An Interactive Approach for Multi-Attribute Resource Allocation in Grids

Lili Ding
College of Economics and Management, Shandong University of Science and Technology, Qingdao, China
College of Physical and Environmental Oceanography, Ocean University of China, Qingdao, China
Email: dinglili0220@sohu.com

Wanglin Kang and Xinmin Liu
College of Economics and Management, Shandong University of Science and Technology, Qingdao, China
Email: wlkang@163.com

***Abstract*—Auction-based models and protocols introduce money and pricing as the technique for coordination between users and producers of resources in grids. In this paper, we propose a multi-attribute reverse auction protocol to allocate grid resource. In order to enhance the information efficiency we develop a novel interactive approach supporting both user agents and producer agents. In this approach, an iterative algorithm used to estimate the resource user's preference utility function can facilitate producer agents to update their bids with incomplete information. Numerical simulating experiments show that our approach can satisfy the resource user's quality demand on multiple attributes, and achieve high efficiency in user utility. The results also provide an idea to analyze the two-side private information problem in gird resource allocation.**

***Index Terms*—grid resource, reverse auction, iterative algorithm, multi-attribute**

I. INTRODUCTION

Grid computing has not become an important field of research in computer science, but also a new paradigm for solving computationally large problems by providing access to large scale shared computing resources. The grid enables resource share and dynamically allocate the computational environments from different domains. The grid resources' features, e.g., highly dynamic, uncontrollable and distributed, increase the difficulties of grid resources allocation. All these characteristics show that grid system needs a dynamic and high-efficiency resources management. Several economic-based resource allocation mechanisms have been proposed. In general, they are better than the classical resource allocation schemes in that they are decentralized in structure and they use incentives for resource users to contribute resources.

There exists two basic economic models in the resource management fields namely commodities markets and auctions [1]. In the commodities market model, a publicly agreed price is proposed for each resource. By contrast, in the auction model, the auction participants would trade-off at a price that is unknown before the auction ends. Also, the resource users and resource providers act dependently and they can negotiate on the trading price. Auction models have advantage over commodities market models for grid resource allocation because they require little global information, have decentralized structure and are easy to implement. Most previous work considers only one type of auctions and compares it with other economic and conventional models. In [2], three types of auction allocation protocols are provided: First Price Auction, Vickrey Auction, and Double Auction. From users' and grid resources' perspective, they wanted to find the most suitable resource allocation mechanisms for the grid environment. The double auction models have been received more attention. Three most popular double auctions are: Preston-McAfee Double Auction Protocol (PMDA), Threshold Price Double Auction Protocol (TPDA), and Continuous Double Auction Protocol (CDA). Huang et al. [3] investigated that a periodic double auction mechanism with uniform price suited for resource allocation in Grid. In their work, the double auction took place in rounds and all exchanges were performed with the same price. Zakian et al. [4] also used a continuous double auction method for grid resource allocation. They provided market-like techniques to provide an incentive for resource providers, and motivated the resource users to trade-off between deadline, budget, and the required level of quality of service. In [5-6], the computational auction mechanism for allocating and scheduling computer resources such as processors or storage space that had multiple quality attributes was proposed. The mechanism was evaluated according to its economic and computational performance. Mirzayi et al. modified the bidding stage using Signcryption model [7]. The results showed that the new model had a good behavior in grid environment and increased security and fairness with this method. Some researchers have paid attention to the multiple auctions. Anthony et al. [8] developed a heuristic decision-making framework through which an autonomous agent could exploit to tackle the problem of bidding across multiple auctions with varying start and end times. Gorbanzadeh et al. proposed two types of hybrid genetic algorithms to improve the efficiency of

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genetic algorithm for solving the winner determination problem. Results declared that the proposed algorithms had good efficiency and led to better answers [9].

In fact, the grid resources have multiple quality attributes in the auction mechanisms. Che [10] originally presented a thorough analysis of the design of multi-attribute auctions. He designed an optimal scoring rule based on the assumption that the buyer knew the probability distribution of the supplier's cost parameter. Branco[11] derived an optimal auction mechanism when the suppliers' costs were correlated based on Che's independent cost model. Another issue in developing an appropriate scoring function lies in elicitation of preferred information for multiple attributes. Teich et al. [12] showed some concept about internet-based implementations and used MAUT technique for bid evaluation in single-sourcing, multi-attribute reverse auctions. The similar techniques also include analytic hierarchy process (AHP) and price out technique [13]. Leskela et al. [14] developed a quantity support mechanism (QSM) by the pricing out approach, which could provide not only suggested price for the bidders, but also quantified decision support. These methods are similar to the value function case. Because all the attributes are converted into monetary values, the multi-attribute problem can become the resulting single-attribute problem.

Different from the original literature, we describe a novel reverse auction-based protocol to model the grid resources allocation problem consisting of multi-attribute resources. In fact, there are many resources types including computer system, network subsystem, file system, database system and so on. Each resource type is associated with one or more attributes with specific values. For example, there are some attributes of a computer system, i.e., CPU architecture, total and available memory, maximum and current degree of multi-programming, and so on. Therefore, the price-only negotiations are not suitable. Other attributes such as resource speed and memory may influence both resource users and providers' decisions. Our concern in this paper is to build a bridge between the grid resource allocation and multi-criteria spheres. We introduce an interactive approach to provide aid both to the resource users and providers for multi-attribute auction. An iterative algorithm is presented to facilitate the estimated preference utility function for resource provider agents to update their bids to be competitive in the next round. Our approach will enhance information efficiency by not only reducing the transmission costs of true information but also decreasing the transmission of false information. Finally, the simulating experiments show that the reverse auction-based protocol and its related iterative algorithm have good behavior in grid environment. They have better performance on user utility value level and market information efficiency.

We organize the paper as follows. Section 2 gives the reverse auction-based grid allocation protocol and model. In section 3, we present the bidding strategies for resource provider agents (*RPAs*). The iterative algorithm is presented to help the *RPAs* efficiently discover the user's true utility preference. The simulating experiment results are presented in section 4. In section 5 we draw conclusions and present future research directions.

II. REVERSE AUCTION-BASED GRID ALLOCATION: MODEL AND PROTOCOL

A. Multi-attribute Reverse Auction Model

The entities in our grid environment are resource users and resource providers. Resource users have one or more independent computational-intensive jobs for execution and are willing to pay for it. Also resource providers have computational resources and are willing to rent them for profit. We use the resource user agent (*RUA*) that works on behalf of the users and the resource provider agent (*RPA*) that works on behalf of resource providers. The user agents and provider agents are two intelligent entities having their own specific objectives. They interact with each other in the form of a multi-attribute reverse auction protocol for obtaining their objectives.

We assume that there are n rounds with the expired time $T > 0$. Different from the current literature, we suppose that in each round there is more than one *RPA* arriving, i.e., there are x resource provider agents, k attributes, and a single resource user agent in each round. We represent the resource provider agent i in round t as s_i^t, where $t = (1, 2, \cdots, n)$ and $i = (1, 2, \cdots, x)$. I.e., in round t, s_i^t arrives and places one multi-attribute bid, denoted by $b_i^t(a_{i1}^t, a_{i2}^t, \cdots, a_{ik}^t)$, where a_{ij}^t stands for the level of the jth ($j \in k$) attribute of the ith resource provider agent in round t. In this paper, we consider a dynamic setting for grid resource allocation. I.e., given the multi-attribute bid vector b_i^t, the resource user agent must decide whether to accept the multi-attribute bid, before entering the next round. I.e., the resource user agent computes an output consisting of the quantity and price for winner(s) in current round. The game ends when the last seller announces his multi-attribute bid during the time of $[0, T]$. In our system shown in Fig.1, the resource user agent acts as an auctioneer. He notifies all available resources provider agents that the resource needs computing service, then each resources provider agent bids according to his own private price. Finally, the resource user agent decides who win the bid according to the auction rules.

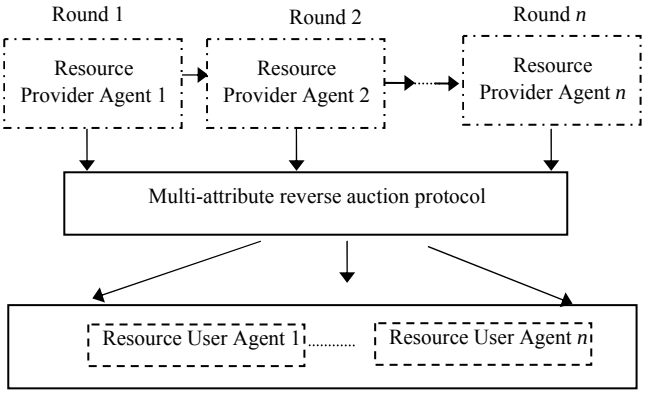

Figure. 1 Scheduling scheme in the proposed framework

B. Multi-attribute Reverse Auction Protocol

In this paper, we consider the problem of reverse auction allocation problem with available grid resources of multiple attributes. The multi-attribute reverse auction (*MRA*) protocol is provided as follows.

MRA protocol:

Phase *I*: Bidding

1. In round *t*, *RUA* sends a task with *k* attributes.

2. RPA_i, $i = 1, 2, \cdots, x$, sends multi-attribute bid $b_i^t(a_{i1}^t, a_{i2}^t, \cdots, a_{ik}^t)$ to *RUA*.

3. For $i = 1$ to *x*, *RUA* receives the bids.

Phase *II*: Completion

1. After *RUA* receives all bids in round *t*, it does the following:

1.1 Compute the utility value $u(s_i^t)$ and make it public for *RPAs* according to the following equation.

$$u(s_i^t) = \frac{[\sum_{j=1}^{k}(w_j(a_{ij}^t - z_j^*))^{\beta}]^{1/\beta}}{p_i^t} \quad (1)$$

where w_j ($\underline{w} \le w_j \le \overline{w}$) indicates the weight of attribute *j*, z_j^* indicates the accepted value of attribute *j* and p_i^t is the price-attribute. *RUA* updates the estimation of the parameters β and w_j of metric L_β in order to provide more accurate information to *RPAs*.

1.2 Determine the temporary winner(s), s_w^t:

$$w = \{i \,|\, u(s_i^t) = \max\{u(s_1^t), u(s_2^t), \cdots, u(s_x^t)\}\}.$$

1.3 Notice RPA_i that he is the temporary winner. Otherwise, send reject messages to RPA_l, $l \ne w$.

2. If $t = n$, then terminate the round.

3. Determine the final winner RPA^* from the temporary winners. If there is more than one winning *RPAs*, the resource user selects by additional information, e.g., cooperation relationship.

4. *RUA* sends the job to RPA^* and RPA^* executes it.

5. *RUA* sends payments to RPA^*.

III. Bidding Strategies for RPAs

In this section, we discuss the case that the utility function of *RUA* is his private information. Thus, the *RPAs* have to estimate this function to provide their bidding strategies. An iterative algorithm is presented to help the *RPAs* discover this private information. I.e., we use a small positive constant threshold of Δ to represent a minimum preference percentage difference by which the *RUA* can distinguish different *RPAs*. For instance if the *RUA* prefers *RPA* of s_i^t to *RPA* of s_h^t, then we require $u(s_i^t) = u(s_h^t)(1+\Delta)$. In each round, the *RUA* computes the value based on the resource user's true preference value function. According to these estimations and their cost functions, *RPAs* update their bids for the next round. In each round, let *SP* and *NSP* denote the sets of preferred and not preferred bids, respectively. Let X^t denote the set of constraints derived from the preferences of the *RUA* in round t. We design the following iterative algorithm for *RPAs* to update their bids and other attributes.

Iterative Algorithm:

Step 1: Set $t = 1$, $X^0 = \Phi$ and $SP = NSP = \Phi$.

Step 2: In round t, there is more than one *RPA* coming and presenting their bids together with other attributes.

Step 3: The *RUA* decides whether to accept these bids. If someone *RPA* improves the preferred utility value by Δ, then notice him that he is the temporary winner. Place the accepted bid in set *SP* and go to Step 4. Otherwise, place the refused bid in set *NSP* and go to Step 6.

Step 4: *RPAs* estimate the resource user's utility function.

Step 4.1: For *RPAs* the objective function is to find the maximum ε satisfying the constraints, where ε is the minimum difference between the utility function of the preferred bid and the other bids.

$$\begin{aligned} &\min \varepsilon \\ &s.t. \sum_{j=1}^{k} w_j = 1 \\ &u(s_i^t) = \left[\sum_{j=1}^{k}\left(w_j\left(a_{ij}^t - z_j^*\right)\right)^{\beta}\right]^{1/\beta} \Big/ p_i^t \quad \forall i \\ &u(s_i^t) \ge u(s_j^t)(1+\varepsilon) \quad \forall s_i^t \end{aligned} \quad (2)$$

Step 4.2: Update the preference constraint set.

$$X^t = X^{t-1} \cup u(s_i^t) \ge u(s_j^t)(1+\Delta)$$

Fit a preference value function that satisfies the constraint set X^t for the smallest positive integer β value. Let the estimated utility value of the accepted bid of the current round be u^*.

Step 5: Move to an improved contour with an estimated utility value of u^t in round *t*, i.e.,

$$u^t = u^*(1+\Delta)$$

Recommend the coming *RPAs* to move onto this contour by providing them with the current β, w_j and u^t. Let the coming *RPAs* update their bids. Go to Step 6.

Step 6: Set $t = t+1$. Go to Step 2. If $t = n$, go to Step 7.

Step 7: Stop. The winning *RPAs*, whose bids are in SP. If there is more than one winning *RPAs*, the *RUA* selects by additional information, e.g., cooperation and reputation.

In this iterative algorithm, the *RUA* uses the resource user's true preference utility function to choose most preferred bid in current round according to Step 2. This information may be less powerful for *RUA* to estimate the true function, but large numbers of rounds could improve efficiency of our approach. In Step 3, if there is more than one winner in round t, the *RUA* could select one of them by other additional information. Step 5 presents the estimated preference value in round t denoted by $u^t = u^*(1+\Delta)$, where u^* is the estimated preference value of the best bid of the current round. As larger value of u^* is preferred, we multiply u^* with $1+\Delta$ to obtain improved bids from the *RPAs*. In this step, *RPAs* can utilize this estimated contour to update their bids and other attributes.

IV. Simulating Experiments

In this section, the simulating experiments are given to describe two attributes about speed and memory, which are important for the resource user to make decision. The simulating experiments facilitate the evaluation of reverse auction resource allocation protocol in terms of resource user's utility level and auction efficiency. In our simulation, a resource user submits requests or jobs to the *RUA*, which in turn initiates an auction for each request or job. The iterative algorithm is utilized to help the *RPAs* discover the true utility function. *RPAs* are the bidders and they bid for executing jobs. Thus, we simulate that there are three *RPAs* in each round, who present bids together with two attributes. Let a_v denote the speed with the weight of $w_v = 0.6$ and a_m denote the memory with the weight of $w_m = 0.4$. For all *RPAs*, the accepted values z_v^* and z_m^* are common information. Suppose that the reserved value of price is $z_v^* = 3$ MIPS, reserved value of memory is $z_c^* = 5\ G$ and $\beta = 3$. Then, the resource user's true utility function is that

$$u = \left[w_v^{\ \beta} \left(a_v - z_v^*\right)^\beta + w_m^{\ \beta} \left(a_m - z_m^*\right)^\beta \right]^{1/\beta}$$

In round 1, three sellers present their bids, together with other two attributes in Tab.1. The *RUA* computes the utility value by the resource user's true preference function. The largest one is 5.943 offered by *RPA* one. Since 5.943 is larger than the initial reserved benefit, the bid of *RPA* 1 is accepted. Before entering into the second round, we use the iterative algorithm to estimate the parameters. Based on this information we start with $\beta = 1$ and find the weights of these two attributes by solving (2), i.e. $w_v = 0.9698$ and $w_m = 0.0302$. The estimated preferred utility value is $u^* = 9.6243$. We inform the coming *RPAs* about the estimated preference curve by providing its form and parameters of β, w_v and w_m. It is shown that the estimated preference utility value in round 2 is $u_2 = 9.6423*(1+0.05) = 10.1055$. Also, we recommend the coming *RPAs* to try to move onto the contour having value of 10.1055 in order to be competitive in next round.

TABLE. 1

BIDS FOR ROUND 1

RPAs	a_v	a_m	p	True u^t	Estimated u^t	
1	20.8	1.3	2.100	5.943	**9.6243**	√
2	20.5	1.2	2.173	5.660	9.1657	
3	19.2	1.7	2.080	5.540	8.9767	

In round 2, the preferred *RPA* is the second one according to the resource user's true value function. Set $\beta = 1$. We can not find the feasible solution, i.e., ε is always smaller than 0.05. Thus, we increase $\beta = 1$ from 1 to 2. The estimated parameter values are $w_v = 0.7770$ and, and $w_m = 0.2230$. The updated bids by *RPAs* on the counter of 8.4893 are in Tab.3.

TABLE. 2

BIDS FOR ROUND 2

RPAs	a_v	a_m	p	True u^t	Estimated u^t	
1	21.3	1.5	2.080	6.144	7.9602	
2	20.9	1.9	2.010	6.240	**8.0850**	√
3	20.3	1.7	2.010	6.060	7.8520	

In round 3, *RPA* 1 is selected and the estimated parameters are $\beta = 2$, $w_v = 0.7060$ and $w_m = 0.2940$.

TABLE. 3

BIDS FOR ROUND 3

RPAs	a_v	a_m	p	True u^t	Estimated u^t	
1	21.5	1.8	1.969	6.5520	**7.7174**	√
2	21.2	1.8	1.945	6.5403	7.7039	
3	20.8	1.9	1.916	6.5140	7.6743	

RPAs update their bids with the given information in round 4. We also can not find the feasible solution when $\beta = 2$. Thus, we set $\beta = 3$ and find $w_v = 0.6066$ and $w_m = 0.3934$. Because the preference utiliy values between the *RPA* 2 in round 4 and *RPA* 1 in round 3 are

within the small threshold Δ value the *RUA* uses. Therefore, the algorithm stops and the provisional winning bidders are in *SP*. The coming *RPAs* can use the estimated utility value function to update their bids in the following rounds.

TABLE. 4
BIDS FOR ROUND 4

RPAs	a_v	a_m	p	True u^t	Estimated u^t	
1	21.6	1.8	1.9012	6.8171	6.8401	
2	21.6	2.1	1.8846	6.8774	**6.9025**	√
3	21.0	1.7	1.8543	6.7937	6.8231	

V. CONCLUSIONS

This paper introduces the multi-attribute reverse auction protocol into the grid resource allocation problem, which extends some results in earlier research. For this protocol, we hope to build a bridge between the grid resource allocation and multi-criteria spheres. We develop an interactive approach to estimate the parameter values of the underlying preference value function of the resource user using his/her past preferences. This decision supporting tool has important potential benefits for all parties participating in auctions, i.e., resource users and resource providers. One of the future directions is to consider more information about input sequence of resource provider agents' bids. The other one is to discuss the better solution for winner determination problem to improve the allocation result and performance, and apply this mechanism to a real grid system.

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Lili Ding received the Ph.D. degree in management science and engineering from Xi'an Jiaotong University. She serves as an associate professor at Shandong University of Science and Technology. Her major interests include combinatorial optimization, online algorithm and online decision-making and pricing theory.