International Journal of Engineering Trends and Technology- May to June Issue 2011

SECOND PRICED DYNAMIC AUCTION MECHANISM

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Absract--

A dynamic auction mechanism to solve the allocation problem of computation capacity in the environment of cloud computing is proposed here. Continuous Double Auction (CDA) mechanism is proposed where resources are considered as provider agents and users as consumer agents. Auctioneer fixes the amount of products based on the products name and demand but bidders will bid the amount based on the need of the product and the time allotted to bid. Truth-telling property holds when a second-priced auction mechanism is

applied into the resource allocation problem. Thus, the cloud service provider (CSP) can assure reasonable profit and efficient allocation of its computation resources.

I.INTRODUCTION

In cloud computing, the allocation method plays a vital role in managing large scale of computation capacity. An efficient algorithm is designed based on the Market oriented allocation rules, which apply pricing mechanism into capacity control. H. Izakian et al. proposed a Continuous Double Auction (CDA) mechanism to solve a resource allocation problem in grid computing. It ensures economic efficiency and system performance.This is efficient in terms of successful execution rates , resource utilization rates and fair profit allocation.

Truth-telling mechanism design is a longstanding problem in economics and game theory, with one of the earlier examples being the Vickrey auction and VCG mechanisms. In computer science theory, recent work has given results describing truth-telling mechanisms for shortest path , multicast , load balancing , allocation of goods , and allocation of digital goods . Many of these problems can be viewed in an online setting (where requests arrive one at a time in an adversarial fashion) and only some of the earlier results consider the online scenario.

The most general result is a truth-telling mechanism for general online combinatorial auctions, assuming an online optimization function exists. In general, combinatorial auctions require exponential size representation of input and exponential computation efforts.

A second-price auction mechanism, which applies the marginal bid (the highest among the unsuccessful bids) to determine the price of the resource, for computation capacity allocation with the assistance of pricing and truth-telliong mechanism.

Two contributions of our study should be addressed:

i. The introduction of peak/off-peak concept into the resource allocation problem and
ii. The systematic analysis containing background and float tasks.

The concept of fixed demand, which does not vary over time is applied by the analysis of resource allocation problem. While in this work, the varying demand can be described by our peak/off-peak concept more exactly and therefore the cloud service provider can further improve both system efficiency and its own revenue.

II.RELATED WORK

The term *Cloud Computing* is currently used in various ways and is often confounded with the term Grid Computing. Grid Computing accrued in the mid 1990s and originally denoted a scientific network to share computation power for computationally intensive jobs. The main characterization of a Grid is the distribution of a computing job in a somehow connected network. Accordingly, jobs for Grids are divided in several small jobs which are distributed to independent servers or desktop computers. This opens the possibility to share resources between institutions that are dispersed among different geographical locations. However, sharing computing resources is also a central aspect of Cloud Computing, but with a focus on virtualized instances that usually run on a server cluster. A server cluster typically distributes computation power among several locally connected servers and hosts the virtual instance, which has been allocated to a certain customer.

In scientific Grids the institutes are provider and consumer similar to P2P networks. Cloud Computing is commercially driven and most of the providers do not consume the resources they offer.

The role between provider and consumer is currently disjointed.

In cloud computing, the methods used for allocation are useful in managing the large scale of computation capacity. The design of a more efficient algorithm is based on the pricing mechanism that are applied by the Market oriented allocation rules into capacity control. Improper allocation rules might cause the inefficiency of the system.

In this paper, we focus on a general resource allocation problem that matches the characteristics of cloud computing platforms and their consumers. Namely, multiple self-interested agents supply or consume multiple types of resources, where 1) consumers dynamically enter and leave the market, 2) consumers have some bounded flexibility over when they require resources, and 3) a single provider cannot satisfy consumers' resource requirements. The first two characteristics are evident in current cloud platforms that are available to the general public, which use them to execute tasks that may or may not have hard deadlines. The motivation for 3) is natural for an infrastructure like GENI that allocates networked resources from multiple providers, and is also becoming more prevalent for profit-making enterprises like Amazon as competitors, such as RackSpace Cloud, become more prominent.

III.PROPOSED METHOD

A Continuous Double Auction (CDA) mechanism, resembling the market mechanism, to solve a resource allocation problem in grid computing is proposed. The centralized auctioneer distributes the resources by matching the values of both sides and the CDA mechanism ensures the allocation to be efficient. Consumer agents aim at executing jobs within their corresponding deadlines and with the minimum cost . The allocated budget for each job determines the maximum cost that a user is willing to pay for executing it. The provider agents aim at obtaining more profit . In continuous double auction method at each time unit, consumers and providers submit bids and requests to the auctioneer in the form of G$/MIPS. An auctioneer maintains a list of the current bids and requests and matches the two offers when the highest bid is higher than or equal to the lowest request. The trade occurs at the average of matching request and bid prices. Determining the bid and request value by consumers and providers can be done autonomously and based on their objectives. In this paper, two decision making methods for determining bid values by consumers and request values by providers is proposed.

i) Determining Bid Values for Consumer Agents
ii) Determining Bid Value Based on the Number of Remaining Resources for Bid
iii) Determining Bid Value Based on the Mean Remaining Time for Bid
iv) Calculating the final bid value:
v) Determining the Request Value for Provider Agents
vi) Auctioneer Role

A. *MODULES*

- **Bidders**
- **Second Price Auction**
- **Resource allocation**

1) *MODULE 1 – BIDDERS:*

The cloud users only demand variable computing capacity is assumed. It means the demand of each user is determined by its own task at certain period.

2) *MODULE 2 – SECOND PRICE AUCTION:*

A *second-price auction mechanism*, which applies the marginal bid (the highest among the unsuccessful bids) to determine the price of the resource, for computation capacity allocation with the assistance of pricing and truth telling mechanism is proposed.

3) *MODULE 3 – RESOURCE ALLOCATION:*

Two contributions of this study should be addressed: I. The introduction of peak/off-peak concept into the resource allocation problem and II. The systematic analysis containing background and float tasks.

IV.SYSTEM ARCHITECTURE

The system model comprises of 2 periods with n cloud users and a cloud service provider (CSP). The CSP has 2 tasks:

1. Performing time-insensitive background computing.
2. Distributing resource to the cloud users in the dynamic process.

It will gain a fixed amount of value, if the input to the background task excess the threshold and it will sell its residual resources to the cloud users after the distribution of resources.

The demand of the users varies in peak and off-peak periods. So the assumption is taken as each user demand one unit of capacity.

The proposed mechanism is based on sealed-bid auction.

The users will submit their bids to the CSP. And it will collect the bids and determines the price. The decision rile of the CSP on background task is to simply divide the task equally into 2 periods is assumed.

V. RESULTS

Extensive stochastic simulations were carried out for all the combinations of variables in Table. 1. For each combination,randomly generated over 5000 experiments and for each experiment, and tried all the three mechanisms and generated average performance measures. Even though extensive stochastic simulations were carried out for all the situations, due to space limitations, we only present the representative results. The length of each experiment is 1000 time units.

The confidence interval for each average value is very tight around the value, so the confidence intervals are not reported.6.3.1 Performance of the negotiation mechanism Iis founded.

Observation 1: NG achieved about 13% higher social welfare than any other evaluated mechanism. Figure 2 shows how the social welfare of different mechanisms changes with resource demand/supply ratio $\psi(r)$. We can observe that in all situations, NG's social welfare is always higher than any other mechanism. Furthermore, when $\psi(r)$ is small (e.g., 0.2), CRA or the Amazon scheme with lower prices (e.g., Amazon-1.5) achieved higher social welfare than with higher prices (e.g., Amazon-8). In contrast, when $\psi(r)$ is large (e.g., 6), the Amazon scheme with higher prices (e.g., Amazon-8) achieved higher social welfare than CRA or Amazon scheme with lower prices. This observation is intuitive: When the resource competition is low, there are plenty of resources and each buyer can find them. However, when the resource competition is high, a mechanism can achieve a high social welfare if tasks with high revenues can be completed. If the price of each resource is low, a task with low revenue may get resources and a task with high revenue may fail to get resources since the resource were prematurely committed to the low revenue buyer and there was no way to decommit from the decision. In contrast, if a high price is set for each resource, only tasks with high revenues can get resources.

First, a mechanism with a higher price has a lower success rate than that of a mechanism with a lower price. NG's success rate is lower than some mechanisms with lower prices due to fact that in negotiation, each agent will not accept or offer any offer worse than its expectation. Second, with the increase of resource competition, the success rate of each mechanism decreases, which corresponds to the intuition that with higher resource competition, it is more difficult to acquire resources.

Observation 2: it shows how the social welfare changes with the average number of resources acquired by buyers, which is r□Rb q(Rb, r). We can observe that the advantage of NG over other mechanisms increases with the number of resources to acquire. Fig. 5 shows that the success rate decreases with the number of resources to acquire, which is intuitive since it is difficult to acquire more resources which have to be provided during the same period.

Observation 3: In some cases, the difference between a deadline and the earliest start time is large and each buyer has more flexility of deciding when to start its task. A buyer b can use the time between est(b) and dl(b) to negotiate for resources. As shown in Figure 7, the success rate of NG increases when buyers have more flexibility to decide when to start task execution. However, an agreement's probability of being decommited increases with more flexibility. Accordingly, a buyer may fail to get resources due to the decommitment. Figure 6 shows that, with the increase of the flexibility, the advantage of NG over the other mechanisms increases at the beginning and slightly decreases when buyers have a lot of flexibility to decide when to start task execution, which is mainly due to sellers' decommitment.

Observation 4: A buyer b can start negotiation at time tg(b) and its task cannot start before est(b). Figure 9 shows that NG's success rate increases with (est(b) − tg(b))/pd(b) since a buyer has more time to negotiate for resources. However, as shown in Figure 8, the advantage of NG does not strictly increase with negotiation time: its advantage decreases when buyers have a long negotiation time. The reason is that a buyer's agreements made at an early stage may be decommited by sellers when there is a long negotiation deadline. Observation 5: In addition to a fully distributed auction (CRA), we also designed a super buyer which receives requests from buyers and buys resources for buyers. The super buyer runs the auction when it has received a certain number of requests or one requesting buyer's deadline is approaching, whichever occurs first. Experimental results show that NG still beat the centralized CRA by 11%. The centralized CRA beat the distributed CRA by no more than 2%.

Observation 5: This paper assumes that each agent knows the demand/supply ratio of each resource. In reality, an agent may not know the demand/supply ratio. We tested the negotiation model without this assumption and alternatively, each agent predicts the demand/supply ratio through its interaction with buyers. Specifically, a seller can estimate the competition of a resource according to 1) the requests for the resource from all the buyers in the last λ time points and 2) the total number of resources provided by other sellers. A buyer can estimate the competition of a resource according to bids from sellers. In this case, we found that the social welfare of NG is still 10% higher than other mechanisms.

Observation 6: This paper also assumes that each agent knows each seller's cost of a resource. We found that that the accuracy of this information does have a slight effect on agents' negotiation performance. When the believed cost is less than half of the actual cost, the average social welfare of NG is 6% lower than that of NG in which each buyer knows the actual cost.

A series of experiments in a variety of test environments using the parameters from Table 3 is performed. The parameters are inspired by the current design of the GENI infrastructure [1]. In the experiments, the number of sellers are in the range of [5, 20], where each seller can provide 2 to 8 different types of resources. The quantity of a resource a seller can provide is in the range of [2, 20]. The cost of a resource per unit time is in the range of [10, 100]. Each buyer needs 2 to 6 different types of resources, and for each type of resource, a buyer needs 2 to 6 units. The length of resource usage is in the range of [10, 50]. The ratio dl(b)−pd(b)−est(b)+1 pd(b) ∈ [0, 7] describes a buyer's flexibility of deciding when to start its task. Similarly, ratio est(b)−tg(b)+1pd(b) ∈ [1, 8] represents a buyer's time to negotiate for resources. Value/cost ratio is used to generate a buyer's maximum value and minimum value based on sellers' cost of providing resources. ψ(r) ∈ [0.2, 10] is the ratio of total resource requirements to total resource supply through the whole experiment horizon. We also report the success rate of mechanisms— the percentage of buyers which successfully complete their tasks.

Variables	Values
Number of sellers	[5, 20]
No. of resource types per seller	[2, 8]
Quantity of a resource per seller	[2, 20]
Unit cost of a resource	[10,100]
No. of resource types per buyer	[2,6]
Quantity of a resource per buyer	[2,8]
Value/cost ratio	[1.2,5]
Length of resources	[10,50]
task execution flexibility	[0,7]
negotiation time ratio	[1,8]
resource demand/supply ratio	[0.2,10]

Tab 3. Variables

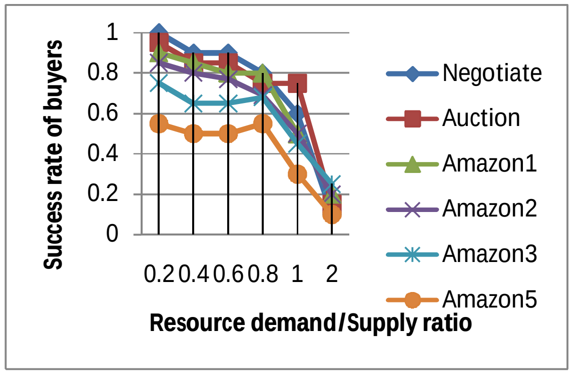

Fig 5.1 Success rate and resource competition

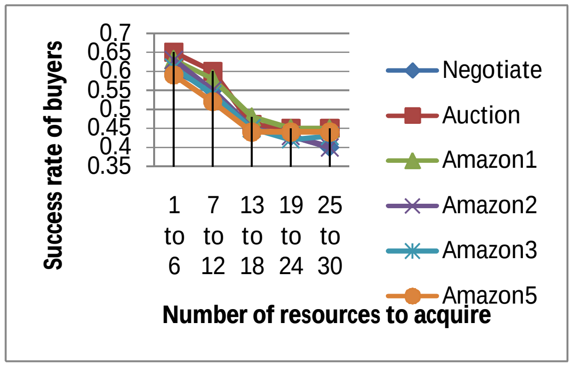

Fig 5.2 Success rate and number of resources to acquire

VI.CONCLUSIONS

A theoretical framework to cope with the capacity distribution under cloud computing framework is proposed to develop a new resource allocation algorithm by applying auction method into the resource allocation problem in cloud computing. The efficient allocation of capacity under simple decision rule and generate appropriate revenue to the CSP is ensured and potential drawbacks of this mechanism proposed by the literature and successfully found the condition underneath is examined.

VII.FUTURE ENHANCEMENT

To extend the application both in the slope and scale, the same task schedule may be applied to the cloud users in the future works since it enables the CSP to build more pricing criteria and thus improving the efficiency of the system. Moreover, it is also possible to develop a dynamic adjustment mechanism on the basis of our finding.

Since there are peak and off-peak demands on the capacity as assumption, the modification can improve not only the efficiency of the system but also the revenue generated for the CSP.

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