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A NOVEL RESOURCE PROCUREMENT MECHANISM SCHEME WITH EFFICIENT COST AND PERFORMANCE OPTIMIZATION USING CLOUD

Dr.P.Latha
Department of Computer Science and Engineering,Shadan College of Engineering and Technology HYD,T.S,INDIA

Abstract—We present a cloud resource procurement approach which not only automates the selection of an appropriate cloud vendor but also implements dynamic pricing. Three possible mechanisms are suggested for cloud resource procurement: cloud-dominant strategy incentive compatible (C-DSIC), cloud-Bayesian incentive compatible (C-BIC), and cloud optimal (C-OPT). C-DSIC is dominant strategy incentive compatible, based on the VCG mechanism, and is a low-bid Vickrey auction. C-BIC is Bayesian incentive-compatible, which achieves budget balance. C-BIC does not satisfy individual rationality. In C-DSIC and C-BIC, the cloud vendor who charges the lowest cost per unit QoS is declared the winner. In C-OPT, the cloud vendor with the least virtual cost is declared the winner. C-OPT overcomes the limitations of both C-DSIC and C-BIC. C-OPT is not only Bayesian incentive-compatible but also individually rational. Our experiments indicate that the resource procurement cost decreases with an increase in a number of cloud vendors irrespective of the mechanisms. We also propose a procurement module for a cloud broker which can implement C-DSIC, C-BIC, or C-OPT to perform resource procurement in a cloud computing context. A cloud broker with such a procurement module enables users to automate the choice of a cloud vendor among many with diverse offerings and is also an essential first step toward implementing dynamic pricing in the cloud.

Index Terms—Cloud computing, mechanism design, cloud broker, resource procurement, reverse auctions, multi-attribute auctions, dynamic pricing

1 INTRODUCTION

CLOUD computing is an increasingly popular paradigm of offering services over the Internet [1]. It is also an active area of research, and the popularity of this paradigm is growing rapidly. Many companies like Amazon, IBM, Google, salesforce.com, Unisys, and so on, now offer cloud services. The main advantage of cloud computing is the ability to provision IT resources on-demand (thus avoiding the problems of over-provisioning and under-provisioning which are commonly seen with organizations that have widely variable requirements due to growth/shrinkage, seasonal peaks, and valleys, etc.). The resources offered may include storage, CPU processing power, IT services, and so on. These resources are often geographically distant from users.

We can say the following:

- A cloud user is a person or an organization (such as an SME—small and medium enterprise) that uses cloud services.
- A cloud vendor is an organization that offers cloud services for use on the payment.
- A cloud broker [2] is a middleware that interacts with service providers on behalf of the user. It is responsible for configuring the user's settings suitably and for procuring resources. Resource procurement of cloud resources is an interesting and yet unexplored area in cloud computing. Cloud vendors follow a fixed pricing strategy ("pay as you go") for pricing their resources and do not provide any incentive to their users to adjust consumption patterns according to the availability or other factors.

Consider, for example, a user who wants to use a service in the form of an application hosted on a cloud. There are cloud vendors who provide versions of that application at different prices and with varying quality-of-service (QoS) parameters. The user has to go through the specifications of each cloud vendor to select the appropriate one, to obtain the service within budget and of the desired quality. In the case of an organization acting as a user, this selection is quite complex and challenging [3]. Also, the companies offering cloud services, and their offerings, change continually. So, given the large and varying multitude of cloud vendors, it is very tedious to select the most appropriate one manually.

Hence, there is a need for a scalable and automated method to perform resource procurement in the cloud. Rauchwerger et al. [4] observe that while cloud vendors do not yet offer standardized services, they will need to do so and that the "federated cloud has huge potential." In that event, it would become possible to mix and interchange resources offered by different cloud vendors and to automate the procurement of such resources.

If resource procurement is automated, then the challenge would be to find the appropriate location where the solution can be deployed. One manner in which our solution may be deployed is by the use of a cloud broker that implements our approach. Cloud brokerages form an important research area [5], and the cloud brokerage business was expected to be worth $150 billion by 2013 [6]. Most cloud vendors use the pay-as-you-go model. Many are loath to negotiate contracts as they lack understanding

of a sound theoretical basis for dynamic pricing. The default agreement offered by a vendor often contractually benefits the vendor but not the user, resulting in a mismatch with user requirements [7]. Hence, this kind of pricing favours the cloud vendor. Also, there is no clear commitment on SLAs [7]. Dynamic pricing is the solution for these kinds of problems [8].

Bichler et al. [9] state that uncertainty about the prices of goods and lack of knowledge about market participants are obstacles to dynamic pricing. Auctions are in particular helpful in this kind of situation [9], [10], [11]. If the buyer is an auctioneer and the suppliers are bidders, then the auction is called a reverse auction. Reverse auctions are widely used across many industries, and also especially by governments to procure resources. Reverse auctions are preferred over other auctions for procuring resources because competitive bidding in these type of auctions reduces procurement costs and limits the influences of undesirable factors like nepotism and political ties [12]. Resource procurement can be accomplished using conventional methods [13], [14], [15] and economic models [16]. The conventional models assume that resource providers are nonstrategic [13], [14], [15], whereas economic models assume that resource providers are rational and intelligent.

In conventional methods, a user pays for the consumed service. In economic models, a user pays based on the value derived from the service [16]. Hence, economic models are more appropriate in the context of cloud services. An important feature of economic models is the distribution of incentives to bidders, which are cloud vendors in our domain. However, this means that cloud vendors may not act truthfully and may seek to maximize their incentives using improper behaviour. Game-theoretic models cannot enforce the structure in games. Mechanism design enables the social planner to design the game according to his wish. So the social planner can implement strategies to motivate participants to act truthfully.

The important contributions of this work are:

. procurement mechanisms for implementing dynamic pricing, and

- novel procurement module based on mechanism design for a cloud broker. Dynamic pricing increases user welfare, facilitates healthy competition among vendors, and increases the efficiency of cloud resource usage [17]. Auctions are one way of implementing dynamic pricing [9]. Dynamic pricing is not only advantageous for cloud users but also maximizes the profit for vendors [18]. The mechanisms proposed in this paper are based on reverse auctions and are more appropriate for implementing dynamic pricing. The procurement module enables the cloud broker to automate resource procurement. In our procurement module, the user sends the specifications to the cloud broker and requests for resources. The cloud broker sends the user specification to all cloud vendors. The cloud vendors respond with cost and QoS parameters of their services. We do not consider implementation issues like caching, refresh, and so on, of cost and QoS by the broker. The cloud broker assigns weights for different QoS parameters using analytic hierarchy process (AHP), which are scaled before computing a weighted QoS score. This step is called normalization. If normalization is not done, then it is not possible to compare different QoS specifications. The cloud broker implements one of cloud-dominant strategy incentive compatible (C-DSIC), cloud-Bayesian incentive compatible (C-BIC), or cloud-optimal (C-OPT) mechanisms. The winner is determined based on the mechanism implemented. The cloud broker notifies both winner and user. Finally, the cloud broker pays money to the cloud vendors according to the payment function of the mechanism. This is called the procurement cost.
- We assume that cloud vendors are selfish (interested in maximizing their own profits) and rational (able to appropriately calculate values and derive choices based on available information, rather than relying merely on past experience). Hence, there is a possibility of overbidding and underbidding [19]. As is standard, our assumption of selfishness is limited only to the pricing aspect, but we assume that vendors are truthful in technical matters; for example, if a cloud vendor claims 99.99 percent uptime for a service, then we assume that this is true information. Incentives are offered to the cloud vendors to make truth revelation the best strategy. The right amount of incentive offered to induce truth is called incentive compatibility. There are two types of incentive compatibility: dominant strategy incentive compatibility (DSIC) and Bayesian incentive compatibility (BIC). These are the only ways of implementing incentive compatibility. In DSIC, the optimal strategy for each cloud vendor is to report true valuation irrespective of other cloud vendor's valuation. In BIC, the optimal strategy is to report true valuation only if all the other cloud vendor's report true valuation.

In this work, we present three possible mechanisms:

- .C-DSIC: This is a dominant strategy incentive compatible mechanism. It is based on the VCG mechanism (see [20] for an explanation of the VCG mechanism). In C-DSIC, the best strategy for a cloud vendor is to bid truthfully. The ratio of cost and QoS is computed for each cloud vendor. The cloud vendor with the lowest ratio of cost to QoS is the winner. The payment rule is based on the VCG mechanism. The user pays the price as per the next lowest bid. C-DSIC is a low-bid Vickrey auction. C-DSIC achieves allocative efficiency (objects are allocated to the cloud vendors who value them most) and individual rationality (cloud vendors get negative payoff if they withdraw from the auction) but it is not budget balanced (there is no external funding in the system). If all cloud vendors use the same probability distribution of price and QoS, then C-DSIC is to be preferred.
- C-BIC: This mechanism is based on the dAGVA mechanism [21]. In C-BIC, each cloud vendor contributes a participation fee. This money is used for paying other cloud vendors. Hence, C-BIC is budget balanced and allocative efficient. In this mechanism also, the vendor with lowest cost and QoS ratio is declared the winner. The procurement cost for the user is less here compared with C-DSIC. C-BIC does not satisfy individual rationality but achieves allocative efficiency and budget balance. C-BIC is suitable for government organizations. Generally, the participants in government-sponsored procurement auctions pay a participation fee and this is the accepted practice in them. The loss of a cloud vendor's money in the C-BIC can be viewed as the fee for participating in procurement auction.

2 RELATED WORK

2.1 Resource Allocation in Grid and Cloud Resource allocation is an important challenge in today's Internet, especially in large distributed systems like Grid, cloud, and so on. Resource allocation is a very active area of research in Grid [16], [28], [29], [30]. These resources are owned by the companies and are mostly distributed geographically. Resource allocation algorithms are generally based on one of these types of models:

1. conventional models, and 2. economic and game-theoretic models. Conventional models [13], [14], [15] require global knowledge and complete information. These algorithms are mostly centralized in nature. The cost models of the centralized algorithms derive cost based on the usage of the resources.

Economic models for resource allocation are very popular. Economic models of resource management are not only decentralized but also offer incentives to participants. These models derive cost based on the value the user derives from the services [16]. Most resource allocation algorithms based on economic models rely on single market mechanisms. Vilajosana et al. [31] develop a configurable auction server that gives the ability to configure markets dynamically. Buyya et al. [16] use economic models like the commodity market, posted price, and so on, for developing a grid resource broker for resource management. Generally, an Internet Service Provider (ISP) sets the price without consulting the consumers. This pricing scheme is not Pareto optimal. Hence, Cao et al. [32] use game theory to determine the pricing based on the quality of service. They model the pricing as a cooperative bargaining game. Also, they extend the work for two competitive ISPs and compute a Nash equilibrium point so that the ISPs and the user cannot decide the price arbitrarily. Narahari et al. [19] describe mechanisms based on the dominant strategy and Bayesian incentive compatibility. Sometimes, economic models are ineffective with respect to sharing. Mingbiao and Shengli [33] overcome this problem. Subramoniam et al. [34] use commodity market models to perform resource allocation in Grid. Xhafa and Kolodziej [35] not only survey game-theoretic-based resource allocation models but also propose their solution based on metaheuristic methods. Parsa et al. [36] use a double auction mechanism for performing resource allocation.

Ismail et al. [37] propose a formal model for evaluating resource allocation algorithms in Grids. Shu [38] uses a "quantum chromosomes" genetic algorithm to solve the problem of resource allocation in Grid. Li et al. [39] use particle swarm optimization to perform resource allocation. Shah et al. [40] present a linear programming formulation of the resource allocation problem and compare the efficiency of existing algorithms which solve this problem. Li and Qi [41] present a grid resource allocation algorithm based on fuzzy clustering. This algorithm assigns resources based on task need and also performs reservation of the resources. Cloud computing is evolved from the Grid. Lin et al. [42] use dynamic auctions (based on the Vickrey auction) to perform resource allocation. Cloud users bid for resources and the highest bidder wins the auction. The winner pays the second highest price. Lin et al. [42] also introduce the concept of off-peak and peak pricing periods. They assume that all users behave truthfully, which is not always the case in the real world. They also do not discuss the enforcement of the truthfulness property. Narahari et al. [19] propose mechanisms for procurement of resources for sweep type jobs in Grid. These mechanisms cannot be applied directly to the cloud. In cloud, the resources are not limited to sweep type jobs. They can be SaaS, PaaS, IaaS, and so on. This work makes use of existing mathematical models like Vickrey auction, and so on. We apply these models to design reverse auctions to procure cloud resources.

2.2 Mechanism Design

The main goal of mechanism design is to implement systemwide solutions to problems that involve multiple selfinterested agents, given private information about their preferences [19], [20]. It can also be viewed as the design of a framework of protocols that would foster particular ways of interaction among agents with known behavioral characteristics, to bring about a globally desirable outcome [19]. The work of Nisan and Ronen [43] is considered seminal in the field of algorithmic mechanism design. They successfully use the concepts of mechanism design [20] for solving scheduling problems. In nonstrategic social choice theory, agents have preferences but they do not try to obfuscate them to maximize their utility [21]. Mechanism design is a strategic version of social choice theory where agents try to maximize their individual payoffs [21]. The goal of mechanism design is to design social choice and payment functions. We refer to standard texts [19], [20], [21] for an in-depth treatment of mechanism design.

Narahari et al. [19] apply concepts of mechanism design to solve sponsored search auctions and resource procurement in grid computing. They design three mechanisms for procuring resources in Grid. The mechanisms presented are incentive compatible and optimal. They also design incentive compatible broadcast protocols for ad hoc networks. 2.3 Optimal Multiattribute Auctions We refer to [11] for a comprehensive introduction to auction theory, including the various types of auctions, their characteristics, and their applications in computing. In traditional auctions, only price is considered. It is difficult to account for nonnumerical attributes like quality, and so on, which are important in the real world. On the other hand, multiattribute auctions take attributes like quality, and so on, into account. Hence, multiattribute auctions are interesting and challenging. Che [44] proposes a scoring rule (weights for each attribute) to compute a final score. Once the final score is computed, then the traditional auction is performed. Branco [45] describes the properties of optimal multiattribute auctions and proposes a two-stage procurement mechanism. In the first stage, the winner is determined. In the next stage, bargaining is performed for desired quality. Bichler and Kalagnanam [46] analyze the problem of winner determination in the case of multiple sourcing. They also extend multi attribute auctions for configurable offers. According to the authors, multi attribute auctions achieve higher market efficiency compared to traditional single attribute auctions. Ronen and Saberi [47] prove that the minimum approximation ratio achieved in deterministic polynomial time ascending auctions is 3

4 . They also prove that if the dependence between the agents' valuations is bounded, then the approximation ratio achieved is close to 1. Chandrashekar et al. [48] present the state of the art in the area of auction mechanisms for electronic procurement. Ronen and Lehmann [49] present a generic method to construct optimal multi attribute auctions, a method that can be applied to various multi attribute auction designs. Wang et al. [50] present two kinds of multi attribute auction models based on the scoring rule and bidding objective functions.

3 SYSTEM MODEL

Our system model is based on Narahari et al. [19]. In game theory, we assume that players are rational and have common knowledge and private information. Rationality implies that goal is to maximize payoff. In our model, cloud vendors are rational. Hence, cloud vendors are risk neutral. The concepts of risk neutral and quasilinear are described in detail elsewhere [21].

Each cloud user has resource requirements. The users perform reverse auctions for procuring resources (which are also called procurement auctions). Cloud vendors offer resources, but with varying costs and quality metrics. The goal of the cloud user is to minimize the total cost of procuring resources without compromising quality of service. To minimize the procurement cost, it is necessary for the cloud user to know the real costs of cloud vendors. A user announces its specifications for desired resources and quality of service to all cloud vendors, with the broker acting as a middleman. The cloud vendors decide whether to participate in the auction based on the user information and submit their bids to the broker. The broker aggregates the bidding information and selects the appropriate cloud vendor. Cloud vendors are rational and intelligent. Hence, one of them might bid with a false valuation to maximize its utility. The goal of providing incentives is to encourage truthful bidding.

Cloud-Optimal Mechanism

The C-DSIC mechanism is not budget balanced. On the other hand, even though the C-BSIC mechanism is budget balanced, it is not individually rational. Hence, we propose the C-OPT mechanism to address the limitations of both the C-DSIC and C-BIC mechanisms. According to Myerson [22], if a mechanism is Bayesian incentive compatible and individually rational, then the mechanism is optimal. Myerson's optimal auction can be applied only to single items with unit demand. In our model, both cost and QoS are correlated. Hence, the design of an optimal auction is not trivial [19], [60]. Iyengar and Kumar [12] propose an optimal mechanism for procurement auctions for suppliers who have finite production capacity (capacitated suppliers). Practically, it is not possible for cloud service providers to guarantee infinite QoS for every cloud user.

4 CONCLUSION AND FUTURE WORK

Currently, the cloud user pays a fixed price for resources or services. This type of pricing is called fixed pricing. Fixed pricing is very popular with telecom providers. On the flip side, there is no provision for incentives for users in the fixed strategy. Resource procurement is not only an important problem in cloud computing but is also an unexplored area. Currently, resource procurement is done manually and there is a pressing need to automate it. To automate procurement, we have presented three mechanisms: C-DSIC, C-BIC, and C-OPT. C-DSIC is a low bid Vickrey auction. It is allocative efficient and individual rational but not budget balanced. If the mechanism is not budget balanced, then an external agency has to provide money to perform procurement.

C-BIC is a weaker strategy compared to C-DSIC and it is Bayesian incentive compatible. In C-BIC, vendors reveal the truth only if other vendors reveal the truth, unlike C-DISC where vendors reveal the truth irrespective of others' choices. C-BIC achieves budget balance and allocative efficiency but not individual rationality. C-OPT achieves both Bayesian incentive compatibility and individual rationality, which the other two mechanisms cannot achieve. This mechanism is immune to both overbidding and underbidding. If a cloud vendor overbids, then the incentive is reduced. If it underbids, then it may not be a winner. C-OPT is more general compared to both C-DSIC and C-BIC—even if cloud vendors use different distributions for cost and QoS, we can safely use C-OPT. Hence, C-OPT is the preferred mechanism in more cases in the real world.

The experiments reveal an interesting pattern. The resource procurement cost reduces as the number of cloud vendors increase, irrespective of the mechanism implemented. The cost in C-BIC reduces more significantly, compared to the other two mechanisms. The procurement module for a cloud broker based on C-DSIC, C-BIC, or C-OPT is able to automate the selection of cloud vendors. The mechanisms presented assume that cloud vendors are rational and intelligent, which is true in the real-world scenario. This work enables the user to select the appropriate cloud vendor, and the mechanism is chosen also decides the price for the resource. This user-centric pricing is a step toward implementing dynamic pricing in the cloud.

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