A New Method for Balancing Cloud Resource

Heng Song, Junwu Zhu, Yi Jiang, Bin Li
School of Information Engineering
YangZhou University
YangZhou, China
Email: song_heng@foxmail.com, jwzhu@yzu.edu.cn, yj@yzu.edu.cn, lb@yzu.edu.cn

Abstract—**With the rapidly growing demands for cloud resource, the task to keep it balanced with supply at all times becomes especially challenging. However, most of existing mechanisms focus on auction-based allocation of cloud resource rather than balancing the demands for cloud resource. In order to address this issue, we formulate the problem of cloud resource consumption shifting between two different time intervals, and then present a directly applicable scheme with three-tiered. Users participating in the scheme, however, are motivated to get extra rewards through shifting certain consumption quantity from high to low demand time intervals. In addition, taking into account the fact that individual shifting costs and reduction capacity vary with the different geographic areas, this scheme firstly allocates rewards to agencies in different geographic areas in the way of equilibrium. And then a strictly proper rule is proposed to reward contributors according to efficiency, which achieves the theoretical properties including equilibrium, individual rationality, and budget balance and truthfulness. At last, to verify the method given by this paper, method analysis and case study is given to illustrate the correctness and effectiveness.**

Keywords—Cloud Resource; Consumption Shifting;Mechanism Design;Equilibrium.

I. INTRODUCTION

As technology evolves, the computing task become more complicated and bothersome, individuals and enterprises aiming to pay for lower costs prefer outsourcing their workloads to the cloud resources provider[1]. Generally, the cloud resource providers offer infrastructure as a service in the form of virtual machine instances characterized by numbers of computing (such as CPU, memory, storage, and networks). For example, Amazon EC2 [2] offers various types of virtual machines (VMs). However, the ever-increasing demands for cloud resource overloads the infrastructure. Therefore, maintaining users' demands curve stability, in particular, can alleviate the risk of disastrous infrastructure collapses, and brings financial benefits---as some VMs can be run on idle or long time overload may damage the VMs and result in users' data loss. In this work, we are motived to design a consumption shifting scheme to balance the demands for cloud resource.

Nevertheless, there exist many challenges in designing a practical scheme for the issue of cloud resource consumption shifting. Three major challenges are listed as below:

• ***Equilibrium***: Game Theory [3] teaches us that equilibrium can ensure the best outcome for each cloud resource agency.

• ***Budget Balance***: Users hope that the sum rewards are complete allocated for them while cloud resource provider aims to the quota can be completely competed accomplished by users to balance the demands for cloud resource. Therefore, a budget-balanced mechanism is preferred.

• ***Truthfulness***: Since users are normally selfish, they always tend to strategically manipulate the shifting scheme in order to get more rewards. Hence, designing a shifting scheme which can prevent users from lying about their bids is essential.

Our contribution: Based on the problem of balancing the demands for cloud resource, we present a novel model of cloud resource consumption shifting. Considering the value ranges of users' shifting cost and reduction capacity for cloud resource are diverse due to geographical differences, we introduce the role of cloud resource agency and propose a shifting scheme with three-tiered. What's more, a method is investigated to maintain the balance between the supply and demand of cloud resource during all periods of time, meanwhile the above listed challenges are also been solved.

The rest of the paper is organized as follows. In section II, we review related work. Section III introduces the model of cloud resource consumption shifting and our shifting scheme. In section IV, we describe our method and analyze it. At last, we conclude the paper and discuss our future work in section V.

II. RELATED WORK

In recent research community, the approaches for cloud resource allocation and the expanding application of Smart Grid attract more and more attention. Nejad et al.[4] design truthful greedy mechanisms for the problem about VM provisioning and allocation, which achieves promising results in terms of revenue for the cloud provider. Fujiwara [5] presents a combinatorial problem of trading cloud services and designs an optimal combinatorial mechanism for resource allocation, however, which allows untruthful bidding and tends to be computationally hard. Fei Teng and Magoules[6] propose a new resource pricing and allocation policy where users can predict the future resource price, which proves that users can receive Nash equilibrium allocation proportion. Akasiadis and Chalkiadakis [7] present a directly applicable scheme for electricity consumption shifting, which allows even agents with initially forbidding shifting cost to participate in. Mohsenian-Rad et al.[8] and Ibar et al.[9] propose some approaches with fixed strategies retained for users to optimize consumption schedules by the way of searching for Nash Equilibrium in specific game setting.

To the best of our knowledge, there is very few work presented in the literature that proposes a problem of cloud resource consumption shifting and designs a scheme to keep the demands for cloud resources preciously balanced with supply.

978-1-4673-9372-0/15 $31.00 © 2015 IEEE
DOI 10.1109/WISA.2015.32

III. PRELIMINARIES AND PROBLEM FORMULATION

A. System Model

In order to formulate our model for cloud resource consumption, we firstly summarize some notations as follows: (1) M_I :The roll-in time interval. (2) M_O :The roll-out time-interval.(3) εq_τ :the consumption quantity of cloud resource which CRP hope to shift, where ε is a positive number.(4)H: the unit-price of cloud resources consumed in M_O.(5)L(r): the unit-price of cloud resources consumed in M_I.(6) Q_j :the reduction capacity of CRA j.(7) C_j : the shifting costs of CRA j.(8) $q^j = < q_1^j, \dots, q_i^j >$, where q_i^j is the reduction(shift) capacity reported by user i who chooses CRA j.(9) $c^j =< c_1^j, \dots, c_i^j >$, where c_i^j is the shifting costs reported by user i who chooses CRA j.(10) R_j: the reduction(shift) allocated by CRP for CRA j.(11) $r^j =< r_1^j, \dots, r_i^j >$, where r_i^j is the reduction(shift) allocated by CRA j for user i.(12) $u^j =< u_1^j, \dots, u_i^j >$, where u_i^j is the reward allocated by CRA j for user i.(13) the set of users who choose CRA j， $B_j = \{1,2,3\dots x_j\}$ where x_j is a positive integer. In our model, we present three roles: cloud resource provider, cloud resource agency and users. Next, we introduce them in detail.

Cloud Resource Provider (CRP): CRP has a set of physical resources (e.g. CPU, RAM, Storage and Network) to provide users with cloud-computing services. In order to alleviate the stress on infrastructure, we assume that there are εq_τ resource consumption quantity that CRP hope to shift. We also proposed two type of time-intervals M_I, M_O , and there exists two different unit-price levels: H > L(r), The high demand time-interval with H price are considered to be peak ones, at which demands need to be reduced. The following must hold: (1) H is constant; (2)L(r) is defined as a continuous unit price curve shown as follows:

$$\mathrm{L(r)} = \begin{cases} kr + H & r \le q_\tau \\ k'(r - q_\tau) + L_m & r > q_\tau \end{cases} \quad (1)$$

Where q_τ is a threshold, under CRP's estimations, allows for the floor price L_m （$L_m > 0$） to be offered to contributing reducers. (3) $\mathrm{k} = \frac{L_m - H}{q_\tau}$, $\frac{k'}{-k} = u$ and $1 \le \mathrm{u} < 2$.

Cloud Resource Agency (CRA): CRAs are designated by CRP according to geographic area. We assume that CRP designates two CRAs, namely A={1,2}. CRA j will determine users set w_j who can participate in the scheme and submit Q_j, C_j to CRP. Obviously, It must be $w_j \subseteq B_j$.

User: We assume that there are two sets of users (i.e. reducers), denoted by B_1 and B_2, who have different value ranges of shifting cost. In this paper, we suppose that users in B_j will choose CRA j according their locations. User *i* will submit its bid to CRA it chooses, a bid of user *i* who chooses CRA j consists of two parameters: q_i^j and c_i^j.

B. Cloud Resource Consumption Shifting Scheme(CRCSS)

CRA j that participates in the CRCSS, is characterized by (a) its reduction capacity Q_j, namely the consumption quantity of resource that it will curtail (e.g., by shifting). (b) its shifting cost C_j（$C_j > 0$）, that is the cost occurs if consumption of a unit of cloud resource is shifted from M_O to M_I. If CRA j shift R_j resources, it gets reward $U_j(r_j, r_{-j}) = \big(H - L(r_s) - C_j\big)R_j$ where $r_s = \sum_{j \in A} R_j$. Similarly, if user *i* shift r_i^j resources, it get reward $u_i^j = \big(H - L(r_s) - c_i^j\big)r_i^j$

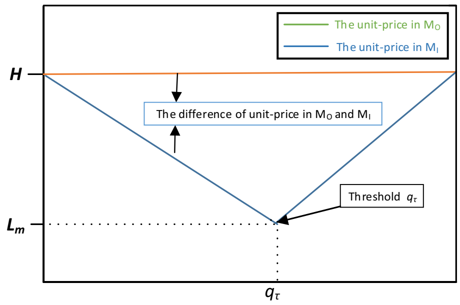

Fig.1. The Unit-Price of Cloud Resource in M_O and M_I

Given the above, the shifting protocol of CRCSS can be shown as follows:

Stage1:CRP announces time-interval M_O and M_I; Moreover, CRP designates two CRAs according to geographic area.

Stage2: Users choose their corresponding CRAs, then report their shifting cost and reduction capacity to CRA.

Stage3: By counting users' bids, CRA determines the users who can participate in the scheme and submit Q_j and C_j to CRP.

Stage4: CRP adjust and announce the price rates L(r) in M_I.

Stage5: CRP allocate the reduction and the rewards to CRA.

Stage6: CRA allocate the reduction and the rewards to users.

C. Definition of Concepts

Designing a practical reduction and rewards allocation mechanism should consider good economic properties [10].

Definition 1(Adjusted Free Disposal): The unit price L(r) in M_I: $R^+ \to R^+$,is a function of r, the consumption quality of cloud resource shifted together, subject to the conditions of adjusted free disposal, i.e., for $0 \le r_2 < r_1$, $L(r_2) * r_2 < L(r_1) * r_1$.This property ensures that the more resources consumed by users, the more bills they should pay for.

Definition 2(Equilibrium): An equilibrium is an reduction vector R^* satisfying that $U_j(R_j^*, R_{-j}^*) \ge U_j(R_j, R_{-j}^*)$ for each $j \in A$.This property ensures: in equilibrium, no CRA has incentive to deviate from choosing other reduction.

Definition 3(Individual Rationality): A mechanism is individual rationality if no users lose by participating in the CRCSS. i.e.. the rewards allocated to user $u_i^j \ge 0$.This property ensures that users are motivated to participate in the CRCSS.

Definition 4(Budget Balance): A mechanism is budget balance if the following hold:①the total rewards allocated to CRAs is equal to the total rewards allocated to users.ie.. $\sum_{j \in A} U_j = \sum_{j \in A} \sum_{i \in w_j} u_i^j$.② the total reduction allocated to CRA is equal to the total reduction allocated to users, which is also equal to the quantity of resource CRP hope to shift. ie.. $\sum_{j \in A} R_j = \sum_{j \in A} \sum_{i \in w_j} r_i^j = \varepsilon q_\tau$ .This property ensures that there are no reward and reduction transfer into or out of system.

Definition 5(Truthful Mechanism): A mechanism is truthful when reporting truthful bid is the dominant strategy for each user, i.e. a user maximize its reward by truthfully reporting regardless of other users' bid. Truthful is essential to avoid market manipulation and ensure allocation fairness and efficiency.

The objective of this work is to design a method for CRCSS to keep users' total shifted consumption quality equal to εq_τ so as to keep the demands for cloud resources balanced with supply.

IV. The Method for Balancing Cloud Resource

A. Method Introduction and Investigation

In our model, CRCSS consists of two consumption shifting allocation problems (CSAPs): CRP allocates reduction and rewards to CRA, CRAs allocate reduction and rewards to users. In this section, we present a method to solve them. The method consists of two processes (Process 1 and Process 2), Algorithm 1 shows the procedure of the method.

In our paper, CRP is reasonable, so it is easy to proof that CRP formulate L(r) satisfied $L_m \geq \frac{H}{2}$, then L(r) subjects to adjusted free disposal. The idea of Process 1 is to allocate the reduction of resources in the way of equilibrium. Next, we show how to set the parameters to reach an equilibrium and get the max total rewards for CRAs.

Firstly, we consider that how to reach an equilibrium. We know that if $r_s < q_\tau$, when CRA j shift R_j resources, it will get reward $U_j(R_j, R_{-j}) = (-kr_s - C_j)R_j$, so for CRA j, he will make his reduction R_j increasing until r_s infinitely near q_τ to get more reward. Similarly, the instincts of CRAs' selfishness make them change their reduction continually, then the result is that r_s will greater than q_τ, it is inconsistent with conditions. If $r_s \geq q_\tau$, when CRA j shift R_j resources, it will get reward $U_j(R_j, R_{-j}) = (H - L_m - C_j + k'q_\tau - k'r_j)R_j$. Suppose $R^* = (R_1^*, R_2^*)$ is an equilibrium, considering the cournot duopoly model[11], then $R_j^* = \frac{H - L_m + \sum_{k \neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}$. Next, we verify the equilibrium: Because it is reasonable that $r_s = \frac{2(H - L_m) - \sum_{j \in A} C_j}{3k'} + \frac{2q_\tau}{3} \geq q_\tau$ and $1 \leq u < 2$, then we get the conclusion that $H - L_m \geq \frac{\sum_{j \in A} C_j}{2-u}$. In addition, since $C_j > 0$, then $H - L_m > \frac{2C_j - \sum_{k \neq j} C_k}{1+u}$, so it follows that $R_j^* > 0$ and $U_j(R_j^*, R_j^*) > 0$. The proof is invertible. Hence, it should be that $H - L_m \geq \frac{\sum_{j \in A} C_j}{2-u}$ and the equilibrium reduction is $R_j^* = \frac{H - L_m + \sum_{k \neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}$.

Secondly, we investigate that how to get the max total rewards for CRAs. Detail information of investigation is listed below:

Step 1: the equilibrium reduction R_j^* satisfied $R_j^* \leq q_\tau$ for each $j \in A$. Because ①If there exists CRA j satisfied $R_j^* > q_\tau$, then $H - L_m < \frac{\sum_{k \neq j} C_k - 2C_j}{2u-1}$, and since $H - L_m \geq \frac{\sum_{j \in A} C_j}{2-u}$, then $\frac{\sum_{j \in A} C_j}{2-u} \geq \frac{\sum_{k \neq j} C_k - 2C_j}{2u-1}$, it is contradictory. ②If $R_j^* \leq q_\tau$ for each $j \in A$, then $H - L_m \geq \max_{j \in A}[\frac{\sum_{k \neq j} C_k - 2C_j}{2u-1}]$, and since $H - L_m \geq \frac{\sum_{j \in A} C_j}{2-u}$, then $\frac{\sum_{j \in A} C_j}{2-u} \geq \max_{j \in A}[\frac{\sum_{k \neq j} C_k - 2C_j}{2u-1}]$, it is reasonable.

Step 2: CRP sets parameters H and L(r) satisfied $H - L_m = \frac{\sum_{j \in A} C_j}{2-(3\varepsilon-2)u}$, then the equilibrium reduction satisfied $\sum_{j \in A} R_j^* = \varepsilon q_\tau$ and $\varepsilon \in [1,2]$. Because $\frac{\sum_{j \in A} C_j}{2-u} \leq H - L_m$ and $H - L_m = \frac{\sum_{j \in A} C_j}{2-(3\varepsilon-2)u}$, then $\varepsilon \geq 1$, and since $\sum_{j \in A} R_j^* = \frac{2*(H - L_m) - \sum_{j \in A} C_j}{3k'} + \frac{2q_\tau}{3} = \varepsilon q_\tau$ and $\sum_{j \in A} R_j^* \leq 2q_\tau$, then $\varepsilon \leq 2$.

Step 3: CRP sets parameters $\varepsilon = 1$ to allocate the max total rewards to CRAs. Because for equilibrium reduction, CRAs will get the total rewards $f(\varepsilon) = (H - L(\varepsilon q_\tau))\varepsilon q_\tau - \sum_{j \in A} C_j R_j$. As $\varepsilon \in [1,2]$, then $\varepsilon q_\tau \geq q_\tau$, so $f(\varepsilon) = (H - k'(\varepsilon q_\tau - q_\tau) - L_m)\varepsilon q_\tau - \sum_{j \in A} C_j R_j$. Therefore, when $\varepsilon \geq \frac{1}{2} + \frac{1}{2u}$, $f(\varepsilon)$ is monotone decreasing. However, since $u \in [1,2)$ and $\varepsilon \in [1,2]$, then when $\varepsilon = 1$, $f(\varepsilon)$ will have the max value.

Conclusion: CRP should adjust u satisfied $H - L_m = \frac{\sum_{j \in A} C_j}{2-(3\varepsilon-2)u}$, and allocate the equilibrium reduction $R_j^* = \frac{H - L_m + \sum_{k \neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}$ to CRA j. In this paper, we mainly discuss the case that the equilibrium reduction exists and CRAs can get the max total rewards from CRP, that is $R_j^* \leq Q_j$ and $\varepsilon = 1$. When $R_j^* > Q_j$, CRP will announce CRA j its reduction capacity is not valid and need to be resubmitted, then CRA will allow that users who have never report bids before can submit their bids to it. After recounting users' bids, CRA will submit its shifting cost and reduction capacity to CRP.

Next, we investigate Process 2 in the method. The idea of Process 2 is that CRAs will determine the winners (users who can participate in the CRCSS) firstly, and then allocate the reduction and rewards to users according their contribution and efficiency. Finally the procedure of offsetting regret-value are executed to address the problem that the reduction allocated to users are beyond their reduction capacity.

CRA j will choose user i whose shifting cost c_i^j satisfied $H - L_m - c_i^j \geq 0$ as winners. We call this procedure as 'winner determine' and define the set $w_j \subseteq B_j$ denote the set of winners.

In this paper, We denote its submitted shifting cost and reduction capacity is $C_j = \frac{\sum_{i \in w_j} (c_i^j)^2}{\sum_{i \in w_j} c_i^j}$ and $Q_j = \sum_{i \in w_j} r_i^j$ respectively, then user i gets the allocated reduction $r_i^j = R_j \frac{c_i^j}{\sum_{i \in w_j} c_i^j}$ and its corresponding rewards $u_i^j = (H - L_m - c_i^j)\, r_i^j$. However, there is still a problem need to be solved: the reduction r_i^j allocated to user i may exceed its reduction capacity q_i^j. We now present an algorithm to solve this problem. In what follows, we explain clearly steps of this algorithm.

To begin, let $d_i^j = q_i^j - r_i^j$ be user i's regret-value; We separate winners in w_j into two sets: $w_j^+ = \{i | i \in w_j \text{ and } d_i^j \geq 0\}$, $w_j^- = \{i | i \in w_j \text{ and } d_i^j < 0\}$. According to PA-CSAP mechanism, CRA j's allocated reduction is less than its reduction capacity, that is $R_j \leq Q_j$, so we get the conclusion that $\sum_{i \in w_j^+} d_i^j + \sum_{i \in w_j^-} d_i^j \geq 0$. The algorithm then proceeds as follows and we call this procedure as offsetting regret-value.

Firstly, for each CRA j, we check the members in w_j^-. If that there is no member, we stop; the problem is inexistent (as all users' allocated reduction is less than their reduction capacity). If that is not the case, then there exist winners who can't shift the allocated reduction.

The algorithm then sets $D_j := -\sum_{i \in w_j^-} d_i^j$, and sets $C_j' := \frac{\sum_{i \in w_j^-} (H - L_m - c_i^j)(r_i^j - q_i^j)}{D_j}$ for each CRA j in A. The algorithm then ranks winners in w_j^+ by d_i^j in decreasing order. Next, starting from the winner with highest d_i^j value, we decrease d_i^j of the top winner until d_i^j is equal to the regret-value of the $k = i + 1$ user below (as long as $D_j \geq 0$), so winner i will get extra reward $g_i^j = C_j'(d_i^j - d_k^j)$. Then we do the same for the second top user until its regret-value reaches that of the third. We continue this way until all winners' failed reduction is transferred, that is $D_j = 0$, or one's regret-value reaches zero. If the latter happens, we move to the top again and repeat.

Algorithm 1: The Method for Balancing Cloud Resource

InPut: $q =< q^1,..,q^j >$: vector of users' reduction capacity vector
$c =< c^1,...,c^j >$: vector of users' shifting costs vector
OutPut: $r =< r^1,..,r^j >$: vector of users' allocated reduction vector;
$u =< u^1,...,u^j >$: vector of users' allocated reward vector

$flag \leftarrow 0$, $\varepsilon = 1$
while flag!=0 **do**
  for all j ∈ A **do**
    $w_j \leftarrow \emptyset, C_j \leftarrow 0, Q_j \leftarrow 0, C_2 \leftarrow 0$
    for all $i \in B_j$ **do**
      if $\mathrm{H} - L_m - c_i^j \geq 0$ **then**
        $w_j \leftarrow w_j \cup \{i\}$
        $Q_j \leftarrow Q_j + q_i^j, C_j \leftarrow C_j + c_i^j, C_2 \leftarrow C_2 + (c_i^j)^2$
    end
    CRP adjusts u satisfied $\mathrm{H} - \mathrm{L_m} = \frac{\sum_{j \in A} C_j}{2-(3\varepsilon-2)\mathrm{u}}$
    flag ← 1
    $R_j \leftarrow \frac{\mathrm{H}-\mathrm{L}_m+\sum_{k \neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}, U_j \leftarrow (H - L_m - \mathrm{C}_j)R_j$
    if $R_j > Q_j$ **then** flag ← 0
  end
end
for all j ∈ A **do**
  for all $i \in \mathrm{w_j}$ **do**
    $r_i^j \leftarrow R_j \frac{c_i^j}{\sum_{i \in w_j} c_i^j}, u_i^j \leftarrow (\mathrm{H} - L_m - c_i^j)\, r_i^j$
    offsetting regret-value is executed to adjust r_i^j and u_i^j
  end
end
return *r* and *u*

B. Method Analysis and Case study

In this section, we analyze the method for balancing cloud resource and investigate its properties. Because there is no winner lose by participating in the CRCSS ($H - L_m \geq c_i^j \Rightarrow u_i^j \geq 0$), then our method is individual rationality. In addition, our method also satisfied budget balance and truthfulness for a user regarding its reduction capacity if there is no other users in $\mathrm{w_j^-}$. Next, we illustrate our method by the following example:

CRP: $q_\tau = 150$, H=200, $\mathrm{L_m}$=120			
CRA	User	Reduction Capacity	Shifting Cost
A1	U11	$q_1^1 = 40$	$c_1^1 = 5$
	U12	$q_2^1 = 45$	$c_2^1 = 7$
	U13	$q_3^1 = 50$	$c_3^1 = 10$
A2	U21	$q_1^2 = 27$	$c_1^2 = 20$
	U22	$q_2^2 = 23$	$c_2^2 = 15$
	U23	$q_3^2 = 30$	$c_3^2 = 25$

Solution: According to our method for balancing cloud resource, all users are winners. The shifting cost submitted to CRP is $C_1 = \frac{5^2+7^2+10^2}{5+7+10} = 7.91$, $C_2 = 20.83$, and the reduction capacity submitted to CRP is $Q_1 = 135$, $Q_2 = 80$. Next, CRP will adjusted parameter u satisfied $\mathrm{u} = \frac{\sum_{j \in A} C_j}{(3-2)(\mathrm{H}-\mathrm{L_m})}$=1.64, then the reduction allocated to A1 is $R_1 = \frac{\mathrm{H}-\mathrm{L_m}+C_2-2C_1}{3k'} + \frac{q_\tau}{3}$ =82.38, the correspond reward is $\mathrm{U_1} = (H - L_m - \mathrm{C_1})\mathrm{R_1} = 5939.2$. Similarity, the reduction and rewards allocated to A2 are R_2 =67.62, $U_2 = 4000.6$. Finally, we will show the details about reduction and rewards allocated to users:

(1)For users who choose A1, we calculate that $r_1^1 = 18.72, u_1^1 = 1404.3$; $r_2^1 = 26.22, u_2^1 = 1913.6$; $r_3^1 = 37.44, u_3^1 = 2621.3$.

(2)For users who choose A2, we calculate that $r_1^2 = 22.54, u_1^2 = 1352.3$; $r_2^2 = 16.91, u_2^2 = 1098.7$; $r_3^2 = 28.17, u_3^2 = 1549.5$.

V. Conclusion

In this paper, we proposed a novel model of cloud resource consumption shifting and studied a method for balancing cloud resource. Considering users in different geographical areas possess different value ranges about their shifting cost and reduction capacity for cloud resource, we introduce the role of cloud resource agency and present a shifting scheme with three-tiered, which makes our scheme more applicable in practice. Moreover, the proposed methods can also simultaneously achieve equilibrium, individual rationality, truthfulness and budget balance. In our future work, we will implement our scheme and investigate the impacts of unit-price curve for the system. In addition, improving our model of cloud resource consumption shifting will be also considered.

Acknowledgements

Project supported by the National Nature Science Foundation of China (Grant No.61170201, No.61070133, No.61472344); Six talent peaks project in Jiangsu Province(Grant No.2011-DZXX-032).Innovation Foundation for graduate students of Jiangsu Province(Grant No.CXLX12 0916), National Undergraduate Innovative Training Program of China(Grant No.KYLX_1349), Natural Science Foundation of the Jiangsu Higher Education Institutions(Grant No.14KJB520041).

References

[1] M. B. Chhetri, S. Chichin, B. Q. Vo, and R. Kowalczyk, “Smart cloud bench-automated performance benchmarking of the cloud”, in IEEE Cloud,2013, pp.414 – 421.
[2] Amazon ec2 spot instances,http://aws.amazon.com/ec2/spot-instances/.
[3] Osborne MJ, Rubinstein A, “ A course in game theory”,MIT Press;1994.
[4] M. M. Nejad, L. Mashayekhy, and D. Grosu, “A family of truthful greedy mechanisms for dynamic virtual machine provisioning and allocation in clouds”,in IEEE Cloud, 2013, pp.188-195.
[5] I. Fujiwara, “Study on combinatorial auction mechanism for resource allocation in cloud computing environment”,Ph.D. dissertation, The Graduate University for Advanced Studies: (SOKENDAI),2012.
[6] Fei Teng, “Resource Pricing and Equilibrium Allocation Policy in Cloud Computing”,Computer and Information Technology (CIT), 2010 IEEE 10th International Conference on.2010,pp.195-202.
[7] Charilaos Akasiadis,Georgios Chalkiadakis, “Agent Cooperatives for Effective Power Consumption Shifting”, the Association for the Advancement of Artificial Intelligence (AAAI),2013,pp.1263-1269.
[8] Mohsenian-Rad,H.Wong,V.Jatskevich,Schober.R,Leon-Garcia. “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid”, Smart Grid,IEEE Transactions on,2010,Vol.1(3),pp.320-331.
[9] Ibars.C,Navarro.M,Giupponi.L, “ Distributed demand management in smart grid with a congestion game”, SmartGridComm,2010,pp.495-500.
[10] M.BabaioK,W.E.Walsh, “Incentive-compatible, budget-balanced, yet highly efficient auctions for supply chain formation”, ACM Conference on Eiectronic Commerce,2003,pp.64-75.
[11] W.Govaerts,R.Khoshsiar Ghaziani, “Stable cycles in a Cournot duopoly model of Kopel”, Journal of Computational and Applied Mathematics,2008, Vol.218 (2), pp.247-258.