On the Auction-Based Resource Trading for a Small-Cell Caching System

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***Abstract*— In this letter, we propose an auction-based resource trading scheme between a network service provider (NSP) and multiple content providers (CPs). The NSP is in charge of a number of small-cell base stations (SBSs), while each CP provides content downloading services to its affiliated mobile users (MUs). By treating the SBSs as a kind of resources, the NSP leases SBSs to the CPs for caching their popular contents, thereby reducing the downloading latency of the MUs. We first establish the utility functions of the NSP and CPs. Then, we maximize the utilities of both sides by formulating an iterative auction problem, in which the NSP (auctioneer) communicates with the CPs (bidders) in an iterative manner for achieving optimal price and resource allocations. Furthermore, to avoid being cheated from the CPs, we adopt an ascending-bid auction mechanism such that the CPs do not have motivations to cheat the NSP for a lower price. Numerical results show that our proposed scheme can effectively allocate SBSs to the CPs and prevent each CP from cheating the NSP for gaining a higher profit.**

***Index Terms*— Small-cell caching, cellular networks, auction game, ascending-bid auction, cheating-proof.**

I. Introduction

NOWADAYS, the burst of mobile data brings the increasing volume of traffic caused by the duplicated download of a small portion of popular contents. To solve this problem, we propose a method of caching at the edge of mobile networks, reducing the transmission latency and mitigating the network congestion.

Shanmugam *et al.* [1] propose the idea of equipping the cellular network with small-cell base stations which can minimize the transmission delay to the greatest extent. Although optimizing data placement has always been a intensive research topic for wireless caching, the system design still involves many issues besides data placement optimization.

It is interesting to consider the topic as the resource trading problem in caching systems from the economic point of view aiming to maximize the profit. The commercialized caching system may contain network service providers (NSP), content providers (CP), and mobile users (MU). The NSPs own the SBSs, while the CPs, e.g., YouTube, provide content downloading services to the MUs. The NSP leases its SBSs to the CPs so the CPs can provide a better service to the MUs by caching popular contents at the SBSs with a reduced transmission latency.

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In this letter, we introduce auction theory to this commercialized caching system. Auction game has already been widely adopted in wireless communications, e.g., spectrum sharing [2]. To the best of authors knowledge, our work is the first of its kind to introduce auction game to the pricing and resource allocation for a small-cell caching system, which is different from the existing ones adopting Stackelberg game [3]–[5] and contract game [6].

In particular, we first develop a profit model of our caching system and investigate the profits gained by the NSP and the CPs from SBS trading. Then we maximize the profits of both sides by formulating an iterative auction problem, in which the NSP communicates with the CPs in an iterative manner for achieving an optimal price and resource allocations. Next, to avoid being cheated from the CPs, an ascending-bid auction mechanism is adopted such that the CPs have no motivations to cheat the NSP for a lower price. Numerical results validate the effectiveness of our proposed scheme for resource allocation and preventing the CPs from cheating in the auction process.

The rest of this letter is organized as follows. We describe the system model in Section II and establish the auction framework in Section III. Numerical results are detailed in Section IV, while our conclusions are provided in Section V.

II. System Model

A. Network Model

The caching system consisting of one NSP, V CPs which are denoted by $\mathcal{V}_1, \cdots, \mathcal{V}_V$, and multiple MUs. The wireless downlink channels spanning from the SBSs to the MUs are independent and identically distributed (*i.i.d.*), and modeled as the combination of path-loss and Rayleigh fading. Also, we assume that the SBSs are distributed according to a homogeneous PPP (HPPP) Φ of intensity λ which represents the number of the SBSs per unit area. We model the distribution of the MUs as an independent HPPP Ψ of intensity ζ.

We consider the steady-state of a saturated network, where all the SBSs keep on transmitting data in the entire frequency band allocated. Thus, the signal-to-interference-plus-noise ratio (SINR) at a typical MU from an SBS located at x is $\rho(x) = \frac{Ph_x\|x\|^{-\alpha}}{\sum_{x'\in\Phi\backslash x} Ph_{x'}\|x'\|^{-\alpha}+\sigma^2}$, where P is the transmission power of an SBS, h_x is the channel gain between the SBS located at x and the MU, σ^2 is the variance of received noises, and α is the path-loss exponent. The typical MU is considered to be covered by an SBS located at x as long as $\rho(x)$ is no lower than a pre-set SINR threshold δ, i.e., $\rho(x) \geq \delta$.

B. Popularity and Preferences

Denote by $\mathcal{F} = \{\mathcal{F}_1, \mathcal{F}_2, \cdots, \mathcal{F}_F\}$ the file including F files, where each file contains an individual piece of content, e.g., movies, which is frequently requested by the MUs. The

MUs make requests of the f-th file $\mathcal{F}_f$, $f = 1, \cdots, F$ independently, with the probability of p_f. Generally, $\mathbf{p}$ can be modeled by the Zipf distribution [7] as

$$p_f = \frac{1/f^\beta}{\sum_{j=1}^{F} 1/j^\beta}, \quad \forall f, \tag{1}$$

where the exponent β is a positive value, characterizing the content popularity. A higher β corresponds to a higher content reuse, where the most popular files account for the majority of download requests. From Eq. (1), the file with a smaller v corresponds to a higher popularity.

We assume that MUs are affiliated with a certain NSP, while they are the content service subscribers of different CPs. Some CPs may have more MU customers, i.e., these CPs are more popular than others. For example, most of the MUs in certain area may be affiliated with YouTube for video resources. The preference distribution among the V CPs is denoted by $\mathbf{q} = [q_1, q_2, \cdots, q_V]$, where q_v, $v = 1, \cdots, V$, represents the probability that an MU prefers to download contents from $\mathcal{V}_v$. The preference distribution $\mathbf{q}$ can also be modeled by an independent Zipf as

$$q_v = \frac{1/v^\gamma}{\sum_{j=1}^{V} 1/j^\gamma}, \quad \forall v, \tag{2}$$

where γ is a positive value, characterizing the preference of the CPs. A higher γ corresponds to a higher probability of accessing the most popular CPs.

C. Caching Procedure

There are two stages. Firstly, the CPs ask the NSP for the portation of SBSs it wants. Secondly, the MUs connect to the SBSs for downloading contents. If an MU affiliated with $\mathcal{V}_v$ cannot obtain the required file from the nearby SBS rented by $\mathcal{V}_v$, its request will be redirected to the central server of $\mathcal{V}_v$ located at the backbone network, triggering a long-distance communication. In specific, we denote by $\boldsymbol{\tau} = [\tau_1, \tau_2, \cdots, \tau_V]$ the fraction vector of the rented SBSs, where τ_v represents the fraction of the SBSs that are rented by $\mathcal{V}_v$, $\forall v$. We assume that the SBSs rented by each CP are uniformly distributed. Hence, the SBSs allocated to $\mathcal{V}_v$ can be modeled as a "thinned" HPPP Φ_v with intensity $\tau_v \lambda$.

Furthermore, we assume that each SBS can cache at most Q video files, and we have $Q \leq F$. In this case, it is natural to assume that each of the rented SBSs will be required to cache the Q most popular video clips $\mathcal{F}_1, \cdots, \mathcal{F}_Q$. When an MU affiliated with $\mathcal{V}_v$ demands a file $\mathcal{F}_f$, we define a successfully download event, namely, $\mathcal{E}_{v,f}$, which represents this MU can directly obtain $\mathcal{F}_f$ from one nearby SBS rented by $\mathcal{V}_v$. Regarding the probability $\Pr(\mathcal{E}_{v,f})$ of the event $\mathcal{E}_{v,f}$, we have the following theorem.

Theorem 1: The probability $\Pr(\mathcal{E}_{v,f})$ of the event $\mathcal{E}_{v,f}$, $\forall v$, f, can be expressed as

$$\Pr(\mathcal{E}_{v,f}) = \begin{cases} \dfrac{\tau_v}{(1-\tau_v)C(\delta,\alpha)+\tau_v A(\delta,\alpha)+\tau_v} & f \leq Q, \\ 0 & F \geq f > Q, \end{cases} \tag{3}$$

where α is the path-loss exponent, δ is the threshold for the received signal-to-interference-plus-noise ratio (SINR), i.e., if an MU $\mathcal{M}$ receives signals from the SBS $\mathcal{B}$ with an SINR larger than δ, $\mathcal{M}$ is considered to be covered by $\mathcal{B}$. Furthermore, in Eq. (3), we have $A(\delta,\alpha) \triangleq \frac{2\delta}{\alpha-2}\ {}_2F_1\left(1, 1-\frac{2}{\alpha}; 2-\frac{2}{\alpha}; -\delta\right)$, $C(\delta,\alpha) \triangleq \frac{2}{\alpha}\delta^{\frac{2}{\alpha}} B\left(\frac{2}{\alpha}, 1-\frac{2}{\alpha}\right)$, where ${}_2F_1(\cdot)$ in the function $A(\delta,\alpha)$ is the hypergeometric function and the Beta function in $C(\delta,\alpha)$ is formulated as $B(x,y) = \int_0^1 t^{x-1}(1-t)^{y-1}\mathrm{d}t$.

Proof: The proof can be readily obtained by following the similar method in [5]. ■

III. Auction-Based Resource Trading

We consider the profits of the NSP and the CPs obtained from the small-cell caching system as the utility functions. The average profit is developed based on stochastically geometrical distributions of the network nodes in terms of per unit area times unit period $(/UAP)$, e.g., $/month \cdot km^2$.

A. Utility Function of the NSP

We denote by S^{rent} the revenue gained by the NSP from leasing its SBSs, and by S^{cost} the cost for maintaining these SBSs. Therefore, the profit of the NSP, denoted by S^{NSP}, can be expressed as $S^{\text{NSP}} = S^{\text{rent}} - S^{\text{cost}}$, and we have

$$S^{\text{rent}} = \sum_{v=1}^{V} S_v^{\text{rent}}, \text{ and } S^{\text{cost}} = \sum_{v=1}^{V} \lambda c \tau_v, \tag{4}$$

where S_v^{rent} is the revenue from the rent of the CP $\mathcal{V}_v$, and c is the unit cost of the NSP for maintaining each SBS. The detailed calculation on S_v^{rent} will be discussed later.

B. Utility Function of a CP

The revenue of each CP comes from providing fast downloading services to the MUs due to the local caching system. Assume that there are average K files requested by each MU during a unit period. Then for the revenue of the CP $\mathcal{V}_v$, denoted by S_v^{cache}, we have

$$S_v^{\text{cache}} = \sum_{j=1}^{F} K p_j q_v \zeta \Pr(\mathcal{E}_{v,j}) s^{\text{ld}}, \tag{5}$$

where s^{ld} is the income gained by the CP for providing the local downloading of a file requested by one of its MUs. Then the profit gained by $\mathcal{V}_v$, denoted by S_v^{CP}, can be expressed by

$$S_v^{\text{CP}} = \sum_{j=1}^{F} K p_j q_v \zeta \Pr(\mathcal{E}_{v,j}) s^{\text{ld}} - S_v^{\text{rent}}. \tag{6}$$

C. Iterative Auction Process

At the beginning of the auction process, the NSP will announce a initial price s to the CPs for renting each SBS and set this price to be the unit cost c. When a CP $\mathcal{V}_v$ bids for the SBSs, it submits to the NSP its demand of the resources, i.e., the fraction of the SBSs τ_v. From the NSP's perspective, the auction strategy needs to find the optimal price that maximizes S^{rent}. For each CP $\mathcal{V}_v$, $\forall v$, the strategy needs to derive the optimal τ_v for maximizing S_v^{CP}. An iterative auction process is thus proposed as follows.

In each iterative process, the CPs $\mathcal{V}_v$, $\forall v$, submits their bids, i.e., the fraction of the resources (SBS) τ_v wanted, to the NSP. At the NSP side, it will sum all the bids up for checking if

TABLE I
THE ITERATIVE AUCTION FOR PRICING AND RESOURCE ALLOCATION

Algorithm 1 :

Input: c, s_Δ, s^{ld}, K, λ, ζ, p_f, q_v, and $\Pr(\mathcal{E}_{v,f})$, $\forall v, f$.
Output: $\tilde{\tau}_v^T$, $\tilde{S}_v^{\text{rent},(T)}$, $\forall v$.
Initialization: $s^{(1)} = c$, $\tau_v^{(0)} = 0$, $\forall v$.
Steps:
(1) The NSP announces the price $s^{(t)}$ at the t-th iteration to all the CPs;
(2) Each CP $\mathcal{V}_v$ computes $\tau_v^{(t)} = \arg\max S_v^{\text{CP}}$ and submits it to the NSP;
(3) The NSP collects $\tau_v^{(t)}$, $\forall v$, and sums them up to obtain $\tau^{(t)}$;
(4) In the case of $\tau^{(t)} > 1$, the NSP calculates $\tilde{\tau}_v^{(t)}$ and $\tilde{S}_v^{\text{rent},(t)}$, $\forall v$, sets $s^{(t+1)} = s^{(t)} + s_\Delta$ and $t = t+1$, and goes to Step 1;
(5) In the case of $\tau^{(t)} \le 1$ at the T-th iteration, the NSP calculates the final resource allocation $\tilde{\tau}_v^T$ and price $\tilde{S}_v^{\text{rent},(T)}$, announces them to the CPs, and terminates the auction process.

the requested resources are greater than the available ones, and adapt the price accordingly. We denote by s the price announced by the NSP for leasing one of its SBSs. Then to the CP $\mathcal{V}_v$, it sets $S_v^{\text{rent}} = \lambda s \tau_v$ when calculating its profit S_v^{CP}.

At the beginning of the auction, the initial price can be set to $s^{(1)} = c$. Without loss of generality, we focus on the t-th iteration of the auction process. We assume that the auction completes at the T-th iteration. It can be verified that $\mathcal{V}_v$'s utility function S_v^{CP} is concave regarding τ_v. Hence, given a price $s^{(t)}$ offered by the NSP, the CP $\mathcal{V}_v$, $\forall v$, can obtain the optimal resource allocation at the t-th iteration $\tau_v^{(t)}$ by taking the derivative of S_v^{CP} over τ_v and letting $\frac{\partial S_v^{\text{CP}}}{\partial \tau_v} = 0$, i.e.,

$$\tau_v = \min\left\{1, \frac{\sqrt{\frac{\sum_{j=1}^{F} K p_j q_v \zeta s^{\text{ld}} C(\delta,\alpha)}{\lambda s}} - C(\delta,\alpha)}{A(\delta,\alpha) - C(\delta,\alpha) + 1}\right\}. \quad (7)$$

This optimal allocation $\tau_v^{(t)}$ is then submitted to the NSP, and the NSP calculates the sum of all the allocations as $\tau^{(t)} = \sum_{v=1}^{V} \tau_v^{(t)}$.

If there is $\tau^{(t)} > 1$, which means the resources needed are more than the NSP can supply, the NSP will increase the price by s_Δ in the next iteration to reduce $\tau_v^{(t)}$. That is, the NSP sets $s^{(t+1)} = s^{(t)} + s_\Delta$ in the $t+1$-th iteration and the auction continuous. In the case of $\tau^{(t)} \le 1$, indicating that the price may be too high such that the CPs cannot afford renting more SBSs, the auction is then terminated.

Regarding the convergence of the proposed auction scheme, since the price $s^{(t)}$ is ascending with iteration number t and $\tau_v^{(t)}$ is a decreasing function of $s^{(t)}$ according to Eq. (7), the auction will converge after a finite number of iterations.

D. Cheating-Proof Mechanism

The above auction process cannot guarantee the optimal outcomes if a CP cheats the NSP by submitting biased bids deliberately. For example, a malicious CP may claim less quota of the SBSs than needed to obtain a lower price from the NSP. In this case, the NSP, as the auctioneer, should adjust the mechanism to prevent being cheated from this CP.

We adopt an alternative ascending-bid auction to solve this problem [2]. In this mechanism, the NSP determines the SBS allocation to each CP based on the other CPs' bids, rather than the one from itself, followed by a cumulative clinch method utilized for calculating the payment in each iteration.

In specific, we focus on the t-th iteration. After computing $\tau^{(t)} = \sum_{v=1}^{V} \tau_v^{(t)}$, the NSP will compare the overall claimed fraction $\tau^{(t)}$ with one. In the case of $\tau^{(t)} > 1$, to avoid being cheated by the CPs, the NSP will compute

$$\tilde{\tau}_v^{(t)} = \max\left(0, 1 - \sum_{j \ne v}^{V} \tau_j^{(t)}\right), \quad \forall v, \quad (8)$$

where $\tilde{\tau}_v^{(t)}$ is the fraction of the SBSs that the NSP allocates to the CP $\mathcal{V}_v$ at the t-th iteration. That is, the NSP allocates $\tilde{\tau}_v^{(t)}$ to $\mathcal{V}_v$, regardless of the bid $\tau_v^{(t)}$ submitted by $\mathcal{V}_v$. Afterwards, the iteration proceeds with price increased by s_Δ.

On the other hand, if there is $\tau^{(t)} < 1$, the NSP terminates the auction. We assume that the auction completes at the T-th iteration. The NSP will normalize bids for achieving $\tau^{(T)} = 1$ at the final iteration. Here, proportional rationing [8] is adopted for normalization:

$$\tilde{\tau}_v^{(T)} = \tau_v^{(T)} + \frac{\tau_v^{(T-1)} - \tau_v^{(T)}}{\sum_{j=1}^{V} \tau_j^{(T-1)} - \sum_{j=1}^{V} \tau_j^{(T)}} \left(1 - \sum_{j=1}^{V} \tau_j^{(T)}\right). \quad (9)$$

After normalization, all the SBSs can be allocated to the CPs.

Meanwhile, the NSP incrementally gains a portion of the overall payment during each iteration, namely, cumulative clinch. To be specific, the revenue to be gained from $\mathcal{V}_v$ in the t-th iteration can be calculated as

$$\tilde{S}_v^{\text{rent},(t)} = \lambda s^{(t)} \left(\tilde{\tau}_v^{(t)} - \tilde{\tau}_v^{(t-1)}\right). \quad (10)$$

After the iterative process completes, the overall revenue gained by the NSP from all the CPs is

$$\tilde{S}^{\text{rent}} = \sum_{v=1}^{V} \sum_{t=1}^{T} \tilde{S}_v^{\text{rent},(t)}. \quad (11)$$

The iterative algorithm is summarised and presented in Table 1. As for the effectiveness of the above cheating-proof algorithm, we have the following theorem.

Theorem 2: In the auction process, if there is a malicious CP who intends to cheat the NSP by submitting a untruthful bid, given other CPs are truthful. The proposed algorithm will guarantee that this malicious CP cannot achieve a higher profit.

Proof: Considering a malicious CP $\mathcal{V}_v$, we define two kinds of utility functions, $S_v^{\text{CP,cheat}}$ and $S_v^{\text{CP,honest}}$, corresponding to the cases that $\mathcal{V}_v$ performs cheating and keeps honest, respectively. In these two cases, the bids submitted in the t-th iteration are denoted by $\tau_v^{\text{cheat},(t)}$ and $\tau_v^{\text{honest},(t)}$. Also, we assume that the auction will converge in T_1 and T_2 iterations in the two cases. Therefore, the corresponding revenues of $\mathcal{V}_v$ in Eq. (5) can be denoted by $S_v^{\text{cache},(T_1)}$ and $S_v^{\text{cache},(T_2)}$.

Note that $\tilde{\tau}_v^{(t)}$, $\forall t \le \min\{T_1, T_2\}$, in the two cases are the same, since it only depends on the bids from the $(V-1)$ honest CPs. Then we have the utility gap

$$\Delta S_v^{\text{CP}} = S_v^{\text{CP,cheat}} - S_v^{\text{CP,honest}} = S_v^{\text{cache},(T_1)} - S_v^{\text{cache},(T_2)} - \sum_{t=1}^{T_1} \lambda s^{(t)} (\tilde{\tau}_v^{(t)} - \tilde{\tau}_v^{(t-1)}) + \sum_{t=1}^{T_2} \lambda s^{(t)} (\tilde{\tau}_v^{(t)} - \tilde{\tau}_v^{(t-1)}). \quad (12)$$

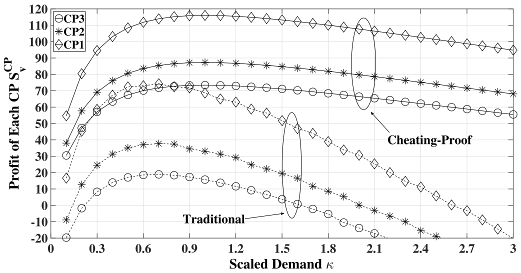

Fig. 1. The three CPs' profit under two schemes versus the factor κ.

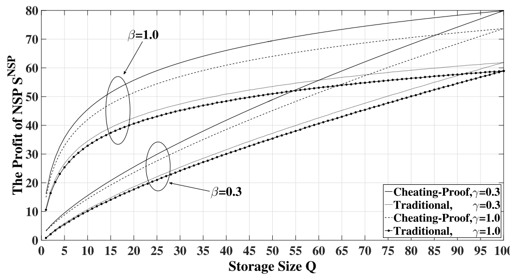

Fig. 2. The profit of the NSP versus Q for different γ and β.

It is obvious that when there is $T_1 = T_2$, we have $\Delta S_v^{\mathrm{CP}} = 0$. In the case of $T_1 > T_2$, since $s^{(T_2)} \leq s^{(t)}, \forall t \geq T_2$, we obtain

$$\sum_{t=T_2+1}^{T_1} \lambda s^{(t)} (\tilde{\tau}_v^{(t)} - \tilde{\tau}_v^{(t-1)}) \geq \lambda s^{(T_2)} \tilde{\tau}_v^{(T_1)} - \lambda s^{(T_2)} \tilde{\tau}_v^{(T_2)}. \quad (13)$$

Then we arrive at $\Delta S_v^{\mathrm{CP}} \leq S_v^{\mathrm{cache},(T_1)} - \lambda s^{(T_2)} \tilde{\tau}_v^{(T_1)} - S_v^{\mathrm{cache},(T_2)} + \lambda s^{(T_2)} \tilde{\tau}_v^{(T_2)}$. When the price growth s_Δ goes to zero, we have $\tau_v^{(T_2)} = \tilde{\tau}_v^{(T_2)}$. In addition, there is

$$\tau_v^{(T_2)} = \arg\max \quad S_v^{\mathrm{cache},(T_2)} - \lambda s^{(T_2)} \tilde{\tau}_v^{(T_2)}, \quad (14)$$

indicating $\Delta S_v^{\mathrm{CP}} \leq 0$. By following the same approach, we can readily prove $\Delta S_v^{\mathrm{CP}} \leq 0$ in the case of $T_1 < T_2$. As the CPs are independent of each other, each CP will suffer from profit loss no matter wether other CPs cheat or not. Therefore, the CPs have no motivation to perform cheating due to a non-positive profit improvement. This completes the proof. ■

According to *Theorem 2*, truthful bidding maximizes the payoff of each CP and and thus forms an efficient equilibrium.

IV. Numerical Results

In this section, we use 'Cheating-Proof' to refer to our proposed cheating-proof mechanism in Subsection D of the previous section, while use 'Traditional' to represent the traditional auction without considering to prevent cheating from the CPs. We consider three CPs in the auction and set $K = 10/month$, $\lambda = 10/km^2$, $\zeta = 50/km^2$, $\alpha = 3$, $\delta = 0.01$, $F = 100$, $s^{\mathrm{ld}} = 1$, and $c = 0.1$.

Fig. 1 illustrates the profits gained by the three CPs under the two schemes versus a scaling factor κ. Here, we have $Q = 50$ and κ is the distortion factor multiplied to the real demands $\tau_v, \forall v$, requested by $\mathcal{V}_v$ on the SBSs for the cheating purpose, with $\kappa > 1$, $\kappa < 1$, and $\kappa = 1$ reflecting a higher, lower, and exact demands of the CPs. We can see from Fig. 1 that the proposed cheating-proof scheme always outperforms the traditional one in terms of the CPs' profits. Moreover, in the cheating-proof scheme, each CP achieves its maximum profit only when $\kappa = 1$, indicating that each CP has no incentive to cheat the NSP by submitting a distorted demand. On the other hand, in the traditional scheme, each CP achieves its maximum profit at around $\kappa = 0.7$, implying that a CP may cheat the NSP by submitting a shrunken demands with $\kappa = 0.7$.

Fig. 2 shows the profits of the NSP in the two schemes versus the storage size Q. We consider the performance with the CPs' Zipf parameter $\gamma = 0.3$ and 1, and the file Zipf parameter $\beta = 0.3$ and 1. From the figure we can first see that the profit the NSP always increases with the growth of Q. With the same Q and γ, a larger β implies a higher profit of the NSP, while give the same Q and β, a larger γ will cause a lower profit of the NSP. Next, we compare the proposed cheating-proof scheme with the traditional one, where we set $\kappa = 0.7$ in the traditional scheme since the CPs are motivated to achieve the their maximum profits by choosing 0.7 according to Fig. 1. We can see that the NSP always gains a higher profit in our scheme than that in the traditional one with $\kappa = 0.7$.

V. Conclusions

In this letter, we have proposed an auction-based SBS trading system consisting of an NSP and multiple CPs. By treating the SBSs as a kind of resources, the NSP leases these SBSs to the CPs through an auction game. We first formulated the expressions of the profits of the NSP and CPs. Then we maximized the profits of both sides under the iterative auction process. Furthermore, we developed an cheating-proof scheme to prevent the CPs from cheating the NSP for gaining a higher profit. Numerical results showed that our proposed scheme can effectively achieve the cheating-proof purpose.

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