게임 이론 기반 동적 협력 클라우드 서비스 플랫폼에서의 클라우드 공급자간 협상 기법

Game Based Cooperative Negotiation among Cloud Providers in a Dynamic Collaborative Cloud Services Platform

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요　약

최근 다양한 분야에서 클라우드 컴퓨팅의 사용이 증가하고클라우드 컴퓨팅의 이상적 가치 실현을 위한 클라우드 공급자간의 동적협력은 필수적인 요소가 되고 있다. 이전의 연구를 통해서 다른 클라우드 공급자 간의 동적 협력 플랫폼으로 경매결합 방식 기반의 클라우드 마켓 모델 "CACM"을 제안한 바 있다. CACM모델은 경매에 참여하기 전에 미리 최적화된 클라우드 공급자들간 그룹을 형성하여 동적 협력을 제공할 수 있도록 하고 있으며, 이에 따라 공급자 간 협상시 발생할 수 있는 문제들을 최소화 하고자 하였다. 그러나 어떻게 최적의 입찰 가격 결정 그룹을 결정할 것인지, 어떻게 안정적인 그룹의 조건을 구할 것인지, 또한 입찰 가능 가격 및 이익을 그룹 구성원 간에 분배할 것인지에 대한 연구는 CACM 모델에서 구체적으로 연구되지 못했다. 본 논문에서는, CACM 모델을 N-person 협력 게임 이론에 대입하여 CACM모델에 추가적으로 위에서 제시한 문제들을 공식화하여 제안하고자 한다. 그룹의 안정성은 그룹의 각 구성원에게 코어와 할당량에 대한 개념을 대입해 게임이론에서의 샤플리 값을 사용하여 분석한다. 여러 계산 결과값을 통해 제안하는 기법의 특성평가를 도출한다.

ABSTRACT

In recent years, dynamic collaboration (DC) among cloud providers (CPs) is becoming an inevitable approach for the widely use of cloud computing and to realize the greatest value of it. In our previous paper, we proposed a combinatorial auction (CA) based cloud market model called CACM that enables a DC platform among different CPs. The CACM model allows any CP to dynamically collaborate with suitable partner CPs to form *a group* before joining an auction and thus addresses the issue of conflicts minimization that may occur when negotiating among providers. But how to determine optimal group bidding prices, how to obtain the stability condition of the group and how to distribute the winning prices/profits among the group members in the CACM model have not been studied thoroughly. In this paper, we propose to formulate the above problems of cooperative negotiation in the CACM model as a *bankruptcy game* which is a special type of N-person cooperative game. The stability of the group is analyzed by using the concept of the *core* and the amount of allocationsto each member of the group is obtained by using *Shapley value*. Numerical results are presented to demonstrate the behaviors of the proposed approaches.

☞ KeyWords : Dynamic cloud collaboration, Group bidding price, Profit sharing and cooperative game theory

1. Introduction

The proprietary nature of existing Cloud providers (CPs) restricts consumers to simultaneously use multiple or collaborative cloud services. That is, interoperability and scalability are two major challenging issues for cloud computing. Forming a dynamic collaboration (DC)[1] platform among CPs can create business opportunities for them to address these issues. A DC platform can facilitate

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expense reduction, avoiding adverse business impacts (e.g. cloud vendor lock in) and offering collaborative or portable cloud services to consumers.

In our previous paper [1], we proposed a novel combinatorial auction (CA) based cloud market model called CACM with a new auction policy that facilitates a virtual organization (VO) based DC platform among CPs. The new auction policy in CACM model allows any *primary cloud provider*(pCP), the initiator of a DC, to dynamically collaborate with suitable partner CPs to form *a group* before joining an auction and thus addresses the issue of conflicts minimization that may occur when negotiating among providers [2]. They publish their *group bid* as a single bid to fulfill the service requirements completely, along with other CPs, who publishes separate bids to partially fulfill the service requirements.This approach creates more chances to win the auctions for the group since collaboration cost (e.g. network establishment, information transmission, capital flow, etc), negotiation time and conflicts among CPs can be minimized.

However, there are several issues about group bidding. In [3], the problem of how groups (or coalitions) are formed is discussed. Another problem arises after groups (or coalitions) are formed. How should the resource/profit/cost be distributed among the members of the group? What are the criteria for distributing resource/profit/cost? There are alsoworks such as resource sharing [4], surplus/cost sharing [5] which are related to these problems.

In this work we focus on the problem of how to determine optimal group bidding prices, how to obtain the stability condition of the group and how to distribute the winning prices/profits among the group members in the CACM model. The decision of the bidding prices of the group can be solved using resource sharing or surplus/cost sharing methods (which directly assigns a price share to each provider). But directly assigning price shares to provider sometimes lead to negative profits.

In this paper, we propose to formulate the problem of cooperative negotiation among Cloud group members in the CACM model as a *bankruptcy game* which is a special type of N-person cooperative game. The objective is to fairly allocate the group price and profit share to each group members. A standard method in cooperative game theory, namely, the *core* is used to obtain the stability condition of the group. Then, to obtain the solutions (i.e., the allocated group price and profit shares), *Shapley value* is used. Simulation results show that there exists a dominant strategy for CPs that can let them obtain maximum profit and also the compromised profit of each individual CP's satisfies each CP's rationality.

The rest of this paper is organized as follows: Section 2 presents the related works. Section 3 describes the proposed CACM model. In Section 4, we present bankruptcy game model and *Shapley value* for its solution Also the OINP and profit allocation using *core* are also presented in this section. Numerical results are presented in Section 5. Section 6 states the conclusions.

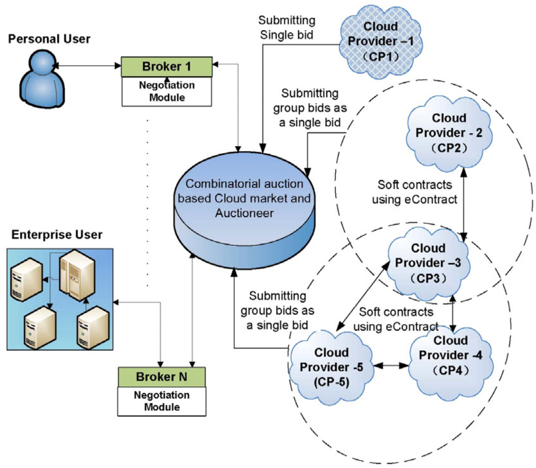
2. Related Works

Game-theoretic framework (e.g., N-person cooperative game) was used to analyze the cooperation among supply chain agents [6]. In [7], a cooperative game of choosing partners and forming coalitions in the marketplace was proposed. In [8], the authors employed a co-evolutionary mechanism to search complex and large spaces in order to find joint efficiency between negotiating agents and to evolve negotiation strategies. A game theoretical approach was then used to distribute the payoffs generated from the co-evolutionary approach in order to find equilibrium. The authors in [9] evaluate and compare different approaches for allocating costs to buyers in a combinatorial auction market using the two key concepts of cooperative game theory: the *nucleolus* and *Shapley value*. So in the literature cooperative game theory is used in many areas but very few works consider using it in determining optimal group bidding price.

3. Combinatorial Auction (CA) Based Cloud Market Model for Dynamic Collaboration Platform

Here we briefly introduce our cloud market model, called CACM, as proposed in [1] to clarify the problem scenario. The proposed CACM model to enable a DC platform among CPs is shown in Fig. 1. The CACM model allows bidders to make groups and submits their bids for a set of services to auctioneer as a single bid while also supporting the bidders to submit bids separately for a set of services. We define the CACM model in which the main participants are brokers, users/consumers, cloud resource/service providers, and trustworthy auctioneers.

Brokers in the CACM model mediate between consumers and CPs.The consumers can be enterprise user or personal user. In the proposed CACM model, each user can bid a single price value for different composite/collaborative cloud services provided by CPs. The responsibility of an auctioneer includes setting the rules of the auction and decides the best combination of CPs who can meet user requirements for a set of services using a winner determination algorithm.



(Figure 1) Proposed CACM model for dynamic collaborative cloud services among CPs

3.1. Terms and Definitions Used in the CACM Model

3.1.1. The Auction Scheme

We utilize secured generalized Vickrey auction (SGVA) [10] approach to address the trust, security and confidentiality issues in CACM model and a dynamic graph programming approach proposed in [11] for winner determination algorithm. The winner is provided the second lowest price.

3.1.2 The Reservation Price, Market Price and Profit

The *reservation price* of a CP is defined as follows: If a service is sold at its reservation price, the service providing agent gains zero profit. If a service is sold at a price lower than the reservation price, the service providing agent gets negative profit, and vice versa.The market price of a service is defined as the regular *individual price* (INP) of a CP that includes the reservation price and profit margin. The profit of a service provided denotes the difference between the INPand the reservation price of the service.

3.1.3. Parameters and Variables

For the convenience of analysis, the parameters and variables for the CACM models are defined as follows:

$R=\{R_j|j=1...n\}$: a set of n service requirements of consumer

$P=\{P_r|r=1...m\}$: a set of m CPs who participate in the auction as bidders

P_{rj} = a cloud provider r who can provide service j

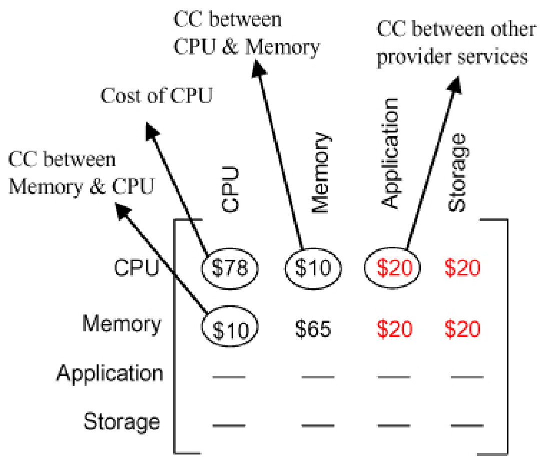
$S(P_r)$ = a set of services $(S_{j=1...n})$ provided by any P_r where $S(P_r)\subseteq R$

$\Omega_{\max}(R,Q)$ = payoff function of the user where R is the service requirements and Q defines SLAs of each service.

3.2. Group Bidding Price Determination in the CACM Model

The group bidding price (sometimes called group price) denotes the price that equals the summation of all the individual prices inthe group. For a bidding group the initial group bidding price (IGBP) can be obtained easily by asking all the bidding agents of the group to declare their initial INPs. But this method will not work since the probable goal group bidding price (GGBP) should be lower than the IGBP. The GGBP is set by the pCP to maximize the group winning probability. The bidding group needs to reduce its bidding price by a certain amount to satisfy the GGBP. In this section, we will present how the group members will calculate initial individual price and initial group bidding price.

3.2.1 Initial Individual Price and Group Bidding Price Determination



(Figure 2) Reservation price matrix M

Let M be a service reservation price matrix of any cloud provider P_r, S be any service in R (i.e. $S \subseteq R$) and G be a group of providers in P (i.e. $G \subseteq P$). To simplify the auction model, we assume that any CP can provide at most two services. The reason is that it is not feasible for a CP to provide almost all kinds of services. The matrix M includes costs of P_r provider's own services as well as the collaboration costs (CC) between services of its own and other providers. Fig. 2 illustrates the matrix M.

We assume that P_r provides two services - CPU and Memory. Let $a_{ii} (i=1...n)$ be the cost of providing any service in M independently, a_{ij} $(i,j=1...n, i \neq j)$ be the CC between S_i and S_j services $(S_i, S_j \in S(P_r))$ and $a_{ik} (i,k=1...n, i \neq k)$ be the CC between S_i and S_k services ($S_i \in S(P_r)$ and $S_k \notin S(P_r)$). We set nonreciprocal CC between $S(P_r)$ services in Mwhich is practically reasonable. If P_r knows other providers or has some past collaboration experience with others, it can store true CC of services with other providers. Otherwise it can set a high CC for other providers. The CCof services with other providers in matrix M isupdated when the providers finish negotiation and collaboratively provide the services of consumers in the DC platform.

Let P_r forms a group G by selecting appropriate partners where $S(P_G)$ isthe set of services provided by G and $S(P_G) \subseteq R, G \subseteq P$. Now the initial INP of any P_r in group G can be determined as follows:

$$\phi^G_{S(P_r)} = C^G_{S(P_r)} + \gamma^G(P_r)$$

where $C^G_{S(P_r)}$ is the total reservation price incurred by P_r to provide $S(P_r)$services $(S(P_r) \subseteq R)$ and $\gamma^G(P_r)$ is the expected profit of P_r. The total reservation price $C^G_{S(P_r)}$ is calculated as follows by using the matrix M :

$$C^G_{S(P_r)} = \sum_{S_i \in S(P_r)} a_{ii} + \sum_{S_i \in S(P_r)} \sum_{S_j \in S(P_r)} a_{ij} + \sum_{S_i \in S(P_r)} \sum_{S_g \in S(P_G) \backslash S(P_r)} a_{ig} + \sum_{S_i \in S(P_r)} \sum_{S_k \notin S(P_G)} a_{ik}$$

where, $i, j, g, k = 1...n$ and $i \neq j \neq g \neq k$

The first term in the equation (2) is the cost of providing services $S(P_r)$ .The second term is the total collaboration cost between $S(P_r)$ services. The term $\sum_{S_i \in S(P_r)} \sum_{S_g \in S(P_G) \backslash S(P_r)} a_{ig}$ denotes the total collaboration cost of services of P_r with other providers in the group. The term $\sum_{S_i \in S(P_r)} \sum_{S_k \notin S(P_G)} a_{ik}$ refers to the total collaboration cost between services of other CPs outside of the group with whom P_r needs to collaborate. This term can be zero if the group can satisfy all the service requirements of consumer. Since P_r knows other group members, it can find the true value of the term $\sum_{S_i \in S(P_r)} \sum_{S_g \in S(P_G) \backslash S(P_r)} a_{ig}$. Moreover, if P_r applies any good strategy to form the group G, it is possible for P_r to minimize $\sum_{S_i \in S(P_r)} \sum_{S_g \in S(P_G) \backslash S(P_r)} a_{ig}$. Hence, this group G has more chances to win the auction as compare to other providers who submit separate bids to partially fulfill the service requirements. So the *IGBP* for the group G can be calculated as follows:

$$\phi^{G}_{S(P_G)} = \Sigma(C^{G}_{S(P_r)} + \gamma^{G}(P_r)), \forall P_r \in G, r = 1...l$$

where l is the no. of providers in G and $\gamma^{G}(P_r)$ is the expected profit of any provider r in the group.

Now to satisfy the requirements of probable GGBP, each CP in the group needs to reduce its initial INP from IGBP by certain amount. But how all the CPs of the group cut their INPs optimally so that the group becomes stable? An optimal Individual price (OINP) allocation algorithm is needed which will be presented in the next section.

4. Determining Optimal Individual Price Allocation for Goal Group Priceand Profit Sharing in the CACM Model

The objective is to fairly allocate the OINPsto each group members when their summations satisfy the probable goal bidding price but the sum of their initial individual pricesexceeds the probable GGBP. Therefore, we use a *bankruptcy game* formulation to obtain the solution of the optimal individual price allocation problem.

In this section, we first describe a standard bankruptcy game. To obtain the solution of this game, the *coalition form* and the *characteristic function* for an N-person cooperative game are presented. Then, the stability of the game is analyzed through the *core*. Next, the solution of the bankruptcy game formulation is obtained by *Shapley value*. Then the optimal individual price allocation algorithm and a negotiation algorithm are presented. The negotiation algorithm ensures that all the group members agree to the optimal individual price allocation. Finally the profit sharing method is described.

4.1. Bankruptcy Game

In a bankruptcy game problem, a certain amount of money (estate) has to be divided among the agents who have a claim to it, when the sum of these claims exceeds the estate. This conflicting situation introduces an N-person game where the players of the game are seeking for the equilibrium point to divide the money.

The standard bankruptcy game (N, E, c) can be expressed [12] by a finite set of agents N, a real positive number E which denotes the amount of money and a nonnegative vector $c \in R^N$ of claims where the condition $\Sigma_{i \in N} c_i \geq E$. If x_i denotes the solution (i.e., amount of money distributed to agent i), the rule of this game can be expressed as follows:

$$0 \leq x_i \leq c_{i,} \qquad \forall i \in N$$

$$\sum_{i \in N} x_i = E$$

4.2. Coalition Form and Characteristic Function

A coalition always exists in a bankruptcy game so that the agents (i.e., players) can cooperate with each other to gain better benefit. Also the bankruptcy game consists of transferable utility which allows *side payments* to be made among the players [12]. This side payment might be used by the players to reach the best strategy. Also, the payoff of coalition is expressed by the *characteristic function*. The *coalition form* of an N-person game is defined by the pair (*N*, *v*) where *v* is a *characteristic function* specifying the value created by different subsets of the players in the game. For the bankruptcy game that we are considering here the characteristic function can be defined as follows [13]:

$$v(S) = \max\left(0, E - \sum_{j \notin S} c_j\right)$$

for all possible coalition of *S* ($S \subset N$).

4.3. The Core

The *core* in a N-person cooperative game is generally used to obtain stability region for the solution. In this case, the concept of *imputation* must be established. Let the payoff vector $X = \{x_1, x_2 ......x_i ......x_n\}$ denote the amount received by agent *i*. This payoff vector is *group rational* if $\sum_{i=1}^{n} x_i = v(N)$. In particular, the highest total payoff can be achieved by forming a coalition among all agents. Also, the payoff vector is *individually rational* if $x_i \geq v(\{i\})$. That is, an agent will not agree to receive money less than that the agent could obtain without coalition. Then, the imputation is defined as the payoff vectors that is both group rational and individually rational, namely [12]

$$P = \left\{ x = \{x_1, ..., x_n\} \mid \sum_{i \in A} x_i = v(N), \text{ and } x_i \geq v(\{i\}), \forall i \in N \right\}$$

An imputation *X* is unstable with coalition *S* if $v(S) > \sum_{i \in S} x_i$. Specifically, if the imputation is unstable, there is at least one agent who is unsatisfied due to the coalition. Then, the core is defined as the set *C* of stable imputations and can be expressed mathematically as follows [11]:

$$C = \left\{ x = \{x_1, ..., x_n\} \mid x \in P \text{ and } \sum_{i \in S} x_i \geq v(S), \forall S \subset N) \right\}$$

The significance of the *core* comes from the fact that every imputation in the core renders the grand coalition stable. However, it may contain several points and in some cases it could be empty. Therefore, the solution that provides the most preferable distribution strategy is required. In this paper, we apply *Shapley value* which is one of the methods to obtain the solution of an N-person cooperative game.

4.4. Shapley Value

The Shapley value is generally used to find the solution of an N-person cooperative game since the computational complexity of this method is small. To compute Shapley value, let us define the *value function* $\phi(v)$ as the worth or value of agent *i* in the game with characteristic function *v*, i.e., $\phi = \{\phi_1, ...\phi_i, ...\phi_n\}$. The *Shapley value*can be obtained by considering the money that an agent receives depending on the order that agent joins the coalition. In particular, the Shapley value is the average payoff to an agent if the agents enter into thecoalition in a completely random order [14]. The *Shapley value* $\phi = \{\phi_1, ...\phi_i, ...\phi_n\}$ can be computed as follows:

$$\phi_i(v) = \sum_{S \subset A, i \in A} \frac{(|S|-1)!(n-|S|)!}{n!} (v(S) - v(S - \{i\}))$$

where n is the number of agents in the game, S is a coalition in the game containing agent i, $S-\{i\}$ is the coalition consisting of all agents from S, except for i, and $|S|$ indicates the number of elements in the set S

4.5. Optimal Individual Price Allocation Algorithm for Goal Group Bidding Price

Based on a standard bankruptcy game as described before, we propose an optimal individual price (OINP) allocation algorithm for the CPs in the group. Here, the goal group bidding price (GGBP) is analogous to the money or estate that has to be divided among the CPs and INPs are the claims of CPs. This situation leads to the similar conflict as in the bankruptcy problem in which the summation of INPs exceeds the GGBP. So we need to find OINP allocation that makes the group stable by satisfying goal group bidding price. The notations and the descriptions of the variables for the bankruptcy game and the optimal individual price allocation algorithm are shown in Table I. The optimal individual priceallocation algorithm will be run by the pCP and it should know the following two parameters before running the algorithm:

* Initial individual price information of partner CPs from their website and existing market
* Probable goal group bidding price $G\phi^G_{S(P_G)}$ that can maximize the group winning probability

Now the steps of optimal individual price allocation algorithm are as follows:

Step 1: Calculate the characteristic functions of all the coalitions using the equation (5).

Step 2: Calculate the core and Shapely value using the equation (7) and (8) and check the condition $\sum_{i \in S} x_i \geq G\phi^G_{S(P_G)}$ and $x_i \in C, \forall i \in S, S \subset N$, i.e. the Shapley value ϕ_i or x_i is in the core and thus the solution is stable. Here x_i is the optimal individual price allocation to agent $i$and C is the core.

(Table 1) Notations and descriptions of the variables for the standard bankruptcy game and proposed optimal individual price (OINP) allocation algorithm

Variables	Standard Bankruptcy Game	OINP Allocation Game
n	Total number of agents	Total number of CPs
M	Money (estate)	GGBP
N	Set of agents	Set of CPs
c_i	Claims of agent i	INP
x_i	Solution of money distributed to agent i	OINP allocated to agent i in the group

4.6. The Negotiation Algorithm

As we know, in a DC platform, each of the group members must agree with the OINP allocation of others against a setof its own policies, some disagreements or conflicts may arise among each other. So anegotiation algorithm is needed to reduce the conflicts.

One of the important factors that need to be considered while designing a negotiation algorithm for a DC platform is the number of times the eContract need to be reviewed by participants before reaching an agreement. We use an efficient sequential contract negotiation algorithm, called Conflict Neighboring Algorithm (CNA) as proposed in [2]. The CNA exploits the concept of localizing re-negotiation process so that the conflicting parties become neighbors to each other. In the CACM model, the group members know each other very well and so it is possible that they may reduce their collaboration costs and thus can agree with the optimal individual price allocation of each other in a very short time as compare to the existing approaches.

4.7. Profit Sharing in the CACM Model

As we use second price auction scheme in the CACM model, the wining price or profit of a group that wins an auction will be more than their GGBP. So every member of the group will get the amount equal to their OINP allocation and the surplus amount will be divided among each member using the *proportional rule*, which is probably the best known and most widely used solution concept. It distributes awards proportionally to claims. It is defined as follows: for all (N,*E*, c*)*, $P(N,E,c)=\lambda c$, with

$$\lambda = \frac{E}{\sum_{i \in A} c_i}.$$

5. Simulations and Results

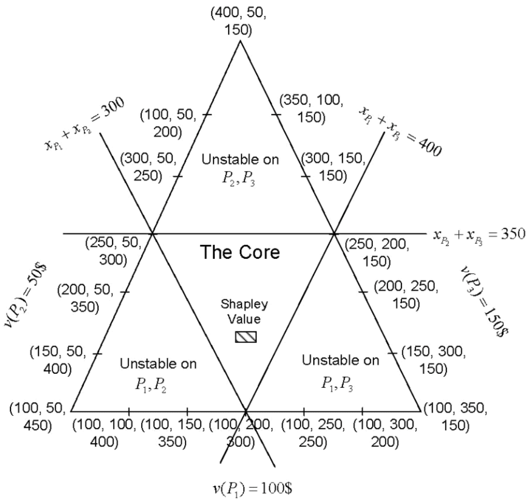
We first show an example of how to calculate the core and Shapely value to determine the OINP allocation and profit sharing among three CPs in a group. Then we present the performance of our CACM model with the existing CA model. We implemented the CACM model (winner determination algorithm) with new auction policy in Visual C++. One of the main challenges in the CACM model is the lack of real-world input data. So we conduct the experiments using synthetic data.

5.1. Synthetic Data Generation

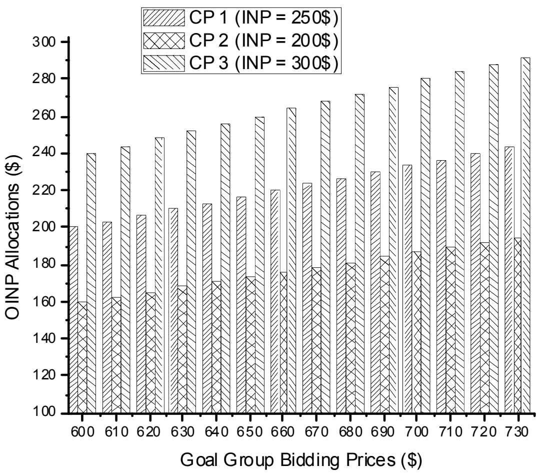
Many CPs (*m*= 100) with different services and also some consumer requirements (*R*= 3-10) are generated randomly. We assume that each CP can provide at most twoservices so that they have to collaborate with others to fulfill the service requirements *R*. Each service may have one or more CPs. Based on *R*, CPs are selected. So it is possible that every CP may not provide the required *R*. Also the cost of any independent service is randomly generated from $80 to $150. The ranges of CC of services as well as the profit are set within $10 - $30 and $10 - $20 respectively. If any provider has more collaboration experience with other providers, the *CC* can be minimized. Thus the initial individual price with reservation price and profit is generated for each provider and it is varied based on CC in different auctions.

5.2. Examples of the Core and Shapley Value for Determining OINP Allocations and Profit Sharing

In this section, we demonstrate the calculation of the core and the Shapley value to determine the OINP allocation among three CPs. Let $\phi^{G}_{S(P_r)}$



(Figure 3) Bar centric coordinates of the core and the Shapley value for the numerical example



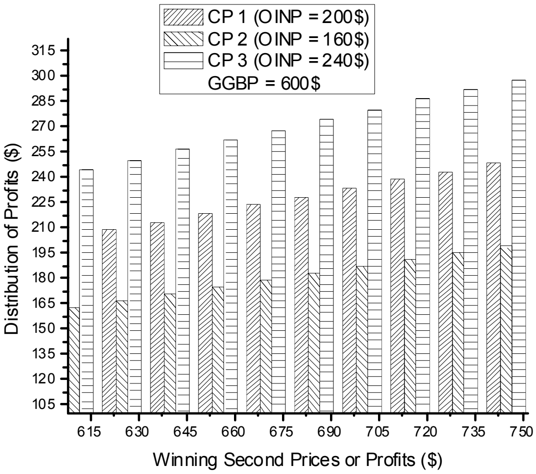
(Figure 4) Examples of INP allocations among three CPs by varying the GGBP using the core and Shapley value

be the INP of any CP r in group G and $\phi^G_{S(P_G)}$ be the IGBP. We assume three providers in a group where $\phi^G_{S(P_1)}$ = 250$, $\phi^G_{S(P_2)}$ = 200$, and $\phi^G_{S(P_3)}$ = 300$. Let us assume that the probable GGBP, $G\phi^G_{S(P_G)}$ = 600$. As the IGBP $\phi^G_{S(P_G)}$ = 750$, is greater than $G\phi^G_{S(P_G)}$, all the group members need to reduce their INPs to some extent so that GGBP's requirement can be fulfilled. According to equation (5), the characteristic functions of all coalitions are as follows:

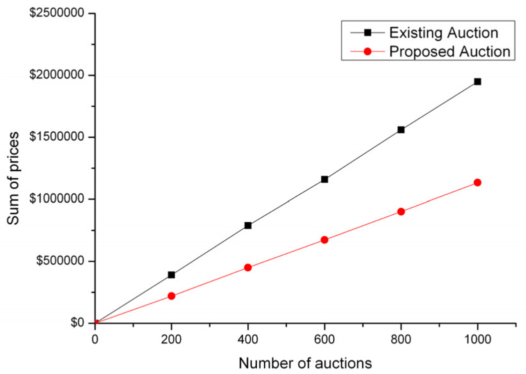
$$\begin{array}{lll} & v(P_1) = 100\$ & v(P_1, P_2) = 300\$ \\ v(\phi) = 0 & v(P_2) = 50\$ & v(P_1, P_3) = 400\$ \\ v(A) = 600\$ & v(P_3) = 150\$ & v(P_2, P_3) = 350\$ \end{array}$$

Since the number of CPs is three, the core can be presented by *barycentric coordinates* as in Fig. 3. In this triangle representation, the plane of the plot is denoted by $x_{P_1} + x_{P_2} + x_{P_3} = v(N) = 600\$$ and the edges of the triangle are the characteristic functions $v(\{i\})$. For example, $v(\{P_2\}) = 50$ represents the uppermost edge. The constraint of the core (i.e. $\sum_{i \in S} x_i \geq v(S)$) is the line drawn across the triangle.

For example, $x_{P_2} + x_{P_3} = v(P_2, P_3) = 350\$$ represents the horizontal line. Based on these constraints, some areas represent the unstable imputations as shown in Fig. 3. For example, the topmost area corresponds to an unstable imputation where the satisfaction for the CPs P_2 and P_3 is not achieved. There is an area (the middle area) that refers to the core (i.e., the solution space that makes the game stable). According to equation (8), the Shapley value (i.e. INP allocation) is $\phi = \{200, 160, 240\}$. Next, we show some examples of INP allocations by varying the GGBP from 600$ to 730$ as shown in Fig. 4.



(Figure 5) Example of distribution of profits



(Figure 6) Economic efficiency of the CACM model as compared to that of the existing CA model

In Fig. 5, we show some examples of profit distributions among three CP members based on the INP allocations obtained by Shapley value for GGBP = 600$.

Our CACM model using proposed approach of cooperative negotiation is beneficial to the consumers as the total price of the services decrease. Fig. 6 shows the economic efficiencies of the two auction-based markets. It can be seen from Fig. 6 that when the number of auctions increases, the CACM model reduces the total service price to consumers as compared to the existing CA model for the same number of service requirements. The main reason is that CCs among the group members are lower as they know each other very well in the group and thus the total service price is reduced.

6. Conclusions

In this paper, we present the problem of group bidding price determin ation and profit sharing in the CACM model that enables a DC platform among CPs. We formulate these problems as bankruptcy games. The stability of the optimal individual price and profit allocations for group members have been analyzed by using the concept of the *core* and the amounts of the allocations for each member of the group have been obtained from the *Shapley value*. We present several examples of optimal individual price allocation and profit sharing in the CACM model. Also the performance of the CACM model is compared with the existing CA model in terms of economic efficiency. In future, we will work on finding an optimal resource co-allocation algorithm for providing the collaborative service in a DC environment.

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References

[1] M. M. Hassan, B. Songand E.N. Huh. "A Novel Market Oriented Dynamic Collaborative Cloud Service Infrastructure". The 5th IEEE SERVICES - II, Bangalore, India, September 21-25, Vol.1, pp. 9-16, 2009

[2] S. Nepal, and J. Zic. "A Conflict NeighboringNegotiation Algorithm for Resource Services in Dynamic Collaboration". The IEEE Int. Conf. on Services Computing, Vol. 2, pp. 283-290, 2008

[3] M. M. Hassan, B. Song and E. N. Huh. "A Multi-Objective Optimization Model for Partner Selection in a Market-Oriented Dynamic Collaborative Cloud Service Platform". The 21stIntl. Conf. on Tools with Artificial Intelligence, New Jersey, USA, November 2-5, Vol. 1, pp. 637-644, 2009

[4] L. He and T. R. Ioerger, "Forming Resource-Sharing Coalitions: A Distributed Resource Allocation Mechanism for Self-Interested Agents in Computational Grids", ACM Symposium on Applied Computing, 2005

[5] J. Yamamoto and K. Sycara. "A stable and efficient buyer coalition formation scheme for e-marketplaces". International Conference on Autonomous Agents, pp: 576 - 583, 2001

[6] M. Nagarajan and G. Sosic. "Game-Theoretic Analysis of Cooperation among Supply Chain Agents: Review and Extensions". European Journal of Operational Research, May 2006

[7] A. S. Belenky,. "Cooperative Games of Choosing Partners and Forming Coalitions in the Marketplace". Journal of Mathematical and Computer Modeling, Vol. 36, pp. 1279-1291, 2002

[8] J-H Chen, K-M Chao, N. Godwin et al. "A Multiple-Stage Cooperative Negotiation". IEEE Intl. Conf. on e-Technology, e-Commerce and e-Service, pp. 131-138, 2004

[9] T.G. Crainic, M. Gendreau et al. "Cost Allocations in Combinatorial Auctions for Bilateral Procurement Markets". CIRRELT report, December, 2009, https://www.cirrelt.ca/

[10] K. Suzuki and M. Yokoo. "Secure generalized Vickery auction using homomorphic encryption". In Financial Cryptography, 7th International Conference, FC 2003, volume 2742 of Lecture Notes in Computer Science. Springer, 2003

[11] M. Yokoo and K. Suzuki. "Secure Multi-agent Dynamic Programming based on Homomorphic Encryption and its Application to Combinatorial Auctions". The first ACM joint International Conference on Autonomous Agents and Multi agent Systems, Bologna, Italy, July 2002

[12] T. S. Ferguson. "Game Theory Text", Mathematics Department, UCLA.

[13] M. Pulido, J. S. Soriano, and N. Llorca. "Game theory techniques for university management: An extended bankruptcy model". Operation Research, vol. 109, pp. 129-142, 2002

[14] L. S. Shapley. "A value for N-Person game". Annals of Mathematics Studies, Princeton University Press, vol. 2, pp. 307-317, 1953

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