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An Auction Framework for DaaS in Cloud Computing and Its Evaluation

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Abstract: Data as a Service (DaaS) is the next emerging technology in cloud computing research. Small clouds operating as a group may exploit the DaaS efficiently to perform the substantial amount of work. In this paper, an auction framework is studied and evaluated when the small clouds are strategic in nature. We present the system model and formal definition of the problem and its experimental evaluation. Several auction DaaS-based mechanisms are proposed and their correctness and computational complexity is analyzed. To the best of our knowledge, this is the first and realistic attempt to study the DaaS in a strategic setting. We have evaluated the proposed approach under various simulation scenarios to judge on its usefulness and efficiency.

Keywords: Data as a Service; Auction; Mechanism Design; Micro Cloud.

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1 Introduction

Taking a specialist's substantial infrastructure instead of creating your own individual set up, has been the key for cloud computing success. In the last decade there has been a significant research to deal with the allocation of resources in cloud computing Feng and Buyya (2016), Terzo et al (2013), Zhang et al (2016), Bandyopadhyay et al (2016), Bandyopadhyay et al (2017). Several companies (such as Amazon EC2, Microsoft Azure etc.) have come up with technologies to support the key viewpoint of cloud computing. Being the industry standard, cloud computing brings new challenges as well Bouchareb et al (2016). One of such challenges is to acquire data on the fly for some business specific queries, leading to the Data-as-a-Service model.

Two broad solutions could be provided:

- Access the data already web-crawled by the big giants (Google, Microsoft, etc.) by their enormous infrastructure but at a high price.
- Some Small to Medium size Enterprises (SMEs) may join hand in hand and collect the data for future use and thereby serving themselves independently several times.

In this paper, this later viewpoint is addressed and an auction framework is proposed.[a] Currently, there are many existing small clouds (representing SMEs) and some of the clouds (henceforth we will use micro-clouds) may collaborate and form a bigger clouds. This collaboration will help collecting a substantial amount of data. Whenever a query is made to any micro-cloud, then two cases may occur:

- Either the data is available with the bigger cloud where it belongs.
- Or the data may be available within some of the other bigger clouds.

If the data is available within the bigger cloud, there is an infrastructural cost it has to pay to access the data. If it is outside the bigger cloud, we run an auction to set the price.

The reminder of this paper is organized as follows: Section 2 presents the literature review of the previous works and then find out the research gap that motivates the need for the evaluation of cloud data-as-a-service business models. Section 3 proposes the system model and problem formulation. Several solution concepts and definitions are introduced in Section 4. In Section 5 we have discussed the proposed mechanism. Section 6 discuss some analytics of the proposed algorithm. In Section 7 we have discussed the simulation results. We present a summary of our work and highlight some future directions in Section 8.

2 Related Work

Data-as-a-Service (DaaS) is coming up as an alternative school of thoughts in cloud computing where data are obtainable as a service through network Terzo et al (2013), Magoules et al (2012), Oliveira et al (2015), Sugawara (2017). In Terzo et al (2013) a

[a] The work done in this paper is an extension of the preliminary version of the paper Bandyopadhyay et al (2018) appeared in EIDWT 2018.

DaaS architecture is presented for data discovery, storing and moving data, and processing of the data with the consideration of big data as a service. A pricing scheme for a query processing in DaaS platform is addressed in Oliveira et al (2015). No auction based work is proposed, to the best of our knowledge, in DaaS environment. In this paper an auction framework is discussed when DaaS is in operation. However in literature several incentive schemes (mostly in monetary aspects) have been proposed in Infrastructure as a Service (IaaS) framework for stimulating the service providers to provide the best possible services to the users. Nielsen (1970) proposes pricing technique for allocating computing resources. Sutherland (1968) proposes a game theoretic auction model approach (based on auction theory) for allocating the processor time in a single computer. An auction mechanism proposed by Amazon is called spot marketing which is prevailing in the current cloud computing market.

In Mihailescu and Teo (2009) a strategy-proof mechanism for the allocation of multiple resources to a buyer in a large scale distributed system is proposed. In Combinatorial auctions (CA) which has been widely studied by the researchers Mashayekhy and Grosu (2014), Milgrom (2004), Nisan et al (2007), Baranwal and Vidyarthi (2015), Fujiwara et al (2010) allow service providers to sell bundle of items rather than individual item and the users (buyers) to bid on any combination of items or services. Das and Grosu (2005) proposed a combinatorial auction-based protocol for resource allocation in grids. They considered a model where different grid providers can provide different types of computing resources. The third party auctioneer collects this information about the resources and runs a combinatorial auction-based allocation mechanism where users participate by requesting bundles of resources. However, when multiple buyers and multiple sellers are present in the market a double auction mechanism is visible Lehmann et al (2002), Archer et al (2003), Mu'alem and Nisan (2008). The double auction mechanism is extended into the online double auction environment in Mu'alem and Nisan (2008), Ibrahim et al (2011), Bartal et al (2003), Zhang et al (2016). In Zhou et al (2017) an efficient online auction mechanism was proposed where cloud user gives their bids for future cloud resources to execute its job. In the model so far in IaaS participating agents were individual in nature. However in our DaaS participating agents may be largely the individual groups. So, the earlier models may not be directly applicable.

3 System Model and Problem Formulation

In this paper, we have a set of Big Cloud(s) (BCs) depicted as $C = \{C_1, \ldots, C_n\}$. Each of C_i (a cluster) consisting of some micro clouds. Depending on the number of micro clouds in each C_i, two cases are possible for any pair of (C_i, C_j):

1. $\mid C_i \mid = \mid C_j \mid$
2. $\mid C_i \mid \neq \mid C_j \mid$

We can generalize the notation and can write $C_i = \{mC_1^i,\ mC_2^i, \ldots,\ mC_{k_i}^i\}$ where $k_i \in \{1, 2, \ldots, m\}$ and $i \in \{1, 2, \ldots, n\}$. This fact is depicted in $Figure.1$. Each micro cloud $mC_j^i \in C_i$ joins C_i with some collection of data and that micro-cloud may be referred at any point of time by the user who needs service. To promote the participation in this model it is assumed that when a mC_j^i joins a cloud C_i, it needs only its data and no registration fees.

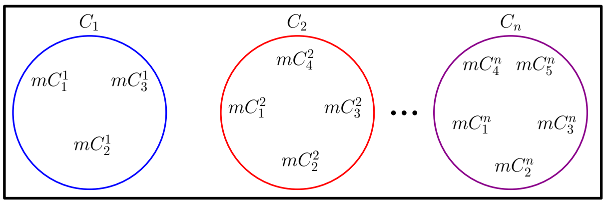


Figure 1: Different micro-cloud forming the cluster

The data is maintained by the existing infrastructure of C_i. However when a query is made, in future, mC_j^i is charged a fixed amount if the data is available inside that C_i as the infrastructure cost. Otherwise, to get the data an auction is run with the other clouds $C_j{}'s$, where the data are available.
So, the payment of mC_j^i can be formulated as p_j^i=$x_j^i \cdot \sigma_j^i$+$\bar{x}_j^i \cdot \bar{\sigma}_j^i$ where x_j^i is the indicator function defined as :

$$x_j^i = \begin{cases} 1, & \text{if data is inside } mC_j^i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

and

$$\bar{x}_j^i = \begin{cases} 1, & \text{if data is not inside } mC_j^i \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

A micro cloud may earn some money also when an auction is run. σ_j^i is the fixed amount charged and $\bar{\sigma}_j^i$ is the payment made by mC_j^i when the data is found outside of the C_i where $mC_j^i \in C_i$. Here sealed bid auction is considered and each $C_i \in C$ will have a private valuation v_i known only to them.

If in the auction cloud C_i wins, in this case a^i is taken as the money won by cloud C_i. then the amount of money $mC_j^i \in C_i$ earns is: $\bar{p}_j^i = y_j^i \cdot (\frac{1}{2}a^i) + \bar{y}_j^i \cdot (\frac{1}{2}a^i w_j^i)$. Here, like the previous case, y_j^i and $\bar{y}_j^i$ are the indicator functions defined as:

$$y_j^i = \begin{cases} 1, & \text{if } mC_j^i \text{ is the contributor in } C_i \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

and

$$\bar{y}_j^i = \begin{cases} 1, & \text{if } mC_j^i \text{ is not the contributor in } C_i \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

If, mC_j^i is the contributor in C_i then it is taken that $\frac{1}{2}a^i$ will be given to mC_j^i and $\frac{1}{2}a^i$ will be divided based on the weight w_j^i corresponding to mC_j^i. It is not a bad idea to give the contributor the half of the amount won, which will definitely boost the contributor and give him the luxury of providing quality services.

It is assumed that each mC_j^i is associated with a weight. When a new mC_j^i joins the cloud C_i, then a small weight w_j^i is assigned to it and its score increases by 1 if its data is invoked by other cloud later. Thereby the remaining amount is divided by a proportional share mechanism. So, the total payment made by an mC_j^i over all transactions can be defined as

$$\hat{p}_j^i = \sum_{i=1}^{\hat{k}_1} p_j^i - \sum_{i=1}^{\hat{k}_2} \bar{p}_j^i \tag{5}$$

where $\hat{k}_1$ is the number of transactions for which mC_j^i is charged some money and $\hat{k}_2$ is the number of transactions where it earned some money.

4 Several solution concepts and definitions

In this section, the brief overview of the substantially used solution concepts and several definitions in the rest of the paper, is provided.

4.1 Mechanism design

Mechanism design−'*The Science of rule making*'− is an elegant and well developed sub area of *game theory* Nisan et al (2007), Roughgarden (October 2013a). It deals with designing the rules of the systems with *strategic* participants (or *players*) Belleili-Souici (2017) that have their own interest, may not be same as that of the *mechanism designer's*. By *strategic* we mean that, the participants can game the system in order to gain. The bottom line is, when you are designing the system like "*a tournament*" or like "*an auction*" or like "*a computer networks*" that have *strategic* participants, it is the rules of the system that matters. Talking in terms of application areas, the field of mechanism design has widespread application domains but not limited to *spectrum auctions* Nisan et al (2007), *kidney exchange* Nisan et al (2007), Roughgarden (October 2013b), *matching residents to the hospitals* Nisan et al (2007), Gale and Shapley (2013), etc.

4.2 Prisoner's dilemma

This is one of the well known and extensively studied problems that is modeled using *game theory* Nisan et al (2007). Two individuals P_1 and P_2 are arrested for allegedly committing a crime and are placed in separate prison cells. Each prisoner is interrogated in their respective prison cell independently and they have two possible choices (or strategies) *confess* (C) or *not confess* (NC). If both the prisoners follow the *strategy* namely NC, then it is impossible for the interrogating officer to prove charges against the prisoners. The consequence to which is, the two prisoners will be imprisoned for the short period of time say for 3 years. On the other hand, if only one of the two prisoners follow the strategy namely C, then in that case his imprisonment time will be reduced from 3 years to 1 year, and will be used as a witness against the other prisoner, who in term will be imprisoned for 8 years. Finally, if both of them follow the strategy namely C, then they both will be incentivized for cooperating with the interrogating officers and will be imprisoned for 5 years each instead of 8 years. The *cost matrix* below shows the cost incurred for these four outcomes.

$P_1 \backslash P_2$	NC	C
NC	$(-3,-3)$	$(-8,-1)$
C	$(-1,-8)$	$(-5,-5)$

The left component of any entry represents the cost incurred by P_1 for that outcome and right component of the entry represents the cost incurred for P_2. The only stable solution or *Nash equilibrium* is the entry $(-5,-5)$, rest other three entries are unstable. By unstable we mean that, at least one of the two prisoners can increase the incurred cost by unilateral deviation.

4.3 Useful Definitions

Truthful: It means that, no participating agent can gain by misreporting their private information(s). More formally, if the utility relation $u_i \geq u'_i$ holds keeping in mind that u_i is the utility of agent *i* when he is reporting his true type v_i and u'_i is the utility of that agent when he is reporting any other type $v'_i \neq v_i$.

Individual rationality (IR): By IR we mean that, by taking part into the auction, the agents receive a non-negative utility. Formally, it can be said that $u_i = p_i - v_i \geq 0$.

Budget balance (BB): By BB we mean that, the sum of all the monetary transfers between the participating agents is less than or equal to zero.

Nash equilibrium (NE): A strategy vector $s \in S$ is said to be a *Nash equilibrium* if for all players *i* and each alternate $s'_i \in S_i$, we have that $u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i})$. More formally, no player can improve his/her payoff by unilateral deviation.

5 Proposed Mechanism

In this section we propose an auction based DaaS algorithm for the framework discussed in the earlier sections. The algorithm is termed as Auction Based DaaS (ABDaaS). The ABDaaS algorithm has five main components:

- `Main_Routine`
- `Identify`
- `Run_Auction`
- `Set_Buyer_Price`
- `Set_Seller_Price`

Algorithm 1 Main_Routine

for $t = 1, 2, \ldots$ **do**
  Query is made for $mC_j^i \in C_i$
  if data is in C_i **then**
/* Update the payment of mC_j^i */
    $mC_j^i \cdot p \leftarrow mC_j^i \cdot p$ + FC
/* FC is some fixed cost to maintain infrastructure */
  else
/* Search for the other clouds for data */
    $\underline{i} = i$
    $S \leftarrow$ Identify (C $\setminus C_i$)
    S', v', mC, $i' \leftarrow$ Run_Auction (S)
/* $S' \rightarrow$ which cloud will provide the data
  $v' \rightarrow$ Second price
  $mC \rightarrow$ which micro-cloud inside S' contributed
  $i' \rightarrow$ The index of S' */
    Set_Buyer_Price ($mC_j^{\underline{i}}$, v')
    Set_Seller_Price (S', v', mC, i')
  end if
end for
end

If the data is available within the BC where the micro-cloud belongs, a fixed payment is made by the micro-cloud. In the else part auction is run. First `Identify` routine (see Alg. 2) searches for the cloud agents who can provide the data and then an auction is run with `Run_Auction` (see Alg. 3) based on the framework of Vickrey auction Vickrey (1961) that is cast into reverse auction setting in our problem. The `Set_Buyer_Price` and set the payment of the buyers and in the `Set_Seller_Price`, the payment of the $mC_j^i \in C_i$ who contributes and the payment of all other micro-clouds in the set $C_i - mC_j^i$ are made.

Algorithm 2 Identify ($\bar{S}$)

$S \leftarrow \phi$
for $i = 1\ to\ |\bar{S}|$ **do**
  if data available to $\bar{S}_i$ **then**
    $S \leftarrow S \cup \{\bar{S}_i\}$
  end if
end for
return S

Algorithm 3 Run_Auction (S)

$v \leftarrow \phi$
/* Collection of Bids */
for $i = 1$ to $|S|$ **do**
    $v_i \leftarrow bid(S_i)$
    $v \leftarrow v \cup \{v_i\}$
end for
/* Selecting Winner */
$i = \text{argmin}_{j:v_j \in v}\, v_j$
$i' = i$ ▷ *Remember the index of the cloud selected*
$S' \leftarrow S_i$
$S = S - S_i$
/* Selecting the second highest bidder for payment */
for $i = 1$ to $|S|$ **do**
    $v_i \leftarrow bid(S_i)$ /* storing all bids except the winner in v_i */
    $v \leftarrow v \cup \{v_i\}$
end for
/* Selecting the second highest bidder */
$i = \text{argmin}_{j:v_j \in v}\, v_j$
$v' = v_i$
$mC \leftarrow$ extract (S') ▷ *Which micro cloud served the data*
return $(S',\ v',\ mC,\ i')$

Algorithm 4 Set_Buyer_Price (mC_j^i, v')

$mC_j^i \cdot p = mC_j^i \cdot p + v'$

Algorithm 5 Set_Seller_Price (S', v', mC, i')

for $j = 1$ to $|S'|$ **do**
    if $mC = mC_j$ **then**
        $mC_j^{i'} \cdot \bar{p} = mC_j^{i'} \cdot \bar{p} + \frac{1}{2}v'$
/* $\bar{p}$ is the payment earned and p is the payment spend */
        $mC_j^{i'} \cdot \bar{p} + \frac{1}{2}v' \cdot \frac{1}{|S'|-1}$ (*equal share*)
        or $mC_j^{i'} \cdot \bar{p} = mC_j^{i'} \cdot \bar{p} + \frac{v'}{2} \cdot \frac{mC_j^{i'} \cdot w_j^{i'}}{\sum_{mC_j^{i'} \in S' - mC} mC_j^{i'} \cdot w_j^{i'}}$ (*proportional share*)
    end if
end for

6 Analytics of the proposed method

6.1 Time Complexity

In each round, time complexity can be measured as follows: the algorithm `Identify` will take $O(n)$ time. The `Run_Auction` will take $O(nlogn)$ time as the simplest implementation of $argmin()$ may be a sorting. For pricing schemes two subroutines are used : 1) `Set_Buyers_Price` and 2) `Set_Seller_price`. `Set_Buyers_Price` will take $O(1)$ time, where as `Set_Seller_price` will take $O(m)$ time where $m < n$. So, the average time complexity is $O(nlogn)$.

6.2 Correctness of the proposed algorithm

For correctness of the algorithm we have to give emphasis on the main aspect of the proposed algorithm $i.e$ pricing. It is to be shown that, when a cloud agent i is securing information, its payment being updated properly. Think all micro-clouds in a two dimensional array; where each row corresponds to a micro-cloud mC_i and the column corresponds to the two attributes $mC_i \cdot p$ and $mC_i \cdot \bar{p}$ along with others.

When a query is made, $mC_i \cdot p$ and $mC_i \cdot \bar{p}$ either incremented by 0 or FC or some quantity Δ (where, $\Delta = \frac{1}{2}v' \cdot \frac{1}{|S'|-1}$ or $\frac{v'}{2} \cdot \frac{mC_j^{i'} \cdot w_j^{i'}}{\sum_{mC_j^{i'} \in S'-mC} mC_j^{i'} \cdot w_j^{i'}}$) as can be observed from the `Main_Routine` or from `Set_Buyer_Price` and `Set_Seller_price`.

- In the `Main_Routine`:

  $mC_i \cdot p = mC_i \cdot p + FC$, /*an increment*/
  or $mC_i \cdot p = mC_i \cdot p + 0$, /*not the corresponding cloud.*/

- In the `Set_Buyers_Price`

  $mC_i \cdot p = mC_i \cdot p + v'$, /*an increment by the auction price*/
  or $mC_i \cdot p = mC_i \cdot p + 0$, /*if not the corresponding cloud*/

- In the `Set_Seller_price`

  $mC_i \cdot \bar{p} = mC_i \cdot \bar{p} + \frac{1}{2}v'$, /*an increment if the micro-cloud is the main contributor */
  or $mC_i \cdot \bar{p} = mC_i \cdot \bar{p} + \Delta$, /*if the micro-cloud is not the main contributor but belongs to C_i */
  or $mC_i \cdot \bar{p} = mC_i \cdot \bar{p} + 0$. /* if the micro-clouds does not belong to C_i. */

This argument shows that the payment of each micro-cloud is updated when the corresponding micro-cloud is involved in the transaction.

Lemma 1: *Fixed payment doesn't affect the auction.*

The payment of any micro-cloud mC_j^i at any round $t \in T$ is given by $p_j^i = x_j^i \cdot \sigma_j^i + \bar{x}_j^i \cdot \bar{\sigma}_j^i$. The **if** part of ABDaaS (`Main_Routine`) is responsible for $x_j^i \cdot \sigma_j^i$ and **else** part contributes $\bar{x}_j^i \cdot \bar{\sigma}_j^i$ and the indicator function depicts the fact that at any round either $x_j^i \cdot \sigma_j^i$ will be resulted or $\bar{x}_j^i \cdot \bar{\sigma}_j^i$ will be resulted. This confirms that fixed payment does not affect the auction. ■

Theorem 2: *Auction proposed in ABDaaS is Truthful*

By truthful it is meant that in the auction cloud agents cannot gain by manipulation. Here the utility for any cloud agent i is defined as:

$$u_i = \begin{cases} p_i - v_i, & \text{reverse auction settings.} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

where p_i is the payment made to the seller who wins and v_i is his original valuation.
Now, we observe that:

Case 1: *If a seller wins and gives a valuation less, he still wins and utility $\hat{u}_i = u_i$. If he gives a valuation $\hat{v}_i > v_i$, then again two cases arise: he can win or lose. In the win case, his utility $\hat{u}_i = u_i$ and we can say no gain is there. In the losing case, $\hat{u}_i = 0 < u_i$ and hence no gain.*

Case 2: *If a seller loses by reporting his true valuation. With a similar argument of Case 1, it can be proved that no gain is achieved in this case also. So by manipulation an agent can't gain.*

■

6.3 Participation of the Agents in ABDaaS

Table 1 Table x.a

	P	NP
P	1, 1	-2, 3
NP	3, -2	-1, -1

Table 2 Table x.y

	P	NP
P		-2, 3
NP		-1, -1

Table 3 Table x.x

	P	NP
P	1, 1	
NP	3, -2	

Now we will analyze (similar in line with Axelrod and Hamilton (1981), Roughgarden (October 10, 2016)) the behavior of the BC from a game theoretic perspective and will show that it is better for the BCs to participate in the auction. When a BC, say $C_i \in C$ needs some data, we have to argue that any other BC, say C_j (where $j \neq i) \in C$ should also participate and gain in the future. So, we can perceive the behavior of the BCs as a game (participate or not) played pairwise by any (C_i, C_j) pair. For any $C_i \in C$, there are two strategies possible either participation (P) or non-participation (NP).

Non-participation (NP) in the auction means enjoying other's service locally and that involves a positive cost 3. Participation (P) against (NP) is that you need to deploy an agent or a set of agents to bid for you which we call an overhead cost (even if he is earning some money by participating) and denoted by -2. In (NP, NP) case neither agent deploying anybody and the service may have to be taken from outside thereby causing each agent $(-1, -1)$. For (P, P) case both will enjoy the service locally and hence a positive payoffs $i.e.$ $(1, 1)$. The whole payoff matrix is given in Table 1. Given this cost matrix, we can observe that the only stable solution (a Nash equilibrium) in this case is $(-1, -1)$ as in this case, any agent deviates unilaterally will be a loser. Say for example, the row player deviates and play P. The other player will be remaining fixed as he is deviating unilaterally. The strategy is shown in the Table 2.

So, from (-1), he is now having (-2) that is even worse. Unilateral deviation will not be fruitful and leads (NP, NP) to Nash equilibrium. We can take any other strategy, say $(P, P) = (1, 1)$. Suppose row player deviates. It will route us to the case (NP, P) and the payoff in isolation is shown in the Table 3.

We perceive that the increase in payoff is $3 - 1 = 2$. Unilateral deviation clinches some amount of gain and hence (P, P) is not an stable solution ($i.e.$ incentive to deviates). Now the observation so far is specified in Lemma 3.

Lemma 3: *In ABDaaS defection (Non-participation) is the equilibrium solution for one round auction.*

Consider any arbitrary pairs (C_i, C_j) as the two players or the agents. From Table 3, it is observed that (P, P) is not the equilibrium solution as at least one player may have better payoff with unilateral deviation. In the similar line we can argue that (P, NP) and (NP, P) case is also not a stable solution $i.e.$ not reaching to the equilibrium solution. However from Table 2 it is clear that (NP, NP) is a stable solution as unilateral deviation of neither player is fruitful for the agent under consideration. ■

We see just now that $C_i{}'s$ may not participate when the data are demanded from some arbitrary $C_j \in C$ and the system (exchanging data as a service) may eventually collapse. To have the system up and running, the agents $C_i{}'s$ should participate. However, the Lemma 3 is showing that participation is not a stable solution. If we take a clinical look we can see that in Lemma 3, we have assumed that only one time the auction will be executed. Here lies the catch. In $ABDaaS$ we will have multiple auction rounds in sequence. Again, if we take a deeper look at Table 1, we can conclude that the game in Table 1 resembles the famous Prisoner's Dilemma game and as the game in Table 1 will be played multiple rounds, we can model the auction rounds in $ABDaaS$ with repeated Prisoner's Dilemma. First let us think the auction repeats for k rounds which is fixed a priori. Will this k number of iterations of the auction rounds be leading to the co-operation (participation) in the long run ? The answer is no. That we can prove by a technique called backward induction. In forward induction we start from the base case and move forward, while in backward induction we first make settlement at last, then go backward till the best possible decision is made in every iteration. Before analyzing the auction rounds in $ABDaaS$ first the rules of the auction rounds to be specified.

- We have a pair of clouds C_i and C_j where $i \neq j$ and they play the Prisoner's Dilemma game for k rounds with $k > 0$.
- In each round they take their decision in parlance of the payoff matrix of Table 1 and the total payoffs they accumulate is the sum of the payoffs of all the k rounds.

- The decision taken in the past is to be considered while taking decision at present. So present can depend on the past.

Once this realistic model is specified, the nontrivial question is, what will happen in this iterative version of the auction rounds a Participation or not? One may think that Participation may emerge in this model. However if we take a bird's- eye view, we can show that, still Participation is not a best response. This is presented in the Lemma 4.

Lemma 4: *For a finite number of auction rounds, defection (Non-participation) is the best response of any arbitrary $C_i \in C$.*

We will prove this by backward induction. With the philosophy of backward induction, we first consider the k^{th} round. By definition, after this round there will be no more rounds and hence every C_i will take the fact into consideration that, it is playing the Prisoner's Dilemma only one time. As we know that defection is the best response for one shot Prisoner's Dilemma, at the last k^{th} round, both the players (C_i and C_j) will defect. Now come to the $(k-1)^{th}$ stage $i.e.$ one round back. Players already has seen that at k^{th} round players will defect by default. So, this $(k-1)^{th}$ stage will appear to both the player as one-shot Prisoner's Dilemma again and hence non-participation (defection) again. We can conclude, that if we back inductively (backward induction) till the first round defection will emerge as the best response.

■

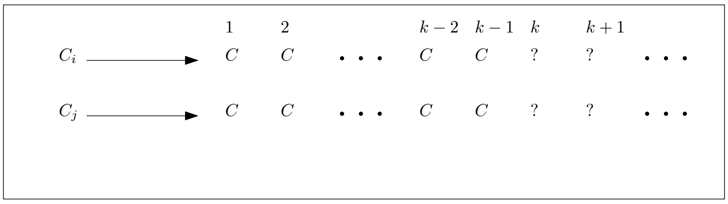
Just now we have seen that if the auction rounds run for a fixed finite number of times, by backward induction it is proved that defection will emerge. However in our case, a-priori we don't know how many auction rounds will be executed. This observation will play a key role to show that in this situation co-operation may emerge. With uncertainty in auction rounds, probability will be involved in the model. We can assume that the auction round stops with probability p and it continues with probability $1 - \mathbf{p}$ $i.e.$ any arbitrary (C_i, C_j) pair plays Prisoner's Dilemma again with probability $1 - \mathbf{p}$. Other modeling criteria $i.e.$ the total payoffs are calculated by summing up the payoffs of each individual auction round. Here the objective of any arbitrary player (C_i) is to maximize his or her expected payoffs. We will further analyze the randomness in auction rounds through the lens of two most famous strategies namely:

- Grim-Trigger (GT)
- Tit-For-Tat (TFT)

Out of these two, GT is more stringent and TFT is more soft. In GT if some player defects in i^{th} stage, then the other player will show him the red card forever from the next round onward, even if the other player shows a good gesture (co-operation) afterward. In TFT if a player defects in one round the other also defects and if he co-operates again the other player forgives his misbehave and comes back to the co-operation from the next round. For our further discussion co-operation and participation will be used synonymously and the same for defection and non-participation.

6.4 Analysis with GT

We start with co-operation, say C_i and C_j co-operates up to stage $k-1$ as follows:



When C_j sees that if C_i participates (co-operates) in $(k-1)^{th}$ stage, then what should be his decision in the next round ? whether he will co-operate or not in k^{th} stage and there on ? First after $(k-1)^{th}$ stage it is known that another round will be there and from $(k+1)^{th}$ stage randomness is inculcated in the auction rounds. We now see the $(k-1)^{th}$, k^{th} and $(k+1)^{th}$ stage in isolation and can summarize the payoffs below:

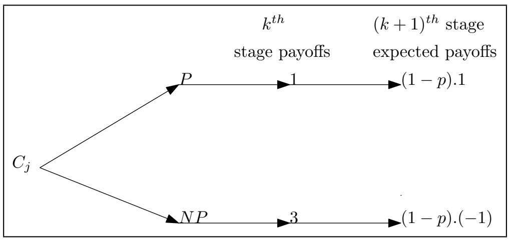


Figure 2: Payoff in isolation

In $Figure.2$ C_j's strategy and its corresponding payoffs are provided under the consideration that in case in $(k-1)^{th}$ stage a co-operation happens, and if we think meticulously we will see that this case is non-trivial. If C_j plays P, then its payoffs is 1 in k^{th} stage as i will also play P according to the GT. Likewise the case for NP $i.e.$ when C_j plays NP. Similarly in $(k+1)^{th}$ stage the payoffs (expected) is calculated, when in k^{th} stage C_j plays P. The expected payoffs in $(k+1)^{th}$ stage is calculated as follows:

When the game stops, the payoff is 0, otherwise the payoffs are decided from Table 1. In any stage the auction round either stops or continues. Let us define a random variable X_i denoting the payoffs in $(k+1)^{th}$ stage onwards for co-operation.

So, by definition of expectation we get the expected payoffs for co-operation.

$$E[X_i] = \sum_x x.P_r\{X_i = x\}$$

$$= 1.(1-p) + 0.(p)$$
$$= (1-p)$$

Here $x = 1$ is the payoff associated with co-operation. Similarly, we can define the $\bar{X}_i$ as the random variable for the defection. So,

$$E[\bar{X}_i] = \sum_x x.P_r\{\bar{X}_i = x\}$$

$$= (-1).(1-p) + 0.(p)$$
$$= -(1-p)$$

If X is the random variable to denote the total payoffs over k rounds after i^{th} round. We can say $X = X_1 + X_2 + \ldots + X_k = \sum_{k=1}^{K} X_k$ where X_1 is the $(i+1)^{th}$ round and so on. If we take expectation both side we get

$$E[X] = E\left[\sum_{k=1}^{K} X_k\right]$$
$$= \sum_{k=1}^{K} E[X_k]$$
$$= \sum_{k=1}^{K} (1-p)$$
$$= K(1-p)$$

Similarly we can find $E[\bar{X}] = -K(1-p)$. At this stage we can formulate our final Lemma 5.

Lemma 5: *When randomness is involved in auction round, participation (co-operation) emerges.*

Let us sum-up the payoffs of i^{th} round and subsequent k uncertain rounds, both for participation and non-participation.
For participation:

$$1 + k(1-p) \tag{7}$$

For non-participation:

$$3 - k(1-p) \tag{8}$$

For participation to be emerges

$$1 + k(1-p) \geq 3 - k(1-p)$$
$$\Rightarrow k(1-p) + k(1-p) \geq 2$$
$$\Rightarrow 2k(1-p) \geq 2$$
$$\Rightarrow k(1-p) \geq 1 \tag{9}$$

If we put $p = \frac{1}{2}$ $i.e.$ with 50% chance the auction repeats, equation 9 becomes

$$k(1-\frac{1}{2}) \geq 1$$

$$\Rightarrow k\frac{1}{2} \geq 1$$

$$\Rightarrow k \geq 2$$

If $p = \frac{1}{3}$, $k \geq \frac{3}{2}$

If $p = \frac{2}{3}$, $k \geq 3$

This k value shows that from any arbitrary i^{th} round, if we consider randomness, very fast the participation payoffs supersede the non-participation payoff even if the auction round stops with high probability ($p = \frac{2}{3}$). This proves our claim. ■

7 Experimental Results

In this section, experiments have been carried out in order to measure the performance of our proposed mechanism $i.e.$ ABDaaS. In order to validate our results we have taken the help of two probability distributions such as uniform distribution (UD) and normal distribution (ND). The bid values of the clouds are generated using UD and ND. The performance of our proposed mechanism is measured on the ground of total payment made to the clouds.

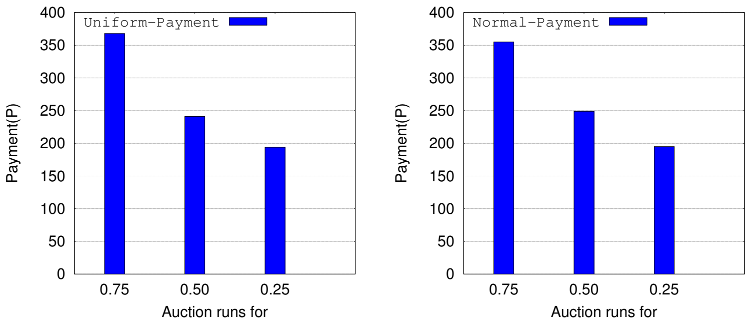
7.1 Simulation Set-up

For the simulation purpose, we have considered the number of $C_i{}'s$, are in between $(50, 70)$ and each C_i consists of micro clouds and the number of micro-clouds are taken in the range $(15, 50)$. In case of UD, the bid value of each C_i is uniformly distributed over $[100, 400]$. The bid value of C_i in case of ND is parameterized by the mean 250 and standard deviation 100. The unit of bid values are in \$.

In our scenario, every time the auction will not be taking place for the data allocation purpose. The auction will be taking place only when the micro cloud fails to get the required data within the in-house cloud. In order to show the impact of data available in-house or outside of the cloud on the total payment made by the micro-clouds, we have considered three cases. The three cases are: 1) $\gamma_1 = .25$ $i.e.$ with probability .25 the requests are fulfilled from outside of the in-house cloud, 2) $\gamma_2 = .50$ $i.e.$ with probability .50 the requests are fulfilled from outside of the in-house cloud and 3) $\gamma_3 = .75$ $i.e.$ with probability .75 the requests are fulfilled from outside of the in-house cloud. The total payment paid by all micro-clouds to all queries made by the users is calculated and depicted in the simulation. The total payment, on one sample run consists of the payment of fixed cost FC_i and Auction cost A_j to be summed up over all queries and could be given by $\bar{P}_k = \sum_{i=1}^{(1-\alpha)*100} FC_i + \sum_{j=1}^{\alpha*100} A_j$. Here, α is how much percentage of the total iterations is devoted to auction. We have run the process on the same data set over $K = 100$ times and then we have taken the average to calculate the final payment P and is given by $P = (\sum_{k=1}^{K} \bar{P}_k)/K$. The different impacts of payment P against the number of times the data are consulted from in-house and outside.

7.2 Result Analysis

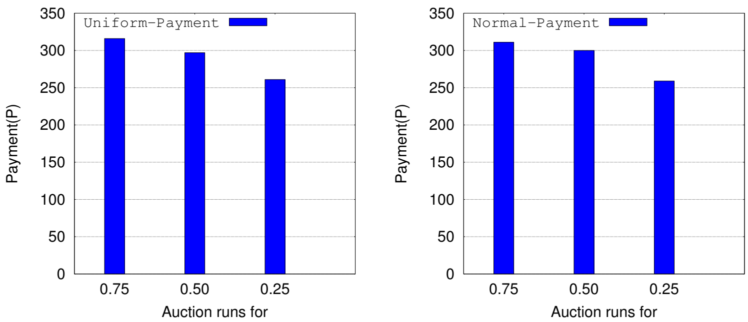
Now for the scenario 1, when the fixed cost (FC) is 100, it can be seen in Figure. 3a and Figure. 3b that the total payment made to the clouds in case of γ_3 is more than the total payment made to the clouds in case of γ_2 is more than total payment made to the clouds in case of γ_1. It is due to the fact that, in this case, when the data are accessed from outside, the in-house cloud $i.e.$ when auction comes into picture the payment made to the clouds are higher than FC.



(a) Total payment when FC=100 UD (b) Total payment when FC=100 ND

Figure 3: Total payment comparison when FC=100

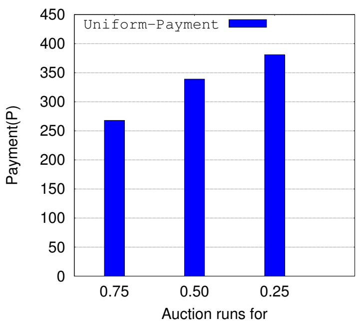
Now for the scenario 2, when the fixed cost (FC) is 250, it can be seen in Figure. 4a and Figure. 4b that the total payment made to the clouds in case of γ_3 is better than the total payment made to the clouds in case of γ_2 and γ_1. In this case, FC=250 and the data are accessed from outside, the in-house cloud $i.e.$ when auction comes into picture the payment made to the clouds are higher than FC.



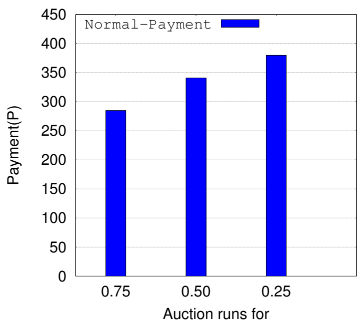
(a) Total payment when FC=250 UD (b) Total payment when FC=250 ND

Figure 4: Total payment comparison when FC=250

Now for the scenario 3, when the fixed cost (FC) is 400, it can be seen in Figure. 5a and Figure. 5b that the total payment made to the clouds in case of γ_1 is more than the total payment made to the clouds in case of γ_2 is more than total payment made to the clouds in case of γ_3. However, in the last scenario the data are accessed from outside, the in-house cloud $i.e.$ when auction comes into picture the payment made to the clouds are higher than FC.



(a) Total payment when FC=400 UD



(b) Total payment when FC=400 ND

Figure 5: Total payment comparison when FC=400

8 Conclusion and future works

In this paper we have proposed an auction framework for Data-as-a-Service (DaaS) in cloud computing. The DaaS model has emerged as an important model in cloud computing to provide data on demand to the users. This model is attractive to data consumers, because it enables the separation of data cost and of data usage from the cloud infrastructure cost. In our proposal, how a subset of smaller clouds collaborate and exchanges information (data) is oriented in an auction framework.

In our future work we will address the issue when a micro-cloud needs data from two or more cloud agents. This setting will lead us to the combinatorial auction. Additionally, we plan to evaluate the proposed auction framework under various multi-provider cloud settings.

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