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Multi-Attribute Auctioning Resource in Grids: Model and Protocols

Lili Ding*[1,2], Xiaoling Wang[1], Wanglin Kang[1]
[1]College of Economics and Management, Shandong University of Science and Technology, China
[2]College of Physical and Environmental Oceanography, Ocean University of China, China
*Corresponding author, e-mail: dinglili0220@sohu.com

Abstract

Auction models and protocols are found efficient in managing resources allocation, which are a key technology in grid computing system. In this paper, a new multi-attribute multi-round reverse auction is proposed, and related reverse auction based protocols are designed. The resource user's satisfaction degree is introduced into the traditional grid resource allocation problem to help the grid resource broker make multi-attribute decisions with incomplete information. Numerical simulating experiments show that our model and protocols can satisfy the resource user's quality demand on multiple attributes, and achieve high efficiency in user utility. The results also illustrate that the on-line multi-attribute algorithm in ONMRA protocol has better performance in an on-line setting for grid allocation.

Keywords: *grid resource, reverse auction, on-line algorithm, competitive analysis*

1. Introduction

Grid resource computing system is defined as the next generation computing platform to solve large scale problems in science, industry and engineering. Computational grids support the creation of virtual organizations which enable the sharing, exchange, selection, and aggregation of geographically distributed heterogeneous resources [1]. Such grid resources may be storage or computer network, and so on. Users and providers based on grid systems can use gird resources or share their grid resources in grid environment. But how to help the users with resource-consuming actives find specific resources providers is an interesting question which has received many researchers' attention [2-4]. Moreover, grid resources' features of highly dynamic, uncontrollable and distributed resources increase the difficulties of grid resources allocation. An appropriate grid resource allocation method can exploit the capability of resources efficiently and satisfy the user's reasonable requests. The previous studies have proved that market based methods, especially auction models, are suitable for solving the grid resource allocation problem.

Different from the original literature, we describe a novel reverse auction-based approach 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. Examples of attributes of a computer system are 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 size may influence both users and resource providers' decisions. In our approach, we present a reverse auction model to help the resource user's satisfaction level maximization by optimally determining the winning resource provider(s) in each round based on his true satisfaction degree function and the current submitted bids. Besides offline information situation, we also consider an on-line setting that the different bidders arrive at different times and the auction mechanism is required to make an immediate decision about each bid as it is received [5]. We argue that in the network environment, all participants could not be willing to wait for a long time for the final decisions. For example, the CPU time allocation, each request (bids) may need an immediate answer. Thus, OFMRA protocol and ONMRA protocol are provided to help the grid resource broker make multi-attribute decisions

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with complete information and incomplete information. Finally, the simulating experiments show that the reverse auction-based approach has good behavior in grid environment. It has better performance on user satisfaction level and market information efficiency.

We organize the paper as follows. Section 2 gives the related literature. In section 3, we present the multi-attribute multi-round reverse auction model. In section 4, OFMRA protocol and ONMRA protocol are designed and an on-line multi-attribute algorithm is presented to help the grid resource broker (GRB) efficiently determine the final winner without knowing the future bid sequences. The simulating experimental results are presented in section 5. In section 6 we draw conclusions and present future research directions.

2. Related Work

Auction models have been widely adopted in the grid resources allocation problem [6]. The reasons are: i) constant price in economic models can't reflect the change of supply-demand relationship in grid resource markets, ii) using auction requires little global information with decentralized structures. We represent related literature from the following two aspects.

2.1. Off-Line Auction-Based Models for Grid Resources Allocation

Off-line auction means that the buyers or sellers play a complete information game, i.e., the bid information is available and obeys some kinds of probability distribution. The most commonly studied off-line auction models for grid resources allocation consider only one type of auctions and compare it with other economic and conventional models. In [7], three types of auction allocation protocols were evaluated: 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 received more attention. Haque et al. [8] used a double auction to model an agent-based economic architecture that supported dynamic management of distributed resources. Izakian et al. [9] developed an agent-oriented double auction model, and proved that the model was good in maximizing profit for providers. Qureshi et al. [10] proposed a continuous double auction, in which market-like techniques were used to motivate the users to trade-off between deadline, budget, and the required level of quality of service. In the field of off-line reverse auction, Wolski et al. [11] allocated two types of grid resources including CPU and disk storage, by using the equilibrium price where equilibrium of supply and demand was realized. Schnizler et al. [12] proposed a multi-unit combinatorial auction based grid resource co-allocation approach. A heuristic algorithm was adopted to achieve economic efficiency and performance effectiveness on resources management.

2.2. On-Line Auction-Based Models

On-line auction that we refer to is in a setting where different buyers arrive at different times and the seller is required to decide whether to accept each bid as it is received without knowing the future bids. Such ***on-line*** auction was first proposed by Goldberg et al. in 1999 [5]. Lavi and Nisan [13] presented an incentive compatible on-line auction for a large number of identical items and proved this auction had an optimal competitive ratio with respect to the revenue and the total social efficiency. Hajiaghayi et al. [14] considered an on-line truth telling mechanism based on the offline Vickrey model. Mehta et al. [15] introduced the on-line setting into ad-auctions problem. About the competitive auction, Blum and Hartline [16] simply defined the notion of an attribute one for modeling the problem of selling items to buyers who were not priori indistinguishable. Buchbinder et al. [17] designed a (1-1/e)-competitive (optimal) algorithm for the online ad-auction based on a clean primal-dual approach, which was useful for analyzing the other on-line problem such as ski rental and TCP-acknowledgement problem. Babaioff et al. [18] presented a generalized secretary algorithm framework for on-line auctions. They pointed out that the secretary framework different from traditional online algorithms assumed that the bidders arrived in a uniformly random order. Chakraborty and Devanur [19] gave a reduction from the on-line auction problem to the allocation problem when the bidders wanted multiple copies of items with decreasing marginal utilities for them. However, the above literature about the on-line setting of auctions focuses on the area about single-item and single-attribute (price-only).

3. Multi-Attribute Multi-Round Reverse Auction Model

The main participants in the multi-attribute multi-round reverse auction model (in Fig.1) are: Grid Resource Provider (GRP), Grid Resource Broker (GRB) and Local Markets for Auctions (LMA). In the following we present each of these participants and describe their roles in the protocol and their characteristics.

Grid Resource Provider (GRP). His job is to decide whether to participate in the auction when receive the invitation from the GRB according to his capability. In the reverse auction mechanisms, after GRB notifies all available computing resource with three attributes, i.e., computational speed, price and memory size, GRPs arrive dynamically with his supply ability. Namely, it assumes that there are *n* rounds during the whole auction and in each round only one grid resource provider arrives. I.e., in round *i* ($i = \{1_i, 2, \cdots, n\}$), the *i*th GRP presents his bid characterized by three-tuple $B_i = (b_i, v_i, s_i)$, where b_i stands for the price for providing a service and is expressed in form of grid units per MIPS (G$ /MIPS), v_i is the computational speed of resource and is expressed in terms of millions of instructions that the resource can process in one second (MIPS), and s_i is the memory size of resource. In this paper, we allow GRPs to declare untruthful types.

Grid Resource Broker (GRB). We usually consider GRB as an agent of a resource user. His job is to search grid resource provider which can meet user's demand according to user's request. In our model, we assume that in round i, a job or a request provided by GRB is denoted by a four-tuple $J_i = (L_i, \mathrm{T}_i, RP_i, S_i)$, where L_i is the length of the *i*th job and is specified by millions of instructions(MI), T_i is the deadline of the job, RP_i represents the secret reservation price and S_i is the minimum memory size. Each GRB aims at executing its jobs within its corresponding deadlines and minimizing the cost. As job's budget is finite, one way to maximize user utility is to reduce computing service's cost. Thus, we introduce the multi-attribute utility into the traditional auction model for grid resource allocation problem [2]. The most important issue for a resource user is to evaluate each relevant attribute through value or scoring functions. In current literature, it is common that weighted linear functions are used as value or scoring functions. This paper uses satisfaction degree to represent the user's utility. This satisfaction degree function gives a value, which is the sum of the user's levels of satisfaction level from various attributes' values, comparing with each attribute's reservation value. For example, the less price, the more satisfaction. Thus, we design a true satisfaction degree function U_i with the multi-attribute bid of GRP$_i$ as follows.

$$U_i = w_1 \frac{RP_i - b_i}{RP_i} + w_2 \frac{T_i - \frac{L_i}{v_i}}{T_i} + w_3 \frac{s_i - S_i}{s_i} \qquad (1)$$

where $0 \le w_1 \le 1$, $0 \le w_2 \le 1$ and $0 \le w_3 \le 1$ indicate the weights of computational speed attribute, price attribute and memory size attribute, respectively. It is clear that $w_1 + w_2 + w_3 = 1$. These weights and the reservation satisfaction degree $\underline{U}$ ($0 < \underline{U} \le U_i \le 1$) is the private information for the user or GRB.

Local Market for Auctions (LMA). GRB and GRP are two intelligent entities having their own specific objectives. They interact with each other through Local Market for Auction (LMA). LMA provides support for GRP to post their characteristics, and enables GRB to find the right resources that match their requirements. LMA takes a request for a task from a GRB specified in an appropriate language and returns the list of resources that match the requirements of the task. The process of the multi-attribute multi-round reverse auction can be described as follows.

(1) User submits his request with three attributes and private information to GRB.
(2) GRB searches GRPs that meet the user's request in LMA, and invites them to participate in the auction.
(3) GRP decides whether to bid according to cost and capability information.
(4) GRB calculates satisfaction degree of each bid, decides the winner and notices the GRP who wins the auction to provide resources and submit resources to user.
(5) User pays for the service.

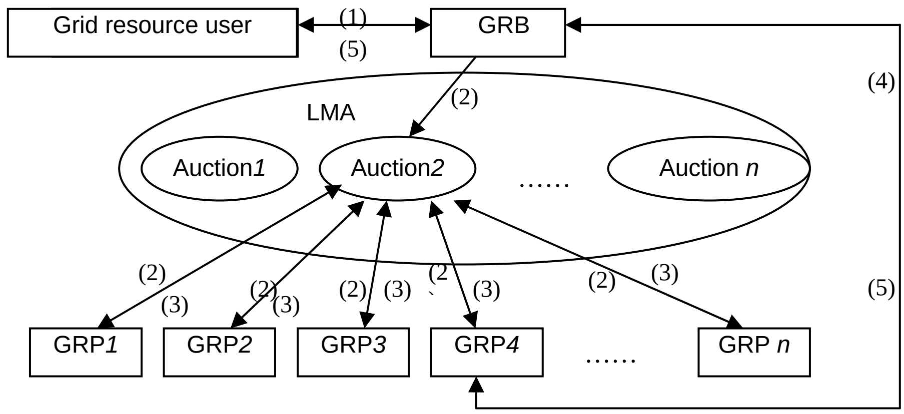

Figure 1. Multi-attribute reverse auction based grid resource allocation

Grid accounting and payment infrastructure already discussed in [2], are needed to support the market trade. In this paper, only the auction model and the resources allocation algorithms are discussed.

4. Multi-Attribute Reverse Auction-Based Protocols

In the first-score sealed-bid auction for grid resources as mentioned in [7], the GRP' prices decide the winner. Considering the multi-attribute characters of gird resources, we propose a multi-attribute multi-round reverse auction to allocate grid resources. Two different protocols are provided according to the bid information, i.e., off-line situation and on-line situation. In these two protocols, we present two kinds of algorithms for the winner determination problem of GRB.

4.1. OFMRA Protocol

From the off-line situation, OFMRA protocol is provided. This formulation represents the GRB's decision model that maximizes his satisfaction degree by optimally determining the winning GRPs of each round until the expired time. The optimal off-line algorithm is to accept the multi-attribute bid with the maximum satisfaction before the end of auction time.

OFMRA protocol:

Cycle:

1. GRP$_i$ sends multi-attribute bid $B_i = (b_i, v_i, s_i)$ to GRB in LMA.

2. After GRB receives the bid, it does the following:

2.1 Compute the satisfaction degree U_i and make it public for GRPs.

2.2 If $U_i > U_{i-1} \geq \underline{U}$, i.e., $i = \{j | U_j = \max\{U_1, U_2, \cdots, U_i\}\}$, then GRB notices GRP$_i$ that he is the temporary winner. Otherwise, GRB sends reject messages to GRP$_l$, $l \neq i$.

3. If $i = n$, then terminate the cycle.

End cycle

3.1 Determine the final winner GRP_i^* from the temporary winners. If there is more than one winning GRPs, the user selects by additional information, e.g., cooperation relationship.

3.2 Sent reject messages to the other temporary winners.

4. GRB sends the job to GRP_i^* and GRP_i^* executes it.

5. GRB sends payments to GSP_i^*.

4.2. ONMRA Protocol

Different form the OFMRA protocol, we provide an ONMRA protocol in an on-line setting, where the GRB as an auctioneer does not know the future bids and has to decide whether to accept the current bid. Competitive analysis has been used extensively to analyze and design on-line algorithms for on-line problems related to computer systems [20]. An on-line algorithm is said to be r-competitive if, given any instance of the problem, the benefit of the solution given by the on-line algorithm is no more than r multiplied by that of an optimal off-line algorithm:

$$Benefit_{on-line}(I)\cdot r \geq Benefit_{off-line}(I) \quad \forall \quad problem \quad instance \quad I \tag{2}$$

The infimum over all r such that an on-line algorithm is r -competitive is called the competitive ratio of the on-line algorithm. An on-line algorithm is said to be best-possible if there does not exist another on-line algorithm with a strictly smaller competitive ratio. On-line algorithms have been used to analyze paging in computer memory systems, distributed data management, navigation problems in robotics, multiprocessor scheduling, and so on. In ONMRA protocol, we assume that satisfaction degree input sequences satisfy $U_i \in [\underline{U}, \overline{U}]$, where $0 < \underline{U} \leq \overline{U}$. For a start, suppose that both $\underline{U}$ and $\overline{U}$ are known to GRB. In this case, we design an on-line multi-attribute algorithm for GRB to decide the final winner from GRPs. I.e., the on-line multi-attribute algorithm is to determine the winner when the first satisfaction degree greater than or equal to $U^* = \sqrt{\underline{U}\cdot\overline{U}}$ before the end of auction time. We call U^* the threshold satisfaction degree. Clearly, the optimal threshold satisfaction degree should balance the competitive ratios resulting by the following two events. Firstly, when the maximum satisfaction degree U_{max} satisfies $U_{max} \geq U^*$, the competitive ratio of on-line multi-attribute algorithm is $\overline{U}/U^*$. Secondly, in the case of $U_{max} < U^*$, the competitive ratio of on-line multi-attribute algorithm is $U_{max}/\underline{U}$. Therefore, the optimal threshold satisfaction degree U^* is the solution $\overline{U}/U^* = U_{max}/\underline{U}$, i.e., $U^* = \sqrt{\underline{U}\cdot\overline{U}}$. Also, we can achieve the optimal competitive ratio for such on-line setting, i.e., $r = \sqrt{\overline{U}/\underline{U}}$.

ONMRA protocol:
Cycle:
1. GRP$_i$ sends multi-attribute bid $B_i = (b_i, v_i, s_i)$ to GRB in LMA
2. After GRB receives the bid, it does the following:
2.1 Compute the satisfaction degree U_i and make it public for GRPs.
2.2 If $U_i \geq \sqrt{\underline{U}\cdot\overline{U}}$, then GRB notices GRP$_i$ that he is the final winner. Otherwise, GRB sends reject messages to GRP$_i$. GRB maximizes the user's satisfaction degree to decide the winner as follows.

$$\min\max\{r \mid r = \frac{U_{\text{off-line algorithm}}(I)}{U_{\text{on-line multi-attribute algorithm}}(I)}\} \tag{3}$$

3. If accept $B_i = (b_i, v_i, s_i)$ or $i = n$ or i is the expiry date, then terminate the cycle.
End cycle
3.1 Determine and notice GRP$_i$ as the final winner GRP_i^*.
3.2 Sent reject messages to the coming GRPs.
4. GRB sends the job to GRP_i^* and GRP_i^* executes it.
5. GRB sends payments to GRP_i^*.

5. Simulation and Experimental Results

In this section the simulating experiments are given to describe OFMRA protocol, ONMRA protocol and some algorithms. In our experiments, we simulate configurations of 20 jobs or tasks with 200G$ /MIPS reserve price, 150s the longest execution time and 1G storage capacity. The length of the jobs are considered as a random integer within the range [5000, 15000]MZ sampled from a uniform distribution. Also the computational capacity of providers is normally distributed within the range [100, 500]MZ/s, storage capacity distributed within [1, 8]G, and the price that resource provider can accept distributed over [100,200] G$/MIPS. The satisfaction degree of each provider's bid is set according to Eq. (1). Also in our experiments, we set w_1=0.3, w_2=0.4 and w_3=0.3.

5.1. Experiment 1

In this experiment GRPs are the bidders and they bid for executing jobs. Firstly, we simulate the process of off-line multi-attribute algorithm in OFMRA protocol and single price auction algorithm in [7] (see Figure 2). Here off-line indicates that GRB knows the number of bidders and their bids. The user's satisfaction degree expresses the comprehensive evaluation about multi-attribute. It satisfies the Eq.(1) with constraint in the real interval [0, 1]. The implementation of these protocols depends on the reverse auction algorithm deployed. The auctioneers conduct several rounds of auction at the resources. Once the auction rounds are over at a resource, the tasks scheduled at the resource are executed using the simulation functionality. After the simulation is over, several parameters such as satisfaction degree and resource utilization are measured.

As shown in Figure 2, there are two vertical axes, denoting the user's utility and the bid price of GRP, respectively. According to the off-line multi-attribute algorithm, the winner is the 13th bidder which has the highest utility. But based on the first price auction algorithm, the winner is the 14th bidder which has the lowest bid price. The 11th bidder with the second lowest bid price becomes the winner according to the second price auction algorithm. From Figure 2, it shows that the off-line multi-attribute algorithm has more efficiency and utility than the other two.

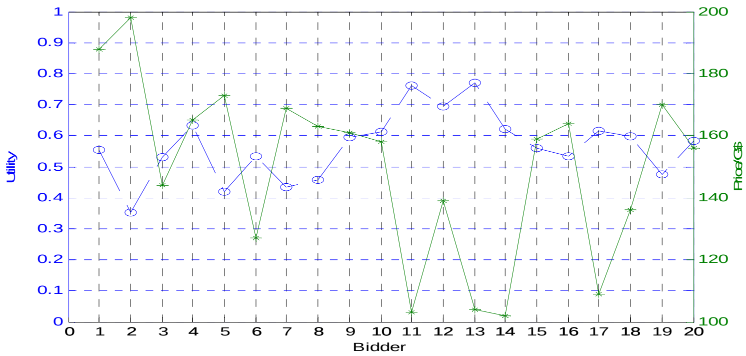

Figure 2. Comparison of bidding process

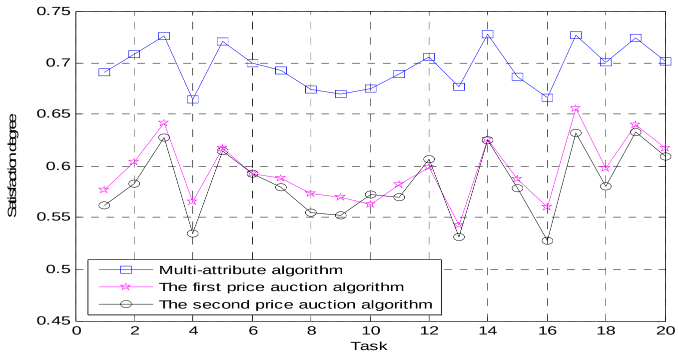

Figure 3. Comparison of different algorithms

As shown, there are 3 lines in Figure 3, which denote the user's satisfaction degree about the winning GRP for different requests or jobs, respectively. Results show that the user's satisfaction degrees of off-line multi-attribute algorithm all exceed 0.65. On the contrary, the satisfaction degrees of the other two algorithms are lower than 0.65 and higher than 0.5. As interpreted previous, the value much closer to 1, the user's satisfaction much higher. Therefore, in a complete information situation, the multi-attribute auction complete information is better than the other two single-valued algorithms.

5.2. Experiment 2

Experiment 1 shows that the off-line multi-attribute algorithm chooses the winner with the highest satisfaction degree. However, in reality GRB has no information about the number of bidders and their bids set, so this paper presents ONMRA protocol for an on-line situation. Competitive analysis is utilized to design an on-line multi-attribute algorithm, which can help the GRB choose the winner without knowing the future bid information. This on-line algorithm has also been proved to be optimal. In experiment 2, we simulate the process of off-line multi-attribute algorithm and on-line multi-attrite algorithm (see Figure 4). Comparison between these two algorithms is described in the Figure 5.

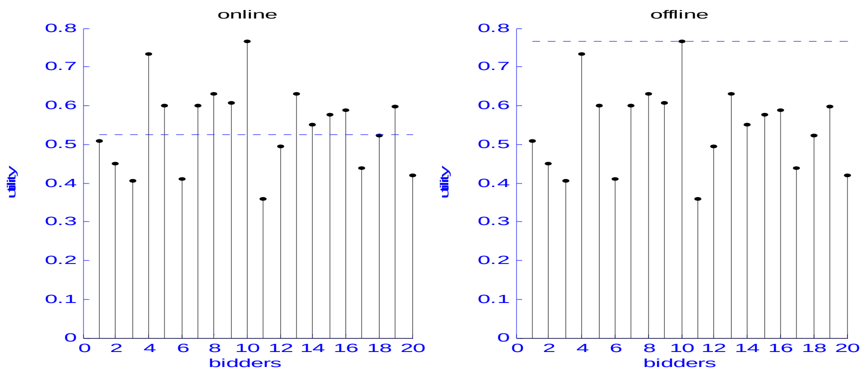

Figure 4. Comparison of bidding process

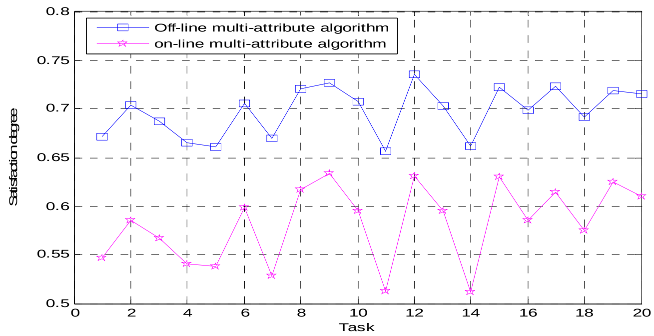

Figure 5. Comparison of on-line and off-line multi-attribute algorithms

Figure 4 shows that in an on-line setting the 4th bidder's utility value higher than the reservation utility value of 0.5289. Thus, the auction end in the round 4 and the 4th bidder becomes the winner for an on-line setting. On the right side, there is another figure which demonstrates the process of bidding for off-line situation. From the figure we find out that the highest utility value of these 20 bidders is denoted by the blue line, which is also the utility value of the 10th bidder. I.e., the 10th bidder is the winner by the off-line multi-attribute algorithm.

According to the competitive analysis of the on-line multi-attribute algorithm, the optimal competitive ratio satisfies that $r < 1.5$. It means that our on-line multi-attribute algorithm achieve better performance. In the worst case, the benefit of on-line multi-attribute algorithm also can be less than 34% than the off-line case. At the same time, utility value of on-line auction higher than 0.5, which means that GRB's threshold satisfaction degree is the harmonious strategy for the resource user when he is in an incomplete information situation.

6. Conclusion

Resources management and allocation are a key and challenging technology in grid system. We propose a multi-attribute multi-round reverse auction for grid resource allocation problems. We investigate the OFMRA protocol, the ONMRA protocol and related some algorithms. The further work is to consider the providing cost, e.g., fixed cost or variable cost, to design the algorithm. The others are to put some artificial intelligence into the auction protocol, present the winner determination problem to improve the allocation result and performance, and apply this mechanism to a real grid system.

Acknowledgments

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