A Novel Resource Pricing Mechanism based on Multi-Player Gaming Model in Cloud Environments

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***Abstract*—Recently, cloud computing has become a promising network platform for non-trivial applications. The key feature of cloud computing is on-demand resource provision by utility paradigm. Therefore, resource pricing mechanism plays an important role for realizing on-demand resource provision. Unfortunately, existing resource pricing mechanism will result in many negative effects on system performance, such as low-efficient negotiation, extra communication costs and etc. In this paper, we present a novel resource pricing mechanism, which is based on multi-player gaming model and capable of realizing batch resource allocation in an efficient manner. In this mechanism, we introduce a set of virtual resource brokers which is responsible for figuring most rationale resource prices in elastic cloud environment. To investigate the effectiveness and performance of our pricing mechanism, extensive experiments are conducted, and we compare its performance with various approaches, include market-based approaches and auction mechanisms. The results show that our pricing mechanism is more effective to realizing batch resource allocation, especially when the system workload is intensive. In addition, our mechanism can significantly reduce the negotiation costs comparing with exiting approaches.**

***Index Terms*—cloud computing, pricing mechanism, virtual resources, computing economy, cooperative game**

I. Introduction

Cloud computing has emerged as an promising technology and it has been increasingly adopted in many areas including science, engineering, and commercial business, due to its inherent flexibility, scalability and cost-effectiveness [1, 2]. Clouds are primarily motivated by the conception of utility computing, in which users have to pay resource providers for executing their applications. While the pay-per-use pricing model is very appealing for both service providers and consumers, conflicting objectives between the two parties hinder its effective application [3, 4]. In other words, the service provider aims to accommodate as many requests as possible with aiming to maximizing their profits, which inevitably conflict with consumer's performance requirements.

In the past few years, there have been plenty of studies exploiting market pricing mechanism for distributed resource allocation, and the well-known distributed systems [5, 6, 7, 8, 9, 10]. Beside this systems, many economic-based policies and scheduling algorithms have also be widely studied, include Resource Auction [11, 12], FirstPrice [13], FirstProfit [14], and Proportional-Share [15]. In typical distributed systems, economic-based model is has been proven to be effective for resource allocation, however, it also raise other problems that cannot be ignored [7, 8, 9]. Firstly, economic models bring about extra communicational and computational overhead to applications [8, 16]; Secondly, when the system is in presence of high-end applications that require co-allocating multiple resources across sites, the price negotiation process is often low-efficient [6, 9, 17].

Currently, many existing cloud systems adopted fixed pricing mechanism whose advantages are easy implementation and low maintain cost [17]. Unfortunately, fixed pricing mechanism will lead to many negative effects on system performance with the increasing of system scale, such as low resource utilization [17, 18; 19], load unbalancing [20], undesirable QoS satisfaction [21, 22]. To address the above issues, in this work we present a cloud resource pricing model with aiming at overcoming the shortcomings of existing price mechanisms in terms of efficiency and fairness. In our pricing model, virtual resource configuration and provision are defined as a two-phrase gaming procedure, in which cooperative gaming model is applied to optimize the resource benefits and non-cooperative gaming model is used to balance the user's costs and provider's benefits.

The rest of this paper is organized as following: Section 2 presents the related work; In section 3, the gaming models are presented with problem description; ; In Section 4 the solutions of game models are presented theoretically; In section 5, experiments are conducted to examine the effectiveness of the proposed approach. Finally, Section 6 concludes the paper with a brief discussion of the future work.

II. Related Work

In December 2009, AWS launched Spot Instances (SI) mechanism [23], in which users are charged at a higher rate when the provider experiences overload. Its original objective is to encourage users to shift their flexible workload from provider's peak hours to off-peak hours

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with monetary incentives. After profiling SI mechanism for about two years, Wee et al. found three interesting observations about SI [24]: (1) SI price is 52.3% cheaper than the standard price of equivalent instance type on average. Therefore users can achieve this cost savings by simply switching to SI instead of shitting their workload to cheaper periods; (2) Additional cost savings from shifting workload to cheaper hours is merely 3.7% on average. (3) Above two observations have not been changed over time. Based on the above observations, Wee concludes that AWS SI does not provide large enough monetary incentive for users to shift their workloads.

In [17], the authors presented a dynamic pricing scheme which takes efforts on improving the efficiency of batch resource trading in federated cloud environments. In their scheme, the whole cloud system is considered as a uniformed resource market where resource supply and demand can be balanced by using macro-economic equivalence theory. Unfortunately, the scheme relies on market self to automatically obtaining equivalent price, therefore it is low-efficient comparing with the opening feature of cloud platform.

In [25], the authors proposed a dynamic second-priced auction mechanism to solve the allocation problem of computation capacity in the environment of cloud computing. During the auction procedure, it assumes that resource pricing will be increased significantly when the system workload is in peak state. Such an assumption is validating for those systems whose resource quantity is constant during a long time interval. Even so, their works proofed that second-priced auction mechanism can ensure reasonable profit for cloud providers.

In [26], the authors presented a three-tier cloud structure, which consists of infrastructure vendors, service providers and consumers. In such a framework, different cloud services are composited for serving user's request, while the prices of cloud services are decided by taking the dependency of different user budget constraint. So, the main objective of their approach is increasing the QoS satisfactions of cloud users especially for those with limited budgets, while it ignores the profits of cloud providers.

In [21], the authors proposed a decentralized economic approach, in which a set of agents were introduced to interact with the underlying infrastructures on behave of user applications. To meet the SLA performance and availability goals, an economic fitness is calculated by metrics including performance constraints, current workload, and resource utilization when allocating resources to an application.

In [22], the authors proposed a hierarchical game model to analyze the decisions of resource providers when cloud resources are shared by both internal users and public users. The game model is composed of two interrelated cooperative games: (1) The low-level game model is to describe the revenue sharing process between various cloud providers, and its game solution can be figured out by stochastic linear programming technique; (2) The upper-level game model formulate the coalitional process when a group of providers contribute their resources to a common pool, and its analytical solution is presented by Markov Chain technique.

III. Framework and Definitions

The framework of resource management in elastic clouds is shown in Figure 1. In such a framework, single cloud providers can serve as independent cloud system when it can provide sufficient resource for user application; if the resource capability of single cloud provider is not enough to satisfy the requirements of some large-scale applications, it can federate together and provide service for users. As shown in Figure 1, each cloud provider are independent in some times meanwhile keeping connected when needed. This work model is very similar to the 'Production Broker' model in normal business area [27]. Motivated by this, we introduce the conception of 'Virtual Resource Broker' (VRB) to describe the working of individual cloud providers with aiming at analyzing the resource provision and configuration in cloud platform.

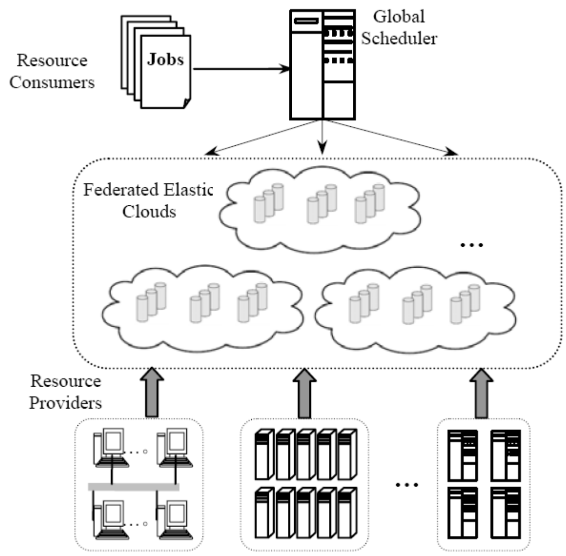


Figure 1. Framework of Federated Elastic Clouds

Let the set of cloud providers be as $\{S_1,S_2,\ldots,S_n\}$, their resource quantity is noted as $\{v_1,v_2,\ldots,v_n\}$. The set of VRB be note as $\{B_1,B_2,\ldots,B_n\}$ and their resource quantity is noted as $\{c_1,c_2,\ldots,c_n\}$. The user application is consist of a set of tasks noting as $\{t_1,t_2,\ldots,t_m\}$, each being characterized as $<r_i, d_i>$, where r_i is the resource requirement and d_i is the deadline constraint. The utility function of cloud provider S_i is noted as $U_i^S = \overline{p} \cdot v_i$, indicating the profits of S_i when it sell its resource with price $\overline{p}$. The utility function of VRB B_i is noted as $U_i^B = \mu_i \cdot p_i \cdot c_i - \overline{p} \cdot c_i$, where p_i is retail price decided by B_i, μ_i is the resource utilization of B_i. Therefore, U_i^B indicating the profits of B_i when it sell its resource to users with price p_i after it obtained resources from cloud providers with price $\overline{p}$. The global utility function of the federated cloud system is noted as $U^G=\sum_{k=1}^{n}\left(U_i^S+U_i^B\right)$, which is summation profits of cloud providers and virtual resource brokers. The utility function of user application is noted as $U^T=\sum_{j=1}^{m}\left(r_j^i\cdot p_i\right)$, where r_j^i is resource quantity that task t_i obtained from B_i.

It is clear that the profits of each VRB will be different after a period of time, since they use different retail prices. Therefore, we categorize them into three set by their profits. The set of VRB with positive profits is noted as $\chi^+(\overline{p})=\{B_i\mid U_i^B>0, i\in[1...n]\}$; that with negative profits is noted as $\chi^-(\overline{p})=\{B_i\mid U_i^B<0, i\in[1...n]\}$; that with zero profits is noted $\chi^0(\overline{p})=\{B_i\mid U_i^B=0, i\in[1...n]\}$. From the perspective of resource configuration, the profits of any VRB is decided by c_i and $\overline{p}$; from the perspective of resource provision, it is affected by retail price p_i and its resource utilization μ_i. Therefore, for any individual $B_i\in\chi^0(\overline{p})$, we say it is in balance state under condition $<\overline{p},\ c_i>$. If $\forall B_i\in\chi^0(\overline{p})$, then we say the whole resource trading system is in balance state under condition $<\overline{p},<c_1,c_2...,c_n>>$.

Combing Figure 1 and the above definitions, we can see that there are three classes of participants: cloud providers, VRBs, and resource consumers. The cloud providers and VRBs cooperate with each other, since they both aim at maximizing resources utilization and resource profits. On the other hand, the relationship between the VRBs and the resource consumers is non-cooperative, as the clients hope to minimize their costs, which would inevitably lower down the benefits of cloud providers.

IV. Gaming Models and Analysis

A. Cooperative Gaming Model

As mentioned in Section 3, the gaming model between cloud providers and VRBs is cooperative, and the former needs to decide an optimal resource price $\overline{p}$, while the latter needs to decide the optimal resource configuration noted as $\{c_1,c_2,\ldots,c_n\}$. Therefore, the solution of this cooperative game can be noted as $<\overline{p},<c_1,c_2,\cdots,c_n>>$.

Since all the resource owned by cloud providers are brokered by VRBs, it satisfies $\sum_{i=1}^{n}v_i=\sum_{i=1}^{n}c_i$. When the whole system is not in balancing state, we can have $U^G=\sum_{i=1}^{n}(\mu_i\cdot p_i\cdot c_i)$. When the system is in balancing state, according to the definitions in Section 2, we know that $\sum_{k=1}^{n}U_i^B=0$, therefore $U^G=\sum_{k=1}^{n}U_i^S=\overline{p}\cdot\sum_{i=1}^{n}v_i$. That is saying, When the whole resource trading system is in balance state, the global profits U^G is independent with $\overline{p}$; otherwise, U^G is decided only by $\overline{p}$.

Assuming that the system is in balancing state and the current condition is $<\overline{p},<c_1,\cdots,c_n>>$, we note the VRBs' profits as $<U_1^B,U_2^B,\cdots,U_n^B>$. When the resource trading system is in balancing state, $\forall B_i$ satisfies $U_i^B=\mu_i\cdot p_i\cdot c_i-\overline{p}\cdot c_i=0$, that is $\mu_i\cdot p_i-\overline{p}=0$. Assume that the VBRs' resource configurations are changed as $<c_1+\Delta c_1,\cdots,c_n+\Delta c_n>$, and their profits are noted as $<U_1^{B'},U_2^{B'},\cdots,U_n^{B'}>$ under condition $<\overline{p}+\Delta\overline{p},(c_1+\Delta c_1,\cdots,c_n+\Delta c_n)>$. So, we obtain that $U_i^{B'}=(c_i+\Delta c_i)\cdot[\mu_i p_i-(\overline{p}+\Delta\overline{p})]=-(c_i+\Delta c_i)\cdot\Delta\overline{p}$. As the total resource is constant, we know that $\sum_{i=1}^{n}(c_i+\Delta c_i)=\sum_{i=1}^{n}c_i=\sum_{i=1}^{n}v_i$. Since the system is in balancing state, we know that $U^G=\sum_{i=1}^{n}(U_i^S+U_i^B)=\sum_{i=1}^{n}U_i^S=\overline{p}\cdot\sum_{i=1}^{n}v_i$. Combing the above equations, under condition $<\overline{p}+\Delta\overline{p},(c_1+\Delta c_1,\cdots,c_n+\Delta c_n)>$, the global profit $U^{G'}$ satisfies

$$\begin{aligned}U^{G'}&=\sum_{i=1}^{n}(U_i^{S'}+U_i^{B'})\\&=(\overline{p}+\Delta\overline{p})\cdot\sum_{i=1}^{n}v_i+[-\Delta\overline{p}\cdot\sum_{i=1}^{n}(c_i+\Delta c_i)]\\&=(\overline{p}+\Delta\overline{p})\cdot\sum_{i=1}^{n}v_i-\Delta\overline{p}\cdot\sum_{i=1}^{n}v_i\\&=\overline{p}\cdot\sum_{i=1}^{n}v_i=U^G\end{aligned}\tag{1}$$

By Equation (1), we know that if the resource trading system is in balancing state under condition $<\overline{p},<c_1,\cdots,c_n>>$, any change of $<\overline{p},<c_1,\cdots,c_n>>$ will not change the global profits U^G. As the pricing policy of VRBs and cloud providers will not improve the global benefits U^G when the resource trading system is in balancing state. Therefore, the Nash equivalent solution of cooperative gaming is the condition $<\overline{p},<c_1,\cdots,c_n>>$ which can make the resource trading system in balancing state.

When the system is not in balancing state under condition $<\overline{p},<c_1,\cdots,c_n>>$, we need to find a feasible approach to improve U^G. It can be done by the following steps: (S1) We pick out any B_k that belong to $\chi^+(\overline{p})\neq\varnothing$ or $\chi^-(\overline{p})\neq\varnothing$;(S2)Change the resource price $\overline{p}$ as $\overline{p}'$, which satisfies $\overline{p}'=u_k\cdot p_k\cap\overline{p}'\neq\overline{p}$. Meanwhile, we keep $<c_1,c_2,\ldots,c_n>$ unchanged. Therefore, under condition $<\overline{p}',<c_1,\cdots,c_n>>$, we have the following conclusions: a) The system is still not in balancing state; b) U^G is unchanged; c) B_k is in balancing state. (S3). According to the second conclusion in Step 2, we know that $\exists B_h$ satisfying $B_h\in\chi^+(\overline{p}')$ or $B_h\in\chi^-(\overline{p}')$. Assuming $B_h\in\chi^+(\overline{p}')$, let the resource configuration of B_h being adjusted from c_h to $c_h+\Delta\delta$, and the resource configuration of B_k being changed from c_k to $c_k-\Delta\delta$, where $\Delta\delta>0$. We have known that the above changing of B_h's resource configuration will increase U^G. At the same time, we also know that the above changing of B_k's resource configuration will not affect U^G, because B_k is now in balancing state. Therefore, under condition $<\overline{p}',(c_1,\cdots,c_l+\Delta\delta,\cdots,c_k-\Delta\delta,\cdots,c_n)>$, we increase the global profit U^G.

B. Non-cooperative Gaming Model

According to the definitions of Section 3, we use $<\overline{M},<p_1,p_2,\cdots p_n>>$ to describe the gaming solution between VRBs and user applications, where $\overline{M}$ is the resource trading matrix. According to definition 2, the profits of B_i is affected by p_i, μ_i, $\overline{p}$, and c_i. During the cooperative gaming procedure, we have decided $\overline{p}$ and c_i. At the same time, μ_i is not adjustable since we can only obtain it by statistics. Therefore, the pricing policy can be noted as $p_i(\mu_i)$, which means that VRBs adjusts their retail price p_i by observing its resource utilization μ_i. Therefore, the key point of solving the non-cooperative gaming model is figure out the pricing function of VRBs.

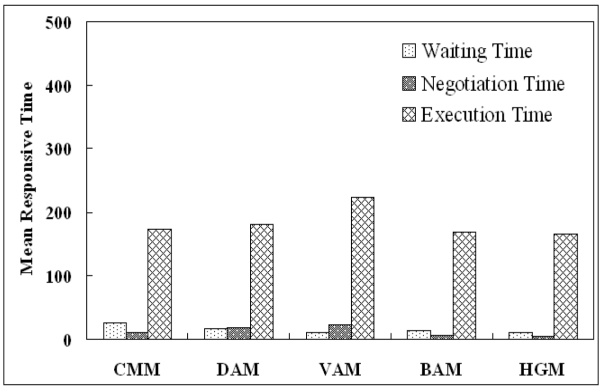
Let $p_i(\mu_i)$ be the pricing function of B_i. According to definition 2, we have $U_i^B = c_i \cdot \mu_i \cdot p_i(\mu_i) - \overline{p} \cdot c_i$. Let $dU_i^B / d\mu_i = 0$ we have the equation $\mu_i \cdot dp_i(\mu_i)/d\mu_i + p_i(\mu_i) = 0$, and U_i^B is maximized if this equation is solvable. By solve this equation, we can have following general solution as $p_i(\mu_i) = K_{i,1} - K_{i,2} \cdot \mu_i$, where $K_{i,1}$and $K_{i,2}$ are positive constant.

If all $\{B_1,B_2,\ldots,B_n\}$ are independent, the condition of obtaining maximized profits is that the pricing function is inversely proportional to resource utilization. We can have multiple pricing function since $K_{i,1}$ and $K_{i,2}$ can be any positive constant. For example, assuming that the pricing bounds of B_i is $[p_i^{\min}, p_i^{\max}]$, then its pricing function can be defined as $p_i(\mu_i) = p_i^{\max} - (p_i^{\max} - p_i^{\min}) \cdot \mu_i$. We can easily know that B_i have maximal profits when $\mu_i = p_i^{\max} / 2(p_i^{\max} - p_i^{\min})$. If $p_i^{\max} = 2\overline{p}$ and $p_i^{\min} = 0.5\overline{p}$, then when $\mu_i = 2/3$ the B_i have maximal profits. Therefore, once B_i decides its pricing function, it can obtain its optimal resource utilization by $\mu_i^* = K_{i,1}/(2K_{i,2})$. During the running time, if it observed that $\mu_i < \mu_i^*$ it can low down its retail price, otherwise increases its price. If $\mu_i = \mu_i^*$, then the current p_i is optimal for maximizing profits.

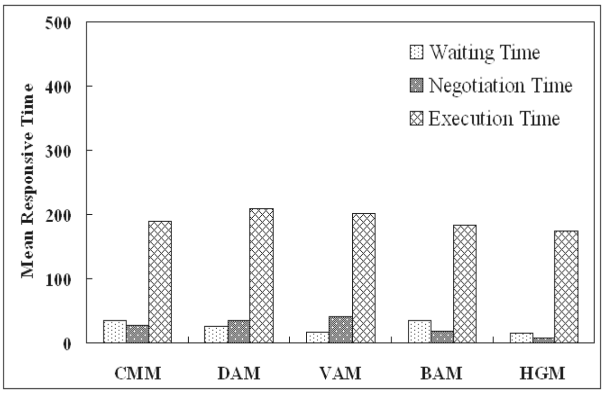
V. Experiments and Performance Evaluation

In the experiments, we use CloudSim [28] to construct a simulative cloud platform, which consists of twelve high-performance clusters as underlying resources. The topology and setting of individual clusters are deprived from the grid test-bed DAS-2. The experimental workload (tasks stream) is generated by using Lublin-Feitelson model, which is derived from the workload logs of real supercomputers. In the experiment, we mainly concentrate on the effects of resource trading on application's execution time.

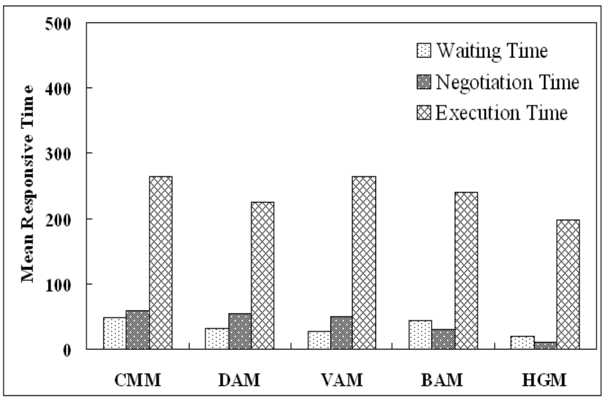
To analyze the performance, our hybrid gaming model (HGM) is compared with other four resource trading model, including Commodity Market Model (CMM) [29], Double Auction Model (DAM) [25], Vickery Auction Model (VAM) [28], Batch Auction Model (BAM) [30]. To examine the efforts of resource requirements on performance, we enlarge the workload's resource requirement β times. The experiments are conducted four time, with increasing β from 1.0 to 2.5. The results are shown in Figure 2.



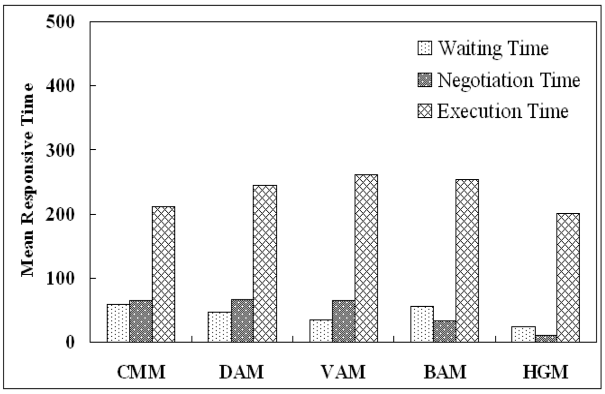
(a) β= 1.0



(b) β= 1.5



(c) β= 2.0



(d) β= 2.5

Figure 2. Comparison of Responsive Time

The experimental results show that resource requirements affect not only the resource negotiation time but also the execution time. When the resource requirements is in low level (β=1.0), the performance of VAM an DAM is significantly higher that other policies, and their negotiation time is about 10.2% and 8.7% of the total completing time. As to HGM and BAM, the negotiation time is about 2.9% and 3.1% of the total completing time. With the increasing of β, the negotiation times of both VAM and DAM increase as well as their proportions to the total completing time. For example, when β = 2.5, negotiation time of VAM is about 3.82 times of the case β = 1.0, and its proportion is increased to 21.3%. BAM is a batch resource trading model, and it is very effective to allocate multiple resources to application. However, it has to take many rounds to complete the auction procedure, especially when the resource requirements are very large. Therefore, when β = 1.0 its performance is almost equal to HGM; however, with increasing of β, the time costs on auction procedure become dominator, which makes BAM's performance reduced.

Comparing with auction model, CMM is effective to reduce communication-related costs. However, our experimental results indicate that its negotiation time increases significantly when β increases to high level. By examining the logs, we found that re-negotiation occurs more frequently than before, that is, the CMM's pricing policy can not efficiently finish the trading for all resource requirements. For example, when β = 2.5 about 43% tasks need to negotiation 2 times to obtain the required resources, and about 7% tasks need to do it at the third negotiation.

By the description of Section 3, we can see that HGM's negotiation costs mainly come from the selection of suitable VRBs. As all VRBs decide their retail price independently according to their resource utilizations, therefore, it can avoids workload concentration which is very important for reducing the costs of re-negotiation. Before HGM is in balancing state, those VRB with positive profits will increase their resource configuration. By this mechanism, they can improve the capability of serving multi-resource requirements. Therefore, we can consider HGM as the combination of BAM and CMM. Based on the above experimental results, our conclusion is that HGM is effective to reduce the negotiation time, which in turn reduce the application execution time.

Secondly, we all investigate the HGM's performance under constraints to costs and deadline. Because of the deadline constraint, we can not compare the policies directly. As a result, we select four typical resource matching algorithms to integrate those pricing mechanisms, including Round-Robin (RR), Capability-based Random (CR), Optimal Miss Rate (OMR) and Hierarchical Gaming Selection (HGS). The experiments conducted four times, each with different λ parameter which is used to define the arrival interval of tasks. The results are shown in Figure 3.

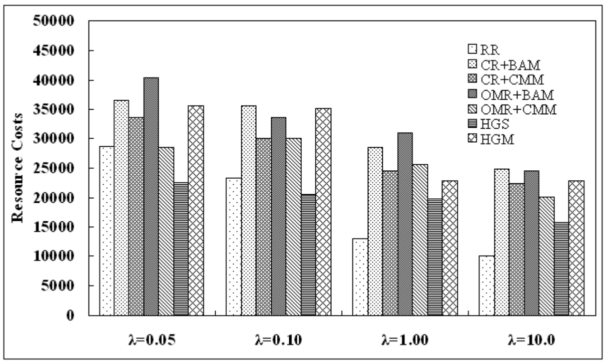


Figure 3. Resource costs with different policies and λ parameter

As shown in Figure 3, the performance of RR is the best if we only consider the resource costs. However, RR will result in high deadline miss rate when λ increases. By our result logs, the deadline miss rate is about 61.22% when λ=10. By our experiment setting, if deadline occurs the user will not pay any cost for resource providers. That is the reason that the resource cost of RR is the lowest. Among the left policies, HGS can obtain lowest resource costs and its changes are very stable for different λ parameters. We notice that the rejection rate of HGS is very high, which is significantly different from HGM. For example, when λ=10 the rejection rate of HGM is only about 6.17%. By the gaming policy, we know that the pricing function in HGM is inversely proportional to the resource utilization. Because of this pricing policy, HGM is capably of maintain a low rejection rate. As shown in the experimental results, when using the same pricing mechanism, CR and OMR perform very similar in terms of resource costs and rejection rate. However, their deadline miss rates are very different. In a whole, OMR is more effective to provide deadline guarantee than other policies especially when λ=0.05 and λ=0.10. However, when we increasing λ from 0.1 to 1.0, the rejection rate of OMR+BAM increases about 2 times, and the deadline miss rate increases about 2.5 times. Such a result happens on OMR+CMM. That is, OMR is effective to reduce deadline miss rate when there is no cost constraint; when cost constraint should be considered, OMR is only suitable for those applications with uniform workloads. Based on this experiment, we can see that HGM is effective to maintain low rejection rate and obtain better tradeoffs between resource costs and cloud provider's profits.

VI. Conclusion

To address the issue of resource pricing mechanism in cloud environments, a hybrid gaming based pricing model is proposed to overcome the demerits of existing price mechanisms in terms of efficiency and fairness. In the proposed pricing model, virtual resource configuration and provision are described as a two-phrase gaming procedure, in which cooperative gaming model is applied to optimize the resource benefits and non-cooperative gaming model is used to balance the user's costs and provider's benefits. The validity and solution of the proposed price model are presented theoretically, and the experimental results indicate that the hybrid gaming model can significantly improve the price negotiation efficiency when a bundle of resources are negotiated concurrently, which in turn reduce the application execution latency that caused by conventional price negotiation mechanisms. In addition, it also outperforms other pricing mechanism in terms of user's QoS requirements, such as resource cost and deadline guarantee, especially when the system workload is very intensive. In the future, we plan to incorporate resource reservation mechanism into our HGM framework, and design some elastic reservation mechanism to improve the QoS performance.

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References

[1] J. Ju, J. Wu, J. Fu, Z. Lin, J. Zhang. "A survey on cloud storage", Journal of Computers, vol.6, no.8, pp. 1764-1771, 2011.

[2] B. XU, N. Wang, C. Li. "A cloud computing infrastructure on heterogeneous computing resources", Journal of Computers, Vol.6, No.8, pp.1789-1796, 2011.

[3] J. Wu, Q. Shen, T. Wang, J. Zhu, J. Zhang. "Recent advances in cloud security". Journal of Computers, vol.6, no.10, pp.2156-2163, 2011.

[4] L. Rodero-Merino, E. Caron, A. Muresan et al., "Using clouds to scale grid resources: An economic model," Future Generation Computer Systems, vol. 28, no. 4, pp. 633-646, 2012.

[5] R. Beck, M. Schwind, and O. Hinz, "Grid Economics in Departmentalized Enterprises," Journal of Grid Computing, vol. 6, no. 3, pp. 277-290, Sep, 2008.

[6] A. Di Stefano, and C. Santoro, "An economic model for resource management in a Grid-based content distribution network," Future Generation Computer Systems, vol. 24, no. 3, pp. 202-212, 2008.

[7] D. J. Veit, and W. Gentzsch, "Grid Economics and Business Models," Journal of Grid Computing, vol. 6, no. 3, pp. 215-217, Sep, 2008.

[8] M. Macias, O. Rana, G. Smith et al., "Maximizing revenue in Grid markets using an economically enhanced resource manager," Concurrency and Computation-Practice & Experience, vol. 22, no. 14, pp. 1990-2011, Sep 25, 2010.

[9] A. Haque, S. M. Alhashmi, and R. Parthiban, "A survey of economic models in grid computing," Future Generation Computer Systems, vol. 27, no. 8, pp. 1056-1069, 2011.

[10] S. Parsa, F.-A. Parand, and H. Navidi, "Micro-economics based resource allocation in Grid-Federation environment," Cluster Computing-the Journal of Networks Software Tools and Applications, vol. 14, no. 4, pp. 433-444, Dec, 2011.

[11] H. Izakian, A. Abraham, and B. T. Ladani, "An auction method for resource allocation in computational grids," Future Generation Computer Systems, vol. 26, no. 2, pp. 228-235, 2010.

[12] R. Prodan, M. Wieczorek, and H. M. Fard, "Double Auction-based Scheduling of Scientific Applications in Distributed Grid and Cloud Environments," Journal of Grid Computing, vol. 9, no. 4, pp. 531-548, Dec, 2011.

[13] B. N. Chun, and D. E. Culler, "User-centric performance analysis of market-based cluster batch schedulers", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 30-38, 2002

[14] F. I. Popovici and J. Wilkes, J., "Profitable services in an uncertain world", Proceedings of ACM/IEEE Conference on Supercomputing, pp. 1-8, 2005.

[15] M. Feldman, K. Lai, and L. Zhang, "The Proportional-Share Allocation Market for Computational Resources," Ieee Transactions on Parallel and Distributed Systems, vol. 20, no. 8, pp. 1075-1088, Aug, 2009.

[16] R. Buyya, D. Abramson, and S. Venugopal, "The grid economy", Proceeding of the IEEE, Vol. 93, No. 3, pp. 698-714, 2005.

[17] M. Mihailescu and Y. M. Teo, "Dynamic resource pricing on federated clouds", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 513-517, 2010

[18] T. T. Huu, G. Koslovski, F. Anhalt et al., "Joint Elastic Cloud and Virtual Network Framework for Application Performance-cost Optimization," Journal of Grid Computing, vol. 9, no. 1, pp. 27-47, Mar, 2011.

[19] L. Wu, S. Garg and R. Buyya, R. "SLA-based resource allocation for software as a service provider (SaaS) in cloud computing environments", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 195-204, 2011.

[20] D. Ardagna, S. Casolari, M. Colajanni et al., "Dual time-scale distributed capacity allocation and load redirect algorithms for cloud systems," Journal of Parallel and Distributed Computing, vol. 72, no. 6, pp. 796-808, Jun, 2012.

[21] N. Bonvin, T. Papaioannou and K. Aberer, "Autonomic sla-driven provisioning for cloud applications", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 434-443, 2011.

[22] D. Niyato, A. Vasilakos and Z. Kun, Z. "Resource and revenue sharing with coalition formation of cloud providers: game theoretic approach", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 215-224, 2011.

[23] N. Chohan, C. Castillo, M. Spreitzer and et al. "See spot run: using spot instances for mapreduce workflows", Proceeding of International Hot Cloud, pp. 1-7, 2010.

[24] S. Wee, S. "Debunking real-Time pricing in cloud computing", IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 585-590, 2011.

[25] W. Lin, Y. Lin and H. Wei, “Dynamic auction mechanism for cloud resource allocation”, IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 591-592, 2010.
[26] Y. C. Lee, C. Wang, A. Y. Zomaya and B. Zhou, “Profit-driven scheduling for cloud services with data access awareness”, Journal of Parallel and Distributed Computing, Vol. 72, No. 4, pp. 591-602, 2012.
[27] M. Osborne, A. Rubinstein, A. A Course in Game Theory, The MIT Press, Cambridge UK, 1994.
[28] R. N. Calheiros, R. Ranjan, A. Beloglazov et al., “CloudSim: a toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms,” Software-Practice & Experience, vol. 41, no. 1, pp. 23-50, Jan, 2011.
[29] R. Buyya, “Economic-based distributed resource management and scheduling for grid computing”, Australia: Computer Science and Software Engineering, Monash University, 2002.
[30] H. Zhao and X. L. Li, “Efficient grid task-bundle allocation using bargaining based self-adaptive auction”, Proceedings of IEEE International Symposium on Cluster, Cloud and Grid Computing, pp. 4-11, 2009.

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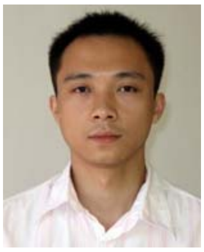

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