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A Participation Incentive Market Mechanism for Allocating Heterogeneous Network Services

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***Abstract*— This paper studies an auction based allocation of network resources for short-term contracts for heterogeneous network services. The combinatorial winner selection yields the optimal resources allocation in a single-round auction for heterogeneous resources. However, the recurring nature of auction for network services causes least wealthy bidders to exit the auction as they persistently lose under the traditional combinatorial winner selection that focuses only on revenue maximization. Such exits decrease price competition and may cause a collapse of the selling prices and revenues of network service providers. We introduce and evaluate a novel winner selection strategy for auctioning of heterogeneous network services. The proposed strategy prevents collapse of the selling prices and the auctioneer revenues, stabilizes auction market, and enhances social welfare by allowing larger subset of users to become occasional winners of auction rounds than the traditional combinatorial winner selection does.**

I. Introduction

Appropriate pricing mechanisms encourage customers to choose service levels adequate to their needs, and achieve efficient network resource allocation in Quality of Service (QoS) enabled networks. Hence, they are regarded as an efficient solution to the congestion control, service admission control, fair allocation of network resources, and revenue maximization. For these reasons, they constitute an essential component of dynamically adaptable service management frameworks for the sale and delivery of a wide range of network services. Several pricing mechanisms for selling multiple classes of network services or allocating shared network resources in QoS enabled networks have been proposed [1-7]. In many existing network service markets, fixed pricing (i.e., flat rate pricing) or static time-differential pricing mechanisms have been used because of their simplicity. However, the flat rate pricing cannot optimize revenue of network service provider because customer's demand dose not follow a step function, but rather gradually shift from on- to off-peak. Accordingly, under-utilization of network resources arises when demand is low and under-pricing happens when demand is high [11]. Dynamic pricing mechanisms that adapt to continuously changing network conditions are more efficient in managing network resources. Additionally, in such pricing mechanisms, price itself becomes an important signal for network management. In such dynamic pricing environments, however, the service provider's price decision and customer's budget planning are difficult. An auction can mitigate such complexities since prices in auctions emerge in a decentralized way based on the customer's willingness to pay. Additionally, auctions are easy to understand, and can supports automatic negotiation process [9].

Generally, auction for network services should be regarded as recurring because network service providers allocate network resource repeatedly to satisfy recurrent requests of customers [11]. In a single-round auction for heterogeneous network services, the combinatorial winner selection of the Generalized Vickrey Auction (GVA) mechanism maximizes revenue of the network service provider by selecting the combination of winners that maximizes the auctioneer's revenue [8]. However, applying the traditional GVA mechanism to a recurring auction for heterogeneous network services results in an inevitable *bidder drop problem* that is caused by '***paradox of incentive compatible mechanism in recurring auction***' [11]. Such dropped bidders decrease the long-term demand for network services, and, consequently, lower the network service provider's revenue.

In this paper, we propose a new auction based network resource pricing mechanism for QoS enabled heterogeneous network services. This mechanism focuses on stabilizing revenue of network service provider. The next section analyzes auction markets for heterogeneous network services and describes the traditional GVA mechanism for heterogeneous network services. In section III, observed challenging problems are discussed. In Section IV, the proposed new auction based network resource allocation mechanism is presented and verified by various simulation experiments described in section V. Finally, the paper concludes with a summary of its contributions and our future work given in section VI.

II. GVA for Heterogeneous Network Services

QoS enabled heterogeneous network services can be regarded as an auction market in which there is one network service provider acting as an auctioneer and many customers participating as bidders. The traded network services are various inelastic network applications, such as real-time voice and video applications that require different fixed amount of network resources to achieve desired quality of service (QoS). Hence, in such a market, bidders request different amount of network resources for their network services. Auction for such network services is *recurring*, because, from the network service provider's point of view, an allocation of network resources needed for a service is made for a specific time only. Once the service is completed, these resources become free and the network service provider needs to offer them to the customers again. From the bidder point of view, network services are requested repeatedly for specific time intervals. The resources such as bandwidth needed for network services cannot be stored in warehouse for future sale, and leaving them unused decreases their utilization, so they are *perishable* [11]. In conclusion, QoS enabled heterogeneous network service market requires a recurring auction in which bidders (i.e., customers) request different amount of time-sensitive, perishable network resources recurrently for specific time intervals. In such a recurring auction, bidders' demand for network resources, bids, and the number of available network resource units may be different in each auction round.

The combinatorial winner selection is the optimal strategy for network resource allocation in a single round. It enumerates all possible combinations of bidders, that we will denote as C_k, where $k = 1,...,2^n - 1$, because $2^n - 1$ combinations of bidders are possible. We will also denote the set of indexes of all feasible combinations as *F*. We call combination C_k feasible if the network resources that are requested by bidders in C_k are available, that is if:

$$\sum_{j \in C_k} r_j \le R^t \,, \qquad (1)$$

where r_j denotes the vector of network resource units requested by bidder j, and R^t denotes the vector of available network resource units at time t. The network service provider selects the combination of bidders C_m that maximizes the sum of products of bids and requested numbers of network resources (i.e., maximizes the resulting revenue) among all feasible combinations of bidders. Hence, the winner selection in the GVA mechanism can be defined as:

$$\max \sum_{i \in C_k} b_i \cdot r_i \qquad (2)$$

To define the price of network resources for the winners selected in GVA, we denote by x^* the vector of winners (if bidder i is a winner, $x_i^* = 1$, otherwise, $x_i^* = 0$). Let $x_i^{*\neg k}$ denote the vector of the optimal combination of bidders without bidder *k* participating in the auction. The price of network resources for winner *k* is computed by deducting the sum of products of bids and requested numbers of network resources for all other bidders (except bidder *k*) in x_i^* from such a sum for all bidders in $x_i^{*\neg k}$ [8]. Hence, the price $G(b_k)$ of network resources for winner *k* is computed as:

$$G(b_k) = \sum_{\substack{i=1 \\ i \ne k}}^{n} b_i \cdot r_i \cdot x_i^{*\neg k} - \sum_{\substack{i=1 \\ i \ne k}}^{n} b_i \cdot r_i \cdot x_i^* \qquad (3)$$

Based on the pricing rule of Eq. (3), the GVA mechanism is incentive compatible because truthful bid (i.e., a bid representing the true valuation of the resource by the bidder) maximizes the bidder's expected utility [8]. The following example illustrates the described combinatorial winner selection and pricing of the GVA mechanism.

Example 1: There are four bidders B1, B2, B3 and B4, and one network service provider. There are three network resource units available. B1, B2, B3 and B4 request 1, 2, 1 and 2 network resource units for their desired network services with bids (i.e., true valuations) of \$3, \$5, \$6 and \$8 for a network resource unit, respectively. In the GVA mechanism, bidder B3 and B4 are selected as winners. Based on pricing rule of Eq. (3), bidder B3 pays (\$19 - \$16) / 1 = \$3 for each network resource unit while bidder B4 pays (\$16 - \$6) / 2 = \$5 per unit.

III. Challenges Arising in Traditional GVA

The combinatorial winner selection of GVA has desirable features such as the optimal dynamic pricing and negotiation mechanisms for efficient network resource allocation. Yet applying it in short-term contract markets for heterogeneous network services can cause market price collapse because of the recurring nature of network resource allocations and perishable nature of network resources. In a recurrent auction, bidders learn from previous auction results, and try to adapt to the market conditions. Hence, the combinatorial winner selection is optimal only for a single round of auction as it focuses solely on revenue maximization (i.e., it only considers current bids during resource allocation). As the result, it can cause starvation for the network resources among the least wealthy bidders (i.e., bidders with low true valuations of resources) in the recurring auction because the true valuations of bidders define their maximum bids. Since the wealth of bidders is distributed unevenly among the bidders, such winner selection strategy will reward only the bidders with the highest wealth (i.e., the highest true valuations). The incentive compatibility of GVA mechanism makes it easy for a bidder who persistently lost in the previous auction rounds to conclude that his true valuation is not large enough to ever become a winner once the winners of the auction starts to repeat (each winner of an auction round may skip several subsequent rounds since her demand for services may be satisfied for a while). When this happens, there is no incentive for persistent losers of the auction to participate in the future auction rounds. Consequently, they drop from the auction and find other ways to satisfy their demand for the desired network services. Such a drop in the number of bidders decreases the price competition in the auction and may ultimately result in revenue collapse of the network service provider. In short, in GVA mechanism, the bidders who do not win for several rounds may drop out of the auction after they conclude that it is impossible for them to win in this auction market. In the long run, only bidders who belong to one of the optimal combinations of subsequent auction rounds are left in the auction market. Then, for at least one auction round, the left and right terms of Eq. (3) will become equal, that is

$$\sum_{\substack{i=1\\ i\neq k}}^{n} b_i \cdot r_i \cdot x_i^{*\neg k} = \sum_{\substack{i=1\\ i\neq k}}^{n} b_i \cdot r_i \cdot x_i^{*} \ \text{ for } \forall i \ \text{ with } \ x_i^{*} = 1 \qquad (4)$$

Hence, based on the pricing of GVA given by Eq. (3), the resulting price of network resource for each selected winner i becomes zero. With all participants becoming winners sooner or later, the auction is no longer incentive compatible, because lowering the bid does not make the bidder ineligible for winning, but merely delays his winning round. Hence, the bidders may decrease their bids below their true valuations, thereby triggering collapse of revenues for the network service provider. We call this phenomenon a '***paradox of the incentive compatible mechanism in recurring auction***' because by achieving the goal of motivating the bidders to bid their true valuations, the mechanism, when applied to a recurring auction, invites the market collapse after only several rounds of auction.

Our previous research demonstrated and evaluated the revenue collapse caused by the bidder drop problem in non-incentive compatible recurring auction mechanisms [11-12]. The following example illustrates it in the incentive compatible recurring GVA auction. Let's consider Example 1 of section II again.

Example 2: Bidders B3 and B4 are selected as winners and pay \$3 and \$5 for a network resource unit, respectively. If those bidders participate in every auction round, bidders B1 and B2 have no incentive to participate in the auction and drop out of it. When bidders B3 and B4 are selected as winners after such a drop, their payments become \$16 – \$16 = \$0 for bidder B3 and (\$6 – \$6) / 2 = \$0 for bidder B4. Therefore, the revenue of network service provider collapses to zero. More interesting case arises if all bidders skip a round after each win. Then, bidders B3 and B4 are winning odd numbered auction rounds, paying \$3 and \$5 for a network resource unit, respectively, while bidders B1 and B2 win even numbered auction rounds, but pay \$0 for allocated resources. All bidders win regardless of the value of their bids, so they may decrease their bids. For example, bidders B3 and B4 may wonder if paying \$3 or \$5 per unit of resource is worth avoiding waiting an auction round for the win. As the result, bids will reflect the true valuation of one-round delay of access to resources instead of the true valuation of ever accessing the resources and the revenue of the service provider will be accordingly lower, reflecting this difference in true valuations.

IV. NETWORK SERVICE ALLOCATION USING PI-GVA

Applying a recurrent auction to short-term contract-based heterogeneous network services requires resolving bidder drop problem to prevent market collapse. To achieve this goal, we introduce the **P**articipation **I**ncentive **G**eneralized **V**ickrey **A**uction (PI-GVA) with one time sealed bidding. Our additional design goals include preserving incentive compatibility and low negotiation cost of the GVA mechanism.

A. *Network Resource Allocation Strategy*

To prevent bidder drop problem from arising, the PI-GVA mechanism rewards bidders for participation in a round of recurrent auction through the winning score $S_r(b_i)$ [12] that is used, instead of a bid, for selecting winners. The bidding score of bidder i in round r is defined as:

$$S_r(b_i) = \frac{b_i}{\mu} \cdot p_{i,r} - w_{i,r} \ , \qquad (5)$$

where b_i denotes the average bid of bidder i until round r, $p_{i,r}$ represents the cumulative number of rounds in which the bidder participated up to and including round r, $w_{i,r}$ stands for the cumulative number of wins until round r, and μ is a constant that controls the effect of bid values on the winning score. Since $(b_i \cdot p_{i,r} / \mu)$ represents the expected number of wins, the winning score $S_r(b_i)$ measures the difference between the expected and real numbers of wins at round r for bidder i. The higher the winning score is, the more below bidder's expectations winnings are and therefore the higher the probability of him dropping out of the auction is.

In each auction round, the PI-GVA mechanism selects as winners the combination of bidders for which the sum of winning scores of all selected bidders is the largest. Hence, the network resource allocation strategy (i.e., the winners selection strategy) using PI-GVA is

$$\max_{k\in F} \sum_{i\in C_k} S_r(b_i) = \max_{k\in F} \sum_{i\in C_k} \left(\frac{b_i}{\mu} \cdot p_{i,r} - w_{i,r}\right) \qquad (6)$$

In each auction round, the feasible network resource allocation is restricted by the resource constraint defined by Inequality (1) and the winning score constraint defined as follows:

$$S_r(b_i) > 1 - \frac{b_i}{\mu} \ \text{for} \ \forall i \in C_k \qquad (7)$$

The winning score constraint requires that the winning score of each winner is higher than zero; a bidder needs to earn enough expected wins before the real win can happen. By Eq. (5), the participation of a loser in the last auction round is rewarded directly by increasing her winning score for the current and future auction rounds. The increased winning score improves the bidder's chances to win in the future auction rounds. Therefore, the PI-GVA mechanism controls bidder drop problem by encouraging bidders' participation in future auction rounds. Since the cumulative average bid b_i is used in the Eq. (5), decreasing a bid during an auction round decreases the expected number of wins, even if the bidder participates in every auction round, thereby decreasing his winning score. Hence, the PI-GVA mechanism encourages the bidders to enter ever higher or at least the same bids during recurring auction.

The coefficient μ controls effect of the average bid on the winning score. If μ is increased, the effect of bid value is diminished, improving the chance of winning by the bidders with lower bids. Reversely, if μ is decreased, the effect of bid value is increased and the chance of winning with lower bids is decreased. Therefore, the optimal strategy for deciding the value of coefficient μ depends on network service provider's goals. In this paper, based on various experimentation results, we set μ equal to the ratio of initial average bids of all bidders to the number of winners (with this value of μ, the sum of all winning scores remains constant if all bidders participate in all rounds with unchanged bids; this selection makes it also easy to satisfy the winning score constraint defined by Inequality (7)).

B. Pricing Network Resources

To describe the pricing rule of the proposed PI-GVA mechanism, we denote by $x^{\oplus}$ the vector of winners defined by the PI-GVA winner selection strategy expressed in Eq. (6) (if bidder i is a winner, $x_i^{\oplus}=1$, otherwise, $x_i^{\oplus}=0$), while $x_i^{\oplus\neg k}$ denotes the vector of such winners when bidder k is removed from the auction round. The pricing rule of the PI-GVA mechanism is a modification of the traditional pricing rule of GVA. The price is established in a two-step procedure. The first step is to compute the payment winning score $I(b_k)$ of the selected winner k with the average bid b_k, according to the following equation:

$$I(b_k)=\sum_{\substack{i=1\\ i\neq k}}^{n} S_r(b_i)\cdot r_i\cdot x_i^{\oplus\neg k}-\sum_{\substack{i=1\\ i\neq k}}^{n} S_r(b_i)\cdot r_i\cdot x_i^{\oplus} \tag{8}$$

Hence, the payment winning score of winner k is computed by deducting the sum of products of winning scores and requested numbers of resources of all winners, except bidder k, in $x_i^{\oplus}$ from such sum for all winners in $x_i^{\oplus\neg k}$. From the payment winning score of the selected winner k defined in Eq. (8) and the winning score function defined in Eq. (5), the payment $G(b_k)$ of winner k for a network resource unit is computed as:

$$G(b_k)=\frac{I(b_k)\cdot b_k}{r_k\cdot S(b_k)} \tag{9}$$

This pricing rule guarantees that the payment of each winner is lower than his bid.

C. Optimal Strategies of Bidders

The bidder's optimal strategy in PI-GVA mechanism can be defined from two perspectives: the bid value and the participation level. In auction for heterogeneous network services, each bidder k tries to choose the bid that maximizes the utility function $U(b_k)$ defined as:

$$U(b_k)=(t_k-G(b_k))\cdot q(b_k), \tag{10}$$

where t_k denotes the true valuation of a resource unit by bidder k, $G(b_k)$ is the price paid for each network resource unit and $q(b_k)$ stands for the probability of winning in auction round r. Based on the pricing rule defined by Eq. (9), the utility function of Eq. (10) can be rewritten as:

$$U(b_k)=(t_k-G(b_k))\cdot q(b_k)=(t_k-\frac{I(b_k)\cdot b_k}{r_k\cdot S_r(b_k)})\cdot q(b_k)$$

As shown in the Appendix, increasing the bid increases the profit factor $(t_k-G(b_k))$ of the above utility function. Moreover, increasing the bid either increases or maintains the probability of winning $q(b_k)$. Therefore, bidding the true valuation maximizes each bidder's expected utility function $U(b_k)$ because the true valuation is the upper bound of the bid of each bidder. In terms of participation, the profit factor $(t_k-G(b_k))$ is an increasing function while the probability of winning $q(b_k)$ is a non-decreasing function of the number of rounds in which the bidder participated. Hence, increasing bidder's participation in auction rounds increases the expected utility of this bidder. Therefore, the dominant bidder's strategy under PI-GVA mechanism is to participate in as many rounds as needed to win and to bid in each of those rounds the true valuation of the network service unit. The detailed proof of the optimality of this strategy is given in the Appendix.

V. EXPERIMENTATION

To evaluate the proposed PI-GVA mechanism, we performed simulation-based experiments. In those experiments, we compared the following two auction mechanisms for short-term contract market for heterogeneous network services: (1) the *Traditional Generalized Vickrey Auction (TGVA)* described in section II as GVA; (2) the *Participation Incentive Generalized Vickrey Auction (PI-GVA)* introduced in section IV.

A. Experimentation Setup

There are 15 bidders who are also customers and an auctioneer who is also the network service provider. In each auction round, 10 network resource units are traded for short-term use by customers requesting network services. Each bidder requests different number of network resource units to satisfy her desired quality of service for heterogeneous network services. Hence, each bidder requests the desired number of units of network resources and bids how much he is willing to pay for each requested unit of network resource. The desired number of units is uniformly distributed between [1, 3]. This number remains constants over the entire simulation. In addition to the perceived intrinsic value of the traded network resources, the wealth of each bidder limits her willingness to pay and impacts her true valuation of the units of network resource. For simplicity, we consider only the distribution of the customer's true valuations here. We use three standard distributions of true valuations with mean 5: the exponential distribution, the uniform distribution over the range [1, 9], and the Gaussian distribution. Hence, without loss of generality, we can assume that the average price of network resource unit is 5. Based on

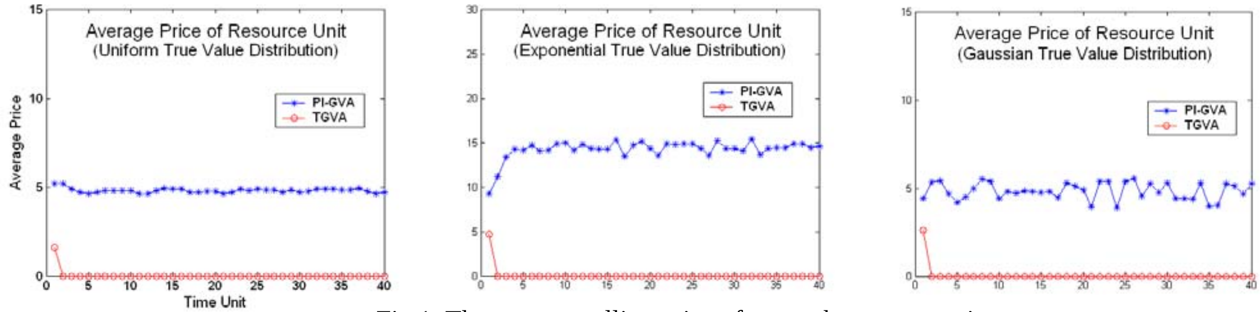

Fig 1. The average selling price of network resource unit

these true value distributions, each bidder bids her true valuation under each auction mechanism to maximize her expected utility in the recurring auction since the two auction mechanisms being compared are incentive compatible. To model bidder drop behavior, we introduce a concept of the Tolerance to Consecutive Losses, abbreviated as TCL. It denotes the maximum number of consecutive losses that a customer can tolerate before exiting an auction [7]. This notion captures the bidders' limited tolerance to loses before they exit the auction concluding that their true valuations prevent them from ever becoming a winner in this auction. Hence, if the consecutive losses exceed the bidder's TCL, the bidder exits the auction. We assume, that the bidders who exited, never return again to the current auction market. TCL of each customer is uniformly distributed over the range of [2, 6].

Based on these settings, each simulation is executed for 2000 auction rounds. At the end, we measure for each mechanism the revenue of network service provider and the bidder retaining ability as measured by the number of remaining active bidders. To estimate revenues of network service provider, we measure the average selling price of network resource unit at the end of every 50 rounds over the entire recurring auction. To compute the bidder retaining ability, we measure the percentage of users dropped in each compared mechanism at the end of the recurring auction.

B. Experimentation Results

As shown in the Fig. 1, in all three distributions of bidders wealth (i.e., the distributions of true valuations), TGVA cannot prevent collapse of the selling price for a network resource unit as a result of bidders dropping out of the auction. The combinatorial winner selection strategy of TGVA focuses on bids only so it excludes the lower true valuation bidders from ever becoming winners. Consequently, those bidders drop out of the auction after TCL rounds, decreasing price competition. Finally, only bidders who at least occasionally become winners remain in the auction and the resulting selling prices drop for those bidders to zero based on the pricing rule of TGVA. This phenomenon illustrates the paradox of incentive compatible mechanism in recurring auction. Therefore in TGVA, the bidder drop is the sole cause of revenue collapse in the recurring auction. In contrast to TGVA, the combinatorial winner selection based on winning score of Eq. (5) in the proposed PI-GVA mechanism allocates network resources efficiently and yet prevents bidders drop out of the auction, thereby maintaining price competition and stabilizing the selling price of network resource units at about $5.

Table 1. Percentage of dropped users

	Uniform	Exponential	Gaussian
TGVA	73.33%	73.33%	66.67%
PI-GVA	40.00%	46.67%	40.00%

In terms of active bidder retaining level, Table 1 shows that the proposed PI-GVA mechanism retains over 50% of the initially active user throughout the entire recurring auction. Only the bidders with very low true valuations are prevented from ever winning by the winner selection based on winning score of Eq. (5). Yet, in TGVA, about 70% of bidders drop out of the auction. Hence, the proposed PI-GVA mechanism achieves higher social welfare because more users benefit from the network resource allocations.

VI. CONCLUSIONS AND FUTURE WORKS

The combinatorial winner selection of the GVA mechanism allocates resources to bidders optimally for a single round of an auction. However, the recurring nature of auction for network resource allocation may cause bidder drop resulting from the paradox of incentive compatible mechanism in recurring auction. Therefore, in designing auction based dynamic pricing mechanisms for heterogeneous network services, the additional phenomenon, bidder dropping, should be considered. We introduced the PI-GVA mechanism that provides a novel combinatorial winner selection strategy. The proposed strategy prevents bidder drop by providing incentive for bidder's participation in each auction round which results in enough bidders remaining in the auction to keep the prices stable in the market. In our future work, we will attempt to design more efficient bidder drop control algorithms and will extend our study to the case in which dropped bidders return to the auction.

APPENDIX

***Lemma 1*:** The profit factor $(t_k - G_k(b_k))$ of the utility function of Eq. (10) is an increasing function of bid value b_k.

Proof: The profit factor $(t_k - G(b_k))$ can be rewritten as $(t_k - (I(b_k) \cdot b_k / r_k \cdot S(b_k)))$. Note that the payment winning score $I(b_k)$ of bidder k does not dependent on bid b_k (see Eq. (9)) and the required number of network resource units r_k and true valuation t_k can be regarded as constants. Hence, the profit factor can be influenced only by a fraction $(b_k / S_r(b_k))$. Hence, to prove Lemma 1, we need to show that increasing the bid decreases this fraction. Indeed, we have:

$$\frac{b_k / S_r(b_k)}{(b_k+\alpha)/S_r(b_k+\alpha)} = 1 + \frac{\alpha \cdot w_{k,r}}{(b_k+\alpha)\cdot(\frac{b_k}{\mu}\cdot p_{k,r} - w_{k,r})} > 1 \quad \text{(A-1)}$$

where bid increment $\alpha > 0$. Inequality (A-1) is true because b_k, α, μ, and $w_{k,r}$ are always larger than zero, and the current winning score $S_r(b_k)$ is also larger than zero thanks to the winning score constrain of Inequality (7). Therefore, increasing the bid increases the profit factor $(t_k - G(b_k))$. □

***Lemma 2*:** The probability of winning $q(b_k)$ in the utility function of bidder *k* is a non-decreasing function of bid b_k.

Proof: In auction round *r*, the winning score coefficient μ, the cumulative number of wins $w_{k,r}$, and the number of rounds in which bidder *k* participated $p_{k,r}$ can be regarded as constants. Hence, increasing bid b_k increases the winning score. The PI-GVA mechanism ranks bidders in the decreasing order of their winning scores given by Eq. (5). Hence, increasing winning score of a bidder will either improve or maintain the rank of this bidder. Since the PI-GVA combinatorial winner selection strategy of Eq. (6) maximizes the sum of winning scores of winners, the following three cases are possible in terms of probability of winning when a bidder increase his bid. Case (1) Rank of bidder is improved and his probability of winning is increased (e.g., the bidder now outranks another bidder in the optimal combination with the same resource request, so the former replaces the latter as the winner). Case (2) Rank of bidder is improved but there is no change in his probability of winning (e.g., the bidder was ineligible to be a part of optimal combination because of resource constraints, so his improved rank does not give him any advantage). Case (3) Rank of bidder is unchanged, and there is no change in his probability of winning. In all of three cases, the probability of winning cannot decrease whenever a bidder increases his bid. Additionally, the increased winning score will carry over to future auction rounds. Hence even if the increased winning score does not change probability of winning by the bidder in the current auction round, it still may increase the probability of winning in the long run. □

Based on Lemmas 1 and 2, we conclude that by increasing his bid, bidder *k* increases his expected utility $U(b_k)$. Additionally, each bidder's bid is limited by his true valuation. Hence, bidding each bidder's true valuation maximizes the bidder's expected utility in the proposed PI-GVA mechanism. In short, PI-GVA is an incentive compatible mechanism. From the participation point of view, increasing the number of rounds in which bidder k participates decreases the fraction $(b_k / S(b_k))$ of the profit factor $(t_k - G(b_k))$. Hence, it increases the resulting profit factor. Additionally, increasing the number of rounds in which bidder participates increases the winning score thanks to participation incentive defined in Eq. (5). As shown in Lemma 2 proof, increasing the winning score increases or maintains the probability of winning by the bidder. Hence, the probability $q(b_k)$ of winning by bidder k is non-decreasing function of number of rounds $p_{k,r}$ in which bidder k participates. Therefore, increasing number of rounds in which the bidder participates increases his expected utility $U(b_k)$. In conclusion, the bidder's optimal strategy in the PI-GVA mechanism is to bid his true valuation and to participate in as many auction rounds as possible.

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