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Resource Management in Cloud Computing with Optimal Pricing Policies

Haiyang Zhang[1], Guolong Chen[2], Xianwei Li[2,3]*

[1] *School of Environment and Geomatics Engineering, Suzhou University, Suzhou, Anhui Province, China*
[2] *School of Information Engineering, Suzhou University, Suzhou, Anhui Province, China*
[3] *Global Information and Telecommunication Institute, Waseda University, Tokyo, Japan*

As a new computing paradigm, cloud computing has received much attention from research and economics fields in recent years. Cloud resources can be priced according to several pricing options in cloud markets. Usage-based and reserved pricing schemes are commonly adopted by leading cloud service providers (CSPs) such as Amazon and Google. With more and more CSPs entering cloud computing markets, the pricing of cloud resources is an important issue that they need to consider. In this paper, we study how to segment cloud resources using hybrid pricing schemes in order to obtain the maximum revenue by means of optimal pricing schemes in what is a largely monopolized cloud market. We first study how the revenue of a cloud provider can be maximised using an on-demand pricing scheme. We then turn to the study of revenue maximization with a reserved pricing scheme and, finally, we compare the revenues obtained from the two pricing schemes.

Keywords: cloud computing, cloud resources, pricing scheme, revenue

1. INTRODUCTION

Cloud computing is a new computing paradigm that can transform a large part of the IT industry. With the increasingly widespread use of cloud services, the long-held dream of computing as a utility almost as valuable as water and electricity, has come true (Armbrust et al., 2010). There are several types of cloud services, among which IaaS (Infrastructure as a Service) cloud is developing much faster (The Future of Cloud Adoption, 2012); therefore, a large number of works focus on the study of IaaS cloud computing. In an IaaS cloud environment, cloud computing resources such as CPU, disk and memory are packaged into different types of VMs (virtual machines) instances which have different configurations, and cloud users pay to access these resources which are delivered by cloud providers over the Internet. Table 1 shows the configurations of some VM instances of Amazon EC2 (2018).

*Corresponding author: lixianwei163@163.com

Table 1. Configuration of Some EC2 Spot Instances (See p. 10 of the Appendix). There are two pricing schemes: usage-based and reserved pricing, which are commonly adopted by leading CSPs such as Amazon EC2 (2018) and Aliyun(2018). The usage-based pricing scheme allows cloud users to pay according to their usage of cloud resources, which is known as on-demand pricing. The reserved pricing scheme permits cloud users to pay an upfront fee to reserve some type of instance for a period of time, and cloud instances can be used for free, or at a considerable discount (Amazon EC2, 2018) during this time.

In this paper, we investigate a monopoly IaaS CSP selling cloud computing resources to cloud users under a capacity constraint in the form of VM instances. Cloud users purchase VM instances to perform their jobs. From the perspective of this CSP, we study how to allocate cloud resources in order to maximize its revenue with different pricing schemes.

The rest of the paper is organized as follows. Section 2 presents the related works and the motivation for our study. Section 3 introduces a system model and problem formulation. In section 4, we study revenue management with the on-demand

Table 1 Configuration of Some Amazon EC2 Instances.

Instance Types	vCPU	Compute Unit	Storage (GB)	Memory (Gib)
i2.xlarge	4	14	800 SSD	30.5
m3.2xlarge	8	26	160SSD	30
c3.large	2	7	32SSD	3.75
c3.xlarge	4	14	80SSD	7.5
c3.2xlarge	8	28	160SSD	15

pricing scheme as the benchmark. We then study, in section 5, the revenue obtained under the reserved pricing scheme and compare it with the revenue obtained by on-demand pricing. In section 6, we present numerical results to confirm our analysis. Conclusions and future works are presented in section 7.

2. RELATED WORKS AND MOTIVATIONS

In this section, we present the related works and the motivations for our study. One stream of research that is relevant to our work is the study of pricing in communication networks. Since Kelly's original work (Kelly, 1997), pricing has been extensively used as an effective tool to study resource allocation in communication networks. Li and Huang (2014) studied revenue maximization with a usage-based pricing scheme in a monopolized communication market. They considered both the users' complete information and the incomplete information to maximize the network service provider's revenue. Wu et al. (2010) applied time-constrained pricing to study an Internet service provider's revenue maximization.

Resource allocation is a core problem in cloud computing. Pricing is an effective and efficient tool for the allocation of cloud resources. Numerous works have explored the problem of resource allocation through the use of pricing. Menache et al. (2011) proposed an algorithm to study admission and resource allocation in order to maximize social welfare in a cloud computing environment. Wang et al. (2012) developed a pricing scheme which is computationally efficient in order to study fair competition for the allocation of cloud resources. A demand-pricing model was designed by Kantere et al. (2011) for cloud caching services; they also proposed a dynamic pricing scheme to maximize profit for the cloud provider. Feng et al. (2014) studied pricing competitiveness in the IaaS cloud market among multiple cloud providers, where demands for cloud resources of cloud users are sensitive to both price and finishing time. However, the aforementioned works studied only the single pricing scheme. Fang et al. (2018) studied the problem of maximizing the profit of cloudlets in a mobile cloud computing environment based on the Lyapunov optimization technique. Li et al. (2016) proposed a pricing strategy for big data processing to maximize the revenue of the many cloud intermediaries who rent cloud computing resources from the IaaS CSPs. Wang et al.(2017) investigated the problem of optimizing the performances of cloud services via the optimal allocation of workloads. They considered two performance metrics: the percentile and the mean response time. Mei et al. (2019) studied the profit maximization problem of cloud brokers.

Unlike previous works that mainly analyzed only one pricing policy, in this paper, we study how to allocate the cloud resources with fixed cloud capacity by using hybrid pricing schemes. Another work that is closely related to ours is that of Wang, Li and Liang (2012) who studied how to maximize revenue using hybrid pricing schemes. However, they took the CSP's perspective while neglecting to consider the cloud users' demand. In this paper, we not only investigate how cloud users buy cloud resources when faced with different pricing choices, but also analyze how CSP revenue can be maximized through the use of hybrid pricing schemes.

3. RESOURCE ALLOCATION WITH USAGE-BASED PRICING SCHEME

As a benchmark, we first study how to establish an optimal on-demand pricing scheme in order to maximize the revenue of this monopoly CSP. We examine a cloud market monopoly where one CSP sells cloud resources to a potential pool of cloud users. As illustrated in Figure 1, we model the interactions between the CSP and cloud users as a two-stage Stackelberg game. In stage I, the CSP sets the price of usage-based VM instances p per unit time to maximize its revenue. In stage II, the cloud users decide how many VM instances to buy in order to maximize their payoff. We use the backward induction method to analyze the relationship between this cloud provider and the cloud users.

3.1 Cloud Users' Resource Demands in Stage II

Each cloud user is represented by a type parameter θ, which is uniformly distributed in [0, 1]. And the usage level of each cloud user is denoted as $d \in [0, 1]$. For a given price p, the utility for a cloud user can be expressed as

$$u(\theta, d) = \theta \ln(1 + kd) \tag{1}$$

where $k > 0$ reflects the elasticity of demand;the utility function above is widely used in the literature (Duan et al., 2013). The cloud user's payoff is the difference between the utility and the payment; i.e.,

$$v(\theta, d, p) = \theta \ln(1 + kd) - pd \tag{2}$$

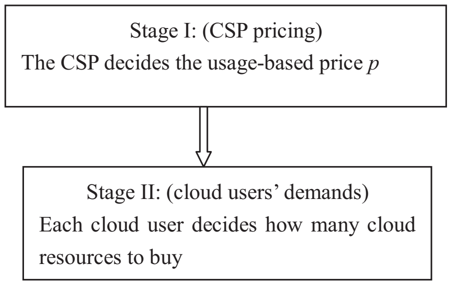

Figure 1 Two-stage Stackelberg game between the CSP and cloud users.

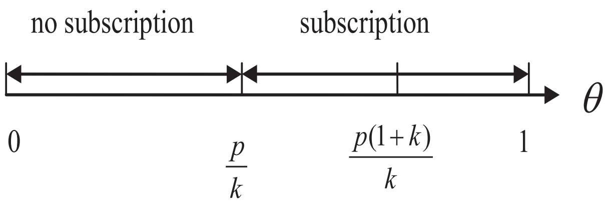

Figure 2 Cloud users' subscription decision.

By solving the maximization of the cloud user's payoff, the optimal usage level with the usage-based cloud resources is

$$d^*(\theta, p) = \min\left(\max\left(\frac{\theta}{p} - \frac{1}{k}, 0\right), 1\right) \tag{3}$$

From (3) we know that cloud users will have non-negative usage level when $\frac{\theta}{p} - \frac{1}{k} \geq 0$; that is, $\theta \geq \frac{p}{k}$. The cloud users' choice is shown in Fig. 2. By setting $\frac{\theta}{p} - \frac{1}{k} = 1$, we get $\theta^* \frac{p(1=k)}{k}$, and when $\theta^* = 1$, we have

$$p^* = \frac{k}{1+k} \tag{4}$$

3.2 CSP's Pricing in Stage I

Next, we consider the CSP's optimal pricing in Stage I. In order to obtain a positive revenue, the CSP needs to set $p \leq \theta k$, so that at least some users can buy positive cloud resources in Stage II. The total demand for cloud resources is

$$d(\theta, p) = \int_{\frac{p}{k}}^{1} \left(\frac{\theta}{p} - \frac{1}{k}\right) d\theta = \frac{1}{2p} + \frac{p}{2k^2} - \frac{1}{k} \tag{5}$$

The CSP chooses price p to maximize its revenue; i.e.,

$$\max \pi(p) = pd = p\left(\frac{1}{2p} + \frac{p-k}{2k^2}\right) = \frac{1}{2} + \frac{p^2}{2k^2} - \frac{p}{k} \tag{6}$$

The first derivative of the objective function in (6) with respect to p is

$$\frac{d\pi(p)}{dp} = \frac{p-k}{k^2} \tag{7}$$

By setting (6) to zero, we obtain the optimal price

$$p^* = k \tag{8}$$

From the above analysis, we conclude that the optimal usage-base price that maximizes the cloud provider's revenue is $p^* = \frac{k}{1+k}$. Accordingly, the optimal revenue under usage-based optimal revenue is

$$\pi\left(p^*\right) = \frac{1}{2} + \frac{1}{2(k+1)^2} - \frac{1}{k+1} = \frac{k^2}{2(k+1)^2} \tag{9}$$

4. RESOURCE ALLOCATION WITH RESERVED PRICING SCHEME

Similar to the previous section, we also model the cloud provider and cloud users as a Stackelberg game. In the first stage, the cloud provider broadcasts the reserved price, and cloud users will make their decision to subscribe to the cloud resource. We use the backward induction method to analyze the relationship between the cloud provider and cloud users.

4.1 Cloud Users' Subscription Decisions in Stage II

Under a reserved pricing scheme, cloud user payments are independent of their usage level; therefore, the usage level $d = 1$. By subscribing to cloud resources with reserved pricer, the payoff a type-θ is

$$v(\theta, r) = \theta \ln(1+k) - r \tag{10}$$

Note that cloud users will subscribe to the cloud resources only when their payoff is non-negative, which implies that $v(\theta, r) = \theta \ln(1+k) - r \geq 0$, from which we obtain a threshold value

$$\theta^* = \frac{r}{\ln(1+\mathrm{k})} \tag{11}$$

4.2 Cloud Provider's Pricing Choice in Stage I

In stage one, the objective of the cloud provider is to maximize revenue by setting an optimal price. The cloud provider's revenue maximization problem is expressed as

$$\max \pi(r) = r\left[1 - \frac{r}{\ln(1+\mathrm{k})}\right] \qquad s.t. r \geq 0 \tag{12}$$

It is easy to very that the objective function of (12) is a concave function, so we can obtain the optimal price by taking the derivative of objective function (12) with respect to r

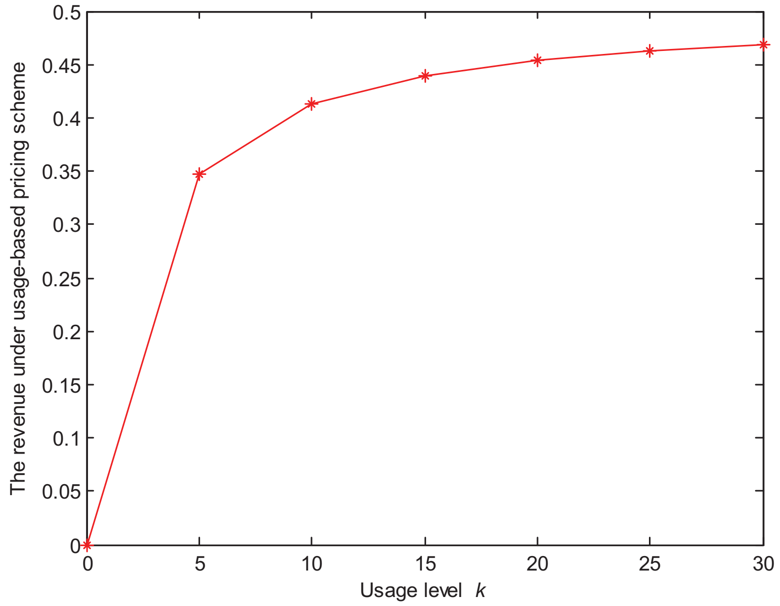

Figure 3 The revenue under usage-based pricing scheme.

$$r^* = \frac{\ln(1+k)}{2} \tag{13}$$

Accordingly, the optimal revenue under the reserved pricing scheme is

$$\pi\left(r^*\right) = r^*\left[1 - \frac{r^*}{\ln(1+k)}\right] = \frac{\ln(1+k)}{4} \tag{14}$$

5. COMPARISON OF REVENUES UNDER USAGE-BASED AND RESERVED PRICING SCHEMES

In this section, we compare the revenues under the two pricing schemes. We first define the ratio between the revenues of usage-based and reserved pricing schemes as

$$R(k) = \frac{\pi\ (r^*)}{\pi\ (p^*)} = \frac{\frac{\ln(1+k)}{4}}{\frac{k^2}{2(k+1)^2}} = \frac{2(k+1)^2 \ln(1+k)}{k^2} \tag{15}$$

It is apparent that $R(k)$ is a concave function and from the derivative of (5) over k we obtain

$$\frac{dR}{dk} = 2\frac{k+1}{k^2}[1 - 2\ln(1+k)] \tag{16}$$

6. SIMULATION RESULTS

In this section, we report on the simulations conducted to verify our analysis in the previous sections. First, we analyzed how the revenue of cloud provider under a usage-based pricing scheme fluctuates according to the cloud users' level of usage. We then analyzed how the cloud provider's revenue varies under a reserved pricing scheme. Finally, we compare the cloud provider's revenues under the two pricing schemes, thereby indicating the optimal pricing choices.

The cloud provider's optimal revenue under the usage-based pricing scheme is shown in Figure 3 which indicates that the revenue increases with the increase in usage level.

The optimal revenue received by the cloud provider under a reserved based pricing scheme is shown in Figure 4; this figure also shows that the revenue increases if the usage level increases.

The comparison of the revenues under reserved and on-demand pricing schemes is shown in Figure 5. This figure shows that when the usage level increases, the ratio value decreases at first. This clearly indicates that when the cloud users' usage level increases, the cloud provider will receive more revenue by implementing an on-demand subscription pricing policy. However, the ratio increases when the usage level increases after a critical point.

7. CONCLUSIONS AND FUTURE WORKS

This paper analysed two pricing schemes: on-demand (usage-based) pricing and reserved pricing, which are commonly adopted by leading cloud providers. We studied not only the cloud users' decision-making, but also the pricing policies from the perspective of the cloud provider. Our analysis showed that the cloud provider's revenue will increase if cloud users create more demand for cloud resources. Moreover, our analysis indicates that the ratio of revenue under the reserved pricing scheme and under the on-demand pricing scheme will decrease as cloud usage increases; also hence, when there is a low level of cloud usage, the cloud provider prefers to adopt a reserved pricing policy. However, with the increasing level of usage, the cloud provider tends to adopt an on-demand pricing scheme.

Our work can be further studied from the following aspects. We analyzed only a monopoly cloud market; however, with more and more cloud providers entering the cloud market, cloud market competitiveness will increase. Therefore, in future

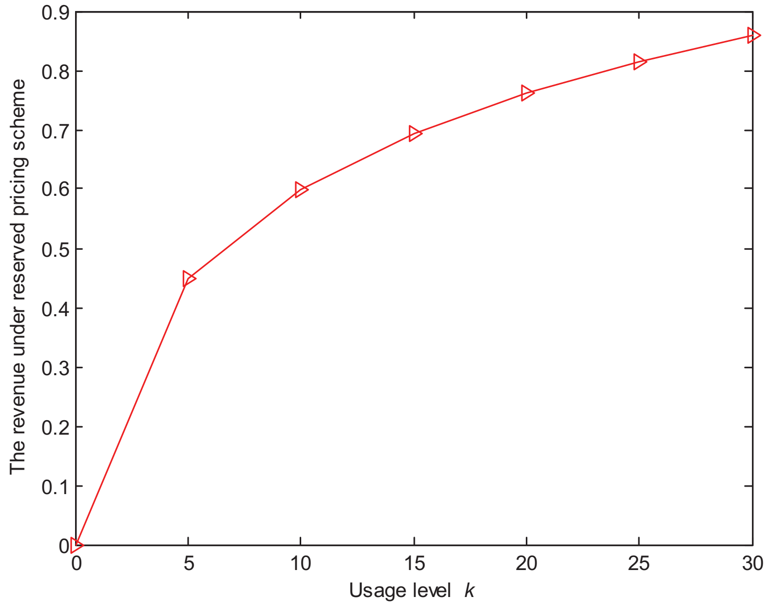

Figure 4 The revenue under usage-based pricing scheme.

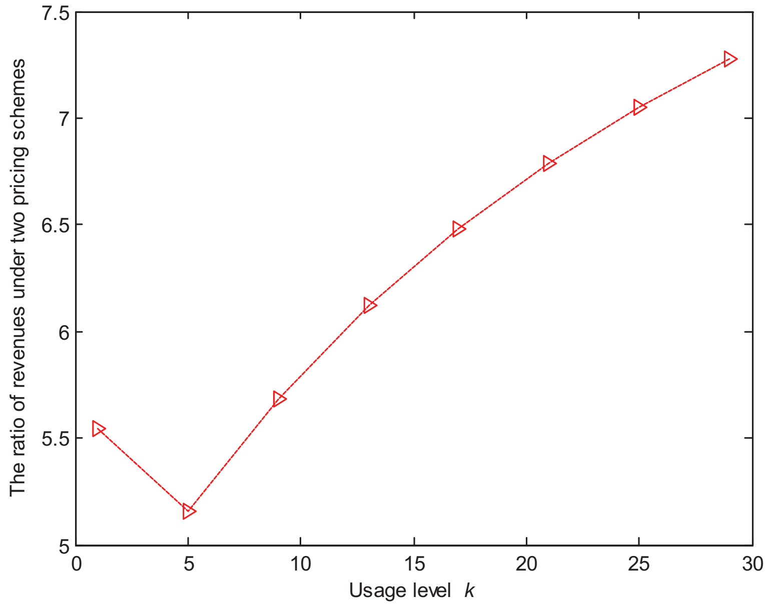

Figure 5 The ratio of revenue under reserved pricing scheme and on-demand pricing scheme.

works, we will consider the case where there are more than one cloud providers in the cloud market, which will be more challenging. Another factor that we did not consider in this paper is how delay influences the decisions of cloud users and providers, an issue which can be incorporated in future works.

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