DFCA: A Flexible Refundable Auction for Limited Capacity Suppliers

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Abstract. This paper proposes a novel auction-based mechanisms named Decreasing Cancellation Fee Auction (DCFA) for task allocation in the environment where a service provider has finite capacities and consumers could withdraw their bids. We consider a new type of auction called the refundable auction, i. e. refund means that a consumer's showing up is uncertain and he can get back partial of his payment if his cancellation or no-show occurs. This mechanism can boost seller revenue, satisfy incentive compatibility, individual rationality and still hold a high efficiency.

Keywords: Refundable auction, price matching, incentive compatibility, VCG mechanism, advance reservation.

1 Introduction

Due to the geographic distribution of resources that are often owned by different organizations with different usage policies and cost models, and varying loads and availability patterns, the task of resource management and scheduling in these environments is a complex undertaking. *Distributed Computational Economy* [3] has been recognized as an effective metaphor for the problem of such management. In particular, auction has been recognized as an effective method for the management of distributed resources [3,6], because it enables the regulation of supply and demand for resources, provides economic incentive for service providers, and motivates the service consumers to trade off among deadline, budget, and the required level of quality-of-service. Typical applications include task assignment, distributed scheduling, etc.

The distributed system has a highly dynamic environment [21] with servers coming on-line, going off-line, and with continuously varying demands from the clients. Therefore, the function of *Advance Reservation* has been strongly recommended into supporting the allocation and scheduling mechanisms, because the computing resources are usually not storable and the capacity available today cannot be put aside for future use [6]. It should be noted that the auction-based advance reservations are currently being added to some economic-based toolkits,

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such as GridSim [1] which has integrated First-Price Sealed-Bid, English, Dutch and Continuous Double auction protocols. However, there may exist many uncertainties of consumers' requests (bids). The possibilities for breaks in actions include [9]: an erroneous initial valuation or bid, unexpected events outside the winning bidder's control, information obtained or events that occurred after the auction, etc. For instance, in Data Mining applications, users may cancel the visualization step when the result is not interesting enough or the mining procedure could not be fulfilled. Hence, an importance feature, as noted in GRAAP-WG[1] the advance reservation protocol should allow consumers to cancel or alter their booked services.

In economics-based allocation methods, *refund policies* are used to control for the selection of potential customers who make reservations but differ with respect to their cancellation probabilities. Refund policy assumes that a consumer pays for the service during the reservation is made, but the consumer gets partial (or all and no) refund when his cancellation or no-show occurs. Refunds are widely observed in almost all privately-provided services and also to some degree in retail in industries. Most noticeably, refunds are heavily used by airline companies. Refundable bookings tend to attract consumers who are likely to cancel or not show up for the service, and deter consumers who are less likely to cancel and are therefore more price sensitive [20]. However, the cancellation and refund issue in auctions has been discussed little in both economics and computer science literatures.

In this paper, we concentrate on the design of *partially refundable auction* mechanism of advance reservation systems in which consumers' show-ups are uncertain and their personal information are unknown by the service providers. We demonstrate the nonexistence of any mechanism which satisfies seller's profit-maximizing, individual rational and incentive compatibility simultaneously. We propose a flexible auction mechanism that can satisfy incentive compatibility, individual rationality, and still obtain a high efficiency. The remainder of this paper is organized as follows. In Section 2, we present the main related work in this area. In Section 3, the basic model of the refund auction is described. We point out that there does not exist any uniform pricing and cancellation fee allocation mechanism that could maximize seller's profit and satisfy incentive compatible at the same time. In Section 4, we present Decreasing Cancellation Fee Auction mechanism. In Section 5, the experimental comparison of our mechanisms with an ideal optimal algorithm and other counterparts are evaluated. Finally, we conclude this paper and discuss future work in Section 6.

2 Related Work

Incentive mechanism design is an important issue not only in Economics but also recently in E-commerce and Distributed Artificial Intelligence, obviously

[1] Advance Reservation State of the Art: Grid Resource Allocation Agreement Protocol Working Group, http://www.fz-juelich.de/zam/RD/coop/ggf/graap/sched-graap-2.0.html

this issue should not been ignored in Grid Economics. Incentive compatibility means the dominant strategy for a bidder is to bid to his true valuation thus bidders'decision-making could be simplified even in the highly complex trading environment [11,12]. The best-known such payment rule is the Vickrey-Clarke-Groves (VCG) mechanism [7,8,23].

Uncertainty is quite common in computer environment for the unexpectable nature of the future events, it makes incentive mechanism design more complex. One long-standing problem in mechanism design is to design the optimal multidimensional incentive mechanism [28]. Porter et al. introduce the notion of fault tolerant mechanism design, they have proved an impossibility result that there does not exist a mechanism that satisfies incentive compatibility, individual rationality and social efficiency when dependencies exist between tasks [16]. Holland and Sullivan present the non-existence of mechanism to incentivize truthful bidding when robust allocations are required in a revocable combinatorial auction [10], however they assume that bid-taker knows bidders' private showup probabilities. Hurberman et al. propose a pricing mechanism induces truth-telling on the part of users reserving the service, one limitation of their work is that they assume all the users have the same valuation about the service [2,13,24], but users' valuation should be different in the real world.

Refunds are wildly observed in almost all privately-provided services which alleviates the consumers' risk of *uncertainty* and also could increase seller's revenue. However, the refundable auction has not been well discussed in both economic and AI literatures. The refundable auction problem are complicated by *incentive compatibility* constraint, multidimensional consumer type and private cancellation uncertainty. Without the cancellation constraint, the incentive compatibility could be guaranteed by strategy-proof protocols such as Vickrey-Clarke-Groves (VCG) mechanism and Price-Oriented Rationing-Free (PORF) mechanism [26]. If the private information could be reduced to one dimension, we could realize seller's profit-maximizing using the method proposed in [5]. If the uncertainty of the future event is public information, we could enumerate all possible allocation plans as proposed in [14] or uses only the part of the bid as the winner scoring rule to find the optimal allocation [4].

This work is greatly inspired by the work of Ringbom and Shy [17,20]. Shy gives a compressive introduction about advance booking and various refund strategies in his upcoming book [20]. They developed methods for calculating optimal rates of partial refunds for profit-maximizing and social surplus maximizing when price of the goods, but their model assumes that price is exogenously given and auction-based mechanism has not been discussed in their current works. We will show in the following, using auction-based mechanism could greatly increase the profit of the service providers.

3 Problem

Suppose a seller (or service provider) has m unit perishable goods (or service) and there are n ($n > m$), consumers are willing to buy only one unit of the good. Consumer i's valuation about a unit of the good is β_i, where $\beta_i \in [0, 1]$. Let $\theta_i \in [0, 1]$ denote the probability that consumer i will show up and consume the service at contracted delivery time. We call θ_i the probability of showing up. Therefore, the probability of a cancellation is $1 - \theta_i$. We assume that the valuation and the probability of showing up are exogenous variables, thus these variables cannot be changed by consumers. Let p denote the price of the service and r denote the *cancellation fee* when the reservation is cancelled by the consumer or the consumer does not show up.[2] We assume that $p \geq r$. We will not distinguish between a cancellation and a non-show-up in this paper. The payoff of the confirmed consumer i as follows:

$$c_i = \begin{cases} p & \text{if show up,} \\ r & \text{otherwise.} \end{cases}$$

The expected utility of the confirmed consumer i is: $u_i = \theta_i(\beta_i - p) - (1 - \theta_i)r$. In this refundable pricing mechanism, consumer i needs pay p if his request has been booked and has been completed, but he needs to pay r if the booked request has been cancelled by himself, and need not pay if the request has been declined. In other words, we assume that all consumers must pay for the service during the reservation is made, so consumer get $p - r$ refund when his cancellation occurs. The expected revenue of the seller from the confirmed consumer i is: $\pi_i = \theta_i p + (1 - \theta_i)r$. To maximize the expected profit, the seller will select m most profitable consumers.

Theorem 1. *There does not exist a uniform pricing and cancellation fee allocation mechanism that could satisfy seller's profit-maximizing and incentive compatible simultaneously.*

Proof (Sketch). If the service provider knows all the private information of bidders, the optimal pair (p, r) which maximize the service provider's expected revenue could be calculated as solving following optimal problem: $\max_{p,r} \sum_{i=1}^{N} x_i \cdot \big[p \cdot \theta_i + (1 - \theta_i) \cdot r\big]$, s.t.$0 \leq r \leq p \leq 1, \sum_i^n x_i \leq m, x_i\theta_i \cdot (p - \beta_i)/(1 - \theta_i) \leq r, x_i \in \{0, 1\}$. However, consumers could fake bids with different combinations which may cause a loss of the service provider's revenue, the detailed example is as described below.

Example 1 (fake bid by loser). Suppose there are four consumers and two unit goods, bidders' valuations and showup probabilities are shown in Table 1(a). If consumers truthfully report their private information, the optimal price and cancellation fee pair should be $(0.45, 0.45)$, which means that bidders 1 and 2 are winners, in that time $u_1 > 0$, $u_2 = 0$, $u_3 < 0$, $u_4 < 0$, and the seller's expected revenue is 0.9. However, if bidder 3 overstates his showup probability from 0.2 to 0.5 while understates his valuation from 0.9 to 0.8, as shown is Table 1(b),

[2] Cancellation fee r can also be interpreted as *advance payment* as the economic model discussed in [2,13,24]. The advance payment assume that the customers pay r before they consume the goods and they pay $p - r$ after their consumptions.

Table 1. Example 1

(a)

	b1	b2	b3	b4
β	**0.8**	**0.5**	0.9	0.3
θ	**0.7**	**0.9**	0.2	0.4

(b)

	b1	b2	b3	b4
β	**0.8**	0.5	**0.8**	0.3
θ	**0.7**	0.9	**0.5**	0.4

then bidders 1 and 3 will win the goods. Based on those fake information, the optimal price and cancellation fee pair would be $(0.8, 0)$, in that time $u_1 > 0$, $u'_3 = 0(u_3 > 0)$, $u_2 < 0$, $u_4 < 0$. In such a case, the seller predicts its expected revenue is 0.96, in contrast, his true expected revenue is $0.56+0.16 = 0.72$, which is less than 0.9. The seller will suffer 20% loss on his expected revenue when the bidder 3 fakes his bid.

Example 2 (fake bid by winner). As in Table 1(a), bidder 1 and 2 also have the incentive to lie. For instance, if they fake their bids as $\beta = 0.4, \theta = 0.5$, each of them can still obtain one unit of goods. In this time, the calculated optimal price and cancellation fee pair is $(0.23, 0.17)$. However, the seller's true expected revenue is 0.436 that is less than half of the ideal value.

Theorem 1 also means that if we cannot guarantee incentive compatibility, the seller's profit-maximizing cannot be guaranteed. The difficulty in designing the optimal incentive compatible auction is that the bids and types are both multi-dimensional, especially with payment uncertainty at the same time [28].

The incentive compatibility constraint can be easily satisfied by extending the standard VCG mechanism. The rules of the extended VCG mechanism are described as follows: 1) all bidders are required to report their expected valuation $\gamma_i = \theta_i\beta_i$ (may not truthful); 2) the closing price p is the *(m+1)*th highest γ_{m+1}; 3) withdrawal after the winner determination phase is not allowed, in another words, it is a no-refundable in this mechanism, which means that $r = \gamma_{m+1}$.

Definition 1. *We define the expected social welfare as the sum of the revenue of service provider and the utility of bidders:*

$$W = \sum_{i \in \Lambda} \Big(\theta_i p + (1-\theta_i) r\Big) + \sum_{i \in \Lambda} \Big(\theta_i(\beta_i - p) - (1-\theta_i) r\Big) = \sum_{i \in \Lambda} \theta_i \beta_i \qquad (1)$$

where Λ is the set of winners.

The first item of Equation (1) indicates the expected revenue of the service provider, and the second item indicates the sum of the winners' utilities. We also simply call expected social welfare as efficiency in the later.

Theorem 2. *The extended VCG mechanism satisfies individual rationality, incentive compatibility and social efficiency.*

Proof. Suppose γ_{m+1} is the *(m+1)*th highest bid, the utility of bidder i is: $U_i = \theta_i(\beta_i - \gamma_{m+1}) - (1 - \theta_i)\gamma_{m+1} = \theta_i\beta_i - \gamma_{m+1} = \gamma_i - \gamma_{m+1}$. From this equation, we can see that the original two dimensional problem now is reduced to one dimensional problem. It is clear that: if bidder i overstates it will cause a non-positive utility when $\gamma_i \leq \gamma_{m+1}$; Meanwhile when $\gamma_i > \gamma_{m+1}$, over-reporting is useless, i.e. it could not increase bidder's utility. Thus, this mechanism satisfy incentive compatibility. For each bidder truthful telling his private information is a dominant strategy and the price is the *(m+1)*th highest bid γ_{m+1}, the individual rationality of this mechanism is immediate. Since the winner of the auction are the m bidders whose bid $\theta_i\beta_i > \gamma_{m+1}$, the expected social welfare as defined in Equation 1 is maximized.

However, the extended VCG mechanism could not guarantee to obtain a sufficient high revenue. For instance, when we apply the extended VCG mechanism given data in Table 1(a), the seller's profit is only $0.1800 \times 2 = 0.3600$, which is far lower than optimal value.

4 Decreasing Cancellation Fee Auction

In the following section, we first discuss the Fixed Cancellation Fee Auction (FCFA) mechanism before we propose the Decreasing Cancellation Fee Auction (DCFA) mechanism. The DCFA can boost seller revenue, satisfy incentive compatibility, individual rationality and still hold a high efficiency.

4.1 Fixed Cancellation Fee Auction

The detailed FCFA protocol is described as below. Firstly, the seller announces a posted cancellation fee r before the auction begins. Then based on the posted cancellation fee r, each bidder reports his maximum acceptable price $p_i = \beta_i - r(1 - \theta_i)/\theta_i$. After all the bidders submitted their bids, the seller selects the m consumers with the most highest price as the winners of the auction. The payment rules are described below: i) If there are more than m consumers, the winners' payment will be determined by the *(m+1)*th highest bid, which is the highest of all losing bids. ii) When there are less than m consumers, all the consumers are winners, the payment is r, the lowest price of the seller to provide the service. iii) As mentioned before, in both cases, if a confirmed consumer cancels its reservation or does not show up at the deliver time, the consumer's payoff is r. First of all, the most important task for the resource provider, in this protocol, is to set an optimal cancellation fee r^* before the auction begins. The algorithm to calculation r^* is discussed in Appendix A.

Theorem 3. *The dominant strategy of bidder i under Fixed Cancellation Fee mechanism is he truthfully reports his private information p_i.*

Proof. The Fixed Cancellation Fee mechanism has simplified the original multi-dimensional problem to one dimensional problem: bidder's private information is indirectly revealed in its maximum acceptable price p_i. The Fixed Cancellation Fee mechanism uses *(m+1)*th-price auction protocol for the winner determination. As discussed in [25], the *(m+1)*th-price sealed-bid auction is incentive compatible for single-unit buyers under the independent private values model. If he reports lower price $p_i' < p_i$, he may face the risk of losing the auction, and it is also useless since he cannot manipulate the closing price by understating p_i. On the other hand, if the bidder reports higher price $p_i' > p_i$, if $p > p_i$ he will obtain a negative utility, and over-reporting is also useless, because its payment p is highest loss price $\hat{p}_{m+1}$ when $k > m$ or cancellation fee r when $k \leq m$. So this mechanism satisfies the incentive compatibility property: a bidder truthfully reports its private information p_i is a *dominant strategy.*

One limitation of the FCFA mechanism is that the number of the qualified bidders may be less than the total number of the goods, this will leave some capacity unutilized thereby resulting in a loss to service providers. Now, in this section, we will extend the FCFA mechanism to the flexible DCFA mechanism. We also assume that the service provider has m units perishable goods (or service). The auction is proceeded iteratively according to a series of the non-negative cancellation fees in the decreasing order $r_1 > r_2 > \cdots > r_l > 0$. Meanwhile, the winners of the auction are selected sequentially based on their bids. The *price matching* method [22] is adopted in this method, i.e. the final cancellation fee and the price is the lowest valuation in all those rounds, thus the bidders need not worry about the possible loss while the cancellation fee and price are decreasing in later rounds.

4.2 Allocation Protocol

The auctions are proceeded in rounds, suppose there are l rounds, and each round holds a Fixed Cancellation Fee auction. The auction rules are described as follows:

1. In round of the auction j, the price p_j must be no less than the cancellation fee r_j, i.e. $p_j \geq r_j$. Intuitively, it will be unrealistic in the real market that the mechanism with cancellation fee is more than the price of the goods.
2. Let m_j represents the number of units available in round j, the number of the valid bids, where $b_i \geq r_j$, is w_j. If $m_j + 1 \leq w_j$, then the bidders with highest m_j bids will be the winners of the auction, the price will be the *(m_j+1)*th highest bids among w_j bids. If $m_j \geq w_j$ and $w_j \geq 2$ then the $w_j - 1$ highest bidders are winners, the price will be the w_j-th highest bid, i.e. the lowest valid bid in round j. In another words, we perform the *(m+1)*th price auction in each round, no matter whether the valid bids are more or less than the number of goods.
3. However, if there is only one bidder in the auction, he could manipulate the price, thus if there is only one bidder in the current round, the auction turns to the next round. It means that the valid bid number in each round should be greater than two, i.e. $w_j \geq 2$, $j \in [1, l]$.

4. All the winners reserve a unit of good with price $p = \min_{j \in [1,J]} \{p_j\}$ and cancellation fee r_J, where J is the round index that the last unit is sold or the last round ($J = l$) when there is still has unsold but with no valid bidders.

The concrete procedure is described in Algorithm 1, where parameter m_j represents the number of units available in round j, and w_j represents the number of the valid bids in round j. The algorithm includes four steps: Step 1 executes *initiation* process (lines 1 to 2) that initializes all the parameters; Step 2 is the *booking* process (lines 3 to 21), which accepts the bids and selects the winners into queue Q; Step 3 is *price matching* step (lines 22 to 24), this step matches all the winners' booking prices and cancellation fees with the lowest ones; In addition, the final step, the *overbooking* step is the optional step and will be discussed in our future work.

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Algorithm 1: Decreasing Cancellation Fee Auction
1: initiate the cancellation fees r[1], r[2],..., r[l];
         /* where r[1]> r[2]>...> r[l]> 0.*/
2: j:= 1; m[1]:= m; p:= 1;
3: while (m[j]>= 0 and j<= l) do
4:     execute the FCFA with cancellation fee r[j];
5:     w[j]:= the number of bids which satisfies b[i]>= r[j];
6:     if (w[j]<= m[j] and w[j]>= 2) then
7:        append the highest w[j] bids in the winner queue Q;
8:        m[j+1]:= m[j]-w[j]+1;
9:     end if
10:    if (w[j]>= m[j]+1 and w[j]>= 2) then
11:       append the highest m[j] bids in the winner queue Q;
12:       m[j+1]:= 0;
13:    end if
14:    if (w[j]>= 2) then
15:      if (p[j]< p) then
16:         p:= p[j];
17:      end if
18:      r:= r[j];
19:    end if
20:    j:= j+1;
21: end while
22: for all bids in Q do
23:    p[i]:= p; r[i]:= r;
24: end for
25: overbooking (optional)
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Theorem 4. *The DCFA stratifies Individual Rationality and Incentive Compatibility properties.*

Proof. The Decreasing Cancellation Fee auction protocol is an variance of Fixed Cancellation Fee Auction protocol, the allocation of goods are separated in multiple rounds. For the cancellation fee and the price of goods are non-increasing in the auction, the individual rational is satisfied. According to the auction rules, the final cancellation fee is based on the round of latest winner in the action, and the price is the lowest price in all those rounds, thus the bidders need not worry about the possible lose while the cancellation fee and price are decreasing in later rounds. In each round, the *(m+1)*th price auction is held in each round, the price could not be manipulated by any bidder. In addition, there is more riskily to be lost of the auction in later rounds. So the bidder's best strategy is to bid as earlier as possible, That is, selecting the round of the auction is useless and risky and thus incentive compatibility property is guaranteed. *Best-response* strategy is bidder's dominant strategy.

Example 3. Now, we give an example to demonstrate the process of this protocol, suppose the bidders' information as shown in Table 1(a), and the cancellation fee series rs are $\{0.35, 0.25, 0.15, 0.05\}$. Auction begin with $r_1 = 0.35$, bidder 1 and 2 bid with price 0.65 and 0.46, according to rule 2, bidder 1 reserve one unit of goods, with the deferred price 0.46, then auction goto the next round $r_2 = 0.25$. For this round, only bidder 2 bids, according to rule 3, the auction move to the next round. When $r_3 = 0.15$, bidder 2, 3, 4 bid with price $0.48, 0.3, 0.075,$, the last unit good goes to bidder 2 with price 0.3. The final allocation result is bidder 1 and 2 each win one unit of goods, with $p = \min\{0.45, 0.3\} = 0.3$ and $r = 0.15$. The expected revenue of the sell is $0.255 + 0.285 = 0.56$, which is higher than that of the extended VCG mechanism and the result of *Example* 2.

This mechanism could be easily extended to support multiple unit demand and still keep incentive compatible property through adapting the similar method proposed in [27], when marginal values of all participates decrease or remain the same. The detailed method is discussed in Appendix B.

5 Experiment and Comparison

We compare our propose mechanism with the ideal situation and the fixed price-refund pair method. In the ideal situation, we assume that the seller knows all the information about bidders, although it is hard to induce all those information as discussed in previous section. An other method, the fixed price-cancellation fee pair method [3], could be calculated based on the distribution of the distribution of users' type. The optimal fixed pair (p, r) could also be calculated by iteratively using the algorithm proposed in [17], they calculate the optimal refund level when price is exogenously given.

5.1 Experimental Setting

In each experimental setting, the bidder's valuation and showup probability are uniformly and independently distributed the interval $[0, 1]$, the minimal

[3] For refund rate is equal to $p - r$, we also called this method fixed price-refund pair method or posted (p, r) pair in short.

Table 2. Comparison of average expected revenue, efficiency, users' utility, price and cancellation fee in different refundable auctions when $(m, n) = (3, 20)$

Mechanism	Revenue	Efficiency	Users' Utility	Price	CF
Decreasing Cancellation Fee	1.6109	1.7396	0.1287	0.5761	0.4170
Fixed Cancellation Fee	1.4888	1.8834	0.4091	0.5470	0.3000
Posted (p, r) Pair	1.3069	1.6030	0.2961	0.6200	0.2100
Optimal	1.7648	1.8782	0.1135	0.7254	0.2139
Extended VCG	1.3965	1.8972	0.5007	0.4655	0.4655

Table 3. Comparison of average expected revenue, efficiency, users' utility, price and cancellation fee in different refundable auctions when $(m, n) = (3, 40)$

Mechanism	Revenue	Efficiency	Users' Utility	Price	CF
Decreasing Cancellation Fee	1.9487	2.0569	0.1083	0.6700	0.5532
Fixed Cancellation Fee	1.8522	2.1844	0.3322	0.6502	0.4300
Posted (p, r) Pair	1.6697	1.9072	0.2375	0.7200	0.2100
Optimal	2.0888	2.1827	0.0938	0.7907	0.2578
Extended VCG	1.8251	2.1999	0.3748	0.6084	0.6084

increment of two random value is 0.01. In each same setting, the auction will be run at least 1000 times.

5.2 Comparison of the Expected Revenue

In this experiment, we compare the average expected revenue, efficiency, users' utility, price and cancellation fee (CF) among different mechanisms. Due to the space limitation, we only draw two experimental results when $(m, n) = (3, 20)$ and $(3, 40)$ to demonstrate the relative performance of those the methods since we get similar result in the other situations. The underlined number in the tables indicates the value is fixed. More specially, we set rs are $\{0.7, 0.6, \cdots, 0.1\}$ in the DCFA method. From Table 2 and 3, we can see that FCFA and DCFA mechanisms can obtain more profit than fixed price-refund pair and extended VCG method. In addition, DFCF can approach to the optimal revenue result as the bidder number increases.

Compared with ideal optimal method which seller knows all bidders' private information, the inefficient of FCFA is mainly because that fixed cancellation fee restrained the bidders' participate the resource competition. Especially, in some cases, it causes the goods could not be totally sold out. For example, in fixed cancellation fee method simulation $(m, n) = (3, 20)$, there are nearly 10% runs that the number of valid bidders are less than the resource number. It causes the major loss of the sellers' revenue. DFCF overcomes this shortcoming by sequentially adjusting cancellation fees.

DFCF auction is insensitive to the selection of r series, but the value of r_1 should at least above r^* that is calculated in FCFA. The experiment results are shown in Table 4(a). On the other hand, as shown in Table 4(b), it is clear

Table 4. The selection of different r series

(a)

r_1	Interval	Number	Revenue	Efficiency
0.9	0.1	9	1.61	1.74
0.8	0.1	8	1.61	1.74
0.7	0.1	7	1.61	1.74
0.6	0.1	6	1.61	1.74
0.5	0.1	5	1.60	1.72

(b)

r_1	Interval	Number	Revenue	Efficiency
0.7	0.0125	56	1.72	1.76
0.7	0.025	28	1.69	1.76
0.7	0.5	14	1.66	1.76
0.7	0.075	9	1.64	1.75
0.7	0.1	7	1.61	1.74

that the bigger r's number the more revenue will be. The seller could trade off the auction lasting time and the revenue through select different r series. Although the implementation of auction-based methods may be more complex than posted-price based methods, auction-based methods could be more flexible and make more profit than the posted-price method and the extended VCG mechanism.

6 Conclusion and Future Work

In this paper, we propose a novel auction-based mechanism for task allocation in environments where service provider has finite capacities and consumers could withdraw their bids. We consider a new type of auction in which winner could withdraw We demonstrate that it is difficult to design an optimal auction protocol that satisfies profit-maximizing and incentive compatibility simultaneously. We explore two auction-based refundable mechanisms for boosting seller's revenue from the single stage and multistage perspectives. These mechanisms can satisfy incentive compatible and individual rational properties. The experimental results illustrate that these methods achieve higher revenue than the counterparts such as fixed price-refund pair method and extended VCG mechanism.

The Decreasing Cancellation Fee Auction mechanism can be easily extended support overbooking in the form of Leveled Commitment Contract [18,19]. We wish to further investigate how to negotiate optimally, or at least fairly, the sequential Leveled Commitment Contracts with different bidders. It is still an open question that how an service provider should allocate its scarce computational resources when evaluating different Leveled Commitment Contracts. Furthermore it will be interesting to extend these mechanisms to deal with the uncertainty in more complex auction protocols, such as double auction and combinatorial auction.

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Appendix A

This is appendix for calculating the optimal r^* in Fixed Cancellation Fee Auction (FCFA) mechanism. Let us consider the participation probability of a rational agent. Obviously, a rational agent will participate in the auction only when his expected utility $u_i = \theta_i(\beta_i - p) - (1 - \theta_i)r \geq 0$, then agent i's acceptable price p_i:

$$p_i \leq \beta_i - r(1 - \theta_i)/\theta_i \tag{2}$$

Notice that $r \leq p_i$, and $\beta_i \leq 1$, substitute into above equation yields: $r \leq \theta_i \leq 1$ and $r/\theta_i \leq \beta_i \leq 1$. Therefore, for given cancellation fee r, the probability of a rational agent participated in the auction is

$$Pr(r) = \int_r^1 \int_{r/\theta}^1 d\beta d\theta = 1 - r + r\ln(r) \tag{3}$$

Clearly, $Pr(1) = 0$ and $Pr(0) = 1$. We define $\psi(r, n)$ is the total expected number of n consumers willing to participate in the auction. Since the possibility of exactly k consumers participate in the auction can be described as:$Pr(r, k, n) = C_n^k Pr(r)^k (1 - Pr(r))^{n-k}$. The following equation is immediate:

$$\psi(r, n) = nPr(r) = \sum_{k=1}^{n} kPr(r, k, n) \tag{4}$$

To calculate the expected revenue of the service provider obtain from these k consumers, we need predict the closing price p of the auction. Because we select m highest bids among these k requests, we should distinguish these two different situation: $k > m$ and $k \leq m$. Suppose there are exactly k potential consumers (whose $u_i \geq 0$) willing to submit their requests.

I) In the case of $k > m$, we sort prices $\{p_i\}$ into a decreasing order as $\{\hat{p}_i\}$, and $\hat{p}_{m+1}$ is the closing price. For any given price p and cancellation fee r, $r \leq p_i < p$ means that $r \leq \beta_i - r(1-\theta_i)/\theta_i < p < 1$. So the probability $Pr(r \leq p_i < p)$ could be calculated as follows:

$$Pr(r \leq p_i < p) = \int_r^{\frac{r}{1-p+r}} \int_{r/\theta}^{1} d\beta d\theta + \int_{\frac{r}{1-p+r}}^{1} \int_{r/\theta}^{p+\frac{r(1-\theta)}{\theta}} d\beta d\theta \qquad (5)$$

The first integral item in the righthand of Equation (5) means $\theta < r\ (1-p+r)$ when $p+r(1-\theta)/\theta > 1$, meanwhile the second integral item means $\theta \geq r\ (1-p+r)$ when $p + r(1-\theta)/\theta \leq 1$. Similarly, the probability $Pr(p_i \geq p)$ is calculated as follows:

$$Pr(p_i \geq p) = \int_r^1 \int_{p+\frac{r(1-\theta)}{\theta}}^{1} d\beta d\theta \qquad (6)$$

Now we describe the estimation of the mean value of $\hat{p}_{m+1}$. Suppose $\hat{p}_{m+1}$ is the *(m+1)*th highest price among k bidders, the distribution function the *(m+1)*th highest price $\hat{p}_{m+1}$ can be describes as:

$$F_{m+1}(p) = \sum_{t=0}^{m} C_k^t Pr(r \leq p_i < p)^t Pr(p_i \geq p)^{k-t} \qquad (7)$$

Let the density $f_{m+1}(p) = F'_{m+1}(p)$, then the expected mean value of *(m+1)*th highest value $\hat{p}_{m+1}$ is:

$$\tilde{p}_{m+1} = \int_r^1 p f_{m+1}(p) dp \qquad (8)$$

For example, the mean value of the second highest value among k bidders is $\int_r^1 pk(k-1)(1-F(p))F^{k-2}(p)f(r)dp$ [15]. Notice that if there are n random variables identically and independently uniformly distributed in $[0, 1]$, the mean value of i-th highest number's is $(n-i+1)/(n+1)$. For $p \in [r, 1]$, $\tilde{p}_{m+1}$ could be approximated using value $\tilde{p}_{m+1} = r + (k-m)(1-r)/(k+1)$. Then, the expected revenue of the seller is:

$$\pi_A(r, m, k) = \frac{m}{1-r} \int_r^1 \theta \tilde{p}_{m+1} + (1-\theta) r d\theta \qquad (9)$$

II) If $k <= m$, the expected revenue of the seller is:

$$\pi_B(r, m, k) = \frac{k}{1-r} \int_r^1 \theta r + (1-\theta) r d\theta = kr \qquad (10)$$

From I) and II), the expected revenue for given r could be calculated as follows:

$$ER(r, m, n) = \sum_{k=1}^{m} Pr(r, k, n) \pi_B(r, m, k) + \sum_{k=m+1}^{n} Pr(r, k, n) \pi_A(r, m, k) \qquad (11)$$

Therefore, the optimal cancellation fee r^* with respect to (n, m) is: $r^* = \arg max_r\{ER(r, m, n)\}$, and the maximal expected revenue is: $MER(m, n) = ER(r^*, m, n)$.

Appendix B

Let the valuations of consumer i as $\beta_{i,1}, \beta_{i,2}, \beta_{i,3}, \cdots$, where $\beta_{i,k}$ represents the marginal value of the k-th unit for i. More specifically, $\beta_{i,k}$ presents the increase of i's utility by obtaining one additional unit when i already has $k-1$ units, and for all i and k, $\beta_{i,k} \geq \beta_{i,k+1}$ holds, under the assumption that the marginal values decrease or remain the same. The assumption that marginal values decrease are widely adopted in economic models. We also assume that $p_{i,k} \geq p_{i,k+1}$ holds for all the bids of bidder i, where $p_{i,k}$ represents the bidding price of the k-th unit for i. A winner i who obtain k units pays the total of $\sum_{l=1}^{k} \max(p_{(l)}^{-i}, r)$, where $p_{(l)}^{-i}$ presents the l-th largest losing bid except those of i. This simple extension of the above to protocol could keep incentive compatible property when marginal values of all participates decrease or remain the same.