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On Cloud Resources Consumption Shifting Scheme for Two Different Geographic Areas

Junwu Zhu, Heng Song, Yi Jiang, Bin Li, and Jin Wang

***Abstract*—With the increasing demands for cloud resources, 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 resources rather than balancing the demands for cloud resources. In order to deal with this problem, this paper presents the problem of cloud resources consumption shifting between two different time intervals in a formularized manner, and then puts forward a cloud resources consumption shifting scheme with three-tier architecture. Users participating in the scheme, however, are motivated to get extra rewards by shifting certain consumption quantity from high to low demand time intervals. So, taking into account the fact that value ranges of individual shifting costs vary with different geographic areas, this scheme first allocates rewards to agencies in different geographic areas in the way of equilibrium, and then applies a strictly proper rule to reward users according to their contributions. In addition, the paper theoretically proves that the scheme is equipped with economic properties such as equilibrium, individual rationality, budget balance, and truthfulness. Finally, extensive simulation results show that the proposed scheme owns the resources shifting efficiency and computational traceability, and it can generate higher and more stable social rewards than the common scheme with two-tier architecture.**

***Index Terms*—Cloud computing, equilibrium, load management, mechanism design, resources consumption shifting.**

I. Introduction

As TECHNOLOGY evolves and the computing tasks become more complicated and bothersome, both individuals and enterprises prefer outsourcing their workloads to the cloud resource provider (CRP) in order to pay for lower costs [1]. Generally, the CRPs offer infrastructure as a service in the form of virtual machine (VM) instances, which are characterized by a number of computing resources (such as CPU, memory, storage, and networks). For example, Amazon EC2 [2] and Microsoft Azure [3] offer various types of VMs.

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However, since the concentration and consistency of users' working hours, a problem occurs: the ever-increasing demands for cloud resources during the peak hour overload the infrastructure. Maintaining the stability of users' demands curve, in particular, can alleviate the risk of disastrous infrastructure collapses, and bring financial and environmental benefits—as some VMs can be run on idle or long time overload may damage the VMs and result in users' data loss. To this end, cloud resources consumption shifting (see Fig. 1) is a directly applicable solution, it can be explained as a lower unit-price of cloud resource provided for users in nonpeak hour, and then users are encouraged to abridge their consuming activities for cloud resources during peak hours, or shift them to nonpeak hours. This is mutual benefit and win–win complexion: On the one hand, it can make the consumption of cloud resource drop to a safety limits and keep the demands balanced with supply for CRP. On the other hand, it can make users pay for lower costs. To the best of our knowledge, there is still few work on this issue. In this paper, we are motived to design an applicable cloud resources consumption shifting scheme (CRCSS) to balance the demands for cloud resources.

Nevertheless, there exist many challenges in designing a practical scheme for the issue of cloud resources consumption shifting. Four major challenges are listed as follows.

1) *Equilibrium*: Equilibrium ensures the best outcome for each cloud resource agency (CRA). Game Theory [4], [5] teaches us that equilibrium is the optimal state where each CRA maximizes its own profit, considering the other agencies' strategic behaviors.
2) *Budget balance*: We consider that CRP and users are self-interested in this paper. Users hope that the sum rewards are completely allocated for them while CRP aims to the quota can be completely competed accomplished by users to balance the demands for cloud resources. Therefore, a budget-balanced mechanism is preferred.
3) *Truthfulness*: Since users are normally selfish, they always tend to strategically manipulate the shifting scheme to get more rewards. However, such behaviors may harm other users' profit. Hence, designing a shifting scheme which can prevent users from having incentives to lie about their bids is essential.
4) *Low execution time*: Cloud computing is a very dynamic environment with large amount of users. The consumption shifting scheme for cloud resources has to have a low computation complexity for deciding winners' reduction and rewards in order to be feasible in real cloud market.

Our contribution: Based on the problem of balancing the demands for cloud resources, we present a novel model of cloud

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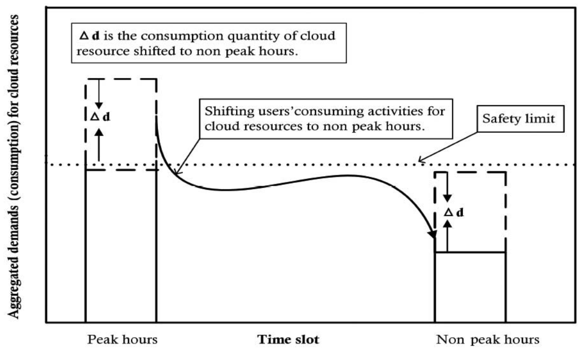

Fig. 1. Procedure of cloud resources consumption shifting.

resources consumption shifting. Considering that the value ranges of users' shifting cost for cloud resources are diverse due to geographical differences, we introduce the role of CRA and propose a shifting scheme with three-tier architecture. What's more, two mechanisms are designed to address the allocation problems: one aims to allocate the reduction and rewards to cloud resource agencies in the way of equilibrium, and the other is mainly used to reward users according to their contributions; meanwhile, the above-listed challenges have also been solved. In addition, we perform a lot of simulation experiments. The experimental results show that the proposed shifting scheme achieves much better performance than the common shifting scheme with two-tier architecture.

This paper is organized as follows. In Section II, we review related work. Section III introduces the model of cloud resources consumption shifting and our shifting scheme. In Section IV, we describe our mechanisms and characterize their theoretical properties. Section V provides the experimental evaluation of our proposed shifting scheme. At last, we conclude this paper and discuss our future work in Section VI.

II. Related Work

In recent years, the approaches for cloud resources allocation and the expanding application of Smart Grid are attracting more and more attention in research community. In this section, we first review related works on cloud resources allocation, and then review the works on Smart Grid.

A. Cloud Resources Allocation

Due to explosive growth of cloud computing in recent years, how to manage the cloud resources efficiently becomes an important problem. For example, Pillai and Rao, [6] proposed a resources' allocation mechanism for VMs by using the principles of coalition formation and the uncertainty principle of game theory, which perform better with respect to lower task allocation time, lower resource wastage, and higher request satisfaction. However, they did not consider the good property of truthfulness in their mechanism. Nejad *et al.* [7] design truthful greedy mechanisms for the problem about VM provisioning and allocation, which achieves promising results in terms of revenue for the cloud provider. Although they are near-optimal solutions, small execution times are only required. Fujiwara [8] presents a combinatorial problem of trading cloud services in different timeslots and designs an optimal combinatorial mechanism for resources allocation, however, which allows untruthful bidding and tends to be computationally hard. Zaman and Grosu [9] devise two combinatorial auction-based mechanisms: one is a greedy mechanism and the other is a linear programming relaxation and randomized rounding mechanism, but they do not consider the resources-associated cost. Besides, Fei Teng and Magoules [10] propose a new resource pricing and allocation policy where users can predict the future resource price, with the constraint of budget and deadline, and prove that users can receive Nash equilibrium allocation proportion. However, their proposed policy did not ensure truthfulness.

B. Smart Grid

Creating a sustainable and energy-efficient society is the main concept of Smart Grid; however, its key challenge is to make user demand adaptive to supply of power. Many mechanisms have been designed to overcome the challenge. For example, Schülke *et al.* [11] propose a mechanism, which aims to optimize the power grid by balancing rising and declining consumption demands, to predict and control the energy consumption. However, no good economic properties (e.g., budget balance and truthfulness) have been considered in the proposed mechanism. Akasiadis and Chalkiadakis [12] present a weakly budget-balanced, truthful reward sharing mechanism for electricity consumption shifting, which even allows agents with initially forbidding shifting cost to participate in it, but they did not consider the property of equilibrium. Mohsenian-Rad *et al.* [13] and Ibars *et al.* [14] propose some approaches with fixed strategies retained for users to optimize consumption schedules by searching for Nash Equilibrium in specific game setting, which significantly reduce the burden over the grid. However, they did not propose a truthful mechanism.

Unlike all the above scenarios about cloud resources allocation, the focus of our work is primarily on solving the problem of keeping the demands for cloud resources preciously balanced with supply by the proposed cloud resources shifting scheme. This is similar to the related work about Smart Grid, but they seldom consider the economic properties such as individual rationality, equilibrium, budge balance, free disposal, and truthfulness. In this paper, we design a feasible and effective cloud resources' consumption shifting scheme which achieves the demands for cloud resources balanced with supply while satisfying the economic properties.

III. Preliminaries and Problem Formulation

A. System Model

In this section, we present our model for cloud resources consumption shifting and formulate the problem about it. All the notations are summarized in Table I.

1) Cloud Resource Provider: CRP has a set of physical resources (e.g., CPU, RAM, storage and network) to provide users with cloud-computing services. CRP requests users to shift certain consumption for resources to alleviate the stress on infrastructure.

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TABLE I
NOTATIONS

M_I	The roll-in time-interval (nightly or non-peak hour)
M_O	The roll-out time-interval (daily or peak hour)
εq_τ	The consumption quantity of cloud resources which CRP hope to shift, where ε is a positive number
H	The unit-price of cloud resources consumed in M_O
$L(r)$	The unit-price of cloud resources consumed in M_I
Q	$Q =< Q_1, \ldots, Q_j >$, where Q_j is the reduction (shift) capacity of CRA j
C	$C =< C_1, \ldots, C_j >$, where C_j is the shifting costs of CRA j
q^j	$q^j =< q_1^j, \ldots, q_i^j >$, where q_i^j is the reduction (shift) capacity reported by user i who chooses CRA j
c^j	$c^j =< c_1^j, \ldots, c_i^j >$, where c_i^j is the shifting costs reported by user i who chooses CRA j
R	$R =< R_1, \ldots, R_j >$, where R_j is the reduction (shift) allocated by CRP for CRA j
r^j	$r^j =< r_1^j, \ldots, r_i^j >$, where r_i^j is the reduction (shift) allocated by CRA j for user i
u^j	$u^j =< u_1^j, \ldots, u_i^j >$, where u_i^j is the rewards allocated by CRA j for user i
B_j	The set of users who choose CRAj , $B_j = \{1, 2, 3 \ldots x_j\}$, where x_j is a positive integer

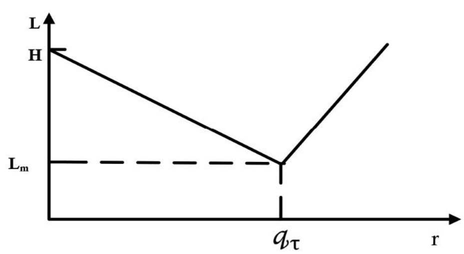

Fig. 2. Graph of $L(r)$.

In order to make the consumption drop to a safety limits,we assume that there are εq_τ resources consumption quantity that CRP expects users to shift. In our model, we propose two types of time-intervals M_I, M_O and there exist exactly two different unit-price levels: $H > L(r)$, which characterizes that the unit-prices of resources in M_I are lower. The high demand time-interval with H price are considered to be peak ones, where demands need to be reduced. The following must then hold: 1) H is constant; 2) $L(r)$ is a continuous unit price curve shown as follows (see Fig. 2):

$$L(r) = \begin{cases} kr + H, & \text{when } r < q_\tau \\ k'\left(r - q_\tau\right) + L_m, & \text{when } r \geq q_\tau \end{cases} \tag{1}$$

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; and 3) $k = \frac{L_m - H}{q_\tau}$, $\frac{k'}{-k} = u$ and $1 \leq u < 2$.

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

3) 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 to 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.

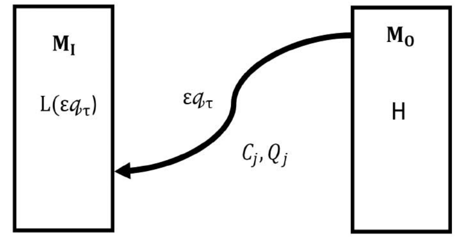

Fig. 3. Cloud resources consumption shifting scheme.

B. Cloud Resources Consumption Shifting Scheme

CRA j that participates in the CRCSS (see Fig. 3), is characterized by (a) its reduction capacity Q_j, namely the consumption quantity of resources that it will curtail (e.g., by shifting), and (b) its shifting cost $C_j (C_j > 0)$; i.e., the cost occurs if consumption of a unit of cloud resources is shifted from M_O to M_I. Given the above, if CRA j shifts R_j resources, it will get rewards $U_j(R_j, R_{-j}) = (H - L(r_s) - C_j)\ R_j$ where $r_s = \sum_{j \in A} R_j$. Similarly, if user i shifts r_i^j resources, it will get rewards $u_i^j = (H - L(r_s) - c_i^j) r_i^j$.

Given the above, the exact shifting protocol of CRCSS with three-tier architecture, and its specific steps are shown as follows (see Fig. 4).

Stage 1: Every day, CRP announces the forecasted (according to its own information / uncertainly) time-interval M_O and the most preferable time-interval M_I; moreover, CRP designates two CRAs according to the geographic areas.

Stage 2: Users choose their corresponding CRAs, then report their shifting cost and reduction capacity to CRA.

Stage 3: By collecting users' bids, CRA determines the users who can participate in the scheme and submit its reduction capacity Q_j and shifting cost C_j to CRP.

Stage 4: CRP adjusts and announces the price rates $L(r)$ in M_I .

Stage 5: CRP allocates the actual reduction and the corresponding rewards to CRA.

Stage 6: CRA allocates the actual reduction to users.

Stage 7: Users shift the allocated reduction and get the corresponding rewards from CRA.

C. Definition of Concepts

To design a practical reduction and rewards allocation mechanism, it should take into account not only financial profit but also economic properties [15]. Next, we introduce some economic properties we would like to achieve.

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 resources shifted together, subject to the conditions of adjusted free disposal, i.e., for $0 \leq r_2 < r_1$, $L(r_2) * r_2 < L(r_1) * r_1$.

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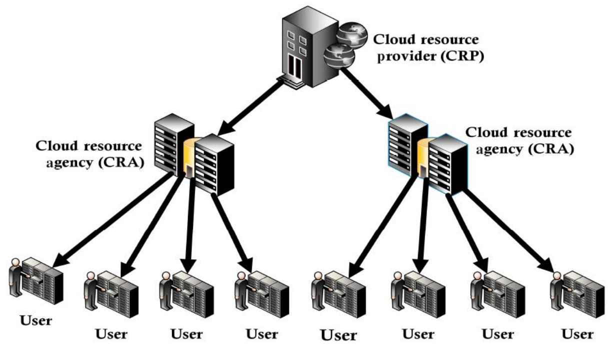

Fig. 4. Shifting protocol of CRCSS with three-tier architecture.

Obviously, it is reasonable that the more resources consumed by users, the more bills they should pay for.

Definition 2 (Equilibrium): An equilibrium is an actual reduction vector R^* satisfying that $U_j(R_j^*, R_{-j}^*) \geq U_j(R_j, R_{-j}^*)$ for all $j \in A$.

This property ensures: in equilibrium, CRA has no incentive to deviate from choosing other reduction.

Definition 3 (Individual rationality): A mechanism is individual rationality if no users loses by participating in the CRCSS, i.e., the rewards allocated to user i is $u_i^j \geq 0$.

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: 1) the total rewards allocated to CRAs is equal to the total rewards allocated to users, i.e., $\sum_{j\in A} U_j = \sum_{j\in A}\sum_{i\in w_j} u_i^j$ and 2) the total reduction allocated to CRA is equal to the total reduction allocated to users, which is also equal to the quantity of resources CRP hope to shift, i.e., $\sum_{j\in A} R_j = \sum_{j\in A}\sum_{i\in w_j} r_i^j = \varepsilon q_\tau$.

This property ensures that there are no reward and reduction transfering 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 maximizes its rewards by truthfully reporting its bid regardless of other users' bid.

Truthful mechanism is essential to avoid market manipulation and ensure allocation fairness and efficiency.

The objective of this work is to design two reduction and rewards' allocation mechanisms for CRCSS with three-tier architecture to keep users' total shifted consumption quality to equal εq_τ so as to keep the demands for cloud resources preciously balanced with supply at all times.

IV. Reduction and Rewards Allocation Mechanisms for CRCSS

CRCSS with three-tier architecture consists of two consumption shifting allocation problems (CSAP): 1) CRP allocates reduction and rewards to CRA and 2) CRA allocates reduction and rewards to users. In this section, we present two mechanisms to solve CSAP, called PA-CSAP (CRP allocates reduction and rewards to CRA for CSAP) and AU-CSAP (CRA allocates reduction and rewards to users for CSAP), respectively.

A. PA-CSAP Mechanism

The PA-CSAP mechanism is presented in Algorithm 1. The algorithm receives CRAs' bidding, which is a reduction capacity vector and a shifting cost vector, respectively. The output of the allocation scheme is the vector of the allocated reduction and corresponding rewards for CRAs.

In this paper, CRP is rational ,so it will formulate unit-price L(r) which subjects to adjusted free disposal, the following shows this proposition.

Proposition 1: If CRP formulates $L(r)$ satisfying $L_m \geq \frac{H}{2}$, then $L(r)$ subjects to adjusted free disposal.

Proof: Note that $f(r) = r * L(r)$, if $r_1 > r_2 \geq q_\tau$, then it must be tenable that $f(r_1) > f(r_2)$. Because $\lim_{r\to q_\tau^-} f(r) = \lim_{r\to q_\tau^+} f(r)$, to prove this proposition, we only need to consider that $f(r)$ is monotone-increasing when $r < q_\tau$. According to the model above, if $r < q_\tau$, then $f(r) = r * L(r) = kr^2 + Hr$. Since $L_m \geq \frac{H}{2}$, then $2 * (H - L_m) \leq H$, and as $k = \frac{L_m - H}{q_\tau}$, then we get $q_\tau \leq \frac{-H}{2k}$, it follows that $f(r)$ is monotone-increasing when $r < q_\tau$. Hence, $L(r)$ subjects to adjusted free disposal. ■

From the proof of Proposition 1, we get the conclusion that the floor price L_m must be at least equal to half of the unit-price H in M_O.

The idea of PA-CSAP is to allocate the reduction in resources in the way of equilibrium. Next, we show how to set the related parameters in our model to reach an equilibrium by Propositions 2–5.

Proposition 2: There exists an equilibrium for CRCSS if CRAs' shifting cost satisfies $\frac{\sum_{j\in A} C_j}{2-u} \leq H - L_m$.

Proof: To prove this proposition, we consider two cases: $r_s < q_\tau$ and $r_s \geq q_\tau$. If $r_s < q_\tau$, we know that when CRA j shifts R_j resources, it will get rewards $U_j(R_j, R_{-j}) = (H - L(r_s) - C_j)R_j = (-kr_s - C_j)R_j$, so for CRA j, it will make its reduction R_j increasing until r_s infinitely near q_τ to get more rewards, then each CRA wants to do this and changes their reduction continually, so the result is that r_s will be greater than q_τ , it is inconsistent with conditions. ■

If $r_s \geq q_\tau$, when CRA j shifts R_j resources, it will get rewards $U_j(R_j, R_{-j}) = (H - L_m - C_j + k'q_\tau - k'r_s)R_j$. Suppose $R^* = (R_1^*, R_2^*)$ is an equilibrium, considering the *cournot duopoly model* [16], [17], then $R_j^* = \frac{H - L_m + \sum_{k\neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}$. As $\frac{\sum_{j\in A} C_j}{2-u} \leq H - L_m$ and $1 \leq u < 2$, then $(2-u)(H - L_m) \geq \sum_{j\in A} C_j$, so $r_s = \frac{2*(H-L_m) - \sum_{j\in A} C_j}{3k'} + \frac{2q_\tau}{3} \geq q_\tau$. 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 $U_j(R_j^*, R_{-j}^*) > 0$. Our claim holds.

Proposition 3: If there exists an equilibrium R^* for $CRCSS$, then the equilibrium reduction R_j^* satisfies $R_j^* \leq q_\tau$ for each CRA j in A.

Proof: Before proving this proposition, we introduce one basic fact: If a, b, and k are all positive numbers, t is a real number and satisfies $t \in [1, 2)$, then $\frac{a+b}{2-t} \geq \frac{a-kb}{2t-1}$ is tenable. The proof is organized as follows. Since $t \in [1, 2)$, then $0 < 2 - t \leq 2t - 1$, and because a,b,k are positive numbers, then

$a+b \geq a-kb$; therefore, $\frac{a+b}{2-t} \geq \frac{a-kb}{2t-1}$ is logical. Next, we prove Proposition 3. Two cases should be taken into consideration.

1) If there exists CRA j satisfies $R_j^* > q_\tau$, then $H - L_m < \frac{\sum_{k\neq j} C_k - 2C_j}{2u-1}$, and since $H - L_m \geq \frac{\sum_{j\in A} C_j}{2-u}$, according to the basic fact, it follows that $\frac{\sum_{j\in A} C_j}{2-u} \geq \frac{\sum_{k\neq j} C_k - 2C_j}{2u-1}$, it is inconsistent and this assumption is incorrect.
2) If $R_j^* \leq q_\tau$ 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 $H - L_m \geq \frac{\sum_{j\in A} C_j}{2-u}$. According to the basic fact, it follows that $\frac{\sum_{j\in A} C_j}{2-u} \geq \max_{j\in A}[\frac{\sum_{k\neq j} C_k - 2C_j}{2u-1}]$. Hence, the assumption is valid and our claim holds. ∎

Proposition 4: When there exists an equilibrium for *CRCSS*, if the unit-price rate H and $L(r)$ satisfy $H - L_m = \frac{\sum_{j\in A} C_j}{2-(3\varepsilon-2)u}$, then the equilibrium reduction satisfies $\sum_{j\in A} R_j^* = \varepsilon q_\tau$ and $\varepsilon \in [1, 2]$.

Proof: From Proposition 2, we know that if there exists an equilibrium, then $\frac{\sum_{j\in A} C_j}{2-u} \leq H - L_m$. Since $H - L_m = \frac{\sum_{j\in A} C_j}{2-(3\varepsilon-2)u}$, then $\varepsilon \geq 1$ and $\sum_{j\in A} R_j^* = \frac{2*(H-L_m) - \sum_{j\in A} C_j}{3k'} + \frac{2q_\tau}{3} = \varepsilon q_\tau$. Next from Proposition 3, we know that $\sum_{j\in A} R_j^* \leq 2q_\tau$, so $\varepsilon \leq 2$. Our claim holds. ∎

Proposition 5: For equilibrium reduction, CRAs will get the max total rewards from CRP if setting $\varepsilon = 1$.

Proof: For equilibrium reduction, according to Proposition 2, we know that CRAs get the total rewards $f(\varepsilon) = \sum_{j\in A}(H - L(\varepsilon q_\tau) - C_j)R_j = (H - L(\varepsilon q_\tau))\varepsilon q_\tau - \sum_{j\in A} C_j R_j$. 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. Our claim holds. ∎

From Propositions 4 and 5, we know that after CRAs submit their reduction capacity and shifting cost, CRP should adjust u satisfying $H - L_m = \frac{\sum_{j\in A} C_j}{2-(3\varepsilon-2)u}$, 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 in equilibrium, i.e., $R_j^* \leq Q_j$ 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 recollecting users' bids, CRA will submit its new shifting cost and reduction capacity to CRP.

B. AU-CSAP Mechanism

The *AU-CSAP* mechanism is given in Algorithm 2. The algorithm receives users' bids, which is a vector of reduction capacity and a vector of shifting cost. The output of the allocation scheme is the vectors of the allocated reduction and the corresponding rewards for users.

The idea of AU-CSAP mechanism is that CRA determines the winners(users who can participate in the CRCSS) first, and

Algorithm 1. PA-CSAP Mechanism

Input: $Q = < Q_1, \ldots, Q_j >$:reduction capacity vector; $C = < C_1, \ldots, C_j >$:shifting cost vector
Output: $R = < R_1, \ldots, R_j >$: the allocated reduction vector; $U = < U_1, \ldots, U_j >$:the rewards vector

$flag \leftarrow 0, \varepsilon \leftarrow 1$
while $flag = 0$ **do**
  users submit their reduction capacity and shifting cost to CRA
  for all $j \in A$ **do**
    CRA j determine winners and submits Q_j and C_j to CRP
  end
  CRP adjusts u satisfying $H - L_m = \frac{\sum_{j\in A} C_j}{2-(3\varepsilon-2)u}$
  $flag \leftarrow 1$
  for all $j \in A$ **do**
    $R_j \leftarrow \frac{H - L_m + \sum_{k\neq j} C_k - 2C_j}{3k'} + \frac{q_\tau}{3}$
    if $R_j > Q_j$ **then**
      $flag \leftarrow 0$
  end
end
for all $j \in A$ **do**
  $U_j \leftarrow (H - L_m - C_j)R_j$
end
return R and U

then allocates the reduction and rewards to users according to their contributions. Finally, the procedure of offsetting regret-value is executed to address the problem that the reduction allocated to users is beyond their reduction capacity.

1) Winner Determination: We know that there exists unit-price $L(\varepsilon q_\tau)$ in M_I when shifting εq_τ resources. From Proposition 5, CRP will allocate max rewards to CRA when setting $\varepsilon = 1$, so in this paper, CRA j will choose user i whose shifting cost c_i^j satisfies $H - L_m - c_i^j \geq 0$. We define the set $w_j \subseteq B_j$ as the set of winners.

After CRA j determines the winners set w_j, it will submit its shifting cost and reduction capactiy to CRP according to CRCSS. In this paper, We denote that its submitted shifting cost and reduction capacity are $C_j = \frac{\sum_{i\in w_j}(c_i^j)^2}{\sum_{i\in w_j} c_i^j}$ and $Q_j = \sum_{i\in w_j} r_i^j$, respectively; then, user i will get 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: 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 clearly explain steps of this algorithm.

To begin, let $d_i^j = q_i^j - r_i^j$ be user $i's$ regret-value, i.e., the difference between user i's reduction capacity and allocated reduction. 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 less than its reduction capacity, i.e., $R_j \leq Q_j$, 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

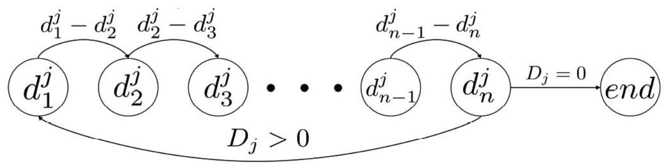

Fig. 5. Procedure of offsetting regret-value.

then proceeds as follows; we call this procedure as offsetting regret-value (see Fig. 5).

First, for each CRA j, we check the members in w_j^-. If there is no member, we stop; the problem is inexistent (as all users' allocated reduction less than its 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. Then, 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 rewards $g_i^j = C_j'(d_i^j - d_k^j)$. 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, i.e., $D_j = 0$, or one's regret-value reaches zero. If the latter happens, we move to the top again and repeat.

Proposition 6: AU-CSAP mechanism is individual rational and truthful for a user regarding its reduction capacity if there is no other users in w_j^-.

Proof: We show that AU-CSAP mechanism is individual rational and truthful, respectively. *Individual rational*: For each winner $i \in w_j$, if it shifts r_i^j resources, its rewards $u_i^j = (H - L_m - c_i^j)r_i^j$. Considering $i \in w_j$, then $H - L_m - c_i^j \geq 0$, so user i get rewards $u_i^j \geq 0$. The claim holds.

Truthful: We should note that a user may submit mendacious reduction capacity; if user i states inflated reduction capacity $q_i'^j > q_i^j$, it runs the danger that it cannot shift its reported reduction, i.e., if $r_i^j \geq q_i^j$, since there is no other users in w_j^-, then its rewards $u_i'^j = (H - L_m - c_i^j)q_i^j$;if $r_i^j < q_i^j$, then its rewards $u_i'^j = (H - L_m - c_i^j)r_i^j$, and both do not depend on $q_i'^j$. Analogously, if user i states lower reduction capacity $q_i'^j < q_i^j$, then it risks suffering a high loss in expected rewards (since user may be allocated lower reduction), i.e., if $r_i^j \leq q_i'^j$, its rewards $u_i'^j = (H - L_m - c_i^j)r_i^j$, which does not depend on $q_i'^j$, or if $r_i^j > q_i'^j$, its rewards $u_i'^j = (H - L_m - c_i^j)q_i'^j < (H - L_m - c_i^j)r_i^j = u_i^j$, lower than the allocated rewards when truthful. Therefore, a user should be truthful when reporting its reduction capacity. Our claim holds. ■

Proposition 7: PA-CSAP Mechanism and AU-CSAP Mechanism are budge balance.

Proof: According to PA-CSAP, we know that $\sum_{j\in A} R_j = q_\tau$. First, we assume that there is no members in w_j^-, user $i's$ allocated reduction and rewards

Algorithm 2. AU-CSAP Mechanism

Input: $q =< q^1, \ldots, q^j >$: vector of users' reduction capacity vector; $c =< c^1, \ldots, c^j >$: vector of users' shifting costs vector
Output: $r =< r^1, \ldots, r^j >$: vector of users' allocated reduction vector; $u =< u^1, \ldots, u^j >$: vector of users' allocated rewards vector

for all $j \in A$ **do**
  $w_j \leftarrow \emptyset$
  for all $i \in B_j$ **do**
    if $H - L_m - c_i^j \geq 0$ **then** $w_j \leftarrow w_j \cup \{i\}$
  end
  $w_j^+ \leftarrow \emptyset, w_j^- \leftarrow \emptyset, u_j^- \leftarrow 0, D_j \leftarrow 0, n \leftarrow 0$
  for all $i \in w_j$ **do**
    $r_i^j \leftarrow R_j \frac{c_i^j}{\sum_{i\in w_j} c_i^j}$
    if $q_i^j < r_i^j$ **then**
      $w_j^- \leftarrow w_j^- \cup \{i\}, D_j \leftarrow D_j + (r_i^j - q_i^j)$
      $u_i^j \leftarrow (H - L_m - c_i^j)q_i^j$
      $u_j^- \leftarrow u_j^- + (H - L_m - c_i^j)(r_i^j - q_i^j)$
    else
      $w_j^+ \leftarrow w_j^+ \cup \{i\}, d_i^j \leftarrow q_i^j - r_i^j$
      $u_i^j \leftarrow (H - L_m - c_i^j)r_i^j, n{+}{+}$
  end
  if $D_j \neq 0$ **then**
    $C_j' \leftarrow \frac{u_j^-}{D_j}$
    Sort w_j^+ in non-increasing order of regret-value d_i^j : $d_1^j \geq d_2^j \cdots \geq d_n^j$
  repeat
    for $i = 1, 2, \ldots, n$ **do**
      $z_i^j \leftarrow d_i^j - d_{i+1}^j$
      if $D_j \geq z_i^j$ **then**
        $D_j \leftarrow D_j - z_i^j$
        $r_i^j \leftarrow r_i^j + z_i^j, u_i^j \leftarrow u_i^j + C_j' z_i^j$
      else
        $r_i^j \leftarrow r_i^j + D_j, u_i^j \leftarrow u_i^j + C_j' D_j, D_j \leftarrow 0$
    end
  until $D_j = 0$
end
return r and u

is $r_i'^j$ and $u_i'^j$, respectively. According to AU-CSAP Mechanism, then reduction allocated to user i is $r_i'^j = R_j \frac{c_i^j}{\sum_{i\in w_j} c_i^j}$, so $\sum_{i\in w_j} r_i'^j = R_j$, and since $c_i^j r_i'^j = R_j \frac{(c_i^j)^2}{\sum_{i\in w_j} c_i^j}$ and $C_j = \frac{\sum_{i\in w_j}(c_i^j)^2}{\sum_{i\in w_j} c_i^j}$, then we get $\sum_{i\in w_j} u_i'^j = (H - L_m - C_j)R_j = U_j$. However, in AU-CSAP mechanism, we should take into account two types of winners: winners in w_j^+ and winners in w_j^-, and then for allocated reduction, we get that $\sum_{i\in w_j} r_i^j = \sum_{i\in w_j^-} r_i^j + \sum_{i\in w_j^+} r_i^j = \sum_{i\in w_j^-} q_i^j + \sum_{i\in w_j^+} r_i'^j + \sum_{i\in w_j^-}(r_i'^j - q_i^j) =$

TABLE II
USERS' SHIFTING COST AND REDUCTION CAPACITY

$\varepsilon q_\tau = 150, H = 200, L = 120,$			
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	$q_2^3 = 30$	$c_2^3 = 5$

$\sum_{i \in w_j^+} r_i'^j + \sum_{i \in w_j^-} r_i'^j = R_j$. For allocated rewards, we get that $\sum_{i \in w_j} u_i^j = \sum_{i \in w_j^-} u_i^j + \sum_{i \in w_j^+} u_i^j = \sum_{i \in w_j^-} u_i'^j - \sum_{i \in w_j^-} (H - L_m - c_i^j)(r_i'^j - q_i^j) + \sum_{i \in w_j^+} u_i'^j + C_j' D_j = \sum_{i \in w_j} u_i'^j = U_j$. Hence, we get the conclusion that $\sum_{j \in A} \sum_{i \in w_j} r_i^j = \sum_{j \in A} R_j = q_\tau$ and $\sum_{j \in A} \sum_{i \in w_j} u_i^j = \sum_{j \in A} U_j$. Our claim holds. ■

C. Mechanisms Example and Scheme Variant

The shifting scheme with three-tier architecture proposed above can thus be summarized as Method 1: Users participate in the scheme where CRP allocate the reduction and rewards to CRA by PA-CSAP Mechanism first, then CRA allocates the reduction and rewards to users by AU-CSAP Mechanism. It has the computational complexity $O(|A||B|\log|B|)$ where $B = \{B_j||B_j| \geq |B_k|, j, k \in A\}$, and the proof is shown as follows. In PA-CSAP mechanism, it runs in $O(|A|)$ for CRP allocates reduction and rewards to CRA. For PA-CSAP mechanism, CRP allocates the reduction and rewards for $|A|$ CRA, so the number of iterations is $|A|$. In each iteration, the major computation is sorting to the list of users according to the regret-value, which runs in $O(|B|\log|B|)$. The procedure of offsetting regret-value in $O(|B|)$ is negligible. Thus, the computational complexity of the proposed shifting scheme with three-tier architecture is polynomial and corresponds to $O(|A||B|\log|B|)$.

In the following, we provide an example to illustrate our reduction and rewards allocation mechanisms for CRCSS. The shifting cost and reduction capacity reported by users are depicted in Table II. First, according to the AU-CSAP Mechanism, all users are winners. The shifting cost submitted to CRP is $C_1 = \frac{5^2+7^2+10^2}{5+7+10} = 7.91, C_2 = \frac{20^2+15^2+25^2}{20+15+25} = 20.83$, and the reduction capacity submitted to CRP is $Q_1 = 135, Q_2 = 80$. Next, CRP will adjust parameter u satisfied $u = 2 - \frac{7.91+20.83}{(3-2)(200-120)} = 1.64$ by the PA-CSAP Mechanism, then the reduction allocated to A1 is $R_1 = \frac{H-L_m+C_2-2C_1}{3k'} + \frac{q_\tau}{3} = 82.38$, the correspond reward is $U_1 = (H - L_m - C_1)R_1 = 5939.2$. Similarly, the reduction and rewards allocated to A2 are $R_2 = 67.62, U_2 = 4000.6$. Finally, according to the AU-CSAP Mechanism, 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 $r_2^1 = 22.54, u_2^1 = 1352.3$; $r_2^2 = 16.91, u_2^2 = 1098.7$; $r_2^3 = 28.17, u_2^3 = 1549.5$.

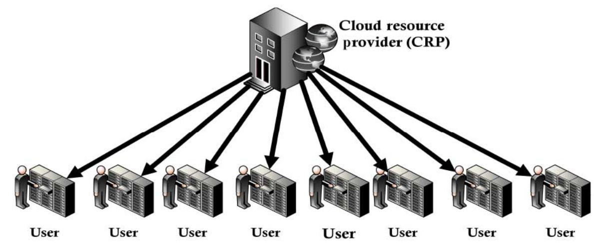

Fig. 6. Common shifting scheme with two-tier architecture.

TABLE III
SIMULATION PARAMETERS

Parameter	Values
Unit price	$H = 200, L \in [120, 150]$
Quality of resources to be shifted	$\varepsilon q_\tau \in [0, 4000]$
Number of users	$x_i \in [4, 13]$
Shifting cost of users	$c_i^j \in [5, 80]$
Reduction capacity of users	$q_i^j \in [400, 500]$

Next, We proceed to consider another variant of this scheme. We note that the variant includes the reduction and rewards transfer phase, unless stated, otherwise retain all the good properties of our original approach. The variant can be summarized as Method 2: Users participate in the scheme where CRP allocates the reduction and rewards to users by AU-CSAP Mechanism directly. Method 2 is a common shifting scheme with two-tier architecture, shown in Fig. 6.

V. EXPERIMENTS

We perform extensive simulation experiments with different instances of CSAP to vertify our conclusions, evaluate the performance of Method 1 and compare it with Method 2 in terms of social rewards (sum of winners' rewards) and reduction(shifting) ratio.

A. Experimental Setup

The simulation code is written in C♯ with .NetFramework 4.0 and run on a local machine (Intel Core 2.4 GHZ, 4 GB memory). The parameters setting for the simulation is listed in Table III.

In this work, we introduce the related simulated data used in our experiments. We generate cloud resources consumption shifting requests corresponding to systems with the number of users varying from 4 to 22 with step of 2. Users randomly request to shift between 400 and 500 units of cloud resources, i.e., users' reduction capacity. The valuation of the shifting cost is distributed over [5, 80]. In addition, we keep the unit-price $H = 200$ in M_O and assume that CRP announces between 120 and 150 unit-price in M_I, i.e., $L_m \in [120, 150]$. We generate the quantity of the shifted cloud resources CPR expected varying 0 to 4000 with increment of 500.

Considering that the simulated data are generated randomly and in order to mitigate the impact of the randomness, all the results of performance are averaged over 200 runs.All the results of experiment are summarized in Fig. 7.

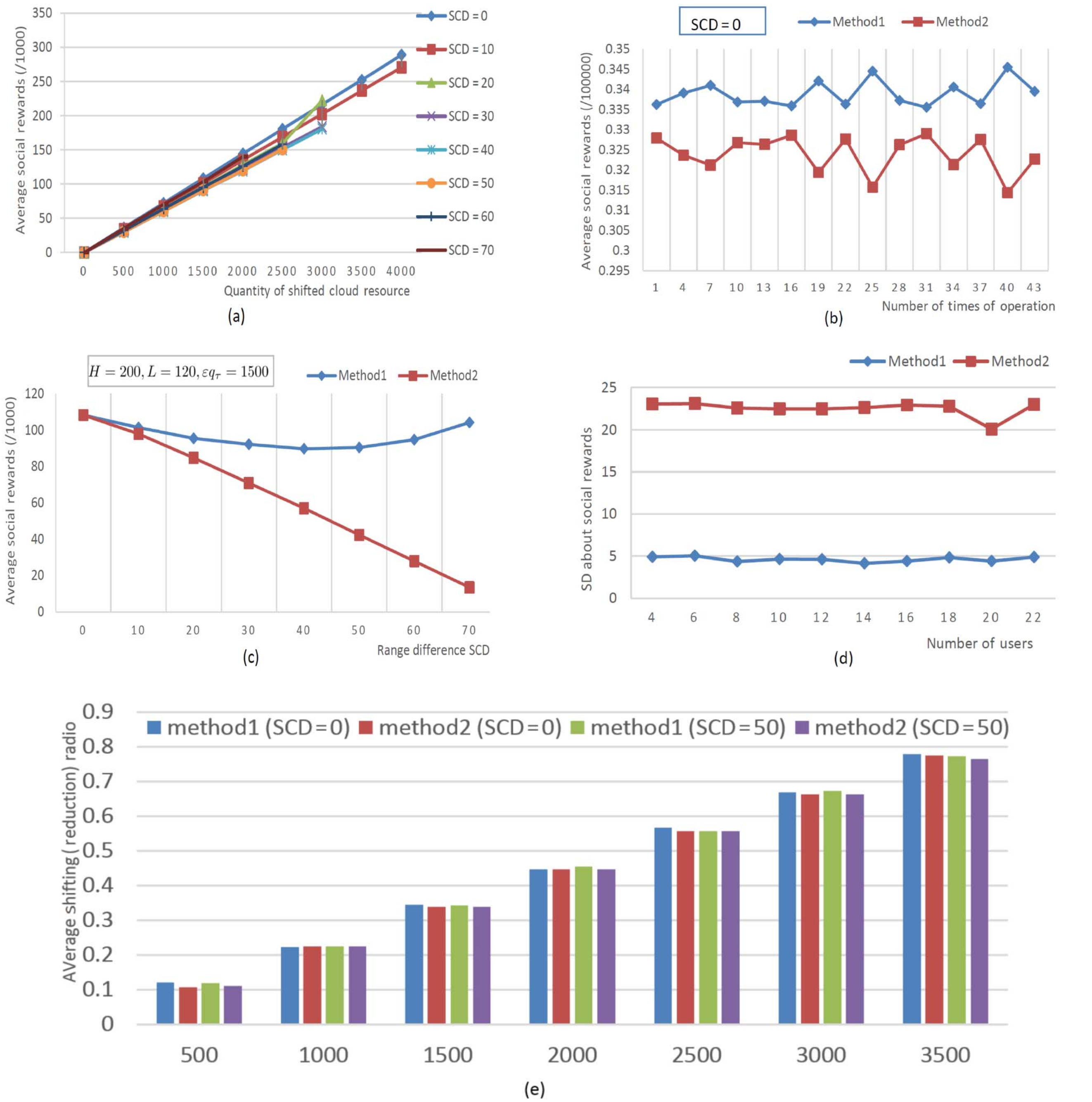

Fig. 7. Performance comparison of Methods 1 and 2. (a)–(c) Average social rewards. (d) SD about social rewards. (e) Average shifting (reduction) ratio.

B. Social Rewards

Social rewards is the sum of the winners' rewards allocated by CRP; its formula is $\sum_{j\in A}\sum_{i\in w_j} u_i^j$. We first define a concept of range difference: let $M = \{x|m \leq x \leq m+k\}, N = \{y|n \leq x \leq n+k\}$, the range difference of M and N is $|M - N| = |m-n|$. In our experiments, we denote the range of shifting cost of users in set B_j as $SC_i = \{x|a_i \leq x \leq a_i + k\}$ where a_i and k are positive numbers. We call the range difference of shifting cost of users in different areas as $SCD = |SC_i - SC_j|$, where $i \neq j$ and $i, j \in A$.

1) Analysis of Fig. 7(a): Range difference SCD is SCD=0, 10, 20, 30, 40, 50, 60, and 70, respectively, and the change of social rewards with the increase in quantity of shifted cloud resources by Method 1 is considered. The quantity of shifted cloud resources are set as 0–4000; the experiment result is shown as Fig. 7(a). From Fig. 7(a), it can be seen that the social rewards increase linearly with different quantity of shifted cloud resources under the condition of different value of SCD; however, the greater is SCD, the lower quantity of cloud resources can be shifted. That is because when SCD is great, CRA who owns lower shifting cost will get more cloud resources, which even exceeds its reduction capacity, then there is no equilibrium.

2) Analysis of Fig. 7(b): Comparing the social rewards of Methods 1 and 2, and consider the change of the value of social rewards with the increase in the number of times of operation. The unit-price H is set as 200, and L is set from 120 to 150, respectively. In addition, the shifted cloud resources q_τ are set from 1000 to 2000, and range difference SCD is set as 0, respectively. The experimental result is shown as Fig. 7(b). From Fig. 7(b), it can be seen that under the condition of same range of shifting cost, Method 1 always outperforms Method 2, but the superiority is not obvious, the maximum is only nearly 9%, and the minimum is even 1.5%.

3) Analysis of Fig. 7(c): The unit-prices are $H = 200$ and $L = 120$, respectively, and the change in social rewards with the increase in SCD is considered. The shifted cloud resources εq_τ is set as 1500, and the experiment result is shown as Fig. 7(c). From Fig. 7(c), it can be seen that under the condition of the same range difference SCD, Method 1 has higher social rewards than Method 2. When the range difference SCD is small, the performance of Methods 1 and 2 is similar. However, with the increase in SCD, the advantage of Method 1 about social rewards shows. The greater is the value of SCD, the greater is the advantage of Method 1 compared with Method 2.

4) Analysis of Fig. 7(d): In order to investigate the stability about social rewards of Methods 1 and 2, standard deviation (SD) about social rewards is selected as a benchmark for the stability about social rewards. Generally, lower SD means more stable social rewards. Range difference SCD is SCD = 0, 10, 20, 30, 40, 50, 60, and 70, respectively; the shifted cloud resources εq_τ are set as 1000; the change in SD about social rewards with the increase in the number of users is considered. The number of users is set as 4–22, and the experimental result is shown as Fig. 7(d). From Fig. 7(d), it can be seen that under the condition of the same number of users, Method 1 has lower SD about social rewards than Method 2, which means that it generates more stable social rewards by Method 1.

C. Reduction (Shifting) Ratio

Reduction (shifting) ratio is the ratio about user's actual allocated reduction to its capacity, its formula is $\sum_{j\in A}\sum_{i\in w_j}\frac{r_i^j}{q_i^j}$.

1) Analysis of Fig. 7(e): We compare the shifting (reduction) ratio of Methods 1 and 2 in different situation. When range difference SCD is $\mathrm{SCD} = 0$ and SCD = 50, respectively, the change of shifting (reduction) ratio with the increase in the quantity of shifted cloud resources is considered. The quantity of shifted cloud resources are set as 500–3500; the experiment result is shown as Fig. 7(e). From Fig. 7(e), it can be seen that the performance of Methods 1 and 2 is similar. It is due to the same quantity of shifted cloud resources.

VI. Conclusion

This paper puts forward a novel scheme about cloud resources consumption shifting designed for different geographic areas, and studies the design of a cloud resources consumption shifting quantity allocation mechanism and a rewards allocation mechanism related to it. Considering that users in different geographical areas differ in the shifting cost scope for cloud resources, we adopt the role of CRA and put forward a shifting scheme with three-tier architecture, which makes our scheme further applicable in practice. Moreover, it is verified in our theoretical analysis that the proposed scheme can simultaneously achieve four important economic properties including equilibrium, individual rationality, truthfulness, and budget balance. In addition, extensive simulation experiments about the social rewards and reduction (shifting) ratio are carried out to verify the effectiveness of the proposed scheme.

In our future work, we will further improve the proposed scheme and explore the impacts of different unit-price curves in both M_I and M_O for the system. In addition, we also intend to make extensions to the proposed scheme to realize equilibrium among multiple cloud resource agencies and prevent users from practicing fraud in both shifting cost and reduction capacity.

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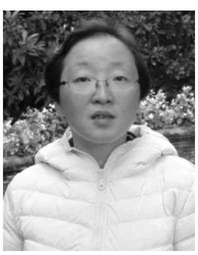

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