Resource Scheduling With Profit Maximization In Cloud Computing Based on Genetic Pricing Model

Rambind Patel[1], Nagendra Kumar[2]
[1]Dept of CSE
[2]Associate professor, Dept of CSE
[1, 2] Shri Ram Institute of Science and Technology, Jabalpur, Madhya Pradesh, India

Abstract- *Current implementations of Cloud markets suffer from a lack of information flow between the negotiating agents, which sell the resources, and the resource managers that allocate the resources to fulfill the agreed Quality of Service. A pricing model may be influenced by many parameters. The weight of such parameters within the final model is not always known, or it can change as the market environment evolves. This thesis models and evaluates how the providers can self-adapt to changing environments by means of new genetic algorithms. Cloud Service Providers that rapidly adapt to changes in the environment achieve higher revenues than Cloud providers that do not.*

Keywords- Pricing model, Execution time, response time, Task Transfer, Service level Agreement, Genetic Algorithm.

I. INTRODUCTION

Traditionally, academic and scientific entities as well as some companies owned big mainframes that had to be shared by their users to satisfy their computing requirements. These systems were managed centrally, considering performance metrics: throughput, response time, load-balancing, etc. The big mainframes paradigm [1] is transiting to a utility-driven paradigm [2], where users do not own their resources and pay for the usage of remote resources. The main advantage is that users do not require spending neither an initial expenditure nor maintenance costs for the hardware, and pay only for the capacity that they are using in each moment. Cloud Computing [3] is currently the most successful implementation of Utility Computing.

Cloud computing is originally developed from distributed computing; it can be defined as a type of parallel and distributed system which has many interconnected computers or servers [4]. It is a promising technology which attracts researchers, academicians and computing industries in great extent because of its computing capability to deliver shared cloud objects dynamically. Ever since its conception, cloud computing has been revolutionizing the way data storage and processing mechanisms are envisioned and implemented. It enabled the on-demand availability of services such as Software, Platform, Infrastructure (through SaaS, PaaS, IaaS respectively) and thus formed an economic solution to meet the ever-fluctuating demand for storage and computational resources by growing businesses.

The maximisation of the profit is the common objective for any business-oriented company. However, we need to differentiate the objective of a company from the BLOs. The BLOs will define the strategy to achieve the final objective of the company. This thesis will show that Profit Maximisation is not the unique BLO that increases the economic profit of a Cloud provider. The BLOs that are related with Risk Minimisation, Trust & Reputation Maximisation and Client Classification lead to increasing the economic profit of the provider.

1.1 Cloud Computing Pricing Model

Cloud computing is transforming information technology around the world. The computational and storage resources provided by infrastructure-as-a-service (IaaS) cloud, through different types of *instances*, are easy to access and maintain. Thus, large investments have been made to move business services into cloud and implementing/managing data centers to support cloud services. This raises a number of concerns with respect to the cost efficiency of the cloud, from the perspectives of both the cloud providers and the cloud consumers or tenants. Upon the request of an *instance* by a tenant, if the cloud has enough resources to host the instance, a virtual machine (VM) is allocated onto a server, so that the cloud tenant could run her applications or other computational tasks on the *instance*, or the VM to be specific. Many research works [5] have been devoted to leverage server virtualization and allocation techniques to optimize data center resource allocation via VM placement optimization. However, optimization from any aspect alone is limiting. The amount of resources that a cloud tenant needs varies from time to time. Traditional resource allocation and provisioning techniques still require data centers to be prepared for the intense resource demand during peak period [6]. Incorrect estimations of user demand levels may lead to costly over-provisioning of resources. Moreover, regardless of how the cloud is considered to be an unlimited resource pool, any resource has fixed capacity. It is obvious that having an optimal resource allocation algorithm to squeeze more capacity to serve more tenants is the key to increase the cloud provider's revenue [13]. It is important to incentivize cloud tenants to request for cloud resources reasonably, by devising a pricing methodology that charges each cloud tenant fairly, so that no one could use up a large portion of the resource and leave few to others. Therefore, user behaviors and usage patterns should also be considered as inputs to the VM placement problem. Many research works [7], [8] have shown that the use of pricing to induce desirable user behavior is a successful approach Furthermore, most cloud providers do not offer their tenants a service-level agreement (SLA) with the exact measures specifying the service provided. For example, Amazon Elastic Compute Cloud (EC2) only describes its central processing unit (CPU) resource in terms of equivalent Xeon processors and its input/output (I/O) performance as "high", "moderate", and "low", which are hardly measurable by cloud tenants [9]. Google Compute Engine advertises that its load balancing technique would let its user achieve maximum performance1 without specifying what "maximum performance" means. For services with best effort, no cloud service provider would promise that the service would meet some definite standards. The SLA of Amazon EC2 guarantees a service availability of 99.95% without mentioning performance.2 Although Xu and Li [9] have pointed out that a number of measurement studies have reported computational performance degradations of cloud services, most cloud tenants understand that they are using a best-effort service with performance variations, and hence, they tolerate minor performance degradations . In fact, it is difficult for cloud tenants to determine whether the performance degradation is due to the lack of resources. For a moment or two, people using applications that are run as a cloud service may experience a slow response time. However, it is almost impossible for an end user to determine if it is the cloud provider or the network provider that should be blamed.

Thus, many researchers have proposed revenue enhancement strategies [9], such as resource over booking, capacity right sizing, and resource throttling, to increase server utilization levels and save maintenance and operation costs. These all proved to be truly revenue-increasing techniques. However, would it be fair to cloud tenants that the cloud provider profits in such a way? First of all, cloud tenants' inability to detect resource shortages or performance degradation is critical for making these techniques feasible and profitable. Second, all the costs of implementing and operating such revenue enhancement techniques are eventually paid by each cloud tenant. It would be unfair to those cloud tenants who have kept their resources highly utilized. Third, a cloud service with a flat rate but utilizes resource throttling and overbooking to try to realize a higher profit is untruthful to its users.

II. LITERATURE SURVEY

The cost benefits that cloud computing offers to its customers has been discussed extensively; however, in the competitive market of cloud computing, little attention has been assigned to the challenges that cloud providers and vendors face to ensure business success. Thanks to the economies of scale, cloud providers are able to maintain large-scale data centers and to offer their services at a relatively low cost; this, however, does not eliminate the need for techniques that help providers to sell their services competitively while still creating profit. Beyond all technological advances, cloud providers endlessly require to reduce cost and increase revenue to remain in business. Among all the potential techniques to achieve such goals, we explore methods such as dynamic pricing, revenue management, and resource allocation. To identify open challenges in the area and facilitate further advancements, a review of the state of the art on the aforementioned topics is presented in this chapter. We review the efforts and studies that help cloud providers to minimize cost and maximize revenue.

2.1 Pricing Factors

We recognized three main factors that cloud providers and vendors should consider when determining the price of a cloud service.

Cost of service: The providers must calculate the cost of service production and then add an extra percentage to set the final price of the service in a way that they achieve the targeted profit. To the best of our knowledge, there are no research studies on cost-plus pricing analysis in clouds and public cloud providers use their own confidential methods for service cost calculation and setting the price. However, there are few works in the literature that examine the costs of service production in cloud data centers. Greenberg et al. [10] quantify data center costs and argue that internal data center network agility, geo-diversifying cloud provider's data centers, and market mechanisms for shaping resource consumption are the key aspects to reduce costs. Negru and Cristea [11] surveyed and analyzed existing cost models in clouds and discussed open issues related to the topic. Their guide on cost break down in today's cloud service data centers is helpful for profit maximization techniques used in this thesis.

Market competition: To remain in business, cloud providers must be aware of prices for the same services by other providers in the marketplace and set their prices competitively. Cloud computing market is moving rapidly towards a highly price-competitive environment which is termed by perfect competition by economists. There are few studies in the literature dealing with this problem. Pal and Hui [12] devise and analyze economic models for cloud service markets where public cloud providers jointly compete for the price and QoS levels. The competition in prices amongst the cloud providers has been envisaged by means of non-cooperative games amongst competitive cloud providers. Similarly, Roh et al. [13] study the resource pricing problem in the economic context from the perspective of cloud service providers.

Value to the Customers: To cloud customers, determining how much they are willing to pay for a service might not be related to the cost of service production by cloud providers. Setting a price for a service based on the perceived value to the customer constitutes considerable amount of subjectivity. Substantial efforts have been made by researchers of the information system sector to measure the service value of cloud computing from a customer perspective [14]. These efforts also help cloud providers to measure how well their services are leading to value and satisfaction for their customers. Market-based pricing mechanisms such as different types of auctions that solicit truthful reports (bids) from customers and subsequently set the service price according their bids can be categorized in this area of research.

2.2 Pricing Models

The most commonly used pricing models in cloud markets, especially in infrastructure as-a-service cloud marketplaces, are usage-based, subscription-based, and demand-oriented pricing models (Figure 2.1).

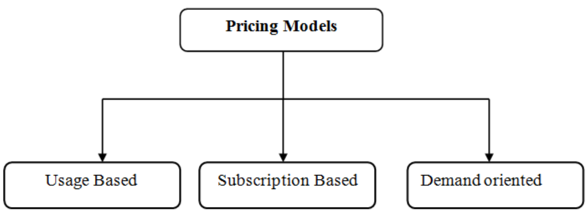

Figure 2.1: Pricing Models.

Usage-based pricing model: Basically, cloud computing can be defined as delivery of on-demand access to computing services on a pay-as-yo-go basis. This usage-based model of billing and metering of service consumption is similar to utility services such as water, electricity, gas, and telephony. A usage-based pricing model (also known as consumption-based) relies on the scheme that customers pay according to the amounts of services that they use or consume. Usage-based pricing model is the most common pricing model considered by IaaS cloud service providers. In this model, the provider quantifies the services that they provide, and charge customers accordingly. For example, an IaaS cloud provider might charge virtual machine (instance) usage per time unit, e.g., instance-minute or instance-hour or might charge storage per gigabyte per month. From the perspective of cloud customers, the pay-as-you-go pricing model offered by cloud providers is interesting in practice as it removes the upfront costs of setting up their own IT infrastructure and it allows organizations to expand or reduce their computing facilities very quickly.

In the usage-based pricing model, cloud providers often charge for services only on a fixed-rate basis. Fixed rate pricing is a relatively simple model and most often requires easily controllable cost-plus pricing strategy. There is a large body of literature on cost analysis of running applications on clouds considering the usage-based pricing model in clouds.

A related work by Sharma et al. [15] developed a cloud resources pricing model that uses financial option model to give a lower bound on the prices and compounded- Moore's law taking into account the metrics such as initial investment, rate of depreciation, and age of resource to give a upper bound on prices for what they call cloud compute commodities.

Subscription-based pricing model: Subscription-based pricing model is a pricing model that allows customers to pay a subscription fee to use the service for a particular time period. This is often popular among Software-as-a-Service (SaaS) cloud providers, where vendors deliver software capability over the Internet. The idea behind subscription-based pricing is that customers pay a fee to subscribe to a service over a predefined time period and they can regularly use the service during the subscription period. Subscription-based pricing models with more or less modifications are used by IaaS cloud provider as well while it is called with different terms such as reservation contract or prepaid scheme. For example, in the case of GoGrid, to use its prepaid plan, customers pay a subscription fee to reserve VM instances for monthly or annual contracts and after which the usage is free for the contract period. In Amazon Web Services,8 the customer pays an upfront reservation fee to reserve an instance for a one or three year term and usage-based rate for that instance is heavily discounted.

Cloud providers can benefit from subscriptions because they are assured a predictable cash flow from subscribed customers for the duration of the contract. This not only provides risk-free income and removes demand uncertainty for the business, but also provides long-term usage commitment to customers. However, the provider is usually liable to provide guaranteed availability for subscriptions to honor the associated Service Level Agreement (SLA). Niu et al. [16] propose a guaranteed cloud service model for cloud bandwidth reservation, where each customer does not require estimating the absolute amount of bandwidth he/she needs to reserve. Their objective is to determine the optimal policy for pricing cloud bandwidth reservations in the presence of demand uncertainty such that the social welfare is maximized, that is, the sum of the expected profits for all customers and the cloud provider is maximized.

Meinl et al. [17] discuss the application of reservation systems in cloud computing environments and point out the benefits for cloud vendors as well as their customers. The authors analyzed the application of derivative pricing techniques and yield management to create a model that can be utilized in real world systems. Mohammadi et al. [17] propose a novel reservation mechanism to protect both providers and customers from the cost overhead of over-provisioning resources. In their reservation mechanism, consumers can communicate their workload forecasts as a prereservation and then claim the pre-reserved resources if the need actually arises for the softly reserved resources in future. Pre-reservations capture the estimated amount of resources that will be required by a customer at a given future point of time as well as the probability of actually needing these resources. The proposed approach encompasses mechanisms to exploit the required information to be exchanged between the provider and the customer in a way that it leverages benefits of both providers and customers.

Similarly, Lu et al. [18] provide a solution for the resource reservation problem in IaaS providers with limited resource capacity. Their proposed method investigates the feasibility of each submitted reservation request and if the provider is not able to accept the request, an alternative way of accommodating the request with backward or forward shifting in time is suggested. They utilize computational geometry to tackle the problem. Wang et al. [19] study the resource reservation management issues inside cloud environments. They propose an adaptive resource reservation approach by selectively accepting reservation requests. The decision is made to maximize the cloud provider revenue while it ensures the quality of service (QoS) for transactional applications.

Demand-oriented pricing model: Demand-oriented pricing model is the process of establishing a price for a service based on the level of demand. The service price is changed according to its demand in a way that when the demand is high the price goes up and when it is low the price goes down. Among all pricing models discussed here, this is the least common pricing model at real-world IaaS cloud marketplaces; however it has received the highest attention from researchers in academia due to its complexities. In the demand-oriented pricing model, the price for a service must be set based on real-time and dynamic level of demand. When done successfully, such a dynamic pricing model maximizes the revenue for the cloud provider. Amazon is one of the IaaS cloud providers that publicly offers a demand-oriented pricing model for selling IaaS resources. The resources are called spot instances and are sold according to a dynamic pricing model that varies the price of instances in real-time based on supply and demand according to Amazon’s claim. A relevant study has done by Niyato et al. [20] where they present an economic analysis of the resource market in cloud computing environment. Three types of resource market between private customers and service providers have been considered, i.e., monopoly, competitive, and co-operative oligopoly. Repeated game model has been used to analyze the cooperation behaviour of the cloud providers to reach efficient and fair profit.

III. PROPOSED SYSTEM

The existing single resource renting scheme cannot guarantee the quality of all requests but wastes a great amount of resources due to the uncertainty of system workload. To overcome the weakness, we propose a renting scheme which not only can guarantee the quality of service completely but also can reduce the resource waste greatly. The main computing capacity is provided by the rented slow or lazy servers due to their low price. The short-term rented servers or speedy servers provide the extra capacity in peak period. Speedy resources are assigned to long length task and Lazy resources are assigned to medium length tasks by task scheduler. So this reduces rental cost. Basically proposed work is divided into two tasks- resource utilization and profit maximization. The proposed architecture is shown below in figure.

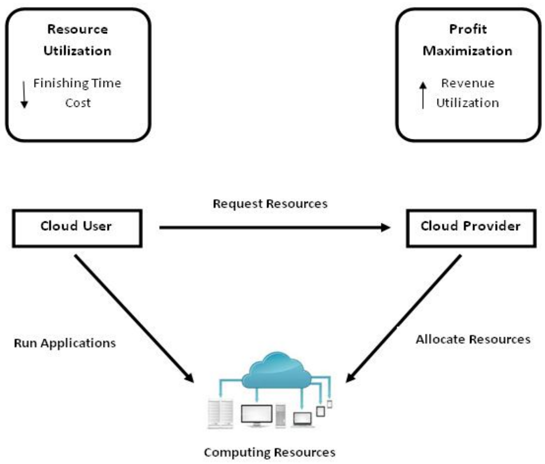

Fig 3.1: Overall Architecture.

Proposed system divides all available resources into two sets where first set is of the slow resources and second set is of the fast resources. This partitioning is done according to the MIPS speed of each resource. Suppose that there are 10 available resources. The first step is to sort these resources into ascending order by considering their MIPS speed and then add first 5 resources into the first set and remaining 5 resources into the second set. When tasks arrived for execution, choose the resource which takes less time for execution among all available resources before assigning any task. If chosen resource is from the first set, then assign average length task to it and if chosen resource is from the second set, then assign the longest task to it. The technique used in proposed algorithm for scheduling tasks is the combination of both Max-Min as well as Enhanced Max-Min. The proposed algorithm minimizes the chances of scheduling a large task to the slow resource with making completion time shorter. Proposed algorithm helps to utilize resources more efficiently and achieve good performance in terms of makespan as compared to existing algorithms. Algorithm is given below:

Input: T is task set, R is Resource set with MIPS speed, and n is total no of Resources
Algorithm ProposedRP (T, R, n)
{
For t_i Ɛ T do
{
Arrange elements of set R in ascending order of execution speed in MIPS.
}

R_{lazy} = R_i form 1 to n/2;
R_{speedy} = R_i form n/2 to n;
While t_i Ɛ T and T is not empty do
{
Find R_i with minimum execution time
If R_i Ɛ R_{lazy} than
Assign medium length task to R_i
Else
Assign long length task to R_i
Delete t_i from T
}
}

3.1 Proposed Profit Maximization Method

How can providers automatically adapt their behaviour to changing environments such as markets? To deal with this uncertainty problem, this thesis also proposes Genetic Algorithms as a model for analysing financial changing markets of cloud computing service providers. The basic idea of Genetic Algorithms is to have an extensive population of generic pricing models (chromosomes) whose parameters are stored as genes. At the initial moment, the genes are random, and some chromosomes are better than others (that is, their pricing models provide prices that are more beneficial for providers). The best chromosomes are selected in base to their pricing accuracy, and they are reproduced and mutated by simulating the natural evolution process. After some iterations of this process, the population of chromosomes will tend to provide prices that maximise the benefit of the provider. As in nature, if the environment changes, the population will self-evolve to become well adapted. Instead of classical Machine Learning techniques, we have chosen Genetic Algorithms because they have demonstrated to be more robust, since they do not break easily in the presence of reasonable outer effects. Also, they may offer significant benefits over typical optimization techniques in large, multi-modal state spaces.

Genetic Algorithms are used because they are simple to implement and dynamic enough to modify themselves (in comparison to the models whose pricing results were dynamic, but the models were static). Such dynamic behaviour will allow the model to self-adapt to changes in the market, and keep providers offering beneficial prices. This thesis proposes a new Genetic Pricing Model that considers the relative simplicity (compared to real financial markets) of Cloud Computing Markets and evaluates it experimentally and compares it with the other pricing models. Finding a good pricing model through Genetic Algorithms implies solving the following three issues:

Define a chromosome: In this thesis, the chromosome is a naive function, whose parameters are some relevant data that could influence in the price model. The relations and weights of these parameters are determined by the genes of the chromosome, which are at least partially different from the genes of other chromosomes. This function is called pricing function, because its evaluation corresponds to the price that a provider will ask for the sale of a Cloud service. The result of the pricing function is named output of the chromosome.

Evaluating the chromosomes: The chromosomes in a population must be evaluated. That means that their output must be compared to a reference value that is given by a teaching entity or by the actual value when trying to do predictions. In this work, the reference value is the price that a client finally pays for acquiring a Cloud resource.

Selection and reproduction of chromosomes: The chromosomes with lowest results in the evaluation are discarded from the population. Pairs of the best adapted chromosomes are selected for reproduction by mixing their genomes, so the population is replenished.

3.2 Definition of chromosomes: Let P = {p1..................pn} be a set of n parameters that contain some relevant information that could influence in the price of a requested task (for example, the amount of demand, the load of the system, the hour of day, the amount of resources, etc.). It must be emphasised that some of these parameters could influence, but actually do not necessarily do. We include all the parameters in our model because, in a complex and changing environment we do not know neither which have a real influence nor the weight of such influence.

Let G= {g1..........gm} be a set of genes that vary across different chromosomes and indicate the weights and mathematical relations between the parameters.
Equation 1 shows the pricing function expressed in each chromosome By P and G.

$$\textbf{Pricing (P, G)} = \frac{\sum^{n}_{i=0} g_i\, \pi_{j=0 \text{ to } n}\, p_j^{\,g\,i+j+1}}{\sum_{i=n2} gi_{+n}\, \pi_{j=0 \text{ to } n}\, p_j^{\,g\,i+j+1}} + g_m \text{ ...... (1)}$$

Where gi represents set of genes and pj represents set of varying prices.

The reference value (Ref-Val) is the lowest price that the buyer has chosen to pay in the last market competition, after the sale is performed. The scoring of a chromosome at time t is

Score = {Pricing (P, G) -- (Ref-Val)}...................... (2)

The closest of Score to 0 is the score the best price has proposed the chromosome at instant t.

IV. IMPLEMENTATION

We have conducted several experiments to test the performance of proposed algorithm in terms of price and this section also shows performance comparison between the proposed algorithm and existing pricing algorithms i.e. fixed pricing and dynamic pricing. Number of Tasks used for simulation is 30, 40 and 50. Numbers of virtual machines are increased per evaluation to check the performance of proposed algorithm in each. Below subsections shows the results of each evaluation.

4.1 Execution time Evaluation for Virtual Machines:

There are different number of tasks are used for this evaluation. Table 1 shows the performance comparison between the proposed algorithms with respect to other pricing models. Figure below shows the graphical representation of the results where number of tasks = 30.

Table below shows the comparisons of average pricing of algorithms based on number of tasks. Results show that the performance of proposed algorithm is better than other pricing models like static pricing, dynamic pricing and utility pricing. Table below shows the comparisons of three algorithm with increased virtual machine size i.e. VM=20 and VM=30.

Table 1: Price Comparison of Algorithms.

ALGORITHM / Number of task	Static Pricing	Dynamic Pricing	Queuing Model	Proposed Model
30	682.8753	725.8602	708.4583	812.9596
40	759.087	724.86127	713.07556	1206.2263
50	769.4391	727.1796	736.58856	1365.2546

Results of above evaluations show that proposed algorithm performs better other pricing models. Performance of proposed algorithm is better than static pricing, dynamic pricing and utility pricing for 30, 40 and 50 tasks. Results shows that proposed algorithm behaves better in terms of pricing factor after testing it with workflows. As we increased a number of task which are used for simulation, the proposed algorithm performs better than other methods.

Results of above evaluations show that proposed algorithm generates maximum profits when number of task are large i.e. when number of requests increases the algorithm performs better while for small number of request it performance is below average. The comparison has been performed with three pricing models, and the proposed algorithm performs better than all the three models.

V. CONCLUSION

The proposed work presents new resource provisioning algorithm based on proper resource utilization aim to profit maximization. This algorithm is implemented using WorkFlowSim simulation tool with Netbeans. Large task is assigned to the fast resource and smaller ones to lazy resources for proper utilizations. In proposed algorithm possibility of scheduling long length tasks to the slow resource is reduced. Solution used in this paper is division of resources into two groups according to MIPS speed. If the fastest available resource is from the second group which is the group of fast resources, then the largest task is scheduled to it. If the fastest available resource is from the first group which is the group of slow resources, then the average length task is mapped to it. Result shows that proposed algorithm done efficient resource utilization and has better profit than existing algorithms.

REFERENCES

[1] J. Basney and M. Livny, \Deploying a high throughput computing cluster," in High Performance Cluster Computing: Architectures and Systems, Volume 1, R. Buyya, Ed.Prentice Hall PTR, 1999.

[2] M. A. Rappa, \The utility business model and the future of computing services," IBM Syst. J., vol. 43, no. 1, pp. 32-42, 2004.

[3] R. Buyya, C. S. Yeo, and S. Venugopal, \Market-oriented cloud computing: Vision, hype, and reality for delivering it services as computing utilities," in 10th IEEE Intl. Conf. on High Performance Computing and Communications (HPCC 2008). Dalian, China: IEEE Computer Society, September 2008, pp. 5-13.

[4] Peter Mell and Tim Grace, "The NIST definition of cloud computing", NIST Special Publication 800-145 (SP800-145), National Institute of Standards and Technology, Gaithersburg, January 2011, pp. 1-52.

[5] M. Abu Sharkh, M. Jammal, A. Shami, and A. Ouda, "Resource allocation in a network-based cloud computing environment: Design challenges," IEEE Commun. Mag., vol. 51, no. 11, pp. 46–52, Nov. 2013.

[6] H. Zhang et al., "Resource allocation for cognitive small cell networks: A co-operative bargaining game theoretic approach," IEEE Trans. Wireless Commun., vol. 14, no. 6, pp. 3481–3493, Jun. 2015.

[7] S. Ha, S. Sen, C. Joe-Wong, Y. Im, and M. Chiang, "Tube: Time dependent pricing for mobile data," SIGCOMM Comput. Commun. Rev., vol. 42, no. 4, pp. 247–258, Aug. 2012.

[8] H. Shen and Z. Li, "New bandwidth sharing and pricing policies to achieve a win-win situation for cloud provider and tenants," in Proc. IEEE INFOCOM, Apr. 2014, pp. 835–843.

[9] H. Xu and B. Li, "A study of pricing for cloud resources," *SIGMETRICS Perform. Eval. Rev.*, vol. 40, no. 4, pp. 3–12, Apr. 2013.

[10] A. Greenberg, J. Hamilton, D. A. Maltz, and P. Patel, "The cost of a cloud: research problems in data center networks," SIGCOMM Computing Communication Review, vol. 39, no. 1, pp. 68–73, 2008.

[11] C. Negru and V. Cristea, "Cost modelspillars for efficient cloud computing: position paper," International Journal of Intelligent Systems Technologies and Applications, vol. 12, no. 1, pp. 28–38, Jan. 2013.

[12] R. Pal and P. Hui, "Economic models for cloud service markets," in Distributed Computing and Networking, ser. Lecture Notes in Computer Science, L. Bononi, A. Datta, S. Devismes, and A. Misra, Eds. Springer Berlin Heidelberg, 2012, vol. 7129, pp. 382–396.

[13] H. Roh, C. Jung, W. Lee, and D.-Z. Du, "Resource pricing game in geo-distributed clouds," in Proceedings of International Conference on Computer Communications (INFOCOM'13), Turin, Italy, April 2013, pp. 1519–1527.

[14] R. S. Padilla, S. K. Milton, and L. W. Johnson, "Service value in IT outsourcing, "International Journal of Engineering and Management Sciences, vol. 4, no. 3, pp. 285–302, 2013.

[15] B. Sharma, R. K. Thulasiram, P. Thulasiraman, S. K. Garg, and R. Buyya, "Pricing cloud compute commodities: A novel financial economic model," in Proceedings of the 12th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid'12), Ottawa, Canada, May 2012, pp. 451–457.

[16] D. Niu, C. Feng, and B. Li, "Pricing cloud bandwidth reservations under demand uncertainty," SIGMETRICS Performance Evaluation Review, vol. 40, no. 1, pp. 151–162, June 2012.

[17] T. Meinl, A. Anandasivam, and M. Tatsubori, "Enabling cloud service reservation with derivatives and yield management," in Proceedings of 12th IEEE Conference on Commerce and Enterprise Computing (CEC'10), Nov 2010, pp. 150–155.

[18] K. Lu, T. Roblitz, R. Yahyapour, E. Yaqub, and C. Kotsokalis, "QoS-aware SLA based advanced reservation of infrastructure as a service," in Proceedings of Third IEEE International Conference on Cloud Computing Technology and Science (Cloud- Com'11),, Athens, Greece, Nov 2011, pp. 288–295.

[19] X. Wang, Y. Xue, L. Fan, R. Wang, and Z. Du, "Research on adaptive QoS-aware resource reservation management in cloud service environments," in Proceedings of IEEE Asia-Pacific Services Computing Conference (APSCC'11), Jeju, Korea, Dec. 2011, pp. 147–152.

[20] D. Niyato, S. Chaisiri, and B.-S. Lee, "Economic analysis of resource market in cloud computing environment," in Proceedings of IEEE Asia-Pacific Services Computing Conference (APSCC'09), Biopolis, Singapore, Dec. 2009, pp. 156–162.