Efficient Grid Task-Bundle Allocation Using Bargaining Based Self-Adaptive Auction

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Abstract—In this paper, to address coordination and complexity issues, we formulate a grid task allocation problem as a bargaining based self-adaptive auction and propose the BarSAA grid task-bundle allocation algorithm. During the auction, prices are iteratively negotiated and dynamically adjusted until market equilibrium is reached. The BarSAA algorithm features decentralized bidding decision making in a heterogeneous distributed environment so that scheduler can offload its duty onto participating computing nodes and significantly reduces scheduling overheads. When a BarSAA auction converges, the equilibrium point is Pareto Optimal and achieves social efficient outcome and double-sided revenue maximization. In addition, BarSAA promotes truthful behavior among selfish nodes. Through game theoretical analysis, we demonstrate that truthful revelation is beneficial to bidders in making bidding strategies. Extensive simulation results are presented to demonstrate the efficiency of the BarSAA strategy and validate several important analytical properties.

I. INTRODUCTION

Task scheduling has been one of the key challenges and widely studied subjects in enabling computational grid systems in the last decade. Many conventional task scheduling strategies, either centralized or distributed, are inefficient and require complicated coordination, which results in performance loss. One solution to mitigate coordination complexity is to utilize an economic model to characterize peer behaviors [1]. Such a model is motivated by the following observations: design similarity between market supply-demand mechanisms and grid scheduling principles, and role similarity between rational market participants and distributed peers seeking for maximum service payoffs. Current market-oriented paradigms mainly fall into two categories: commodity market mechanism design where buyers and sellers negotiate directly and auction mechanism design where several buyers compete for optimal market outcomes. This paper follows the latter approach and proposes a task-bundle allocation algorithm which is socially efficient in computational grids.

To implement the proposed mechanism, we adopt a hierarchical open grid model which precisely captures the physical administrative features of the realistic grid system. In addition, in contrast to conventional grid model which applies to homogenous cluster computers, we introduce highly heterogeneous and volatile P2P desktop nodes, referred to as computing peers, to the lower level of the proposed hierarchical model, leveraging the convergence of P2P and Grid technologies [2]. In the proposed model, users authorized to a grid system pay money (real or virtual) in exchange of acquiring grid computational services for job execution. Each submitted job is further divided into small tasks, allowing for simultaneous execution on multiple computing peers for better resource utilization and high performance. Now the problem becomes how to find an allocation of task-bundles to participating peers that will achieve maximum market efficiency. Instead of holding auction for each task, we propose a combinatorial auction algorithm BarSAA where peers can bid on bundles of individual tasks in a Bags-of-Tasks (BoT) fashion [3]. Combinatorial auction was well studied in economic research and is well known for its benefit of allowing bidders to better express their valuations and preferences for enhanced competition and improved market efficiency [4]. However, the core problem of combinatorial auction design is how to minimize the cost of valuation determination for exponential possible combinations, known as the preference elicitation problem. BarSAA addresses this problem through adaptive bargaining between auctioneers and bidders iteratively until market equilibrium is reached, known as the Walrasian tâtonnement process [4]. The dynamic bargaining process is a modification of simultaneous ascending combinatorial auction [5] for grid environment, and helps to distribute winner determination among bidders. Moreover, BarSAA allows for adaptive and focused bidder strategy adopted in auction game, therefore lead to enhanced revenue and market efficiency compared to conventional single-sided one-shot auction used in grid scheduling. The contributions of this paper are as follows: (1) We propose an iterative bargaining auction mechanism BarSAA for task-bundle allocation in a highly dynamic distributed environment composed of egocentric computing peers; (2) We analytically and experimentally demonstrate important features of BarSAA, including socially efficient outcome with market equilibrium, Pareto optimality, and promote truthful behaviors.

The rest of the paper is organized as follows. Section II presents an overview related work. Section III presents the problem formulation. Section IV presents the BarSAA algo-
rithm for intra-site task-bundle allocation and analysis of its key properties. Section V presents simulation results. Section VI concludes the paper.

II. RELATED WORK

Recently we have witnessed a burst of game and related economic theory applications in various research fields including but not limited to protocol design [6], power management [7], workload balancing [8] and incentive mechanism design [9]. In grid computing, game theory is extremely helpful in modeling behaviors of benefit-driven agents. Typical game theoretical methods in grid mechanism design define objective functions in term of utility, and converge to system equilibrium state on the basis of revenue maximization. For example, in computational grid, scheduling and job execution strategy in non-cooperative game are investigated in [10] and [11] respectively, both demonstrate that Nash equilibrium is not the best outcome. The economic and game theoretical research also spurs development of market-oriented grid systems. For example, Buyya et al. have proposed Nimrod/G [12], a resource broker which coordinates resource allocations in grids by integrating multiple economic models. Popcorn [13] is a Web-based computing system for parallel application scheduling, in which CPU times of distributed workstations are traded to jobs in different auction mechanisms, including Vickrey, first-price and k-price double auction.

Current literature of auction-based scheduling mainly focuses on single item auction. Grosu et al. [14] have investigated popular auction methods and proposed double auction protocols for resource allocation. On the other hand, combinatorial auctions [5], although have been researched intensively in economic study for years, did not receive sufficient attentions in computer science until recently. A number of heuristic methods [15], [16], [17] aiming to solve the winner determination problem (WDP) have been proposed. However, these methods focused on approximation of WDP. To the best of our knowledge, we are the first to apply the simultaneous ascending auction method [5] and systematically model it to suit realistic grid environments. Inspired by Wolski’s G-commerce [18] and Ghosh’s bargaining methods [19] in mobile grids, The proposed BarSAA algorithm is novel in that we combine the supply-demand adjustment of commodity markets in G-commerce and bargaining process in Ghosh’s methods with auction theory. The allocation process is dynamically adaptive and achieves Vickrey-Clarke-Groves (VCG) outcome for both auctioneers and bidders. The most relevant research is proposed by Garg et al. [20], in which a continuous double auction is employed by the meta-scheduler for resource mapping in global grids.

III. PROBLEM FORMULATION

A. System Model

A grid system is viewed as a cluster of loosely coupled computers orchestrated together to solve computationally hard problems. As the grid scale grows the flat organization of grid no longer holds. Instead, the fast development of network technologies paves the way for enhanced grid cooperation among different organizations. Therefore we believe that a hierarchical grid structure is more suitable for large-scale grids [11]. As P2P and grid further converge, we adopt a P2P desktop grid model at the lower level for better scalability and mitigating complexity issues emerged in grids. In representative systems such as SETI@home [21], desktop machines interconnected by Internet voluntarily participate in the scientific experiment using cycle scavenging. However, due to potentially selfish behaviors of end-users, voluntary participation is not incentive compatible and might harm the overall system performance. To solve this problem grid economy is introduced in order to motivate desktop users to contribute resources in exchange of profits. In this paper the system model is built upon a virtual grid market in which resource competition is achieved by auctions. The model organization is shown in Figure 1.

Figure 2 further illustrates details about task allocation and execution process. In the figure, we observe the following major roles.

- **Grid User (GU):** Grid user submits jobs to global scheduler by registering it via user interface provided by general grid application. After the execution GU pays for services based on pre-signed service charging
agreements.

- **Global Scheduler (GS):** GS acts as the auctioneer in inter-site game. Jobs waiting to be scheduled are inserted into a global FIFO job queue. At each auction GS assigns an associated job ID and announces its price to all the local site schedulers. During the auction it monitors the bidding process and determines the winner. After the job is dispatched to the winner site GS waits for execution results and returns it back to GU.

- **Local Site Scheduler (LSS):** The dual role behaviors of LSS are of most research interests in the hierarchical grids model. As a bidder LSS contends for maximum site profits. On the other hand, LSS institutes the intra-site auction rule, further breaks job into tasks and generates the current available list of desktop peers participating in the auction. After the allocation is determined bundles are dispatched to computing peers working at the smallest level of granularity.

- **Computing Peer (CP):** Each CP contributes resources for GU rewards. At intra-site auction CP bids for task-bundle according to its budgets. CPs are interacted in a P2P manner and behave selfishly for their own benefits.

### B. BarSAA Scheduling

In this paper we mainly focus on the intra-site scheduling problem. Let $\mathbb{T} = \{t_1, ..., t_m\}$ denote the set of tasks with identical attributes including computational size ($S_{cp}$) and communication size ($S_{cm}$). Here we assume that the workload model is BoT (Bags-of-Tasks), denoting a large sets of independent tasks with no communications involved. In addition there is no order constraint on execution sequence. Let $\mathbb{B} = \{b_1, ..., b_n\}$ denote the set of bidders. The bundle of tasks allocated to $b_i$ is represented as $x_i (x_i \subseteq \mathbb{T})$. $b_i$’s budgets reflect in its current available resources controlled by GU including CPU speed $cp_i$ and bandwidth $cm_i$. We also assume a private value model, in which task valuation is evaluated by every participating bidder who is mutually blind to each other. In the P2P network desktop nodes are highly volatile, denoting dynamic join and leave behaviors and node failures. In BarSSA this issue is addressed that after each auction starts newly joined CPs willing to participate in the auction are delayed to join the next auction. Also assuming that after the auction is finished if a CP decides to leave the system it may further trade its winning tasks to other CPs. As such the volatility is partially set aside and is handled at later task trading stage that will be included in future research. Node failure is taken care of in BarSSA as well. If node fails during the auction process, it automatically drops out of the auction and tasks will be distributed to other active nodes. On the other hand, if node failure happens between auction rounds, it will not be included in the auction since BarSSA periodically updates active node list at each auction round.

Next we map the characteristics of the task-bundle auction into economic terms as follows:

- **Circulating Currency:** the benefits and payments of bidders are expressed using virtual grid dollars (G$).

- **Market Supply (SP):** the number of unallocated tasks.

- **Task Price:** the monetary value of one task setup by LSS. The price for task $t_i$ is denoted by $p_i$.

- **Market Clearing Price:** the market clearing price $p^*$ is the price where market supply and demand are equal.

- **Bidder Demand:** let $\mathbb{D} = \{d_1, ..., d_n\}$ denote the bidder demand vector in which $d_i$ represents the number of tasks maximizing $b_i$’s payoffs at current market price.

- **Market Demand(MD):** the summation of all the bidder demands. $MD = \sum_{i=1}^{n} d_i$ where $d_i \in \mathbb{D}$.

- **Bidder Valuation:** in the private value model let $V(d_i) \geq 0$ denote the valuation of $b_i$ for demand $d_i$. The valuation of each bidder follows the constraints such that $V(\emptyset) = 0$ and $V(d_i) \geq V(d_j)$ for all $d_i \geq d_j$.

- **Bidder Utility:** $b_i$’s utility (or payoffs) $U_i$ is given by $U_i = V(d_i) - P(d_i)$, where $P(d_i)$ is defined as payments of $b_i$ for bundle demand $d_i$. With all the notations and assumptions the intra-site scheduling problem can be abstracted as a dynamic $1$-to-$N$ non-cooperative auction game played by LSS (auctioneer) and CPs (bidders). Each CP has no knowledge of any market information that they can use to play against the other CPs. The game is played iteratively in discrete time until market equilibrium is reached. The auction rounds are represented as $r = \{1, ... R\}$. The strategy $\varsigma_i$ of each bidder $b_i$ is defined as any function mapping the observable bidding history $H^r_i$ to current demanding quantities $d^r_i$ that conform to the auction rule constraints and budgets: $\varsigma_i : \{1, ... R\} \times H^r_i \rightarrow d^r_i$. Accordingly the strategy space $\Omega_i$ for $b_i$ is defined as the set of all possible $\varsigma_i$. In BarSAA each participant acts independently from each other, seeking their own interest, assuming that all other participants will also seek for utility maximization. Therefore we are interested in finding a feasible allocation where maximum market efficiency is achieved. In market economy the term social welfare is defined as the aggregate of valuations at final allocation $\sum_{i} V(x_i)$. The following definition defines a socially efficient allocation in term of social welfare.

**Definition 1. Socially Efficient Allocation:** Let $\Gamma$ denote the set of all possible allocations, a socially efficient (or efficient) allocation is the allocation $\mathbb{S} = \{x_1, x_2, ..., x_n\}$ to all bidders which will maximize the social welfare.

\[
W = \max_{\mathbb{S} \in \Gamma} \sum_{i \in \mathbb{B}} V(x_i) \\
\text{s.t. } x_i \cap x_j = \emptyset, \forall i, j
\]  

To distinguish how individual actions affect the behavior of the whole auction game, we have the following definition of competitive equilibrium.

**Definition 2. Competitive Equilibrium (CE):** let $P(S)$ denote the price function applied on bundle $S$, a competitive
equilibrium is a state of prices $P$ and allocation $\hat{S}$ such that:

$$U(P, \hat{S}) = \max_{\hat{S} \in \Gamma} \left[ V(\hat{S}) - P(\hat{S}) \right]$$

$$\Upsilon(P, \hat{S}) = \max_{\hat{S} \in \Gamma} \sum_{i \in B} P(x_i) \tag{2}$$

Now we formally connect the two definitions with the following theorem [5] and our goal becomes clear: find the socially efficient allocation for maximum market efficiency with suitable scheduling strategy design.

**Theorem 1.** Allocation $\hat{S}$ is said to be supported in competitive equilibrium if and only if $\hat{S}$ is a socially efficient allocation.

### IV. Design and Analysis of BarSAA Algorithm

#### A. BarSAA Algorithm

The BarSAA algorithm is presented in Algorithm 1 and Algorithm 2 for LSS and CP respectively. At the initialization phase, task associated information and marginal valuations of task-bundle are interchanged between LSS (auctioneer) and CPs (bidders). The auction starts from a price representing the lowest valuation from all CPs and goes up monotonically. At each round, CPs decide their demands according to the current market price. As the price rises market demands will drop until matching the supply. The payment policy is specified in later analysis of this section.

#### B. Policies and Properties of BarSAA

1) **Monopoly avoidance:** The target of competitive equilibrium belongs to a Pareto Optimal state. Note that the notion of Pareto Optimal is only associated to market efficiency, not to market fairness. The research scope of this paper focuses on finding the market efficient algorithm in allocation. In extreme cases, CPs with super computing ability may take over all the tasks in auction, referred to as monopoly. We argue that by limiting the maximum number of tasks $N_{\text{max}}$ a CP can win in auction, such effects caused by the monopoly phenomenon can be depressed, like government acts in real economy.

2) **Marginal valuation matrix:** To guide bidding at each round, CP needs to evaluate deal prices at different quantities before the auction formally started. The marginal valuation matrix preserves such price information. To be concise, the marginal valuation defines the amount of profits arises when the bidder demand quantity increases by one unit. If tasks are identical and follow the BoT execution model, the execution time $t_i$ for one single task at host $i$ is given by ($t_{\text{setup}}$ is fixed),

$$t_i = t_{\text{setup}} + t_{\text{trans}} + t_{\text{exec}}$$

$$= t_{\text{setup}} + \frac{S_{\text{cm}}}{C_{m_i}} + \frac{S_{\text{cp}}}{C_{p_i}} \tag{3}$$

The execution time for $k$ tasks is $k \times t_i$. But how much GU is willing to pay for its task execution services? Different grids have different payment rules and both GU and users of CPs should abide by the agreement. The general rule is that GU would like to pay more money for faster service per task. Here without loss of generality we map the execution time to user payment by simply taking the reciprocal: $V(x_i \mid |x_i| = 1) = \frac{1}{t_i}$.

However, if the marginal profits for CP $b_i$ of all tasks are identical, when offered price goes up beyond that value, $b_i$ will dropout the auction completely. For example, if the marginal valuation for tasks is $5G\$ without discrimination, when offered price rises to $6G\$, CP’s utility for every task would be $5G\$ - $6G\$ = $-1G\$, causing CP to drop out of the auction since current profit is negative, we call this phenomenon sudden dropout. In contrast, BarSAA differentiates the marginal profits by introducing a parameter $\alpha$ called execution discount (ed). Let $\psi^k_i$ be the execution costs for $k$
Algorithm 2 BarSAA algorithm For CP $b_i$

\begin{verbatim}
/* BarSAA Initialization */
1: RECEIVE: system and task parameters FROM LSS.
2: Calculate marginal matrix vector $\overrightarrow{\tau}_i$ and send to LSS.
3: Get $P^1$ from LSS and send initial requests $d^1_t$ to LSS.
/* Iterative bargaining begins here... */
4: while Bidding process is continue do
5:   UPDATE: current reserved quantities and save current price.
6:   SEND: $d^{r-1}_t$ TO LSS.
7:   RECEIVE: $P^{r+1}$ FROM LSS.
8: end while
9: Send final payment information to LSS and make payments.
10: Execute assigned job bundle on local processor.
\end{verbatim}

Now the valuation profits are distinguished and this assumption helps CPs to decrease their demand quantities smoothly. The marginal valuation matrix is defined as an $n \times m$ matrix, in which $v_{i,j}$ denotes for the marginal valuation of task $t_j$ at CP $b_i$.

$$v_{i,j} = \left\{ \begin{array}{ll}
\psi_i^j - \sum_{k=1}^{j-1} \psi_i^k & \text{if } j \leq N_{max} \\
0 & \text{if } j > N_{max} 
\end{array} \right. \quad (5)$$

In the last section we have defined bidder utility as valuation subtracting payment. Hence, suppose at round $r - 1$ CP $b_i$ demands for $d^{r-1}_t$, with valuation matrix the CP $b_i$’s demands at round $r$ is given by:

$$d^r_t = \max\{j | v_{i,j} - P^{r-1} > 0\} \quad (6)$$

3) Pricing policy: At each round of BarSAA CPs respond to the tentative price offered by LSS until market equilibrium is reached. Theoretically in an ascending auction, the tentative prices are linear increasing, passing through each marginal value point at which aggregate demands drop. However the continuous pricing strategy is impractical to implement due to discrete rounding. Observe that although CPs barely know market information of each other, LSS operated by grid administrator possesses more control of market at local site. For that reason at the initialization phase each CP will report its marginal valuation vector to LSS. After collecting the valuation information from CPs, LSS sorts entries of marginal valuation matrix in ascending order excluding entries with value 0. The sorted price vector is denoted as tentative price vector $\overrightarrow{P}$, at time $r$ auctioneer will offer $r$th price $p^r \in \overrightarrow{P}$ for market demand adjustment. Apparently this process provides an $m \times n$ upper bound in convergence achievement. An even faster way to achieve convergence is to sort the entries with binary tree. In this case tentative offered price will start at the middle of the vector and CP’s demands will be adjustment in two directions. Two questions naturally arise concerning the market clearing price: 1) does such a price exist? 2) If so is it unique? With quasi-linear utility function and monotonic decreasing pricing strategy, these two questions can be affirmed with confidence [22]. An intuitive proof is provided in Figure 3, in which both the demand and the supply curve take only integer quantity values. With strictly decreasing pricing adjustment, the demand curve and the supply curve intersect at the unique price $p^*$. Note that the demand curve merely reflects the downward sloping trend of our pricing model and it is impossible for LSS to calculate the varying bidder demand curve beforehand.

4) Tie breaker: To guarantee the convergence of competitive equilibrium we must ensure that no two CPs withdraw demand quantities at the same time. In other words, identical values occurred in the marginal valuation matrix might cause the iterative process oscillate around the convergence point back and forth. This problem is solved at the time when auctioneer sorting the tentative price vector. If two or more identical entries are found, LSS will generate a very small random number $\tau$ denoted as the tie breaker parameter. Suppose there are $n$ entries found identical, then the $i$th identical entry is added by $\tau$ for the purpose of breaking ties.

5) Payment policy: Suppose payment is made linearly in auction, meaning that if market clearing price is $p^*$ at final round $R$ and $b_i$ wins $d^R_t$ tasks, then $b_i$ pays $p^* \times d^R_t$ for task-bundle execution. Apparently the linear payment method will yield to strategic bidding and destroys the market equilibrium. For example, some CPs might choose to deceive LSS by reporting decreased valuations, thus to drag the market clearing price $p^*$ down for more benefits. In order to avoid market manipulation behaviors in linear payment method, we adopt a non-linear payment approach introduced by Ausubel [23]. According to Equation 6 and monotonically increasing price rule, $b_i$’s demands at round $r$ cannot be higher than its demands at previous round. Therefore when demands from $b_i$’s opponents decline, $b_i$ guarantees to win at least the difference of market supply and cumulative demands from its opponents. In contrast with linear payment, this approach restores bidders’ incentives and restrains market power. The following definitions are used to formulate the payment policy in BarSAA.

Definition 3. Aggregate Reserved Bundle: Suppose $b_i$ wins bundle $d^R_i$ of final quantity $|d^R_i|$ at final round $R$, the aggregate
reserved bundle for CP $b_i$ is given by:

$$
\eta^r_i = \max\{0, SP - \sum_{j \neq i} d_j^r\} \\
\eta^R_i = |d^R_i|
$$

**Definition 4. Current Reserved Bundle:** With aggregate reserved bundle defined above, current reserved bundle for $b_i$ is defined as the difference of the aggregate reserved bundle at adjacent rounds:

$$
\lambda_i^0 = \eta_i^1 \\
\lambda_i^r = \eta_i^r - \eta_i^{r-1}
$$

Obviously at each round CP cannot bid less than what the aggregate reserved bundle, combined with monotonically decreasing demands we have the following bidding rule for BarSSA:

**Bidding Rule.** All CPs participating in BarSSA must report their current demands no greater than the quantities in the previous round, and no less than the prior aggregate reserved quantities:

$$
\eta_i^{r-1} \leq d_i^r \leq d_i^{r-1} \\
\text{for all } 1 \leq i \leq n \text{ and } 1 \leq r \leq R
$$

Similarly we define that if $b_i$ bids monotonically increasing in quantity, the excess demands of opponents are "overdraft" for $b_i$ and the concept of aggregate and current overdraft bundle are defined symmetrically, which is useful in binary tree organized acceleration of auction convergence mentioned in pricing policy discussed above.

Finally the total payment of bidder $i$ is given by:

$$
P(d_i^R) = \sum_{r=1}^{R} p^r \lambda_i^r
$$

6) **Truthful revelation VS. Tricks:** Previously we demonstrate that the non-linear payment policy used in BarSSA prevents CPs from playing tricks. In this part we reveal the reason why truthful revelation is favored by CPs in BarSSA through game theoretical analysis. Generally there are two types of tricks a CP may choose to play: either over-exaggerating its requests called bluffing or under-reporting called humble bidding. By contrast, if a CP honestly reports its demands at each round, it must strictly follow Equation 6 and the bidding rule defined before. We claim that compared with tripping strategies, truthful revelation played by every CP form an ex post perfect equilibrium, in which the strategies adopted by all CPs constitute a Nash Equilibrium at every round following any history. And we have the following theorem [23] for truthful revelation:

**Theorem 2.** Truthful revelation of demands by all CPs in BarSSA is a weakly dominant strategy, and will lead to ex post perfect equilibrium.

**Proof Sketch:** With bidding rule constraint and non-linear payment methods described above, truthful revelation by $b_i$ will result in market clearing price $p^*$ and maximum payoffs in final allocation. Moreover, rival CPs do not respond to $b_i$’s change of strategy. These facts, along with the definition of aggregate reserved bundle sufficiently prove that $b_i$’s action has no effect on others. Therefore it is an ex post perfect equilibrium for all CPs. Because rival bidders are not able to recognize strategy change in $b_i$, truthful revelation is weakly dominant. Complete discussion can be found in [23].

In fact, the mechanism of reservation allocation at each round and the unique existence of market clearing price combined yield to Walsrasian equilibrium, which is equivalent to the competitive equilibrium we have defined in Section III, according to Theorem 1, we have the following conclusion for the proposed BarSAA algorithm:

**Theorem 3.** The proposed BarSAA algorithm results in a socially efficient allocation of task-bundle.

V. PERFORMANCE EVALUATION

A. Simulation Setup

To validate the effectiveness and efficiency of allocation in heterogeneous distributed environment we have implemented BarSAA using SimGrid [24], a popular grid simulation toolkit. BarSAA is developed using the MSG interface integrated in the latest public distribution of SimGrid. MSG is suitable for simulating heterogeneous desktop grids [25]. The simulation system is configured as a 20 desktop nodes (computing peers) interconnected in a P2P style. The network deployment as well as the computing platform are presented in a XML configuration file. Figure 4 illustrates system snapshots of available computing and network resources each CP willing to contribute. The computing speed is represented in FLOPS and the transfer rate is represented in BPS.

We have performed three sets of experiments. In the first two sets, jobs are submitted to LSS in constant rate. There are totally 32 rounds of jobs arriving. At each round, jobs are further divided into multiple tasks. The first round has 30 tasks for auction and after that the task number is one more than the previous round for scalability test. In the third experiment we fix task number to 80 and investigate allocation performance with different system metrics. In all

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1 Thanks Dr. Daniel Grosu for providing the source code of their simulator.
three experiments we use the execution discount rate $\alpha = 0.05$ and network setup overhead 5 milliseconds. The following metrics are used throughout our simulation.

- **Auctioneer Revenue**: Profits earned by auctioneer at one round of auction.
- **Average Bidder Profits**: Average profits earned by bidders at one round of auction.
- **Social Welfare**: Overall valuation gained at final allocation at one round of auction.
- **Fairness Index**: Let $T_i$ denotes the average task completion time of CP $b_i$, the fairness index $FI$ is defined as:

$$FI = \frac{(\sum_{i=1}^{n} T_i)^2}{n \sum_{i=1}^{n} T_i^2}$$
(11)

- **Degree of Heterogenous (DoH)**: The Degree of Heterogenous (DoH) is defined as the average value of standard deviation of computing speed and transfer speed.

$$\text{DoH} = \frac{1}{2} \left( \sum_{i=1}^{n} (cp_i - \overline{cp})^2 + \sum_{i=1}^{n} (cm_i - \overline{cm})^2 \right)$$
(12)

- **Turnaround Time**: Average time spent by each job in the system.

**B. Results and Analysis**

1) **Performance impact of computation ratio**: In the first set of experiments we measured the expected revenue of auctioneer and bidders against increasing number of scheduling tasks with time. At each auction the task size is kept fixed and the ratio of computational size to communication size is varied. The results are shown in Figure 5, in which three types of task are compared: **EQ** (Cp size equals Cm size), **Cp intensive** and **Cm intensive**. We observe that the expected revenues of auctioneer and bidders are scalable and stable with time. Another conclusion made according to the results is that transfer latency is more dominant in making more profits.

2) **Effects of truthful revelation**: To verify the effects of truthful revelation as presented in Section IV we randomly picked bidder $b_6$ and allowed it to play tricks at each round of auction. At each round, bidder $b_6$ either overstate its demands, or report less than its requests. As defined in Section IV the first strategy is labeled as **bluffing**, and the second strategy is labeled as **humble bidding**. Other CPs keep truthfully reporting their valuations to auctioneer throughout all rounds. Figure 6 presents the metrics measured under different strategies. Figure 6(a) demonstrates the social welfare in all rounds. For comparison we also implemented random task allocation. We observed that with truthful revelation the proposed protocol achieves maximum social welfare. As one randomly picked bidder playing deviated strategy from truthful revelation strategy, the social welfare decreases slightly in each round. Besides, the proposed auction protocol outperforms random allocation in every round, verifying that the auction process achieves socially efficient outcome. In Figure 6(b) we compared the profits gained by the random chosen CP playing different strategies in BarSAA. Results reveal that the trick-playing CP experiences profits decreasing if it makes single-sided move from truthful revelation. Therefore there is no incentive for a single player to deviate from sincerely reporting, forming the ex post equilibrium proved in Theorem 2. The next two figures show the effects of tricks in auctioneer revenue and average bidder profits. If the CP chooses to bid aggressively (bluffing), the competitive equilibrium price is pushed up by higher bid prices which will lead to slightly higher auctioneer revenue yet dragging down average bidder profits dramatically. Alternatively if CP bids conservatively the average bidder profits will slightly goes up but harm the overall auctioneer revenue badly. In summary, trick strategies lead to lower social welfare and present no benefits to auction participants. In that case, truthful revelation is the unique optimal strategy for CPs.

3) **Fairness and Turnaround Time**: To evaluate the system performance, we fix task number to 80 and applies monopoly avoidance in BarSAA. At each round we set maximum number of tasks one bidder can get at the start of the auction. The value
of fairness index (FI) reflects workload balancing situation. The strategy is perfectly fair if the value of FI is 1.0. From Figure 7(a) we observe that when the maximum number is 4 auction is meaningless in scheduling (80 tasks onto 20 bidders), leading to poor FI value. Also we observe that FI value converges after certain maximum constraints. This is because that maximum constraint is also the maximum allocation to single bidder in auction if no monopoly control is applied. The trend of FI in between indicates that monopoly avoidance is effective in fair allocation. Figure 4 shows the heterogeneity of the P2P desktop system. Here we compare systems of different heterogeneous degrees and demonstrates how DoH (degree of heterogeneity) affects the fairness of allocation. Results show that higher degree of heterogeneity will decrease fairness of final allocation. Therefore, for the next stage of intra-site task scheduling we are aiming at designing effective load balancing strategy in addition to current revenue maximizing auction design.

In Figure 7(b) we observe that higher degree of fairness does not necessarily yield to less turnaround time. This is because with no monopoly avoidance applied, CPs with faster link and computational speed will get more tasks, which complies with the design goal of BarSAA that tasks are allocated to the bidders who value them most. However, better fairness does yield to better response time since tasks are executed in parallel. In other words, not the average task cost but the longest execution time on single host counts in this scenario.

VI. CONCLUSION

In this paper we proposed BarSAA as a negotiation-based combinatorial auction algorithm to achieve socially efficient allocation of task-bundles in hierarchical computational grids. There are two major contributions of our design. First BarSAA is self-adaptive in a way that market price is iteratively adjusted through dynamic negotiation between auctioneer and bidders until equilibrium is reached. Secondly, through mathematical analysis we reveal that truthful revelation is a dominant strategy for bidders to make decisions. BarSAA is incentive compatible and enhances market contention for double-sided revenue maximization. Extensive simulations verify the efficiency of BarSAA. In our ongoing work, we incorporate load balancing strategies for both time-sensitive and budget-sensitive task allocation and further explore the relationship and interaction between two levels of games in inter-site and intra-site scheduling.

REFERENCES


