Agents' Bidding Strategies in a Combinatorial Auction Controlled Grid Environment

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1 Simulation Setting

We present an agent-based simulation environment for resource allocation in a distributed computer system that employs a combinatorial task scheduler. Our environment enables the simulation of a mechanism for the simultaneous allocation of resources like *CPU time (CPU), communication bandwidth (NET), volatile (MEM)* and *non-volatile memory (DSK)* in the distributed computer system. In contrast to traditional grid allocation approaches, our allocation process considers production complementarities and substitutionalities for these resources making the resulting resource usage much more efficient. The central scheduling instance of our system is comparable to an auctioneer that performs an iterative *combinatorial auction (CA)*. Proxy-agents try to acquire the resources needed in computational tasks for the provisioning of *information services and information production (ISIP)* by submitting package bids for the resource combinations. The system simulates a *closed loop* grid economy in which the agents gain monetary units for resources they provide to other grid system participants. The simulation environment allows the utilization and benchmarking of different proxy-bidding strategies in various system load situations. For the comparison of the bidding strategies we introduce a utility function that allows to represent different preferences of agents.

1.1 Scenario for a PCRA in a Combinatorial Grid Scheduler

The general *price controlled resource allocation (PCRA)* scenario used within the combinatorial grid simulator is constructed as follows:

- *Task agents* are engaged in acquiring the resources needed to process the ISIP task in the distributed computer system on behalf of real world clients. They do this by bidding for the required resource combination via the mediating agent.
- *A mediating agent* (auctioneer) receives the resource bids and calculates an allocation profile for the available resources managed by the *resource agents* according to the allocation mechanism.
- *Resource agents* manage available resources on their particular host IT systems and offer them to the task agents via the mediating agent. If a bid is accepted via the auctioneer the acquired resources are reserved.

A two-dimensional *bid-matrix (BM)* is used to represent the bids. One dimension of the BM describes the time t at which the resource is required within the request period. The other dimension r denotes the resource types MEM, CPU, NET, DSK. The request for a quantity of an individual resource r at time t is then denoted by a matrix element $q_{i,j}(r,t)$. A price $p_{i,j}$ is assigned to each BM expressing the agent's *willingness-to-pay (W2P)* for the resource bundle. In both variables the indices i and j identify the bid matrix. The value q^{bmax} denotes the maximum resource load that can be requested by a bidder for a single BM element $q_{i,j}(r,t)$. These elements are occupied with *time slot occupation probability* p^{tso} and have a maximum allocable resource quantity $q^{max}(r,t)$ at time t.

1.2 The System's Budget Management Mechanism

Each task agent holds a monetary budget that is initialized with a fixed amount BG^{ini} of *monetary units (MUs)* when the negotiations begin. At the beginning of each round k, the task agents' budgets are refreshed. In order to avoid an expiration of the agents' budgets during the iterative auctioning process the agents are integrated into a monetary circuit in the *closed-loop* grid economy regarded in this work. Task and resource agents act as a unit of consumer and producer both owning the resources of their peer system. The resource agent does the reporting of resource usage and provisioning for the task agent. The agents on the peer computer are compensated for the resources provided to the system. The budget circulating in the system is kept constant for the *closed grid economy.*

1.3 The Combinatorial Auctioneer

The combinatorial auctioneer controls the iterative allocation process of the grid. For this purpose the auctioneer awaits the bids i that are submitted in the form of j XOR-bundled BMs and represent the task agents' requested capacity $q_{i,j}(r,t)$ of the resources r at time t. After having received all alternative BMs submitted by the task agents, the auctioneer has to solve the *combinatorial auction problem (CAP)* which is NP-hard [1]. The CAP is often denoted as the *winner determination problem (WDP)*, according to the traditional auctioneers task of identifying the winner. The formal description of the CAP is [2]:

$$\max \sum_{i=1}^{I} \sum_{j=1}^{J_i} p_{i,j}\ x_{i,j} \tag{1}$$

$$\begin{aligned} \text{s. t.} \quad q(r,t) = \sum_{i=1}^{I} \sum_{j=1}^{J_i} q_{i,j}(r,t)\ x_{i,j} \leq q^{max}(r,t), \\ \forall_{r\in\{1,\ldots,R\}, t\in\{1,\ldots,T\}} \text{ and} \\ \sum_{j=1}^{J_i} x_{i,j} \leq 1, \quad \forall_{i\in\{1,\ldots,I\}}. \end{aligned} \tag{2}$$

The auctioneer's goal is to maximize the received income under the resource constraints. In order to accelerate the price-finding process, the auctioneer provides feedback information to the bidders to adjust their W2Ps $p_{i,j}$. It is not always possible to calculate *unambiguous prices* for the individual resources in a CA.[1] Kwasnica et al. describe a pricing scheme for the individual goods in a CA by approximating the prices based on a LP approach [3]. Like in a similar approach by Bjørndal and Jørnsten they employ the *dual solution* of the relaxed WDP to calculate the shadow prices $sp_{r,t}$ [4]. In the simulation model presented here, the dual LP approach of Kwasnica et al. is adopted:

$$\min \ z = \sum_{r=1}^{R} \sum_{t=1}^{T} q^{max}(r,t) \cdot sp_{r,t} \tag{3}$$

$$s.t. \quad \sum_{r=1}^{R} \sum_{t=1}^{T} q_{i,j}(r,t) \cdot sp_{r,t} + (1 - x_{i,j}) \cdot \delta_{i,j} = p_{i,j} \tag{4}$$

Here $\delta_{i,j}$ are called reduced cost. The proposed SP calculation uses *LPSOLVE 5.5* to solve the LP problem in Eq. (4). The SPs are weighted by the resource usage and grouped to shadow prices for each resource. Now the *market value of a resource unit* v_r can be calculated while using the shadow prices and summarizing the utilized capacity of each resource r for all accepted bids:

$$v_r = \frac{\sum_{t=1}^{T} sp_{r,t} \cdot q(r,t)}{\sum_{t=1}^{T} \ q(r,t)} \quad \forall_{r \in \{1,\ldots,R\}} \tag{5}$$

Bid prices are assumed to be non-linear in this framework. This means that shadow prices $sp_{r,t}$ can not be calculated in each round, i.e. there is no solution of the LP [4]. In such cases the auctioneer relies on an approximation of the market values $\hat{v}_r$ as the averaged market values calculated in the last n rounds.

1.4 The Task Agents' Bidding Model

The task agents of the combinatorial simulation model try to acquire the resources needed for ISIP provision. Besides the market values of resources, the task agents' bidding behavior is determined by their budget and by a *bidding strategy*. At each round k the task agents generate M new bids. The task agents submit several bids as exclusively eligible bundles (OR-of-XOR). If the budget of a task agent is exhausted due to the continued acceptance of bids by the auctioneer, no further bids are submitted until the budget has recovered. The task agents repeat bidding for rejected bids in the following round while modifying the W2P with respect to the current pricing information.

Depending on the market value v_r of the resources required for the ISIP provision process, task agents have to formulate their W2P for the bids. To calculate the bundle prices, two cases must be considered:

[1] In many cases, explicit resource prices can only be calculated for each individual bid.

- In the first round, a market value of the resources is not provided to the bidders. Therefore, bidder agents formulate the W2P for their *initial bids* by dividing the budget by $L \cdot M \cdot J$ to calculate a mean bid price that guarantees the task agents' budget to last for the next L rounds if $M \cdot J$ new sets of XOR-bids are added.
- In the following rounds, the task agents employ the market values v_r of the resources to determine their W2P. The requested amounts of capacity is multiplied by the according market value and if the bid is initialized, a factor p^{ini} is included in the calculation so that initial bids may start below or above the current price level of the resource market. To control the price adaption process, an additional price acceleration factor p_i^{inc} is introduced. At each round, p^{inc} is incremented by a constant Δp.

$$p_{i,j}(k) = \sum\nolimits_{r=1}^{R} \sum\nolimits_{t=1}^{T} v_r \cdot q_{i,j}(r,t) \cdot p_i^{inc} \tag{6}$$

If a bid is rejected, the corresponding W2P is adapted by

$$p_i^{inc} = p^{ini} + (l_i \cdot \Delta p)\,, \tag{7}$$

resulting in the above mentioned value of p^{ini} in round $l_i = 0$. Recalculating the price based on the current market value v_r results in a faster adoption process. Rejected bids are *repeated* with an updated W2P until the bid is accepted. Bids are *discarded* if they have not been accepted after L rounds. When an agent's budget is exhausted, it formulates no new bids until the budget is refreshed.

2 Testing Bidding Strategies

In our simulations we try to find the utility maximizing strategy for the proposed agent types. While the amount of acquired ISIP resources has an positive impact but diminishing marginal impact on the agent's utility, the number of periods an agent waits until its bids are accepted has a negative impact. The utility U_a of an agent is calculated by the following function with B_a denoting the set of agent a accepted bids.:

$$U_a = \left(\sum\nolimits_{(i,j)\in B_a} x_{i,j} \cdot \sum\nolimits_{r=1}^{R} \sum\nolimits_{t=1}^{T} \; q_{i,j}(r,t) \right)^{\alpha} \cdot \bar{l_a}^{-\beta} \tag{8}$$

To calculate the decreasing impact of the waiting time, we use a time index $\bar{l_a}$ (the averaged number of periods an agent bids until it has placed a successful bid) and β to adjust the force of the waiting time's impact. The impact of the quantity is defined by α. Using this utility function we introduce two agent types:

- A *quantity maximizer* ($\alpha = 0.5$, $\beta = 0.01$) that tries to acquire a high amount of resource capacity. The hypothesis is that this agent follows a *smooth bidding strategy*, i.e. he increases the bid prices slowly. The economic rationale for this type of proxy agent strategy can be the fact, that it bids for resources required for the fulfillment of an ISIP task that is not time-critical.

– An *impatient bidder* ($\alpha = 0.5$, $\beta = 1.0$) that suffers if he can not use the resources instantaneously and will use an *aggressive bidding strategy*. This agent has to submit high initial prices, but overpaying will reduce the quantity he can acquire. The economic motivation of this behavior can be a proxy agent that bids for the execution of time-critical tasks in an ISIP system.

Beginning with three bundles containing three XOR bids in the first round, both agent types generated three additional bid bundles at each further round k. The task agents increase the W2P of rejected bids over a maximum of $L = 5$ rounds. The pattern of new generated bids is identical to the structured BM ($q_{bmax} = 3, p_{tso} = 0.333, t_{max} = 4$). The auctioneer was able to allocate a maximum load of $q_{max} = 8$ per resource while $T = 8$. The number of agents was set to 4 and the number of bids per agent (M) to 3. Three agents use a *default bidding* behavior with constant values of $\Delta p = 0.2$ and $p^{ini} = 0.5$. The value of Δp has to be sufficient high to guarantee fast price adaptation in case of resource failures, while a high value of p_{ini} leads to overpaying in case of low demand.

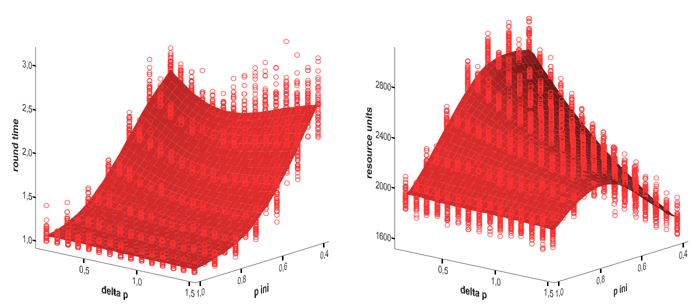

Fig. 1. Mean acceptance time and quantity of resource units for test bidder with varying price increment Δp and initial price p^{ini}.

Fig. 1 shows the resource units acquired by the test agent and the averaged bid acceptance time $\bar{l_a}$ of 50 simulation runs for each Δp, p^{ini} combination (steps of 0.1). All task agents receive the same budget in each round of the simulation. Fig. 1 illustrates that for small Δp and p^{ini} the highest amount of resource units can be acquired by the task (test) agents. An aggressive strategy with high Δp and p^{ini} leads to a declining amount of acquired resources. While a reduction of acceptance time is mainly achieved by high p^{ini}, increasing Δp has only impact on average acceptance time if p^{ini} is low.

Fig. 2 depicts the utility resulting from varying price increment Δp and initial pricing p^{ini}. In case of a quantity maximizing preference ($\beta = 0.01$) the test agent's utility is high for small initial bids and little price increments with a maximum utility value of $U_a = 53.36$ at $p^{ini} = 0.5$ and $\Delta p = 0.1$. It pays

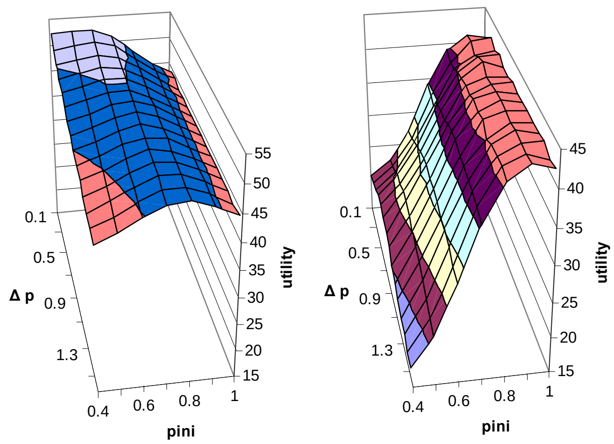

Fig. 2. Utility of the test bidder for quantity maximizing preference $\beta = 0.01$ (left) and impatient bidding behavior $\beta = 1.0$ (right) for determination of the optimal bidding strategy under varying price increment Δp and initial pricing behavior p^{ini}.

off for the patient bidder to wait if its bids fit into the current allocation at a relative low price (low increment and initial price). In contrary, the impatient bidder gains low utility from such a strategy (Fig. 2 right side). The impatient agent receives the highest utilities by using an initial bid price close to the market value of the resources ($p^{ini} = 0.9$). Interestingly, the price increment in the following round does not have much impact on the acceptance time and therewith on the utility of the impatient test bidder. However, for bids exactly at market value utility declines sharply, signaling the peril of "overbidding" or simply paying too much for the required ISIP resources. This underlines the importance of accurate market value information to achieve good allocations. The shadow price controlled combinatorial grid enables agents to implement efficient bidding strategies according to the users utility functions. Of course a high impact of the competitors' behavior remains as challenge.

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