Distributed Resource Allocation for Data Center Networks: A Hierarchical Game Approach

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Abstract - *Emerging storage problems developed and deploy the large data centers, the demand for storing the data in cloud-based services get increased day by day. In this paper, we analyse the resource allocation problem for the data center networking system when multiple data center operators (DCOs) simultaneously serve multiple service subscribers (SSs). We formulate a hierarchical game to analyze this system where the DCOs and the SSs are regarded as the leaders and followers, respectively. In the proposed game, each SS selects its serving DCO with preferred price and purchases the optimal amount of resources for the SS's computing requirements. Based on the responses of the SSs' and the other DCOs', the DCOs decide their resource prices so as to receive the highest profit. When the coordination among DCOs is weak, we consider all DCOs are non-cooperative with each other, and propose a sub-gradient algorithm for the DCOs to approach a sub-optimal solution of the game. When all DCOs are sufficiently coordinated, we formulate a coalition game among all DCOs and apply Kalai-Smorodinsky bargaining as a resource division approach to achieve high utilities. The solution of the above mentioned problems constitutes the Stackelberg Equilibrium. In our proposed system we evaluate the performance of the system.*

Keywords— Datacenter, hierarchical game, game theory, resource management.

I.   Introduction

In order to fulfill the requirement of the users Data center operators (DCOs) build large scale data centers. Cloud computing plays a vital role in store large amount of data. This attracts significant interest in recent years due to the popularity of data services and applications. To meet the demand for the data-intensive cloud computing applications, huge investments have been made by companies, commonly referred to as the data center operators (DCOs) to build large-scale data centers. Through data center, the user and admin can share multiple data's among them. Each data center consists of a large number of facilities and computing resources, which can be accessed and shared by multiple service subscribers (SSs) at the same time. For example, companies such as eBay, Facebook, Google, Microsoft, and Yahoo nowadays are able to provide data computing or data storage services for SSs with large-scale data centers, which significantly improve the SSs' efficiency and convenience. As more and more companies join the cloud computing market, the competition among different DCOs becomes intense. How to optimize their services and prices so as to attract more SSs and maximize the revenues is one critical problem for DCO. Due to the availability of multiple DCOs a user has to specify SSs for their requirement. Based on the SS's perceptive, different SSs have different expectations in price, delay, etc., of various cloud computing services provided by the DCOs. Therefore, how to choose the optimal DCO that meets its requirements is an important problem for each SS. Nevertheless, the existing works didn't consider any relationship among multiple DCOs, which motivates the work of this paper. In this paper, we investigate resource allocation among multiple competitive or cooperative DCOs, each of which processes resources that can be accessed by SSs at a certain price. The main objective of each DCO is to maximize its profit by adjusting the price offered to the SSs. So each SS has to determine the services provided by DCO. Based on the requirement of the user the rate and resources get to differ. The user can buy any resources from DCO based on the price affordability, the SS should decide the appropriate DCO and the number of resource blocks to procure based on the offered price. We designed a hierarchical game model to analyze the joint optimization of the decision making processes for both DCOs and SSs. In this process, all the DCOs are considered as a leader because there are deciding the price rate for the resources. The SSs is the follower because they are purchasing the resources from them where prices declared by the leaders. When the coordination among all DCOs is weak, we consider all DCOs to be non-cooperative with each other and propose the sub-gradient algorithm for the DCOs to approach a sub-optimal solution of the game. If the DCOs are sufficiently coordinated with each other then it is easy to formulate a coalition game among all the DCOs. Each DCO has a revenue proportionality based on its capability due to avoid the competition among all DCOs in the coalition game, each DCO should obtain revenue proportional to its capability. Accordingly, Kalai-Smorodinsky bargaining is adopted as a resource division approach to achieve fair and efficient utilities.

II.   Related work

In the networking center, resource allocation problem plays a vital role in the system. Brandic et al [8] performed a comprehensive analysis of energy efficiency in a general infrastructure supporting the cloud computing paradigm. Wang et al [9], overview the construction prototype of the data center to improve the agility for multi-tenant demands in the cloud,

responsiveness, and scalability. Gu et al [10], he studied problems in large scale data center including task assignment, data placement, and data movements, used optimization algorithm for minimize the total cost during the big data computing services. Wang et al[11] analysis multiple popular network sharing policies, such as SecondNet [12], Oktopus [13], Gatekeeper [14], Seawall [15], NetShare [16], and FairCloud [17], in order to enhance the user security and improvise the sharing network. Zhang et al[18], the authors showed a class of data center network structures based on hypergraph theory and combinatorial block design theory. Compared with the classic fat-tree model, the new structures of constructing large data center networks are more flexible and scalable. Shang et al [19], the authors made a comprehensive comparison study for typical data center networks with regard to their Network Power Effectiveness (NPE). The results showed that Flattened. Kim et al [20], the author evaluated the butterfly network topology and NPE flat tree. Zhang et al [23] designed a Hierarchical Energy Optimization (HERO) model to reduce the power consumption of network elements. Wang et al [24], tried to achieve high energy efficiency. It can be done by virtual machines to servers and reducing the number of active switches and balance traffic flows. In order to achieve high energy efficiency, the authors in [25], took advantage of the application characteristics and topology features and proposed TE-VMA and TER algorithms to assign virtual machines and routing traffic flows, respectively. Shu et al [26], a novel architecture Proposed work Operation of Cloud-integrated Cyber-Physical System. The paper provided solutions for energy resource management techniques, the scheduling of cloud resources and life cycle management from the perspective of the CIA. Wang et al [27], the authors focused on the performance guaranteed energy-saving schemes as well as determining the transmission speed for every flow. Polverini et al [28] proposed a GreFar algorithm to optimizes the energy cost and fairness among different organizations. Wei et al [29], the authors considered a QoS-constrainedresource allocation problem with the game theory. Ren et al [30], the authors considered the adaptive and stable application deployment in clouds with a multi-objective evolutionary game-theoretic framework. Chen et al [33] proposed a new simulation tool, called Data Center Simulator with small scale operating system and storage.

III.   **Proposed work**

SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider the cloud computing system consists of multiple DCOs labeled as o1, o2, . . . , oM with different amounts of computing facilities that can be accessed to and shared by N SSs, labeled as s1, s2, . . . , sN. All the DCOs offer computing resources over the internet to all the SSs at the time. We use the term "computing resource block" to denote the unit of time and computing speed measured by service rate that can be allocated to each SS. Let Si be the total number of computing resource blocks allocated by DCO O_i. We use μ_ii to denote the service rate of each computing resource block of DCO O_i . Let $\lambda_j$be the Workload arrival rate of sj . Let λ_{ij} be the workload arrival rate generated from SS sj, which will be processed using the resources of DCO O_i. We have

$$\lambda_j = \sum_{i=1}^{M} \quad \lambda_{ij} \quad \textbf{(1)}$$

In this paper, we focus on the delay-sensitive applications in which quality of service (QoS) of each SS is relative with both the data rate and the total delay during the service. The main objective of each SS is to choose the DCO that can provide the highest QoS at the lowest price. $u_i(p_i|\alpha, m, p_{i-1}) = \sum_{j=1}^{N} \quad \alpha_{ij}m_{ij}p_i - e_i \ \forall_i \in \{1,2,...,M\}$ Where α=<α_{ij}> i∈{1,2,...M}, j∈{1,2,...N} is the pairing probability between DCOs and SSs, m=<m_{ij}> i∈{1,2,...M}, j∈{1,2,...N} contains the strategies of all SSs, p^*_{-1} contains the optimal prices set by all other DCOs except DCO oi, and p=<p_i> i∈{1,2,...M}, contains the prices charged by the DCOs. $p_i \geq 0, \forall_i$ Each SS tries to achieve a high utility from the service while minimizing both the service delay and payment to DCOs

List of Notation

M-Total number of DCOs

N-Total number of SSs

s_i-Number of computing resource blocks for the DCO O_i

μi- Service rate of computing resource blocks in the DCO O_i

λ_j-Workload arrival rate for the SS S_j

p_i-Price per unit of computing resource block of the DCO O_i

p_i^{max}-Maximum service price of the DCO O_i

W_{ij}-Cost of queuing delay of SS s_j at DCO O_i

$d_j^{z_1 z_2 \dots z_N}$ − Cost of network delay of SS s_j when each SS s_j is served by DCO O_{z_j}

r_{ij}-Cost of total delay of SS s_j at DCO O_i

m_{ij} -Number of computing resource blocks from DCO i to SS s_j

e_j-Energy cost of DCO O_i

k_j-Weight factor between the benefits from the workload and the total cost of SS s_j

c- Cost of purchasing one watt power

q_i- Power requirement of each computing resource block in DCO O_i

α_{ij} -Probability for SS s_j to choose DCO O_i

b_{jz_j} j- Motivation of price reduction on one unit of network delay for the SS s_j

u_i -Utility of DCO O_i

u_i^{max} -Maximum utility of DCO O_i

v_j -Utility of SS s_j

r_{th}- Upper bound of total delay cost

$q_{ij,s}$- Static power requirement when DCO O_i serves SS s_j

$q_{ij,c}$-Computing power requirement when DCO O_i serves SS s_j

x_{ij} -Speed of computing workloads when DCO O_i serves SS s_j

α- Pairing outcomes between DCOs and SSs

m -Strategies of all SSs

p -Prices set by all DCOs

$$u_i(p_i|\alpha,m, p_{i-1}) = \sum_{j=1}^{N} \quad \alpha_{ij} m_{ij} p_i - e_i \quad \forall_i \in \{1,2,\dots,M\} \quad (2)$$

Where α=<α_{ij}> i∈{1,2,...M}, j∈{1,2,...N} is the pairing probability between DCOs and SSs, m=<m_{ij}> i∈{1,2,...M}, j∈{1,2,...N} contains the strategies of all SSs, p_{-1}^* contains the optimal prices set by all other DCOs except DCO o_i, and p=<p_i> i∈{1,2,...M},

contains the prices charged by the DCOs. $p_i \geq 0, \forall_i$ Each SS tries to achieve a high utility from the service while minimizing both the service delay and payment to DCOs. We hence can define the utility of SS sj as

$$v_i(m_j|m_{-j}, P) = k_j\lambda_j - \sum_{j=1}^{N} \quad \alpha_{ij}T_{ij} \quad \forall_i \in \{1, 2,..., M\} \qquad (3)$$

where mj is the strategy of purchasing computing resources from all DCOs for SS sj , m−j is the strategy of purchasing computing resources for all the other SSs, and kj is the weight factor. Accordingly, the first term kj_j represents the weighted revenues achieved by each SS sj from the services.

The second term $\sum_{j=1}^{N} \quad \alpha_{ij}m_{ij}p_i$ is the amount of money that SS sj is required to pay the DCO oi for the service. The third term $\sum_{j=1}^{N} \quad \alpha_{ij}T_{ij}$ is the cost of the total delay in service. If the delay is large, the user experience of the SSs is poor, and the corresponding utilities are small. Let Tth be the maximum delay that can be tolerated by SSs. Thus, $r_{ij} \geq 0$ and $r_{ij} \leq r_{th}$

GAME ANALYSIS

According to the formulated problems in the modeled multileader multi-follower Stackel berg game, the optimal solutions can be achieved when the Stackel berg Equilibrium can be achieved between the DCOs and SSs. The concept of Stacekel berg Equilibrium can be defined as follows.

Definition 1. [38] Let ((X,A), (g, f)) be the multi-leader multi-follower Stackelberg game with m leaders and n followers. X = X1×X2×...×Xm and A = A1×A2×...×An are the strategy profiles of leaders and followers, respectively. g = (g1(x),..., gm(x)) is the payoff function of leaders for x ∈ X, and f = (f1(α),..., fn(α)) is the payoff function of followers for α∈ A. Let xi be a strategy profile of leader i, x−i be a strategy profile of all the leaders except leader i, αj be a strategy profile of follower j, and α−j be a strategy profile of all the followers except leader j. A set of strategy profiles x∗ ∈ X and α∗ ∈ A is the equilibrium of the multi-leader

multi-follower game if ∀i, ∀j, xi ∈ Xi, αj ∈ Aj ,

$$g_i(x_i^*, x_{-i}^*, \alpha^*) \geq g_i(x_i^*, x_{-i}^*, \alpha^*) \geq g_i(x_i^*, x_{-i}^*, \alpha^*),$$

$$f_j(x, \alpha_j^*, \alpha_{-j}^*) \geq f_j(x, \alpha_j, \alpha_{-j}^*) \qquad (4)$$In following parts of this section, we first consider a simplified version of our problem and analyze the Stackelberg Equilibrium for a single-DCO and single-SS cloud computing system, in order to analyze the basic relationship between the DCO and SS. We then extend our model to the case with multiple DCOs and SSs, and discuss the competition or coalition among all DCOs.

A. Single-DCO single-SS Stackelberg game

Consider the scenario where there is only one DCO and one SS in the game, i.e., M = 1 and N = 1. Based on the cost of the SS, we have the following lemma.

Lemma 1. *In a single-DCO single-SS scenario, for a given price* p1 *of the DCO, the optimal number of computing resource blocks chosen by the SS is given by* $m_{11}^* = \frac{\lambda_1}{\mu_1\sqrt{p_1}} + \frac{\lambda_1}{\mu_1}$ **(5)**

The optimal strategy for each SS has a closed form solution under the given price of the DCO, which can be pre-calculated and pre-stored in a table in the SS. In real scenarios, the SS can then use a simple table searching method to obtain its optimal solution with low implementation complexity. Therefore, for the SS in the game, the computation requirement is very low. Furthermore, because of the first-move advantage in the Stackelberg game, the DCO is able to predict the optimal strategy of the SS. Therefore, we substitute (1) into (2), and the profit of the DCO can be derived as $u_1 = \frac{\lambda_1}{\mu_1}\sqrt{p_1} + \frac{\lambda_1}{\mu_1} + \lambda_1 d_1^1 \leq r_{th}$ **(6)**

Thus in the single-DCO single-SS scenario, when the DCO sets price $p_1^{max} = (r_{th} - 1 - \mu_1 d_1^1)^2$ the profit of the DCO is maximized. In the single-DCO single-SS scenario, the Stackelberg Equilibrium can be achieved. Both the DCO and the SS have their optimal utilities, respectively, and neither of them is able to change their strategy to achieve higher values.

B. Multi-DCO multi-SS hierarchical game

In a multi-DCO and multi-SS scenario, each SS has multiple choices on its serving DCOs, and each DCO may also be able to serve multiple SSs to receive higher profits. Accordingly, there exists competition or coordination among DCOs and SSs. In this section, we analyze and propose strategies for each SS and DCO so as to receive the optimal utility.

We consider the data center network system with N SSs which can choose service from M DCOs. When SS sj chooses DCO ozj , ∀j ∈ {1, 2, . . . ,N}, following the results in the single-DCO single-SS scenario, each SS makes its decision on the optimal number of computing resource blocks m∗ zjj , where

$$m^*_{zjj} = \frac{\lambda_j}{\mu_{z_j}\sqrt{p_{z_j}}} + \frac{\lambda_j}{\mu_{z_j}}$$

(7). Accordingly, the utility of SS sj is denoted as $v_j^{z_1 z_2 \ldots z_N,}$ i.e., $v_j^{z_1 z_2 \ldots z_N,} = k_j \lambda_j - \frac{\lambda_j}{\mu_{z_j}}(\sqrt{p_{z_j}} + 1)^2 - \lambda_j d_j^{z_1 z_2 \ldots z_N}$ Based on the utility of each SS in different situations, we assume that each SS sj , ∀j ∈ {1, 2, . . . ,N} is able to determine the probability to be served by each DCO ozj , i.e., αzjj , ∀zj ∈ {1, 2, . . . ,M}. Therefore, in order to achieve high utilities with low service price and network delay for each SS sj , we refer the incentive mechanism method in [39] and set the probability for each SS sj to choose DCO ozj as

$$\alpha_{ij} = \frac{b_{jzj}}{\sum_{z_j=1}^{M} b_{jzj}}$$ With the prediction of all SSs' behaviors, each DCO expects to set its service price so as to receive the optimal utility. Therefore, substitute (13) into (5) and the utility of DCO oi can be denoted as

$$\alpha_{ij} = \frac{b_{jzj}}{\sum_{z_j=1}^{M} b_{jzj}}$$ With the prediction of all SSs' behaviors, each DCO expects to set its service price so as to receive the optimal utility. Therefore, substitute (8) into (2) and the utility of DCO oi can be denoted as

$$u_i = \sum_{j=1}^{N} \quad \alpha_{ij}(\frac{1}{\mu_i}\sqrt{p_i} + \frac{\lambda_j}{\mu_j} + \frac{\lambda_j}{\mu_i}c\beta_{ij} \quad \frac{\lambda_j}{\mu\sqrt{p_i}}\cdot c\beta_{ij}\frac{\lambda_j}{\mu_j}) \text{(8)}$$

Therefore, when setting the price for the SSs, there is a competition between DCO o1 and DCO o2. Either DCO should estimate the behavior of the others, balance the setting price and number of the expected SSs and make decisions so as to achieve high revenues. In the general situation with M DCOs and N SSs, the figures become M +1 dimensions, which can be separated into M + 1 regions. In each region, the tradeoff among DCOs' decisions works in a similar way. However, for each DCO in the game, it is hard to predict the behaviors of other DCOs, causing unstable and unsatisfying results for each other. In the following sections, based on the different benefits of the SSs and DCOs, we propose both the competitive and the coordinated strategies for the DCOs to achieve the highest utility given the actions of other DCOs. In the real situations where some DCOs coordinate with some other DCOs and some still compete with other DCOs, the DCOs that can cooperate with each other will coordinate with each other first. Then, each coordinated DCOs can be regarded as a coalition and compete with other DCOs outside of the coalition using the competitive algorithm.

A competitive Behavior among DCOs

We used the sub-gradient algorithm, each DCOs consider there are no competitions with other DCOs so they increase their price at the maximum to receive the high utility. At each iteration, the DCO tries to increase or decrease its price with a small step and predict the resulting utility, if the adjustment increases its utility, the DCO will increase or decrease its price in the next iteration. Otherwise, the DCO will keep the current service price unchanged. More specifically, for each SS, based on the observation of the announced prices from all DCOs, each SS determines the optimal amount of computing resource block to purchase. In other words, all the DCOs also do not need to make decisions at the same time, and the algorithm can still converge to the same Stackelberg equilibrium.

Coalition formation in DCOs: In order to improve their benefits, DCOs joined together and offer proce for SSs. Therefore, in order to guarantee fairness and avoid the competition among all DCOs in the coalition game, each DCO should set its price in the feasible region and obtain revenue proportional to its capability. In order to achieve the fair results and high revenues for all DCOs in the coalition game, we consider the Kalai-Smorodinsky bargaining as a resource division approach within all DCOs.

Algorithm 1 Strategy of each DCO in a multi-DCO multi-SS scenario.

1. Initially, each DCO ignores the existence of other DCOs, and sets its price at the maximum value to receive the highest revenue from all SSs.

2. **while** at least one DCO adjusts its price **do**

3. **for** SS sj **do**

4. Based on the prices set by all DCOs, each SS

5. determines the probability to be served by each DCO and purchases the optimal amount of resource blocks from each DCO.

6. end for

7. **for** DCO oi **do**

8. Each DCO stores the current value of service prices.

9. **p**old = **p**;

10. Each DCO adjusts its price with a small step _i and calculate its own payoff based on the prediction of the followers' optimal strategies.

11. **if** ui(poldi , pold−i) ≤ ui(poldi + _i, pold−i) **then**

12. pi = min{pmax

13. i , poldi +_i}; % Increase the price

14. **else**

15. **if** ui(poldi , pold−i) ≤ ui(poldi −_i, pold−i) **then**

16. pi = max{0, poldi − _i}; % Reduce the price

17. **else**

18. pi = poldi ; % Keep the price unchanged

19. **end if**

20. **end if**

21. **end for**

22. **end while**

IV.   Results and Discussion

Here we evaluate the simulation result of the proposed system in Matlab. We set the service rate of each computing resource block in both DCOs as 0.3 (ms)−1. The workload arrival rates for SS s1, SS s2, and SS s3 are 0.7 (ms)−1, 0.6 (ms)−1, and 0.6 (ms)−1, respectively. We model the distance between source and data center, divided by the transmission speed of 200km/ms, resulting in delay ranging in [0, 8] ms, and the delay tolerance of all SSs is set to 8 ms. The above settings are reasonable for the existing data center networks. [36] In the proposed sub-gradient method, we assume that the price step sizes for both DCOs are 0.01 dollar.
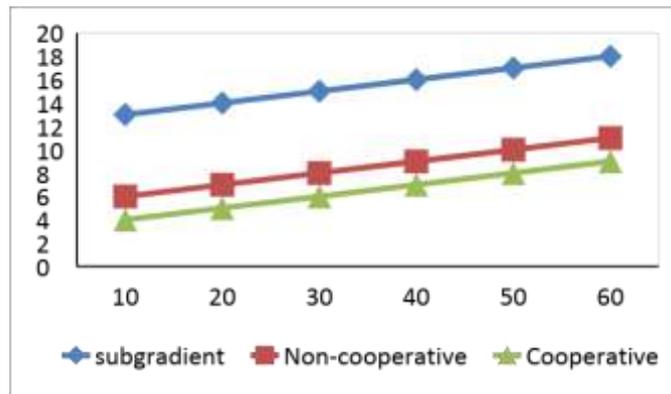
Fig. 3: Social welfare vs delay tolerance of SSs with different approaches

The social welfare achieved by the Kalai-Smorodinsky bargaining follows the results of cooperative behaviors. As shown in Fig. 3, with the increased delay tolerance rth of SSs, all DCOs are able to set a high price to meet the service requirements of the SSs, and the performance of the SSs deteriorates. Therefore, social welfare generally reduces with rth increasing.
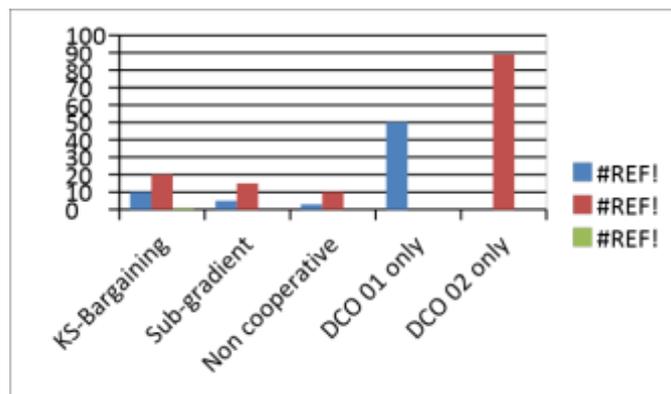
Fig. 4: The utility of each DCO with different approaches

In Fig. 4, we compare the utility of each DCO in coalition formation with Kalai-Smorodinsky bargaining, noncooperative scenario with sub-gradient algorithm, ordinary noncooperative behavior, and the situation where only DCO o1 or DCO o2 monopolizes the market.
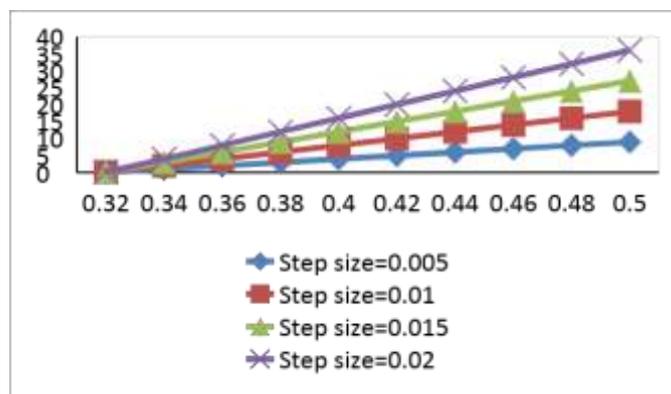
Fig. 5: The converge route in the proposed sub-gradient strategy with different steps

In Fig. 5, we evaluate the impact of the step size in the proposed sub-gradient strategy. In the simulation, we fix the step size of DCO o2 as 0.01, and change the step size of

DCO o1 to 0.005, 0.01, 0.015, 0.02, respectively. According

to the algorithm of the proposed sub-gradient strategy, with

a different step size of DCO o1, both DCOs compete with

each other and gradually reduce their prices in the game

V.   Conclusion

In our proposed system we tried to overcome the resource allocation problem when multiple data center operators (DCOs) and service subscribers (SSs) coexist in the networks. To evaluate the relationship between the multiple DCOs and SSs, we designed a multi leader and multi follower hierarchical game. In this model, DCOs act as leader and SSs act as a follower. We proposed a subgradient algorithm in the non-cooperative game and coalition game by predicting the behaviours of all SSs and reactions of other DCOs. In this system, the analysis is based on Kalai-Smorodinsky bargaining strategies to gain the benefits in terms of social welfare and the utilities of the DCOs, respectively. Simulation results have demonstrated that for the benefits of SSs, all DCOs compete with each other and all DCOs adopt the proposed sub-gradient strategies to achieve high social welfare of the game. On the other hand, for the benefits of DCOs, DCOs form a coalition and perform Kalai- Smorodinsky bargaining behaviors so as to achieve high and Fair revenues. These strategies, analysis the relationship between DCOs and SSs which provide a structure for multi-DCO multi-SS scenarios. Future work is in progress to consider the resource allocation problem including both the massive and edge data center networks

VI.   REFERENCES

1. Greenberg, J. Hamilton, D. A. Maltz, P. Patel, "The cost of a cloud: research problems in data center networks," ACM SIGCOMM Computer Comm. Review, vol. 39, no. 1, pp. 68-73, Jan. 2009.

2. Amazon Web Service, available at "http://aws.amazon.com".

3. Google app engine, available at "http://code.google.com/appengine/".

4. Google docs and spreadsheets, available at "http://docs.google.com".

5. Microsoft office live, available at "http://office.live.com".

6. Windows Azure, available at "http://www.microsoft.com/azure/".

7. Yahoo! Mail, available at "http://mail.yahoo.com". T. Mastelic, A. Oleksiak, H. Claussen, I. Brandic, J.-M. Pierson and V. Vasilakos, "Cloud computing: Survey on energy efficiency,"ACM

8. Computing Surveys (CSUR), vol. 47, no. 2, pp. 1-36, Jan. 2015.

9. B. Wang, Z. Qi, R. Ma, H. Guan and A. V. Vasilakos. "A survey on data center networking for cloud computing,"Computer Networks, vol. 91, pp. 528-547, Nov. 2015.

10. L. Gu, D. Zeng, P. Li, and S. Guo, "Cost minimization for big data

11. processing in geo-distributed data centers," IEEE Trans. Emerging Topics in Computing, vol. 2, no. 3, pp. 314-323, Sep. 2014.

12. T. Wang, Z. Su, Y. Xia and M. Hamdi, "Rethinking the data center networking: architecture, network protocols, and resource sharing," IEEE Access, vol. 2, pp. 1481-1496, Dec. 2014.

13. C. Guo, G. Lu, H. J. Wang, S. Yang, C Kong, P. Sun, W. Wu, and Y. Zhang, "SecondNet: A data center network virtualization architecture with bandwidth guarantees," in Proc. 6th Int'l COnference (Co-NEXT'10), Philadelphia, PA, Dec. 2010.

14. H. Ballani, P. Costa, T. Karagiannis, and A. Rowstron, "Towards

15. predictable datacenter networks," in Proc. ACM SIGCOMM'11, vol. 41, no. 4, pp. 242-253, Toronto, Canada, Aug. 2011.

16. H. Rodrigues, J. R. Santos, Y. Turner, P. Soares, and D. Guedes, "Gatekeeper: Supporting bandwidth guarantees for multi-tenant datacenter networks," in Proc. USENIX WIOV, Portland, OR, Jun. 2011.

17. A. Shieh, S. Kandula, A. Greenberg, C. Kim, and B. Saha, "Sharing the data center network," in Proc. 8th USENIX Conf. Netw. Syst. Design Implement (NSDI), pp. 309-322, Boston, MA, Mar. 2011.

18. T. Lam, and G. Varghese, "NetShare: Virtualizing bandwidth within the cloud," UCSD Technical Report, 2009.

19. L. Popa, A. Krishnamurthy, S. Ratnasamy, and I. Stoica, "FairCloud: Sharing the network in cloud computing," in Proc. ACM SIGCOMM Conf.Applications, Technologies, Architectures, and Protocols for Computer Comm., pp. 187-198, Helsinki, Finland, Aug. 2012.

20. J. Zhang, Z. Fang, G. Qu, and S. Q. Zheng, "A new class of data center network structures," in Proc. IEEE Globecom'13, Atlanta, GA, Dec. 2013.

21. Y. Shang, D. Li, J. Zhu, and M. Xu, "On the network power effectiveness of data center architectures," IEEE Trans. Computers, vol. 64, no. 11, pp. 3237-3248, Nov. 2015.