allocation algorithm. In general, the frequently accessed video segments are cached in the local proxy to reduce network traffic. The proxies are logically connected by direct or indirect links. They cooperate with each others by sharing the cached segments among themselves, that is, a proxy can request for a video segment cached in other proxies.

An example of the cooperative caching multimedia system is the COPACC architecture proposed in Ip et al. [2005], which is a cooperative proxy-and-client caching system. The system aims at reducing the aggregated transmission cost by allocating efficiently the video segments to the cache provided by the proxies and clients. According to the cache allocation algorithm, videos are partitioned into prefix (P^i), prefix-of-suffix (Q^i) and the remaining suffix, and the proxies and clients are responsible to cache the prefix and prefix-of-suffix respectively. Based on the video transmission scheme used (either unicast or multicast), the optimal partitioning of the videos are computed to minimize the aggregated transmission cost. The optimal prefix and prefix-of-suffix are further divided into smaller segments in order to fit in multiple proxies and clients. Optimal placement of these segments into the proxies and clients is also considered to minimize the cost. The merit of the COPACC relies on the proxy cooperation. However, COPACC and other cooperative multimedia streaming systems did not address the "*incentive issues*" for the proxy's participation. That is, what motivates each proxy to provide the cache space and how much cache space should be allocated. We extend the cooperative multimedia streaming system by proposing a revenue-rewarding scheme to provide incentive for the proxies to cooperate.

In order to increase profit, the NSP is keen to admit new clients. However, since the capacity of the network links is limited, the NSP may not be able to serve a large number of video-streaming users having high bandwidth and short startup latency requirements. Unfortunately, upgrading the network facility is not desirable because the investment cost is usually high. A cost-effective approach is to setup a cooperative caching system, so as to reduce the aggregated transmission cost in the network. As such, the same link capacity can support more clients. Hence, the NSP has a strong incentive to encourage the proxies to participate in the cooperating caching.

In general, if there are more caches, the better the performance of the system is. From the NSP's prospective, it wants a higher contribution of caches because it can support more users at a lower operating system cost. However, resources are not supplied for free. The proxy has to pay certain cost to maintain the resources, although the cost is usually implicit. Therefore, the proxies participated in the incentive-based system have to decide carefully the amount of cache storage to be contributed. If they contribute too little storage, the reward is small; if they contribute too much storage, the cost of maintaining the cache is higher than the reward. In this article, we assume that the cost follows the general rule of increasing marginal cost, that is, the cost of providing an additional unit of cache is higher than that of the previous unit. Thus, proxies are reluctant to provide too much resources to the system.

Therefore, a revenue-rewarding scheme is established by the NSP to reward the contributing proxies. The reward, in terms of credit, is determined based on the amount of resource shared by the proxy and it should be proportional to the proxy's contribution. Proxies are rewarded regularly for every fixed period of time. Only the proxies with full participation throughout the period are qualified for the rewards. This encourages the proxies to stay in the network until the end of each period, thus avoiding the unpredictable proxy departure from the system.

An authority, such as the NSP, is responsible to define a price value, which specifies how much "credit per unit" storage should be granted to the participating proxy. Ideally, the price should match the demand and supply of resource such that social optimal is achieved. It is important to point out

Table I. A Summary of the Notations.

Notation	Definition
H	Number of proxies.
s_i	Cache space supplied by proxy i.
$\hat{S}_i$	Storage capacity of proxy i.
q	Total cache space supplied to the system.
$C_i(s_i)$	Cost of supplying s_i unit of cache space by proxy i.
$R(q)$	Revenue of the system with q units of cache space supplied.
$P(q)$	Credit granted to the proxy for each unit of cache space supplied.
$U_i(s_i)$	Utility of supplying s_i unit of cache space by proxy i.
$E(q)$	Net profit of the NSP in the system with q units of cache space supplied.
$SU(s_1, s_2, \ldots, s_H)$	Social Utility of the system.
A_i, θ_i, b_i	Parameters defining the cost function of proxy i in COPACC
A, θ, b	Parameters defining the revenue function of the NSP in COPACC

that proxies are selfish in nature, they strategically allocate the amount of storage that maximize their benefit only, that is, maximize the reward minus cost, regardless of other proxies. Meanwhile, the NSP wants to achieve the largest benefit by giving out less reward. This forms a noncooperative game between the NSP and the proxies that often leads to a nonoptimality condition. In this case, the proxies tend to over-supply the resource.

2.2 Model Formulation

We use a game-theoretic approach to model the economic of the resource supplying from the proxies. There are two types of player, NSP and proxy. The NSP provides network connectivity to the proxies, while the proxy provides cache storage to reduce the transmission cost of the system. The notations used in the paper are summarized in Table I.

There are H proxies cooperating in the system. Let s_i be the unit of cache space that proxy i decided to allocate to the system, and $\hat{S}_i$ be the maximum cache capacity of the proxy i. A feasible s_i is the unit of cache space the proxy i can supply, that is, $0 \leq s_i \leq \hat{S}_i$. The sum of the cache space supplied to the system is $q = \sum_{i=1}^{H} s_i$. In order to supply s_i units of cache space, proxy i has to pay $C_i(s_i)$, where $C_i(s_i)$ is the cost function of supplying s_i from proxy i, and the cost function can be heterogeneous between different proxies. In this article, we consider the cost function to be strictly increasing with convex shape. The cost function for proxy i is defined as following:

$$C_i(s_i) = \begin{cases} A_i \exp \theta_i(s_i - b_i), & 0 < s_i \leq \hat{S}_i \\ 0, & s_i = 0. \end{cases} \tag{1}$$

Note that this cost function is quite general. This form of exponential cost function is suitable because it reflects the general rule of increasing marginal cost. The parameter A_i defines the initial cost of setting up the proxy, while θ_i determines the increasing rate of the cost. For example, a cost function with large value of A_i and θ_i have a high cost. When θ_i is set to zero, the cost function becomes a constant A_i, meaning that the cost is fixed regardless of the amount of cache supplied. The last parameter b_i provides better modeling of the cost by shifting the exponential function. Each proxy can have different values and can assign its own cost function by adjusting the parameters A_i, θ_i and b_i.

The NSP is in charged to estimate the revenue $R(q)$ in the system. For example, the revenue function can be obtained from the cooperative proxy system by approximating the transmission cost reduction with respect to the total cache space q. In general, the more resources supplied by peers, the higher the revenue. However, the marginal revenue is decreasing as the resource increased. When the cache space reaches a specific amount, the cost reduction approaches the limit. Thus, we model the revenue

function as a non-decreasing and concave function, which is defined as

$$R(q) = \frac{A}{\theta}[1 - \exp(-\theta(q - b))], \quad q > 0. \tag{2}$$

The price is a function of q, which is the total cache space in the system, and it is set according to the revenue curve. The product of the price and the total available cache unit q should not exceed the corresponding revenue. The NSP has its freedom to decide how much revenue is to be rewarded to the proxies, by setting an appropriate price function. We suggest two possible ways to define the price function.

(1) *Total-Rewarded Pricing*. The price function $P_T(q)$ is defined as the revenue divided by the total resource supplied, that is, $P_T(q) = R(q)/q$ for $q > 0$.
(2) *Marginal-Rewarded Pricing*. The price function $P_M(q)$ is defined as the marginal gain of the system, that is, $P_M(q) = R'(q)$.

In general, $P(q)$ is a decreasing function with a convex shape. When the amount of resource tends to infinite, the price of each unit of resource approaches to zero. The total and marginal-rewarding price are defined as following:

$$P_T(q) = \frac{A}{\theta q}[1 - \exp(-\theta(q - b))], \quad q > 0. \tag{3}$$

$$P_M(q) = A\exp(-\theta(q - b)), \quad q > 0 \tag{4}$$

We like to emphasize that this methodology is not restricted to the use in the caching system, but it may also be applied to other P2P system with the cost and the rewarding function setup properly. We now present the resource allocation game among the proxies in the COPACC.

3. RESOURCE ALLOCATION GAME

We model the behavior of the proxies and the NSP as a strategic game. All proxies (or system administrators who manage the proxy) are rational, and they strategically choose the amount of cache s_i so as to maximize their benefit. We use a utility function to represent the level of satisfaction of the proxy. The utility $U_i(s_i)$ of proxy i can be measured in terms of its net gain, which is equivalent to the reward earned minus the cost to provide the cache. The utility is expressed as follow:

$$U_i(s_i) = s_i P(q) - C_i(s_i). \tag{5}$$

The resource allocation game is a repeated and asynchronous game. Each proxy can make or change its decision about the amount of cache at the beginning of each round. To be realistic and scalable, we assume imperfect knowledge of each proxy, meaning that the proxy only knows about the total cache space supplied to the system, q, and the price function, $P(q)$. The NSP (or proxy coordinator) can publicize the current price and the total amount of cache space such that other proxies can obtain the information easily. Based on these information, the proxy updates its own strategy in each move so to maximize its utility.

3.1 Noncooperative Game

In the noncooperative game, the proxies make decision regardless of the other proxies. They choose s_i based on the public information: the aggregated cache space q and the price function. The objective of each proxy is to maximize its own utility with respect to s_i over $[0, \hat{S}_i]$. Formally, proxy i needs to perform:

$$\max_{0 \le s_i \le \hat{S}_i} U_i(s_i) = s_i P(q) - C_i(s_i). \tag{6}$$

Given the total cache space q and the price function $P(q)$, the proxy can determine its best strategy s_i by solving the maximization problem. Note that q is implicitly depends on s_i. If the value of s_i is changed, the value of q, as well as $P(q)$, will be changed accordingly. Thus, in the optimization, the value of q would be better presented in terms of s_i. Let s_{-i} be the amount of cache collectively supplied by the proxies except proxy i, then $s_{-i} = q' - s_i'$, where q' and s_i' are the total amount of cache and the amount of cache supplied by proxy i respectively in the previous round. The equivalent optimization problem is shown as following:

$$\max_{0 \le s_i \le \hat{S}_i} U_i(s_i) = s_i P(s_i + s_{-i}) - C_i(s_i). \tag{7}$$

Specifically, the objective function can be written as

$$\max_{0 \le s_i \le \hat{S}_i} U_i(s_i) = \begin{cases} s_i A \exp(-\theta(s_i + s_{-i} - b)) - A_i \exp(\theta_i(s_i - b_i)), & 0 < s_i \le \hat{S}_i \\ 0, & s_i = 0. \end{cases} \tag{8}$$

The marginal-rewarded pricing is used here. This maximization problem is simple, and the first-order condition is sufficient to solve the optimal value of s_i. In general, the game will converge to a Nash equilibrium. However, the Nash equilibrium may not be unique as the *order* of move will influence the equilibrium point. The first mover (i.e., or the first proxy which decides on the amount of supplying cache) is more likely to get advantage over the later mover by supplying more cache space at the beginning. The outcome of this noncooperative game is not desirable since there is no guarantee that the equilibrium is socially optimal.

In the noncooperative environment, the proxies act selfishly to maximize their utility. The outcome, however, may not meet their expectation: that is, the utility may be worse than the achievable individual optimal, in which the proxies cooperatively decide how much cache to supply. Under the noncooperative situation, each proxy seems to optimize their individual benefit, but actually the system-wide behavior does not reflect the optimization of any objective. Without the whole system view, it is difficult to determine whether the outcome (or the Nash equilibrium) is Pareto optimal or not. According to different kinds of player in the game, either one of the following system-wide objectives can be achieved:

(1) Maximize the net profit of the Network Service Provider (NSP);
(2) Maximize the social utility among all proxies involved in the system.

To achieve the above objectives, we suggest two *cooperative resource allocation games*, namely the *Profit Maximizing Game* and the *Utility Maximizing Game*.

3.2 Profit Maximizing Game

Being the NSP, the objective is to maximize its net profit of the cooperative proxy architecture. The net profit, $E(q)$, of the NSP is defined as the revenue earned minus the reward paid to the proxies, which can be expressed as

$$E(q) = R(q) - qP(q). \tag{9}$$

As shown in Eq. (9), the net profit is determined by the total cache space q supplied to the system, and the NSP can only influence the value of q by setting the price function $P(q)$ at the beginning of the game. Once the price function is set and publicized, the NSP has no control about the value of q, which is the Nash equilibrium point resulting from the moves of the proxies over many iterations.

The noncooperative game is not desired in maximizing the NSP's profit because it does not lead to a unique Nash equilibrium. For a defined price function, the system may converge to different equilibrium, depending on the sequence of move of the proxies. There is no guarantee for the NSP to set a particular

marginal-rewarded pricing function that leads to a desirable outcome, which maximizes its net profit. To ensure the existence of a unique, predictable Nash equilibrium, we simplify the price function to a constant p. That is, the price no longer depends on the cache supplied to the network. By setting a constant price, we show that the game admits a unique Nash equilibrium, and the NSP can choose a proper price p to maximize its net profit.

With this assumption, we model the interaction as a Stackelberg game [Basar and Olsder 1999] that has one leader (the NSP) and H noncooperative Nash followers (the proxies). The NSP strategically decides the price p, and the proxies react with the best amount of cache s_i to supply. This defines a noncooperative game between each independent proxy in the network, with the underlying solution being the Nash equilibrium. Each proxy selfishly selects s_i to satisfy its objective function:

$$\max_{0 \le s_i \le \hat{S}_i} U_i(s_i) = s_i P(q) - C_i(s_i) = s_i p - C_i(s_i). \tag{10}$$

If the net utility of a proxy is less than or equal to zero, it will not participate in the system, and it will be removed from the list of proxies. Note that there is a boundary constraint for the variable s_i, that is, $0 \le s_i \le \hat{S}_i$. The problem is formulated as a constrained optimization, which can be solved by the method of Lagrangian Multiplier.

Let $\{s_i{}^*\}_{i=1}^{H}$ be a set containing the amount of cache supplied by the proxies to the system such that it satisfies

$$\max_{0 \le s_i \le \hat{S}_i} U_i(s_i) = U_i(s_i{}^*). \tag{11}$$

One can analytically find the value of s_i^* based on the value of p, using the first-order condition.

$$U_i'(s_i) = p - C_i'(s_i) = 0 \tag{12}$$

$$C_i'(s_i) = A_i \theta_i \exp(\theta_i(s_i - b_i)) = p \tag{13}$$

$$s_i = \frac{ln(p/A_i\theta_i)}{\theta_i} + b_i. \tag{14}$$

By solving s_i in Eq. (13), one can obtain the solution of s_i^*.

$$s_i^* = \begin{cases} 0, & s_i \le 0 \\ s_i, & 0 < s_i \le \hat{S}_i \\ \hat{S}_i, & s_i > \hat{S}_i. \end{cases} \tag{15}$$

The following theorem states the important result of having one unique equilibrium point.

THEOREM 1. *The profit maximizing game admits one and only one Nash equilibrium*

PROOF. Consider the second derivative of the utility $U_i(s_i)$,

$$U_i''(s_i) = -C_i''(s_i). \tag{16}$$

Since the cost function is defined as a strictly increasing function with convex shape, the second derivative should always be positive, that is, $C_i''(s_i) > 0$. It shows that $U_i''(s_i)$ is always less than zero, and the utility function admits at most one maximum. Thus, the strategy of proxy i is either s_i^* that satisfies the Eq. (13) if the maximum located in the range of $(0, \hat{S}_i)$, or the boundary value 0 or $\hat{S}_i$. As each proxy has it own unique optimal strategy s_i^* independent of others, a unique $\{s_i{}^*\}_{i=1}^{H}$ does exist. □

Thus, given the value of price p, the NSP can predict the total cache space q^* contributed to the system, that is

$$q^* = \sum_{i=1}^{H} s_i^*. \tag{17}$$

If the NSP knows the parameters A_i, θ_i and b_i of all the proxies, it can formulate its own maximization, which aims at maximizing the net profit with respect to q^*.

$$\max_{p \geq 0} E(q^*) = R(q^*) - q^* p \tag{18}$$

Since the total amount of cache space q^* solely depends on the value of price p through Eqs. (15) and (17), one can rewrite the objective function by substituting q^* in terms of p. In the cooperative proxy caching system, if all the s_i do not violate the feasible constraints, the objective function can be rewritten as:

$$\max_{p \geq 0} E(p) = R\left(\sum_{i=1}^{H}\left(\frac{ln(p/A_i\theta_i)}{\theta_i} + b_i\right)\right) - p \cdot \sum_{i=1}^{H}\left(\frac{ln(p/A_i\theta_i)}{\theta_i} + b_i\right). \tag{19}$$

The derivative of q^* and $E(p)$ with respect to p are shown below. The optimal price, p^*, can be obtained by solving the first-order condition in Eq. (23).

$$\frac{dq^*}{dp} = \frac{1}{p}\sum_{i=1}^{H}\frac{1}{\theta_i}, \tag{20}$$

$$E'(p) = A\exp(-\theta(q^* - b)) \cdot \frac{1}{p}\sum_{i=1}^{H}\frac{1}{\theta_i} - q^* - p \cdot \frac{1}{p}\sum_{i=1}^{H}\frac{1}{\theta_i}, \tag{21}$$

$$= \frac{A}{p}\left(\sum_{i=1}^{H}\frac{1}{\theta_i}\right)\exp(-\theta(q^* - b)) - q^* - \sum_{i=1}^{H}\frac{1}{\theta_i}, \tag{22}$$

$$E'(p) = 0. \tag{23}$$

Although it is difficult to find the close-form solution of p^* for Eq. (23), one can solve this optimization efficiently using numerical method, for example, Newton method is applied to solve the value of the optimal price p^*. Once the NSP finds the optimal price, it can calculate the value of all s_i^* using Eq. (15). If all s_i^* are inactive, that is, they satisfy the condition $0 \leq s_i^* \leq \hat{S}_i$, the net profit of the NSP is guaranteed to be maximum by setting the optimal price to p^*.

For this optimization, we also need to consider other scenarios, that is, what if some of the constraints are active and they do not satisfy the boundary condition of s_i? The problem becomes more complicated, but one can still find the optimal value of p mathematically. The solution is based on the techniques of Lagrangian multiplier. It can be shown that the objective function $E(p)$, without considering the cache constraints, is a concave function, and all the constraints regarding s_i are linearly. Thus, it is a concave programming problem, and there exists a unique solution that satisfies the KKT-conditions in Eqs. (25)–(30).

$$L = E(p) - \sum_{i=1}^{H}\mu_i^l s_i + \sum_{i=1}^{H}\mu_i^u(s_i - \hat{S}_i) \tag{24}$$

Profit Maximizing Algorithm:

```
1:  declare P = { 1, 2, ... , H};      // indexes of proxy that it's s_i has not been determined yet
2:  declare P^l = {};      // indexes of proxy that it's s_i is zero
3:  declare P^u = {};      // indexes of proxy that it's s_i is Ŝ_i
4:  for i := 1 to H
5:     s_i = 0;
6:  end for
7:  while (true) do
8:     q = Σ_{i∈P} s_i + Σ_{i∈P^u} Ŝ_i = Σ_{i∈P} [ln(p◁A_iθ_i)/θ_i + b_i] + Σ_{i∈P^u} Ŝ_i;
9:     Solve the optimal price p that maximize E(p) = R(q) − p•q (or find p such that E'(p) = 0);
10:    for i := 1 to H
11:       s_i = ln(p◁A_iθ_i)◁θ_i + b_i;
12:    end for
13:    if 0 ≤ s_i ≤ Ŝ_i ∀i ∈ P then
14:       break;      // end the while loop
15:    end if
16:    declare p^t = {};      // a temporary set
17:    for i := 1 to H
18:       if s_i ≤ 0 then
19:          P^t = P^t ∪ {i};
20:       end if
21:    end for
22:    if (P^t − P^l) ≠ ∅then
23:       P^l = P^t;
24:       P = P − P^t;
25:       continue;      // next iteration of the while loop
26:    end if
27:    for each i ∈ P
28:       if s_i ≥ Ŝ_i then
29:          P^u = P^u ∪ {i};
30:          P = P − { i};
31:       end if
32:    end for
33: end while
34: return p;      // p is the optimal price
```

Fig. 2. Profit maximizing algorithm for the NSP in the profit maximizing game.

$$\frac{\partial L}{\partial p} = \frac{\partial E(p)}{\partial p} - \sum_{i=1}^{H} \mu_i^l \frac{\partial s_i}{\partial p} + \sum_{i=1}^{H} \mu_i^u \left(\frac{\partial s_i}{\partial p} - \hat{S}_i \right) = 0 \tag{25}$$

$$\mu_i^l \geq 0, \quad i = 1, \ldots, H \tag{26}$$

$$\mu_i^u \geq 0, \quad i = 1, \ldots, H \tag{27}$$

$$\mu_i^l s_i = 0, \quad i = 1, \ldots, H \tag{28}$$

$$\mu_i^u (s_i - \hat{S}_i) = 0, \quad i = 1, \ldots, H \tag{29}$$

$$0 \leq s_i \leq \hat{S}_i, \quad i = 1, \ldots, H. \tag{30}$$

We now present an algorithmic approach to find the optimal value of p, which is derived directly from the KKT-conditions. Figure 2 illustrates the profit maximizing algorithm for the NSP in the profit

maximizing game. It first assumes that the boundary constraints of all s_i are inactive, i.e. all the cache space s_i lie between 0 and $\hat{S}_i$. Thus, the Eqs. (28) and (29) hold only if the μ_i^l and μ_i^u are zero. The optimization problem is now similar to the unconstrained problem in Eq. (19), and we can apply the numerical method stated previously to calculate the optimal price p^* as well as all s_i. If the s_i are feasible, we have obtained the best solution. Otherwise, we know that some of the boundary constraints are violated, and the corresponding values of μ_i^l or μ_i^u are not equal to zero. In that case, the value of s_i is forced to be the boundary value (either 0 or $\hat{S}_i$) followed by Eqs. (28) or (29). We can identify the active constraints of s_i from the result obtained in Eq. (23). If the optimal s_i found in the unconstrained optimization is less than zero, the proxy should not participate in the system. Therefore, we remove the proxy from the system by setting $s_i = 0$. If the optimal s_i is greater than the maximum capacity the proxy can provide, the proxy supplies $\hat{S}_i$ units only, and $s_i = \hat{S}_i$. After hard-setting the value of certain s_i, we execute the algorithm again to find the numerical solution for the optimal value of p. If the outcome of all s_i are feasible, we get the best solution. Otherwise, we repeat the previous steps to adjust the value of s_i and execute the algorithm until the resulted s_i are feasible. In practice, integral value of cache quantity is desired. Thus, an additional checking on $\lceil s_i \rceil$ and $\lfloor s_i \rfloor$ as the solution should be made to assure optimality.

Until now, we assume the NSP knows the characteristic of the cost function of each proxy such that it can determine the behavior of the proxies, and it can construct its own objective function. But one interesting question to ask is whether the NSP can maximize its net profit *without knowing the individual cost function of each proxy*. As such, the NSP can only observe the action of each proxy by setting a probing price. The NSP keeps adjusting the price gradually until a desirable profit is obtained. It is similar to a commodity market, where the price is determined by tatonnement process [Uzawa 1960] through numerous iterations of refinement. However, the optimization objective is different. The tatonnement process selects a price to achieve social optimal by matching the demand and supply of goods, while the profit maximizing game selects a price to maximize the profit for the NSP.

Although the NSP does not know the exact amount of total cache space q supplied to the system for each p, it is always true that increasing the price leads to a nondecreasing movement of the total cache space. Figure 3 plots a sample relationship between the total cache space q and the price p. The quantity q is calculated for different price p using equation (14). Both p and q move nonlinearly in the same direction. Due to the boundary constraints of s_i, the function relating p and q is continuous but not differentiable. Figure 4 plots a sample relationship between the net profit $E(p)$ and the price obtained from Eq. (9). We observe that the value of $E(p)$ in Eq. (19) generally increases with a small increase of p. Then it reaches the global maximum, and decreases with increased value of p.

Let us propose a *Price Establishing Protocol* for the NSP to determine the optimal price used in the system. We assume the proxies choose the best s_i to maximize their net utility, stated in Eq. (10), based on the price p given from the NSP. The NSP keeps announcing different value of price p, and the proxies reply to the NSP with the amount of cache space it agrees to contribute. Based on the total cache space q supplied by the proxies, the NSP decides the best pricing strategy to maximize its net profit. It can be thought as a search problem for an optimal value of p without a formal equation.

At the beginning of the protocol, the NSP makes an initial guess of the probing price, say $\dot{p}$. It announces the price to the proxies, and retrieves the corresponding value of q. The net profit $E(\dot{p})$ can be calculated based on the value of $\dot{p}$ and q. In each iteration, the NSP decides a new probing price based on the old price and the percentage change of the net profit. It then sets a new price and measure the change of the net profit as compared with the old one. The process goes on until the price converges to an optimal value, which achieves the maximum profit.

The search method stated above is the simplest one of the zero-order method (or maximization method without derivatives) in the literature. However, this simple search method may result in local optima.

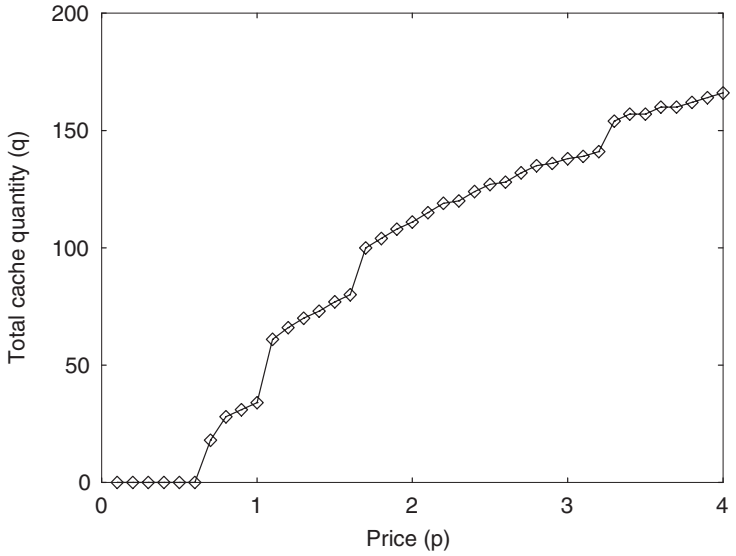


Fig. 3. A sample plot of total cache space q v.s. price p.

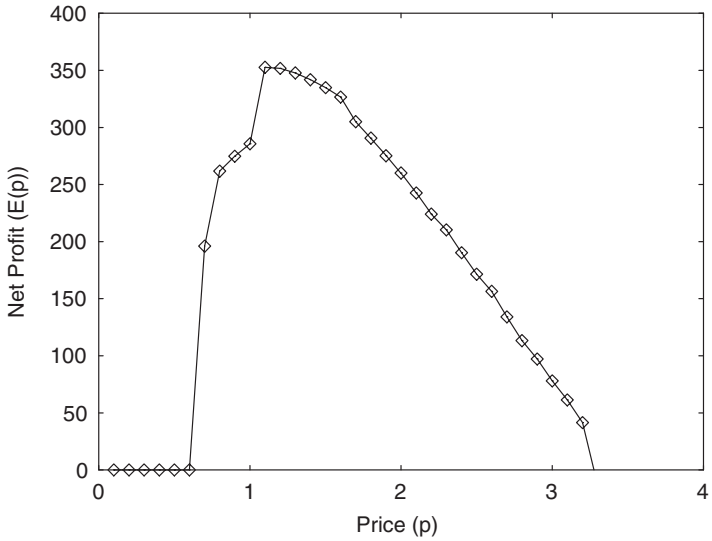


Fig. 4. A sample plot of net profit $E(p)$ v.s. price p.

Thus, some advanced direct search methods should be applied in the *Price Establishing Protocol* to achieve global optimization with fast converging speed. Pattern Search Method [Kolda et al. 2003] can be used to find the optimal price in the protocol. Other search method that guarantee global optimal can also be applied.

So far we have presented the way for the NSP to maximize its net profit by setting up proper price. Sometimes, the NSP has no preference about maximizing its net profit. Instead, the proxies may prefer to maximize the social utility among themselves. In this situation, the objective of the optimization

becomes maximizing the social utility, which is defined as the total net utility summed over all proxies. In what follows, we will present the utility maximizing game.

3.3 Utility Maximizing Game

Another system-wide property we would like to achieve is the social utility. It reflects the level of satisfaction of the proxies participating in the network. In this section, we present a resource allocation game that aims at maximizing the social utility of the system. Cooperation of the proxies is essential in this optimization.

The net utility $U_i(s_i)$ of each proxy supplying s_i units of cache is shown in Eq. (5). We define the social utility as the individual utility summed over all proxies, which is

$$SU(s_1, s_2, \ldots, s_H) = \sum_{i=1}^{H} U_i(s_i). \tag{31}$$

The global objective is to maximize the social utility with respect to s_i subjected to the boundary constraints $0 \leq s_i \leq \hat{S}_i$, that is

$$\max_{0 \leq s_i \leq \hat{S}_i} \sum_{i=1}^{H} U_i(s_i) = \max_{0 \leq s_i \leq \hat{S}_i} \sum_{i=1}^{H} [s_i P(q) - C_i(s_i)]. \tag{32}$$

As the value of q equals to $\sum_{i=1}^{H} s_i$ and the current price is calculated based on the value of q, the net utility $U_i(s_i)$ of proxy i does not solely depends on s_i supplied by itself, but also depends on the cache space s_{-i} contributed by the other proxies. The multi-variable optimization of the above objective function becomes difficult. It is desirable to break down the problem into smaller subproblems, and each subproblem can be handled easier.

To solve the above problem, one can observe that the objective function in Eq. (32) can be simplified as:

$$\max_{0 \leq s_i \leq \hat{S}_i} \sum_{i=1}^{H} U_i(s_i) = \max_{0 \leq s_i \leq \hat{S}_i} \left[q \cdot P(q) - \sum_{i=1}^{H} C_i(s_i) \right]. \tag{33}$$

The first term is equivalent to the credit rewarded to the proxies, while the second term represents the total cost of providing q units of cache by the proxies. Note that with the fixed quantity of cache space q, the first term is always constant regardless of the s_i. The social utility varies only by adjusting the allocation of s_i. Hence, the best social utility with a fixed cache quantity can be obtained when the total cost of providing the cache is minimized. The objective function in Eq. (32) can be rewritten as below:

$$\max_{0 \leq s_i \leq \hat{S}_i} \sum_{i=1}^{H} U_i(s_i) = \max_{0 \leq q \leq \hat{Q}} \left[q \cdot P(q) - \min_{0 \leq s_i \leq \hat{S}_i} \sum_{i=1}^{H} C_i(s_i) \right] \tag{34}$$

$$\text{s.t.} \qquad q = \sum_{i=1}^{H} s_i \tag{35}$$

$$\hat{Q} = \sum_{i=1}^{H} \hat{S}_i. \tag{36}$$

Thus, the problem can be decomposed into two subproblems, namely *Minimal cost caching problem* and *Optimal cache quantity problem*.

(1) *Minimal Cost Caching Problem* (MinCost): Find the minimal cost to provide q units of cache by the cooperative proxies with respect to s_i.
(2) *Optimal Cache Quantity Problem* (OptQ): Find the quantity of cache space q that guarantee best social utility.

These two subproblems are linked together by the common variable q. In the first subproblem, given the value of q, we claim that it is always possible to find a unique set of allocation s_i that minimizes the total cost. Thus, there is a one-to-one mapping between q and $\{s_i\}_{i=1}^{H}$. Once the first subproblem is solved, the whole problem depends only on the variable q, while not the actual allocation $\{s_i\}_{i=1}^{H}$. We then solve the second subproblem by finding the optimal value of q, as well as the price $P(q)$, to generate maximum social utility.

We now present the concrete formulation and the proposed solution to the subproblems.

3.3.1 *Minimal Cost Caching Problem.* This subproblem is about finding the cheapest way to supply q units of cache space among the proxies. We are also interested in the cache space $\{s_i\}_{i=1}^{H}$ allocated by the proxies that minimize the total cost. The minimal cost caching problem is formulated mathematically as:

$$\textbf{MinCost:} \quad MinCost(q) = \min \sum_{i=1}^{H} C_i(s_i) \tag{37}$$

$$\text{such that} \quad 0 \le s_i \le \hat{S}_i, \quad i = 1, \ldots, H \tag{38}$$

$$\sum_{i=1}^{H} s_i = q. \tag{39}$$

This optimization problem can be solved algorithmically using the the dynamic programming method. Let $B(i, j)$ be a two-dimensional matrix that stores the minimum cost of contributing j units of cache by the first i proxies, where $1 \le i \le H$ and $0 \le j \le q$.

$$B(i, j) = \begin{cases} C_1(j), & 0 \le j \le \hat{S}_1 \\ \infty, & i = 1, \ \hat{S}_1 < j \le q \\ \min\limits_{0 \le k \le j, k \le \hat{S}_i} & B(i-1, j-k) + C_i(k), \quad 2 \le i \le H, \ 0 \le j \le q. \end{cases} \tag{40}$$

The matrix can be filled in plane-order starting from $B(1, 0)$ to $B(H, q)$, and the latter gives the minimum cost of providing q units of cache. The corresponding s_i of each proxy can be obtained through backtracking the iterations. This dynamic programming algorithm has time complexity $O(q \cdot H \cdot M)$, where $M = \max_{1 \le i \le H} \hat{S}_i$.

Although the dynamic programming method solved the MinCost problem, it is not always desirable because it is a centralized algorithm which requires a dedicated node in the network to execute the algorithm. As a consequence, a distributive algorithm is generally preferred to solve the problem in the network.

Before proceeding, it is a good idea to understand the mathematical solution of this cost minimization problem using optimization theory. Consider the problem stated in Eq. (37), the following theorem states some important property of this optimization problem.

THEOREM 2. *MinCost is a constrained convex optimization problem.*

PROOF. To show this, we have to prove the truth of the following two statements.

(1) The feasible region of the solution space s_i under the constraints is convex.
(2) The summation of the individual cost function is a convex function.

Statement (1) follows directly from the fact that all the constraints for s_i are linear. It is obvious that the equality constraint involving q and the boundary constraints for each s_i are linear equation of s_i. Thus, the feasible region is a convex set.

Consider the Hessian matrix of the total cost function,

$$\nabla^2 \left[\sum_{i=1}^{H} C_i(s_i) \right] = \begin{bmatrix} C_1''(s_1) & 0 & 0 & 0 \\ 0 & C_2''(s_2) & 0 & 0 \\ 0 & 0 & C_3''(s_3) & 0 \\ 0 & 0 & 0 & \dots \end{bmatrix} \tag{41}$$

or

$$\nabla^2 \left[\sum_{i=1}^{H} C_i(s_i) \right]_{ij} = \begin{cases} 0, & i \neq j \\ C_i''(s_i), & i = j. \end{cases} \tag{42}$$

Since the cost function $C_i(s_i)$ is strictly convex, the value $C_i''(s_i)$ are always positive. The Hessian matrix is positive semi-definite. Thus, the total cost function is a convex function. Statement (2) holds. □

Convexity is an important property in constrained optimization. In a convex optimization, the local minimum guarantees to be the global minimum. As a result, the KKT-condition is the sufficient and necessary condition for optimality. In other words, a set of $\{s_i\}_{i=0}^{H}$ that satisfies the KKT-condition is the solution to our cost minimization problem. The KKT-condition for the MinCost problem is shown below:

$$L(s_i) = \sum_{i=1}^{H} C_i(s_i) - \lambda \left(\sum_{i=1}^{H} s_i - q \right) - \sum_{i=1}^{H} \mu_i^l s_i + \sum_{i=1}^{H} \mu_i^u (s_i - \hat{S}_i) \tag{43}$$

$$\frac{\partial L}{\partial s_i} = C_i'(s_i) - \lambda - \mu_i^l + \mu_i^u = 0, \quad i = 1, \dots, H \tag{44}$$

$$\mu_i^l \geq 0, \quad i = 1, \dots, H \tag{45}$$

$$\mu_i^u \geq 0, \quad i = 1, \dots, H \tag{46}$$

$$\mu_i^l s_i = 0, \quad i = 1, \dots, H \tag{47}$$

$$\mu_i^u (s_i - \hat{S}_i) = 0, \quad i = 1, \dots, H \tag{48}$$

$$0 \leq s_i \leq \hat{S}_i, \quad i = 1, \dots, H \tag{49}$$

$$\sum_{i=1}^{H} s_i = q. \tag{50}$$

The MinCost is a convex optimization problem, meaning that there exists a unique solution $\{s_i\}_{i=1}^{H}$ satisfying the Eqs. (44)–(50). The optimal cache allocation s_i can be determined by solving the set of linear equations. We are now ready to present our distributed approach to the cost minimization problem.

We start with a simplified version of the MinCost problem in Eq. (37), having the storage constraints removed from each proxy. It becomes an equality constrained problem, which can be solved by the method of Lagrange multiplier. The necessary condition is similar to the KKT-condition stated previously, but with the equations involving μ_i^l and μ_i^u omitted. Note that the plus or minus sign of the multiplier term does not affect the solution.

$$L(s_i) = \sum_{i=1}^{H} C_i(s_i) - \lambda \left(\sum_{i=1}^{H} s_i - q \right) \tag{51}$$

$$\frac{\partial L}{\partial s_i} = C_i'(s_i) - \lambda = 0, \quad i = 1, \ldots, H \tag{52}$$

$$\sum_{i=1}^{H} s_i = q. \tag{53}$$

We instantiate the cost function according to some cooperative caching systems, for example, systems presented in Ip et al. [2005]. Given Eq. (52), we can derive s_i in terms of λ.

$$C_i'(s_i) = A_i \theta_i \exp(\theta_i(s_i - b_i)) = \lambda \tag{54}$$

$$s_i = \frac{ln(\lambda / A_i \theta_i)}{\theta_i} + b_i. \tag{55}$$

The variable λ is called shadow price, which is introduced by the proxies to establish implicitly the best cache allocation among them. The equation of s_i is similar to the one shown in Eq. (14), but in here we have one more condition about the total cache quantity (in Eq. (53)) to hold. By substituting s_i to Eq. (53), we can solve the value of λ, and thus, the values of all s_i.

$$\sum_{i=1}^{H} \left[\frac{ln(\lambda / A_i \theta_i)}{\theta_i} + b_i \right] = q \tag{56}$$

$$\lambda = e^{\frac{q + \sum_{i=1}^{H} [ln(A_i \theta_i)/\theta_i - b_i]}{\sum_{i=1}^{H} 1/\theta_i}}. \tag{57}$$

If we have all the parameters about the individual cost function of each proxy, we can find the optimal λ as well as the s_i directly. However, in the distributed approach, we must rely on iteratively refining the value of λ until the optimal value is reached. The resulted total cache space is used as an indicator for optimality. The minimal cost is achieved when $\sum_{i=1}^{H} s_i$ is equal to q. In order to use the distributive algorithm, we assume the proxies are cooperative, and they do follow the cost minimization protocol to determine the amount of cache contributed to the system. The protocol runs collaboratively with assistance from a proxy coordinator.

The coordinator first make an initial guess of the shadow price λ, and notifies the proxies. Each proxy reacts to the shadow price with a s_i obtained by Eq. (55), which is privately known to the proxy. Then, the coordinator updates the shadow price based on the total cache space contributed to the system. If the total cache space is more than required, that is, $\sum_{i=1}^{H} s_i > q$, the shadow price is set too high, and it should be reduced. If the cache supply is insufficient, the shadow price should be increased. The process

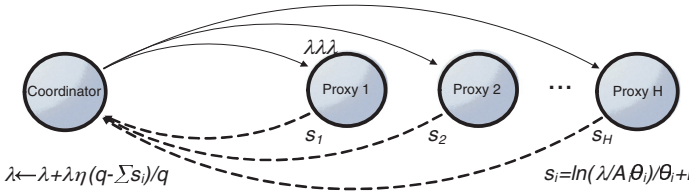


Fig. 5. Mechanism of the cost minimization protocol.

continues until the optimal value is achieved, where the total cache supplied matches the requirement, i.e. $\sum_{i=1}^{H} s_i = q$.

The remaining technical issue is how to update the shadow price according to the cache supplied. The updating rule should be selected carefully as it determines the effectiveness of the protocol. Since the problem is shown to exist only one minimum, one can use any standard numerical search method to find the optimal solution.

Figure 5 shows the mechanism of the cost minimization protocol. We adopt to a simple updating rule, which increase/decrease the value of λ in proportional to the difference between the desirable cache space q and the total contributed cache from the proxies. The updating rule of λ is

$$\lambda \leftarrow \lambda + \lambda\eta \left(\frac{q - \sum_{i=1}^{H} s_i}{q} \right). \tag{58}$$

The parameter, η, is a factor that controls the converging speed and the accuracy of the protocol. A large value of η is used initially to speed up the convergence, and it starts to decrease gradually in order to obtain an accurate solution. The protocol is executed periodically to ensure that the cost remains minimal after any join or leave of the proxies. In steady state, the λ leads to a cache allocation with minimal cost.

The solution of this simplified MinCost problem can be extended to the original problem with the cache constraints. The participating proxies react to the shadow price similarly as in the simplified MinCost problem. The only difference is that the proxy coordinator has an additional task to determine whether the cache constraints of the proxies are violated.

Consider the Eq. (47) in the KKT-condition, either μ_i^l equals zero or s_i equals zero. Similarly in Eq. (48), either μ_i^u equals zero or s_i equals $\hat{S}_i$. To solve the set of linear equations, we have to examine whether μ_i^l and μ_i^u are equal to zero. Assume both μ_i^l and μ_i^u are zero, the formulation of the original problem reduces to the simplified version. We apply the cost minimization protocol to obtain the best cache allocation for a total of q units of cache space. However, the resulted s_i may not satisfy the boundary constraints specified in Eq. (49). In that case, depending on the value of s_i, one of the μ_i^l and μ_i^u is not zero. If s_i is less than or equal to zero for certain proxy i, we are sure that this s_i has optimal value of zero, and the corresponding μ_i^l is not zero. The proxy is not eligible for contributing as the cost of supplying the cache is comparatively high. Similarly, if s_i is greater than $\hat{S}_i$, we are sure that the s_i of the proxy has optimal value of $\hat{S}_i$. This proxy should provide as much cache as possible since the cost is comparatively low. Thus, we can eliminate some proxies, whose value of s_i is known already, from the problem formulation and resolve the s_i for the remaining proxies. Note that the total required cache space q of the eliminated problem should be updated accordingly, by subtracting the $\hat{S}_i$ of the oversupplied proxies. The algorithm for the cost minimization protocol used by the coordinator is shown in Figure 6.

By the cost minimization protocol with a given fixed total cache quantity, the proxies can cooperatively allocate the best amount of cache space to achieve minimal cost.

Cost Minimization:

declare P = { 1, 2, ... , H}; *// indexes of proxy that it's s_i has not been determined yet*
declare $P^l = \{\}$; *// indexes of proxy that it's s_i is zero*
declare $P^u = \{\}$; *// indexes of proxy that it's s_i is $\hat{S}_i$*
while (true) **do**
  the new cache requirement $q' = q - \sum_{i \in P^u} \hat{S}_i$;
  // solve the Simplified MinCost Problem distributively with the cache requirement of q' among proxy $i \in P$
    // and get the optimal s_i for proxy $i \in P$
  $\lambda = 1$; *// initial guess of λ*
  while (true) **do**
    send λ to all proxies and receive $s_i = \frac{ln(\lambda \lhd A_i \theta_i)}{\theta_i} + b_i$;
    if $q' = \sum s_i$ **then**
      break; *// optimal s_i obtained*
    end if
    adjust λ according to $\sum s_i$;
  end while
  if $\forall i \in P, 0 \leq s_i \leq \hat{S}_i$ **then**
    break; *// end the while loop*
  end if
  declare $p^t = \{\}$; *// a temporary set*
  for each $i \in P$
    if $s_i \leq 0$ **then**
      $P^t = P^t \cup \{i\}$;
    end if
  end for
  if $P^t \neq \emptyset$**then**
    $P^l = P^l \cup P^t$;
    $P = P - P^t$;
    continue; *// next iteration of the while loop*
  end if
  for each $i \in P$
    if $s_i \geq \hat{S}_i$ **then**
      $P^u = P^u \cup \{i\}$;
      $P = P - \{i\}$;
    end if
  end for
end while

Fig. 6. Cost Minimization Protocol for the proxy coordinator.

3.3.2 *Optimal Cache Quantity Problem.* The next problem is to determine the optimal amount of cache quantity. The optimal cache quantity problem refers to the problem of finding the total quantity that results in maximum social utility. Let $M(q)$ be the minimum cost of providing q units of total cache. For each q, the value of $M(q)$ can be evaluated by solving the corresponding MinCost problem, using the cost minimization protocol. The OptQ problem can be formulated as

$$\textbf{OptQ:} \quad \max_{0 \leq q \leq \hat{Q}} \left[q \cdot P(q) - M(q) \right] \tag{59}$$

$$\text{where } \hat{Q} = \sum_{i=1}^{H} \hat{S}_i.$$

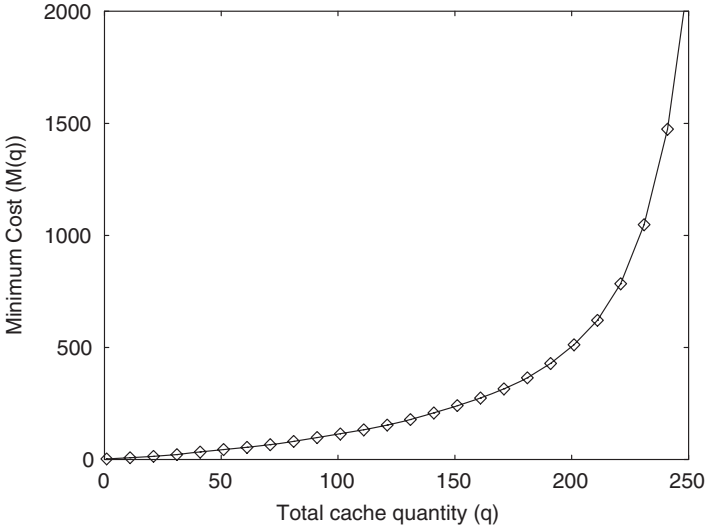


Fig. 7. A sample plot of minimum cost versus cache quantity q.

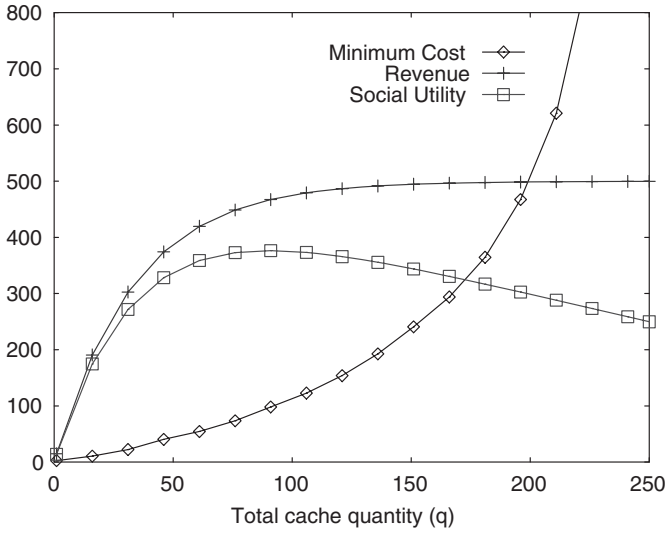


Fig. 8. A sample plot of social utility versus cache quantity q.

Obviously, the objective function depends on the variable q only, where $P(q)$ is a decreasing function of q and $M(q)$ is an increasing function of q (see Figure 7). In fact, the objective function may contain multiple maxima, depending on the cost functions and revenue function used in the system. Figure 8 plots the revenue, minimum cost and social utility with respect to cache quantity in the COPACC system. In this example, the social utility is calculated using the total-rewarded price, and the maximum is achieved when the cache quantity is around 75.

Since we do not have the close form solution for the MinCost problem, we cannot rely on any optimization method that involves derivative of the objective function. In order to find the optimal cache

quantity, we suggest to use direct search method, which is similar to the one used in the profit maximizing game. Pattern search with multiple initial guesses is a good approach to the optimal cache quantity problem.

In the pattern search method, an initial step size s is chosen and the search is initiated from a starting point q. The method involves the steps of exploration and pattern search. In the exploration step, it tries to probe the value of the social utility by increasing or decreasing the cache quantity. Let $q' = q$, the objective function is evaluated at $q'+s$. If the value increases, then q' is updated to $q'+s$. Otherwise, the function is evaluated at $q' - s$. If the value increases, q' is updated to $q' - s$. In case both of them fail in the test, the original value of q' is retained. An exploration is said to be successful if the function valued at q' is higher than q by a predetermined amount. The pattern search algorithm starts from a quantity q. The exploration step is made in q. If the exploration fail, the step size is reduced by a factor of r, that is, $s \leftarrow rs$. Otherwise, a new base point of q is established according to the exploration. The search continues until the cache quantity q converged. To avoid trapping in the local maxima at the steady state, the proxy coordinator should periodically probe the system to see if the cache quantity is still optimal.

The solution of the optimal cache quantity problem is indeed the optimal quantity for the original utility maximizing problem. It guarantees maximal social utility in the network. Moreover, the optimal cache space supplied by each individual proxy is determined through the cost minimization protocol, and the price is set according to the price function.

In this section, we have presented the utility maximizing game, which aims at maximizing the social welfare of the proxies in the network. The performance of the three resource allocation games are being evaluated in the next section.

4. PERFORMANCE EVALUATION

The main focus of this section is to evaluate the effectiveness of the proposed revenue-rewarding scheme in encouraging the participation of the NSP and the proxies. We show that the scheme can provide a strong incentive for different entities to join the system. We have examined the use of revenue-rewarding in the three resource allocation games, that is, noncooperative game (*NonCoop*), profit maximizing game (*ProfitMax*), and utility maximizing game (*UtilMax*). We have studied the net profit of the NSP as well as the social utility of the proxies in the games. We have also compared the individual utility of the proxies in each game. The results demonstrate that under different resource allocation games, different level of incentive are given to different entities in the network. Moreover, an economical cache supply is achieved in the ProfitMax and the UtilMax, where the "good" peers, which have cheaper cost in providing cache, are retained to participate in the system.

Unless otherwise specified, the following default settings were used in the evaluation. We considered a proxy caching network consisting of five proxies, which operated under the same NSP. The revenue function was approximated by the experimental results from the cost reduction in the COPACC system. Each proxy was assigned with an exponential cost function. The parameters used for the cost and revenue functions are shown in Table II, and the corresponding functions are plotted in Figure 9. Note that proxy 1, 2 and 3 have similar cost function with different level of expensiveness. Proxy 4 supplies cache with low initial cost but high variable cost. In contrast, proxy 5 has high fixed cost but low variable cost. For simplicity, each proxy has the same storage capacity. Lastly, the marginal-rewarded pricing was applied in the non-cooperative game and the utility maximizing game.

The evaluation of different rewarding schemes were done based on mathematical simulation, which was implemented in MATLAB 7.0. The built-in Pattern Search Tool, provided in the Genetic Algorithm and Direct Search Toolbox of MATLAB, was used to solve the search problem.

Table II. Parameters Used in the Resource Allocation Game.

Proxy i	A_i	θ_i	b_i	S_i	Cost
1	10	0.06	0	50	Normal
2	10	0.06	15	50	Low
3	15	0.08	0	50	High
4	8	0.12	10	50	Low for small quantity, high for large quantity
5	10	0.04	0	50	High for small quantity, low for large quantity

A	θ	b
15	0.03	0

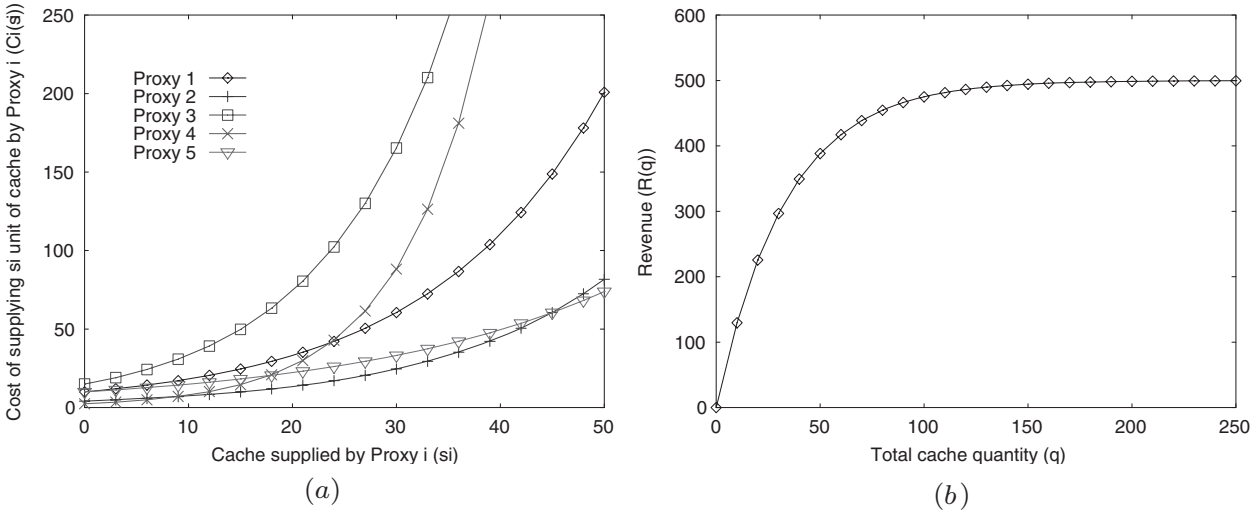


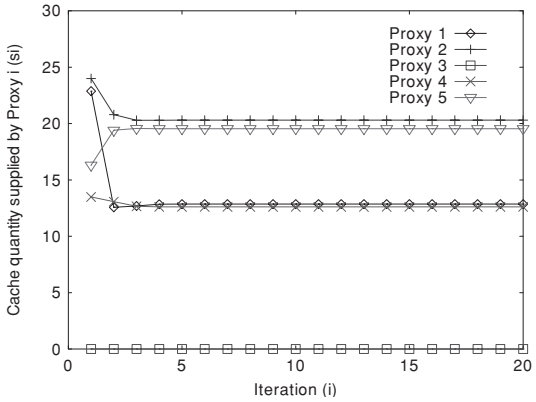
Fig. 9. Cost and revenue functions being used in the evaluation.

4.1 Convergence

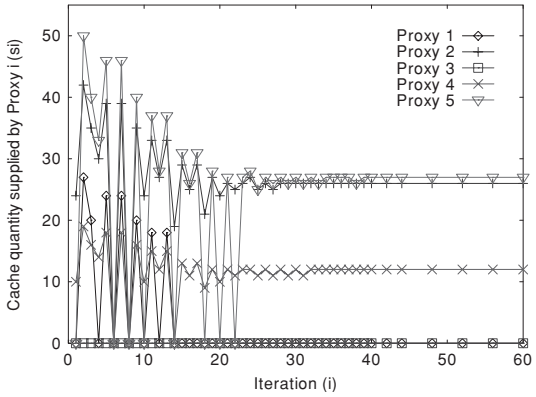
The first issue we are looking at is the convergence. It is a basic requirement that the resource allocated by the proxies should converge in each game. We analyze the behavior of each game based on the cache contributed at the steady state. Figure 10 depicts the quantity of cache supplied by the five proxies in each iteration. It demonstrates that all three resource allocation games converge to a steady state after a number of iterations. It is observed that the NonCoop converges fast, while it takes more iterations for the ProfitMax and the UtilMax to stabilize. For the ProfitMax and the UtilMax, the speed of convergence is depended on the direct search method implemented. In the pattern search method, a large step size is used initially, therefore, the cache quantity varies dramatically at the beginning. As the step size decreases gradually, the cache quantity stabilizes and converges to the optimal value. Fortunately, the converging speed does not affect the performance of the game. As long as the search method converges to an optimal value, the corresponding objective function is optimized, and the goal is achieved.

4.2 Participation Incentive

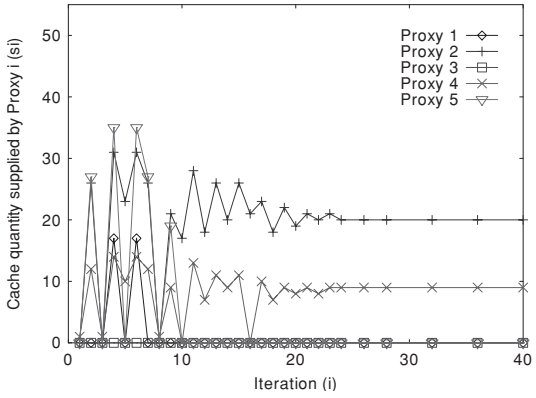
The primary design objective of this work is to present an incentive mechanism to encourage participation of the entities in the network. The evaluation results show that this incentive mechanism applied in the COPACC system provides a strong incentive for both the NSP and the proxies. In addition, the incentive for the NSP is different from that of the proxies. The NSP is motivated by the attractive net profit to setup the COPACC system in its network, while the proxies are encouraged by the positive net



(a) Non-cooperative Game

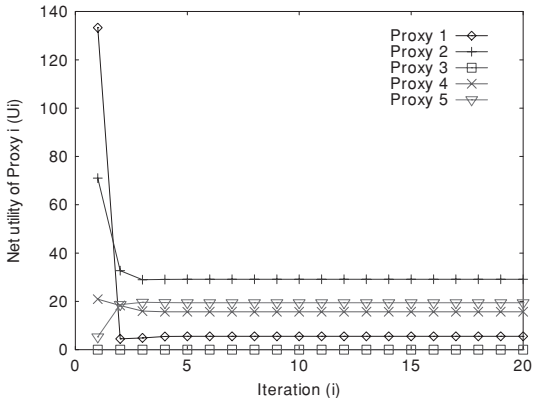


(b) Profit Maximizing Game

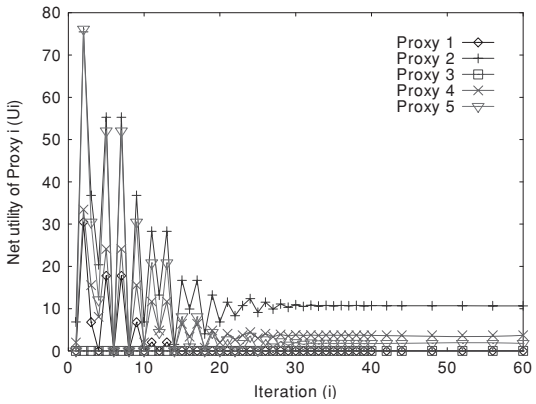


(c) Utility Maximizing Game

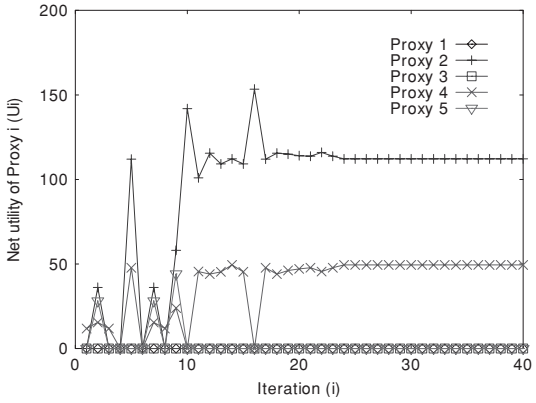
Fig. 10. Quantity of cache supplied by each proxy.



(a) Non-cooperative Game



(b) Profit Maximizing Game



(c) Utility Maximizing Game

Fig. 11. Net utility of each proxy.

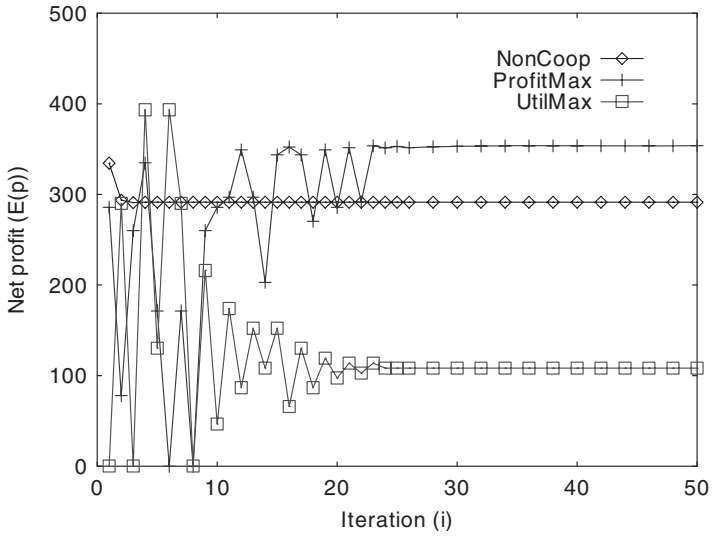


Fig. 12. Net profit in each resource allocation game: NonCoop, ProfitMax and UtilMax.

utility to supply cache to the system. Hence, in this subsection, we evaluate the two incentives in the three resource allocation games.

4.2.1 *Net Profit.* Figure 12 plots the net profit of the NSP in the three resource allocation games. As we expected, the profit maximizing game generated the highest net profit among the three games. The net profit of the ProfitMax was 352.8, which was 21% higher than that of the NonCoop, and it was 2.26 times of the net profit in the UtilMax. The UtilMax performed the worse because it tried to maximize the benefit in other dimension, social utility, by trading off the net profit.

We also evaluated the performance of the three games under systems having different revenue function. All the revenue functions had the same ratio of A/θ, but the value of θ varied from 0.01 to 0.08. Remember that the larger the θ, the higher the revenue is for the same quantity of cache. The net profit of the NSP in the systems with different revenue function is plotted in Figure 13. The result further illustrates that the ProfitMax achieves the highest net profit among the three games.

We are also interested in the amount of rewards given to the proxies. The total reward paid to the proxies in the ProfitMax is 73.6, which is only 17% of the total revenue. Most of the revenue become the net profit for the NSP. Thus, we conclude that the profit maximizing game provides a strong incentive for the NSP to setup the revenue-rewarding scheme in the COPACC system.

4.2.2 *Social Utility.* In this subsection, we evaluate the social utility in different games. Figure 11 demonstrates the individual utility of the proxies under different games. Only the proxies having positive net utility supplied cache to the system. It illustrates that the positive net utility provides an initiative incentive to the rational proxies to cooperate.

Figure 14 shows the social utility of all proxies in the three games. The social utility achieved by the UtilMax was the highest among the three. In this example, the social utility of the UtilMax was 161.7, which was much higher than that of the ProfitMax (16.1) and the NonCoop (69.9). In Figure 15, the social utility of different games were examined under the systems with different revenue function. The result also agrees that the UtilMax outperforms other games in utility maximization.

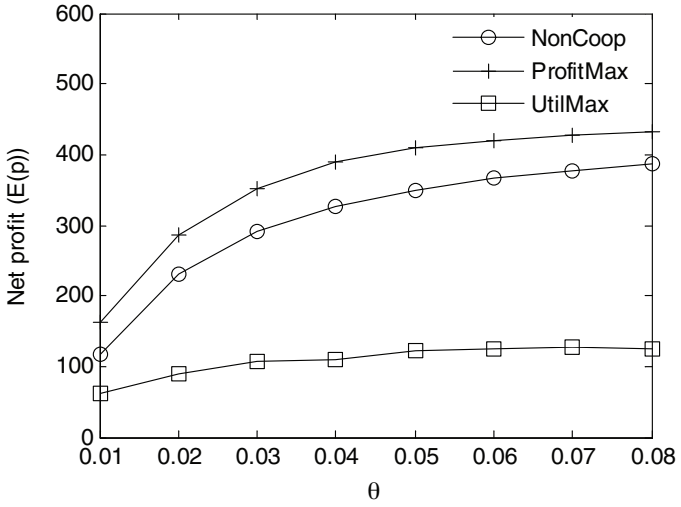


Fig. 13. Net profit of the NSP in the system with θ varied from 0.01 to 0.08.

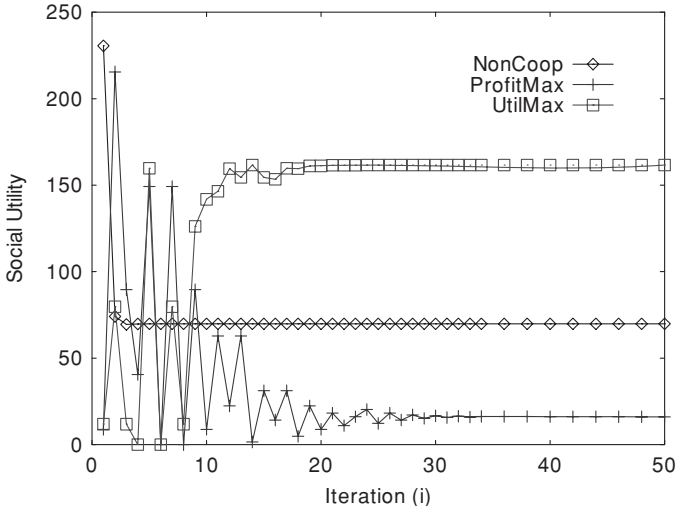


Fig. 14. Social utility in each resource allocation game: NonCoop, ProfitMax and UtilMax.

Since the ProfitMax is designed to maximize the net profit by trading off the social utility, the utility achieved in the ProfitMax is the lowest. Note that the social utility of the ProfitMax and the NonCoop decreased with an increase of θ. It shows that more utility is traded for the net profit when the θ is large.

We are also interested in the total reward received by the proxies and the cost in providing the cache. As the UtilMax performs better in utility maximizing, we focus this specific game. The total reward granted to the proxies was 182.1, and among those, 20.4 (around 11% of the reward) was used to maintain the cache. The remaining of the reward (about 89% of the total) was owned by the proxies. When we consider the return on investment, which is defined as the ratio between the utility and the cost, that is, 7.9, it can definitely encourage the proxies to participate. In contrast, the return on

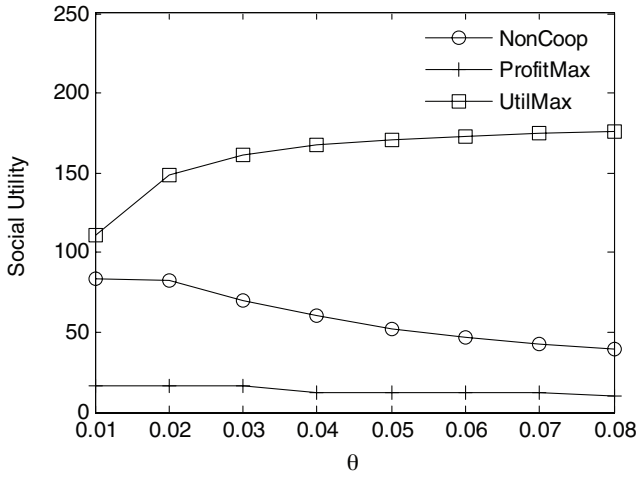


Fig. 15. Social utility in the system with θ varied from 0.01 to 0.08.

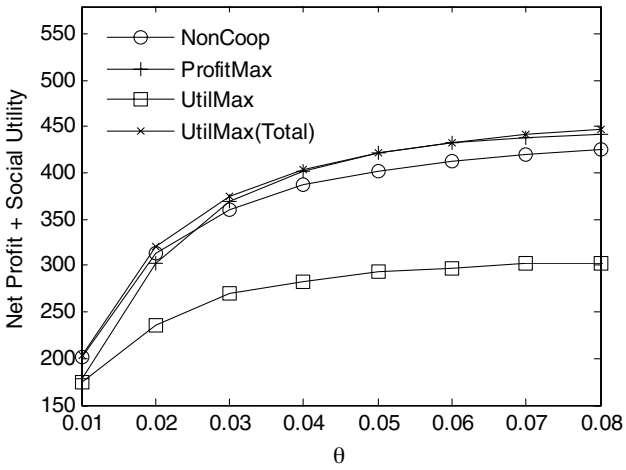


Fig. 16. Sum of the social utility and the net profit in each resource allocation game with 5 proxies where θ varied from 0.01 to 0.08.

investment of the ProfitMax was 0.28. Thus, under the UtilMax, the proxies have a strong incentive to contribute cache in the system.

4.2.3 *Discussion.* In fact, the ProfitMax and the UtilMax have different design objective: the former one optimizes the net profit, while the later one optimizes the social utility. The key discussion here is which approach, the ProfitMax or the UtilMax, is better. There is no strict answer to this question. It depends on the objective of implementing the incentive mechanism, and whether to benefit the NSP or the proxies. There is a trade-off between the net profit and the social utility.

Indeed, one can compare the performance of the ProfitMax and the UtilMax by looking at the sum of the social utility and the net profit as shown in Figure 16. It can be seen that the UtilMax is not performing well as compared to the ProfitMax and the NonCoop. The reason is that under marginal-rewarded pricing, the price of resource drops quickly as the quantity increases. As a consequence,

Table III. Cost per Unit Cache Supplied by the Proxies in Different Game.

	Cache Supplied			Cost per Unit Cache		
	NonCoop	ProfitMax	UtilMax	NonCoop	ProfitMax	UtilMax
Proxy 1	13	0	0	1.68	–	–
Proxy 2	21	26	20	0.68	0.74	0.67
Proxy 3	0	0	0	–	–	–
Proxy 4	13	12	9	0.88	0.85	0.79
Proxy 5	20	25	0	1.11	1.09	–
Overall system	67	63	29	1.04	0.9	0.71

the UtilMax tries to keep a high price by avoiding large quantity of cache supplied to the system. Thus, only a small revenue is obtained, and the achievable sum of the social utility and the net profit becomes less. We also examined the UtilMax using the total-rewarded pricing, in which the net profit of the NSP is always zero. The UtilMax(Total) showed in Figure 16 demonstrates that by using total-rewarded pricing, it achieves the best performance. In fact, we can show that the social utility obtained in UtilMax(Total) is equivalent to the maximal achievable sum of the social utility and the net profit. Consider the objective function of maximizing the sum of the social utility and the net profit, that is

$$\max_{0\le s_i\le \hat{S}_i}\left[E(q)+\sum_{i=1}^{H}U_i(s_i)\right]=\max_{0\le s_i\le \hat{S}_i}\left[R(q)-\sum_{i=1}^{H}C_i(s_i)\right]. \tag{60}$$

Since $P(q) = R(q)/q$ in the total-rewarded pricing, the optimization objective of the UtilMax(Total) is equivalent to the above objective. Hence, it is the maximal achievable social utility.

In general, the ProfitMax is suitable for the system that contains a centralized authority, like the NSP, and the UtilMax is good for a non-coordinated P2P-like application. By applying the revenue-rewarding scheme, the network entities are stimulated to participate in the system.

4.3 Cost Effectiveness

It can be seen in Figure 10 that not all the proxies playing in the resource allocation game participate in the system at the steady state. In fact, all the proxies in the network used the same strategy to decide the amount of cache to contribute, excepted that they had heterogenous cost function. In this subsection, we study how the cost function influences the behavior of the proxies. We show that only the cost-effective proxies contribute cache to the system.

Table III lists the quantity of cache supplied in each game. The quantity of cache admitted in each game was different. The NonCoop admitted the largest amount of cache, while the UtilMax admitted the smallest. It is due to the underlying game rule, which induces the "best" quantity (or price) of cache for the system. Clearly, the overall cost for a unit cache in the UtilMax should be the lowest because it equips with a cost minimization protocol to achieve the lowest cost. In addition, the UtilMax tends to employ few proxies, which have low cost among the proxies, to participate. Hence, we conclude that the UtilMax provides a cost-effective resource supply to the system.

We further investigate the cost of maintaining the cache for each individual proxy, which is listed in Table III. Actually, the three resource allocation games implicitly choose the best proxies to cooperate. We observed that Proxy 3 was rejected in all the games because its cost was the most expensive. Proxy 2 had a low cost function, thus, it contributed cache in all the games. Proxy 4 only contributed small amount of cache as the cost for large quantity was high. In contrast, Proxy 5 supplied large quantity due to the lowest cost. These results illustrated a desirable property of the system: the game automatically admits the best set of proxy to contribute, depending on the heterogenous cost function adopted by the proxies.

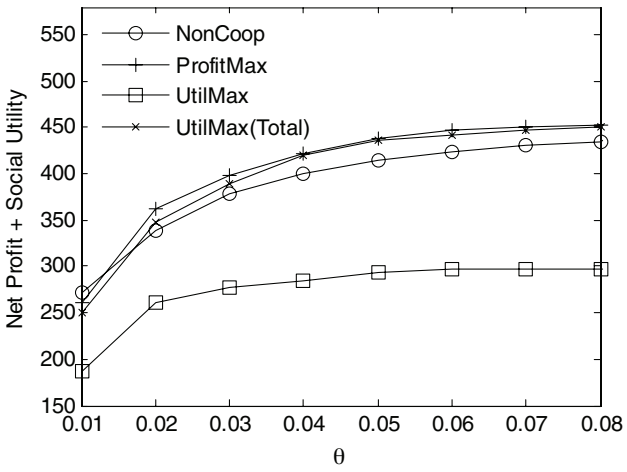


Fig. 17. Sum of the social utility and the net profit in each resource allocation game with 20 proxies where θ varied from 0.01 to 0.08.

4.4 Scalability

In this subsection, we examine the scalability issue of the proposed revenue-rewarding scheme. A graph similar to Figure 16, but have number of proxies increased to 20, is plotted in Figure 17. Note that the five categories of proxy shown in the Table II are preserved in this simulation. The comparison of these two figures demonstrates that the overall gain of the system increases with more proxies participating in the system, especially for the system having small θ. Recall that the small θ implies more quantity of cache is required to obtain the same amount of revenue. And large number of proxies means they can supply cache with less cost. Thus, it takes advantage in our revenue-rewarding scheme. For instance, when θ equals 0.02, the overall gain of RevMax and UtilMax(Total) are 362.6 and 348.3, which are 19.6% and 8.4% higher than that of 5 proxies scenario.

We then look into the system with θ equals 0.03, and we plot the overall gain against the number of proxies in Figure 18. As we expected, the overall gain increases with the number of proxies in different cache allocation game. Obviously, large cooperating system can provide a better choice of cache allocation (in terms of operational cost) among the proxies. In steady state, only the proxies that provide cost-effective cache are remained. Thus, the performance of the large system is often better.

In summary, the evaluation results demonstrated that the proposed revenue-rewarding scheme applied in incentive-based COPACC system provides a strong incentive for both the NSP and the proxies to participate in the system, and the gaming approach yields a cost-effective resource allocation from the proxies.

5. RELATED WORK

There has been a lot of research work on multimedia streaming and video-on-demand services, from fault-tolerance [Golubchik et al. 1998], to dynamic replication [Lie et al. 2000], I/O redution techniques [Golubchik et al. 1996; Lau et al. 1998]. In the past few years, researchers consider how to provide multimedia services in a P2P environment. Also, recently a lot of efforts have been made to address the problem of *free-riding* and *tragedy of the commons* [Hardin 1968] in the cooperative network. Various incentive mechanisms have been proposed to encourage the selfish nodes to cooperate by sharing their own resources with the community. In particular, *differential service-based incentive* has been well studied in the literature. Under such scheme, the peers that contribute more resource receive better

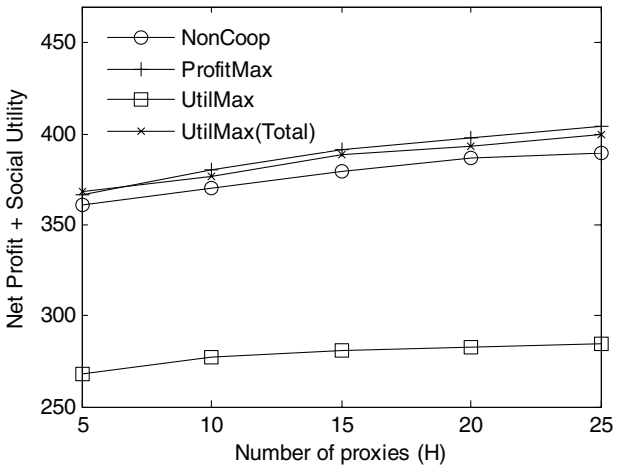


Fig. 18. Sum of the social utility and the net profit in each resource allocation game with different number of proxies where θ equals 0.03.

quality of service, while the selfish peers contributing less are discriminated. Buragohain et al. [2003] have suggested a game theoretic framework to improve the system's performance by eliminating non-cooperative users. Ma et al. [2004a, 2004b, 2006] proposed a service differentiated scheduling policy that allocates bandwidth according to the peer's contribution. It showed that the social welfare is maximized when all peers have the same contribution value. Habib and Chuang [2004] have suggested to differentiate the service in peer selection process of P2P streaming. By using the rank-based peer-selection mechanism, the contributors are rewarded with flexibility and choice in peer selection.

Another well-known incentive model is *Reputation-based incentive*. The reputation reflects a peer's overall contribution to the network. The peers with high reputation value have extra privilege over the others. Reputation can also be used to identify how reliable and trustful a peer is [Kazaa]. Gupta et al. [2003] suggested two alternative computation mechanisms to compute dynamically the reputation score of each peer in the network. The peers having high reputation is more likely to obtain better service. Based on the reputation system, Ye and Makedon [2004] suggested how to monitor the users behavior in a streaming network, and it tried to maintain a satisfactory level of service for the collaborative peers. Feldman et al. [2004] used the generalized prisoner's dilemma to model the system, and they proposed a family of incentive techniques. Similar approach was adopted in Jiang et al. [2003, 2005]. They used iterated prisoner's dilemma to model the peers' interaction, and proposed a reputation-based trust model with incentive mechanism incorporated.

Our work is different from the above schemes that we follow the *Contribution reward-based incentive* approach, where monetary reward is given to the peers in proportional to their contribution. Golle et al. [2001] have proposed a micro-payment mechanism to reward users for upload. The results demonstrated that the users are encouraged not only to upload files, but also to share new files to the P2P system. In Tamilmani et al. [2004], a credit-based trading mechanism have been presented for P2P file sharing. In the model, peers ,who exchange pieces of a file, use a pairwise currency to reconcile trading differences with each other. The monetary scheme provides a clean economic model for the incentive mechanism. However, it is argued to be impractical in P2P system, where a reliable accounting infrastructure has to be established to track the transactions between every peers. In contrast, its application in our coordinated system with centralized authority is viable because the payment is made in a single direction only, that is, from the NSP to the proxies. Wang and Li [2003] also considered revenue rewarding to

the contributed peers. They modeled the P2P system as a Cournot Oligopoly game and used control-theoretic to maximize individual net gain. System performance requirements, like storage utilization and bandwidth stress, were considered as the global desirable properties. Our work is different from it as we model the system as a Stackelberg game, and we focus on maximizing the net profit and social utility in the network.

Our work relies on pricing to regulate users' contribution. The pricing aspects of P2P network have received much attention recently. Turner and Ross [2004] presented a currency model that can be used to exchange peer resources. Based on this paradigm, Adler et al. [2004] suggested how to define the price for the multimedia content in a P2P network. A charge-per-usage pricing model was studied in Basar and Srikant [2002], where the users are charged for their bandwidth usage. By analyzing the strategies of the users toward the price, the optimal price is computed to maximize the revenue of the service provider. It also showed that the pricing scheme provides an incentive for the service provider to increase the network capacity. Campos-Nanez and Patek [2003] proposed an adaptive pricing strategy that adjusts the price in realtime, and the objective is to maximize the revenue for the service provider. Their work assumed *prior* knowledge about the user arrival pattern, and thus it may not be appropriate for the P2P system with highly dynamic nodes. On the other hand, He and Walrand [2005] proposed a fair revenue-sharing policy to distribute profit between cooperative providers. The fair allocation policy encourages collaboration among the providers, and hence produces higher profit for all the providers. We also adopt the proportional fairness in rewarding the revenue to the proxies. Gupta and Somani [2004] described a pricing strategy for carrying out lookups in P2P networks. We apply similar approach to reward the contributors in the cooperative network, but suggest different pricing strategy to achieve different objective.

6. CONCLUSION

In this article, we introduce a revenue-reward mechanism to address the incentive issue of a cooperative proxy caching system for media streaming. We study the problem of what motivates each proxy to provide cache space and how much cache space should be allocated. We propose a revenue-rewarding scheme to encourage proxy cooperation. In this scheme, credits are granted to the proxies for their contribution. A game theoretic model is used to analyze the interactions between proxies under different resource allocation games. It is shown that no system-wide property is achieved under a non-cooperative environment. Thus, we propose two *cooperative resource allocation games* that lead to two different optimal situations: maximized net profit and maximized social welfare. Both centralized and distributed algorithms are presented for the games to achieve different optimal situation. We also carried out extension simulations to show the merits of our distributed algorithms. In general, a significant improvement in terms of performance and cost-effectiveness of resource can be allocated when the cooperative schemes are used. Note that the proposed pricing and incentive mechanisms can be implemented via the micro-payment methods Adler et al. [2004], which can faciliate the transactions and deployment. Currently, we are working on the issue of cheat-proof mechanism so as to detect and avoid peers to check their contributions.

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