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Research Article

Quality Adaptive Online Double Auction in Participatory Sensing

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Abstract. Agents (specially humans) with smart devices are stemming with astounding rapidity and that may play a big role in information and communication technology apart from being used only as a mere calling devices. Inculcating the power of smart devices carried by the agents in several different applications is commonly termed as participatory sensing (PS). In this paper, a quality adaptive participatory sensing mechanism is presented in an online double auction environment. The proposed algorithm is simulated with a benchmark mechanism that adapts the existing *McAfee's Double Auction* (MDA) directly in the online environment.

Keywords. Participatory sensing; Smart devices; Truthfulness; MDA; Online environment

MSC. 91-XX (Game theory; Economics, social and behavioral sciences)

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1. Introduction

The combination of telephony and computing (concept of intelligence, data processing power, increased memory, and visual display screens) has moulded the era of mobile devices to an unprecedented new era of devices called as *smart devices*. Several remarkable types of smart devices as of the time of writing this paper are smartphones (devices running on Android operating system, Apple iphone, Asus zenfone etc.), smartwatches, smartbands, phablets, tablets etc. Recently, smartphones are becoming increasingly popular around the globe. According to one of the independent market research companies, eMarketer, the number of smartphone users around the globe will surpass 2 billion in 2016 after nearly getting their in 2015 (1.92 billion). The possible usage of participants (*participants and agents will be used interchangeably*) holding a smart devices to acquire and share up-to-date and fine grained information of topics of interest gives rise to a new paradigm in the field of sensor networks called *participatory sensing* (PS). The key benefit of this paradigm is that it empowers crowd of agents to collect and share sensed data from their surrounding environments using their smartphones, for taking several decisions. PS has a wide range of advantages over traditional sensor networks which necessitate the deployment of large number of static wireless sensor devices:

- It is economically feasible because of the existence of smartphones and wireless communication.
- Due to the natural mobility of smartphones, in a particular time period data from large geographical areas can be gathered by the agents.
- The involvement of ordinary citizens and not the professionals in the sensing loop may bring a drastic change (positive) in the lifestyle of the ordinary citizens and they can be mobilized in multifarious social activities with or without money.

PS encompasses a wide range of application areas such as: monitoring the environmental activities, *intelligent transportation systems* (ITS), study on healthcare and well-being, and social network etc. Some examples that could reflect the motivation for this emerging field of sensor networks are:

(1) Road traffic congestion level in a particular city can be analysed by the data sent by the several agents carrying smart devices.

(2) A non-profit group of people (doctors, engineers, professors etc.) can document the damaged condition of the road in the city and can provide the document to the community by means of smart devices.

(3) A fit sports person can upload his daily groove with the help of multiple sensors embedded in his cell phone and few wearable sensors hoping to make changes in the lifestyle of the huge community.

(4) Tracking the physical location of the jeopardized/endangered species (Tiger, Deer, etc.) by the information provided by the agents (agents with smart devices).

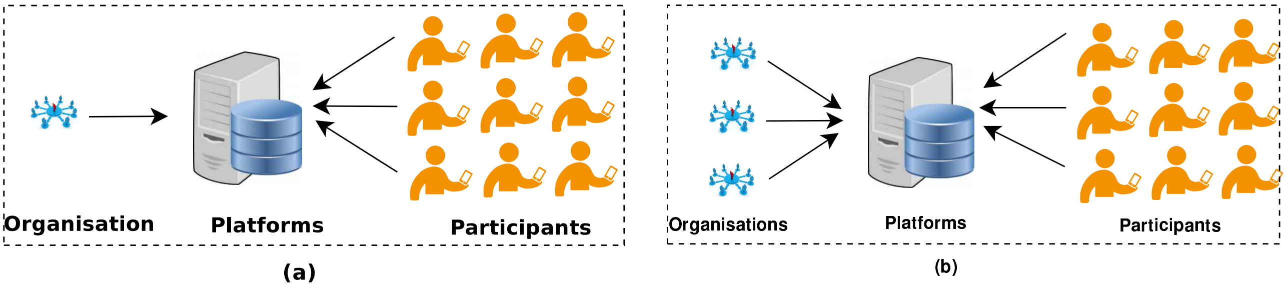

Figure 1. **(a)** Single seller multiple buyers. **(b)** Multiple sellers multiple buyers.

The process of collecting the data by an agents carrying smatphones becomes challenging because of the following issues: (1) How to motivate the agents with smartphones to take part in the system? (2) As the agents, taking part in the system are utilizing their resources (such as CPU, power consumption, etc.), they need to be given some incentives in return of that. If the incentives are provided, how much can be offered? (3) If some agents are providing the data of distinct quality, how to grab such data, so as to serve the organization with quality rich data. In Figure 1(a) and Figure 1(b), the architecture of the most discussed models in the PS is depicted. The setup with which the literature of the PS started growing since its inception is that, a single task publisher (organisation or buyer) wants to complete their single task by multiple agents as shown in Figure 1(a). The issues related to the challenges mentioned in point 1, 2, and 3 for the setup shown in Figure 1(a) have been endeavoured rigorously in the past. In our paper [2] [28], the set-up shown in Figure 1(b) is taken into consideration. We have considered the problem that there are multiple buyers in the market who are trying to collect the data of a single task from the several sellers present in the PS market in an online environment where the agents appear and depart dynamically. The novelty that is introduced in [2] is to develop the game theoretic approach to tackle the challenges mentioned in point 1 and 2. The quality of the data provided by the sellers are not considered in [2] [28]. In [43], though they have addressed the problem in the same double auction environment, but quality sensitive online double auction is not addressed. In this paper a quality sensitive model is developed in an ***o**nline **d**ouble **a**uction **e**nvironment* (ODAE). In our future references, seller, task publisher, an organization will be used interchangeably.

The main contributions of this paper are as follows:

- In the PS, first time quality adaptive multiple sellers-multiple buyers case in an online setting is addressed. As multiple sellers and multiple buyers are present, it is a good choice to model the PS setup with double auction.
- A general framework, in an online environment is proposed when multiple sellers and multiple buyers are present.
- First time a *partial* truthful mechanism is proposed motivated by [4] in ODAE taking quality of data under consideration. By partial we mean that the mechanism is truthful in terms of the arrival and departure time (the discussion of arrival and departure time is given later) but not in terms of valuations.

- A substantial amount of simulation is done to validate the performance of our proposed algorithm with a benchmark scheme.

The remainder of the paper is organized as follows: In Section 2, we discuss about some previous works in related domain. In Section 3, we describe the system model and formulate the problem in ODAE. In Section 4, the essential properties exhibited by the **p**roposed **o**nline **d**ouble **a**uction (PODA) are presented. The detailing of the PODA is discussed and presented in Section 5. Further analysis is done in Section 6. The simulation results are given in Section 7. Conclusions and future works are given in Section 8.

2. Literature Review

PS activities being carried out by a large number of users (say *crowd*), who are geographically distributed over a vast area, have shown a great potential in fetching context-aware information over a wide variety of application domains such as healthcare ([13], [23]), places characterization ([5]), indoor localization ([39], [32]), environmental monitoring ([16], [31], [25], [14], [36]) and transportation ([17], [27], [37], [8]). In [16] a novel PS application referred as 'Ikraus' is developed that make use of the data (say sensor data) collected during the countryside flights by the para-gliders to study the thermal effects in the atmosphere. The obvious problem that exists in the PS is to stimulate the agents to contribute in the data collection process ([10], [18], [15]). In [7] the two major research challenges: (a) how to motivate large number of participant to take part in the sensing process, and (b) evaluation of their contribution that exists in the PS is discussed. Some of the recent PS applications ([17], [27], [37], [33]) are based on the voluntary participation. While participating in the PS campaign, smartphone users consume their own resources such as the CPU, power consumption, and more importantly they expose their locations with potential privacy threats. Thus, to drag large number of participants into the PS market some incentive mechanisms are necessary to provide participants with enough incentive as their participation cost. Most of the existing PS applications ([37], [29], [33]) does not consider this point, which may lead to the dissipating of the smartphone users and the deterioration of such a pragmatic field of study. The first study that incorporated incentives in PS is made in [19], [34] by using reverse auction. In [12], [15], [18], [11], [41], [1], some recent ingenious incentive schemes are discussed in detail. In [22] the incentives are paid to the participants chosen as the winner, is the initial *fixed value* decided by the organizer. The problems that may originate in the *fixed value* scheme are: **1)** The participant may not be satisfied by the incentives provided. **2)** The control of giving incentive is with the buyer only. One tool that has got widespread application to model such a situation is the field of auction theory [26] [3]. In [15], the data based on the location is studied under the banner of budget. The payment of the winning agents in [15], is based on [18]. As the participating agents are rational, they may manipulate their bid values to get some extra incentives from PS market. Some incentive compatible mechanisms for the PS environment is proposed in [42], [9], [11]. The literatures discussed above did not consider the quality of the data provided by the agents.

Some quality adaptive schemes are discussed in [42] [38], [40], [1]. In [42], [38], [40], the quality of the data earned by the agents are not combined with the bid values of the agents to have a joint effect in the auction that will be taking place for selecting the winners in the PS system. In [1] an effort is made in that direction by emphasising on the fact that the valuation of an agent is determined jointly by the quality of the data and the bid value of an agent. Recent works in the PS environment are also addressing one of the important metrics in the PS viz. the privacy of the agents supplying the data. Some initial steps are taken by [10], [38], [20], [6], [35] to preserve the privacy of the agents so that, their private information associated with the data are not leaked. In [21], the set-up with multiple buyers and multiple sellers is discussed in static environment. In this, the multiple tasks are to be allocated to multiple participants carrying smartphones and each participant will be allocated a single task.

3. The Model

The double auction scenario in this paper is online in nature that renders the fact that the agents arrive and leave the market dynamically. After a certain interval one auction will be run and we consider a time span $T = \{1,2,\dots,n\}$ on which all the auctions will be explored. The time span T could be 24 hours or 5 days or so. In each discrete time interval $t \in T$, one auction can occur. In the PODA, we have a set of n sellers denoted by $C = \{1,2,\dots,n\}$ and a set of m buyers denoted by $G = \{1,2,\dots,m\}$. In each discrete time interval $t \in T$, a subset of the sellers $C_t^* \subseteq C$ are present, where $C = \bigcup_t C_t^*$ and a subset of the buyers $G_t^* \subseteq G$ are present, where $G = \bigcup_t G_t^*$. At time $t \in T$, pairing between sellers and buyers will be determined i.e. a seller may be anchored with a buyer. When a seller is anchored with a buyer, we call a transaction is occurred. In each discrete time, all the transactions can be expressed as a function $h : T \to R$, where $h(t)$ is the number of transactions that will be occurred during the time period t. In this ODA, an agent (either a buyer or a seller) is characterized by four attributes.

3.1 Private Information

A seller has a private information with which he/she (henceforth he) wants to sell his collected information and is expressed in the ODA in a sealed bid manner. The bids of the ith seller is denoted by $\widehat{b}_i^s$ and henceforth will be mentioned by sell-bid(s) and is also expressed in the ODA in a sealed bid manner. Similarly the buyers' private information with which he buys the sellers' information is termed as buy-bid(s) and is symbolized as $\widehat{b}_i^b$ for the ith buyer.

3.2 Arrival Time and Departure Time

As the modelling is done in an online environment, an agent has to report his arrival time and departure time. The arrival time signals, when an agent, first time, enters into the market. This arrival time is represented by $\widehat{a}_i^s$ for ith seller and $\widehat{a}_i^b$ for ith buyer. The departure time is represented as: $\widehat{d}_i^s$ for ith seller and $\widehat{d}_i^b$ for ith buyer. The departure time signifies, when an agent leaves the market. These two attributes: arrival time and departure time make the design of truthful auction complicated in online environment. By misreporting the arrival and departure time an agent can gain in ODA environment. They can misreport within the arrival-departure window. This assumption is realistic in an online environment [4], [2], [30].

3.3 Quality

This is another important attribute, that is contemplated in this model. In this paper, only the seller side quality is considered which is realistic, as the fabrication of the future course of action by the service provider (buyers) will be decided based on the quality of information that is produced by the seller. The quality is denoted by q_i for agent i. The quality vector is denoted by $q = \{q_1, q_2, \ldots, q_n\}$. The quality function over time t is $Q : T \to R$. As the seller will be weighted by their quality, the specification of the quality is designated as: lesser is the number better is the quality. The quality of an agent can be calculated on the fly based on his past performance and present information content. For our simulation purpose, the quality will be generated randomly based on a random number generator. These four attributes, in combination, will be termed as the type of an agent. The type of ith agent can be formally defined as:

$$\widehat{z}_i = \{\widehat{a}_i, \widehat{d}_i, \widehat{b}_i, q_i\}$$

The type of ith seller will be denoted by $\widehat{z}_i^s$ and is given by:

$$\widehat{z}_i^s = \{\widehat{a}_i^s, \widehat{d}_i^s, \widehat{b}_i^s, q_i\}$$

The type of ith buyer will be denoted by z_i^b, where

$$\widehat{z}_i^b = \{\widehat{a}_i^b, \widehat{d}_i^b, \widehat{b}_i^b, q_i\}$$

Here, the quality of each buyer i is considered as 1 $i.e.$ $q_i = 1$.

One more notation that will be used frequently is $\widehat{z}_{-i}$. By $\widehat{z}_{-i}$ we mean all the agents except i. So, $(\widehat{z}_i, \widehat{z}_{-i})$ will indicate all the agents. This notation may be interpreted in the same way for (a_i, a_{-i}), (d_i, d_{-i}), (q_i, q_{-i}), (u_i, u_{-i}), and the case may be. By R^r we mean the corresponding vector comprising either the buyers or the sellers, where $R \in \{z, a, d, b, u, \widehat{z}, \widehat{a}, \widehat{d}, \widehat{b}, \widehat{u}\}$ and $r \in \{b, s\}$. The agents are individually rational and they have their own private information in terms of arrival time, departure time and bid values. The quality is not the private information as it is calculated by the third party. Based on the rule of the auction, an agent may be tempted to misreport his arrival time, departure time and bid values. As the enticement is there for misreporting the attributes, the true type of ith agent can be symbolized as $z_i = \{a_i, d_i, b_i, q_i\}$. As an example if $z_i^s = \{10, 12, 20, 1\}$, then $\widehat{z}_i^s$ could be $\{10, 12, 20, 1\}$ or with some misreport $\{11, 12, 18, 1\}$. Throughout the paper it will be assumed that an agent can misreport only within its true arrival and departure time. This assumption is realistic in a sense that, if an agent misreports his arrival time before its true arrival, then he may get the item in some $t \in T$ when he is not there in the market. Similar case will happen for departure time as well. The auctioneer has the flexibility of deciding the interim period between two consecutive auctions. This interval may be 10 minutes or may be 1 hour or anything as demanded from the situation of the market. As the agents are individually rational, they are utility maximizing. The utility of a buyer u_i^b can be defined as the true value of a buyer minus the payment that is to be paid by him if he wins, otherwise 0. This can be represented formally as:

$$u_i^b = \begin{cases} b_i^b - p_i^b & \text{if } i \text{ wins} \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

Here, p_i^b is the payment made by the buyer i, if he wins in the proposed ODA. Likewise, the utility of a seller can be defined. This will be denoted by u_i^s. In u_i^s, the role of bid values and payment are interchange so as to ensure that the utility is positive. The proposed ODA will be designed in such a way that the payment to a seller is at least greater or equal to its bid values. The u_i^s can be formally represented as:

$$u_i^s = \begin{cases} p_i^s - b_i^s & \text{if } i \text{ wins} \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

Unlike the previous paper [2] [28], here, the type information comprising of one more attribute called quality q_i. The more challenging fact is that, the multiplicative valuation function that is comprising of the declared bid values and the quality of an agent is defined below:

The valuation of a buyer is defined as $v_i^b = b_i^b$ and the valuation of a seller is defined as $v_i^s = b_i^s * q_i^s$. Motivated by [4] [2] we will propose a truthful mechanism in this paper. However, the main challenge is to show that in presence of the quality constraint in the valuation function and in the type profile of the agents, the resulting mechanism is truthful. This quality constraint was absent in [4] [2].

4. Essential properties

The proposed double auction will have several desirable properties that may attract the agents (the seller, the buyer, and the auctioneer). These properties are:

- **Individual rationality (IR):** This property will ensure that by taking part in the auction, the agents receive a non-negative utility. Formally, it can be said $u_i^b \geq 0$, $u_i^s \geq 0$. In the double auction, it also ensure that $p_i^a \geq 0$, where p_i^a denotes the payment received by the auctioneer.
- **Budget balance (BB):** Buyer pays the money, auctioneer collects it, and pays back to the seller. The budget balanced property ensures that $\sum_i p_i^b - \sum_i p_i^s \geq 0$.
- **Truthfulness:** Market needs stability. By truthful property, the ODA reaches to the stability without hassle as every agent's true declared type can provide him more or at least as much as utility than any other declared type. Formally, if z_i is the true type of an agent and $\widehat{z}_i$ is the declared type other than z_i, then this property tells that $u_i \geq \widehat{u}_i$, where u_i is the utility when z_i is reported and $\widehat{u}_i$ is utility when $\widehat{z}_i$ is declared. In this paper a truthfulness is achieved in terms of arrival time, departure time, and with winning agents' bid values and with losing buyers' bid values. It is shown that by declaring manipulated

arrival and departure time an agent can't gain. It is also shown that the winning agents' and even the losing buyers' best response is to report their true bid values. However, the losing sellers may gain by misreporting their sell-bids. As the losing sellers may gain by manipulation of their sell-bids, we call such type of truthfulness as the partial truthfulness.

5. PODA: The Proposed mechanism

5.1 Main Challenge

The main challenge of the proposed mechanism is to emphasise on the quality of the information provided by the seller.

To emphasise more on quality, for finding the valuation the bid value is multiplied by the quality. In other words, the valuation is now the weighted bid value. So, $v_i^s = b_i^s * q_i$. In this paper, $q_i \in \mathbb{N}$. Now, the challenging fact is to associate a number for the quality of an agent. However, another problem appears in front of us that in our proposed algorithm, the seller will be sorted in ascending order based on their valuations. One approach to associate a number to the quality can be: the more number tag is associated with the quality, the better will be the quality. But this may lead to the problem. The bidder with a high bid will still lose as quality will be multiplied. To fix this problem, we have taken a reverse approach, the less will be the number that is tagged with a quality, the better will be the quality. This may give a lower value to a bidder with a high bid and the valuation of a bidder with a low bid can be increased substantially if the quality is bad. For example, in our problem, if $q_i = 1$ and $q_j = 3$, where $i \neq j$, then the quality of the ith seller is better than the quality of the jth seller.

5.2 McAfee's DA: The benchmark mechanism

One of the standard mechanisms that is used in the static environment for fixing the seller-buyer pairs in the double auction setting is the McAfee's DA [24], [4]. Directly adapting the McAfee's DA (MDA) in online environment in each auction round will be our benchmark mechanism. This MDA is extended and applied in the PODA which will be discussed later. To understand the challange of adapting the quality into the system, an example is depicted in Figure 2 by the McAfee's DA.

Illustrative Example. Figure 2 shows a detailed functioning of McAfee's DA. For understanding purpose, the number of buyer is 4 *i.e.* $m = 4$ and the number of seller is 4 *i.e.* $n = 4$ as shown in Figure 2(a). It is to be noted that, the first row in Figure 2(a)-(f) represents the buyers with the buy-bids, the sellers with the sell-bids are represented in the second row of Figure 2(a)-(f). The third row in Figure 2(c) represents the quality values of the respective sellers. In Figure 2(a) and Figure 2(b) the quality parameter of the sellers are not taken into consideration. Meanwhile, in Figure 2(c), the quality parameter is adapted along with the sell-bids. In Figure 2(d) the revised valuation of each seller i is calculated using $v_i^s = b_i^s * q_i$.

The buyers are sorted based on the non-increasing order of their valuations and the sellers are sorted in non-decreasing order of their valuations as shown in Figure 2(e). In Figure 2(b) the winning sellers are with sell-bids 5 and 6 whereas in Figure 2(f) it is shown that the winning sellers are with sell-bids 8 and 10 and these sellers were not in the winning set previously without quality.

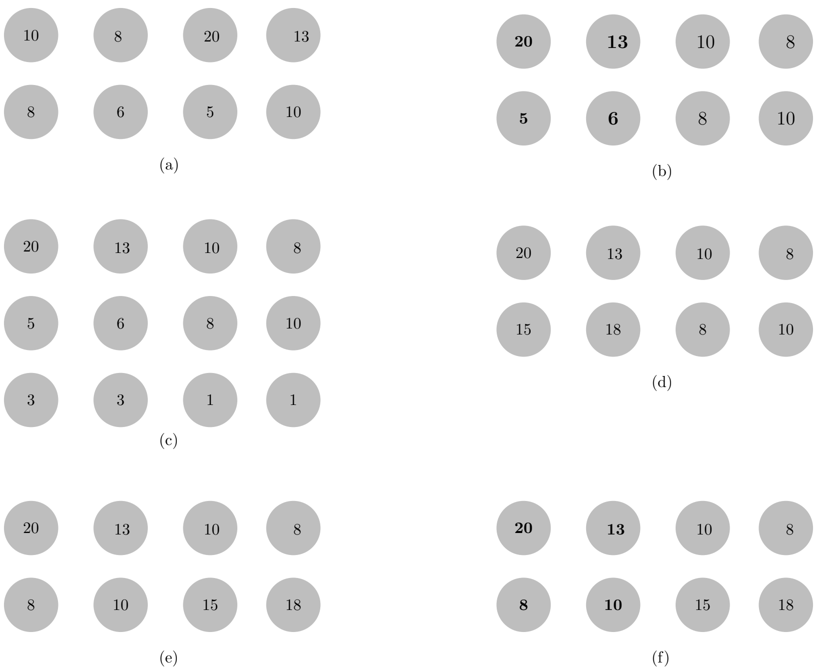

Figure 2. Interpretation of McAfee's DA.

5.3 Calculation of Payment

The PODA mechanism is heavily dependent on a payment function which has to be agent independent i.e. for calculating the payment for a particular agent, he has to be out of the market. Motivated by [4] [2] we have designed the payment function. When a buyer's payment is to be calculated that buyer and the seller with minimum sell-bid is to be taken out of the market. While for a seller, that seller and the maximum bid will be taken out of market. This heuristic will help us to apply the modified McAfee's rule [4] of the static DA, after taking an agent out of the market. All the valuations of the buyers are sorted in descending order and all the valuations of the sellers are sorted in ascending order. For calculating the payment of each agent, the first index of the sorted list is to be returned, comprising the condition v_i^b-$v_i^s < 0$. We will denote this by $x = F(v^b, v^s)$.

Here the function $F(\cdot)$, will return that index and that will be stored in x. For defining the payment, we further require to fetch the valuation of the buyer and the seller at the index position x. Let us further denote the valuation of the buyer at the index position x by $val^b(x)$ and by $val^s(x)$ the valuation of the seller at x. For calculating the payment, we will take the average of the valuation of seller at index x and the valuation of buyer at x $i.e.$ $avg = \frac{val^b(x)+val^s(x)}{2}$. This is the extension of the McAfee's DA, that may increase a valid transaction in each auction round. Now, the payment rule as follows:

for ith buyer:

$$p_i^b(t) = \begin{cases} avg & \text{if } val^b(x-1) > avg \text{ and } val^s(x-1) < avg \\ val^b(x-1) & \text{otherwise} \end{cases} \tag{5.1}$$

for ith seller:

$$p_i^s(t) = \begin{cases} avg & \text{if } val^b(x-1) > avg \text{ and } val^s(x-1) < avg \\ val^s(x-1) & \text{otherwise} \end{cases} \tag{5.2}$$

In this mechanism, for any particular auction round $t \in T$, there might be two categories of agents. 1) A fresh arrival and 2) agents which are still active. For a fresh arrival the payment is calculated by the following payment function:

$$\alpha^b(t) = max_\tau\{p_i^b(\tau)\}, \quad \text{where } \tau \in \{d_i - k, \dots, t\} \tag{5.3}$$

$$\alpha^s(t) = min_\tau\{p_i^s(\tau)\}, \quad \text{where } \tau \in \{d_i - k, \dots, t\} \tag{5.4}$$

Here k is the tolerance of an agent which is the maximum gap allowable between the arrival and departure of any arbitrary agent i. This k signifies the true online environment.
For the active agents the payment function will be

$$\alpha^b(t) = max\{\alpha^b(t-1), p_i^b(t)\}. \tag{5.5}$$

$$\alpha^s(t) = min\{\alpha^s(t-1), p_i^s(t)\}. \tag{5.6}$$

If buyer is selected as the winner, then $p_i^b = \alpha^b(t)$, and similarly for a seller $p_i^s = \alpha^s(t)$.

5.4 Sketch of PODA

The principal components of the PODA mechanism is to compute a bid independent payment function and then according to that set the transactions i.e to pair a buyer with a seller. In a nutshell, the algorithm first collect all the bids who are active at time $t \in$ T. The active bids, consist of the bids that are not priced out in the earlier auction round and bids which are fresh arrival i.e those bids for which $a_i = t$. The algorithm then computes the payment of each buyer under fresh arrival category by *equation 5* and the payment of seller under fresh arrival category by *equation 6*. For the buyers belonging to the still active category the payment is calculated using *equation 7*. *Equation 8* determines the payment of the sellers belonging to the still active category. If $v_i^b > \alpha^b(t)$ then those buyers remain active *i.e.* not priced out. Similarly, if $v_i^s > \alpha^s(t)$, those sellers are not considered as priced out. The sellers and buyers who are still not priced out are termed as *priceless*. The priceless buyers and sellers are sorted according to their payment in descending and ascending order. Next, the mechanism selects those seller-buyer pairs satisfying the condition $\alpha^b(t) - \alpha^s(t) \geq 0$.

The input to the PODA mechanism are: the set of n sellers C, the set of m buyers G, and the agents are provided in a piece-meal fashion as the environment is online in nature. The output of the PODA is the seller-buyer pairs. More formally, the PODA consists of three phases: *Main routine* (Algorithm 1), *Allocation* (Algorithm 2), and *payment* (Algorithm 3).

First the sub-part of the PODA *i.e.* the *Main routine* phase is discussed and presented. Next the *allocation* phase is addressed. Finally, the *payment* phase is discussed.

The input to the *main routine* are: the set of initial sellers, and the set of initial buyers. The output is the set of transactions (seller-buyer pairs). In line 2 of the *main routine*, the z^s data structure holds the initially present sellers in the market. In line 3, the z^b data structure keeps track of buyers initially present in the market. Line 4 initializes the payment data structure for sellers *i.e.* P_1^* and the payment data structure for buyers *i.e.* P_2^* to ϕ respectively. The *while* loop in line 5 iterates over all $t \in T$. Line 6 captures, all the active sellers $z_i \in z^s$ at any instance $t \in T$ in β_1^* data structure. In line 7, β_2^* data structure holds all the active buyers $z_i \in z^b$ at any instance $t \in T$. In line 8, the β_1 data structure holds the set of fresh arrived sellers from all the available sellers in z^s.

Algorithm 1 Main routine (z^s, z^b)

1: **begin**
2: $z^s \leftarrow$ Initial sellers.
3: $z^b \leftarrow$ Initial buyers.
4: // Subset of sellers and buyers are selected.
5: **while** $t \in T$ **do**
6: $\quad \beta_1^* \leftarrow$ all active $z_i \in z^s$, where $t > a_i$ and $t < d_i$
7: $\quad \beta_2^* \leftarrow$ all active $z_i \in z^b$, where $t > a_i$ and $t < d_i$
8: $\quad \beta_1 \leftarrow z_i \subseteq z^s$, where $a_i = t$
9: $\quad \beta_2 \leftarrow z_i \subseteq z^b$, where $a_i = t$
10: $\quad$ **for** each $z_i \in \beta_1$ **do**
11: $\qquad z_i.v_i^s \leftarrow z_i.b_i^s * q_i$
12: $\quad$ **end for**
13: $\quad \beta_1 \leftarrow \beta_1^* \cup \beta_1$
14: $\quad \beta_2 \leftarrow \beta_2^* \cup \beta_2$
15: $\quad \beta_1 \leftarrow$ Sort_ascend(β_1, v^s)
16: $\quad \beta_2 \leftarrow$ Sort_descend(β_2, v^b)
17: $\quad$ Payment (β_1, β_2)
18: $\quad$ Update z^s and z^b based on γ^s and γ^b to indicate who are still active
19: $\quad z^s \leftarrow z^s \cup \{new\ sellers\}$
20: $\quad z^b \leftarrow z^b \cup \{new\ buyers\}$
21: $\quad \gamma^s \leftarrow \phi$; $\gamma^b \leftarrow \phi$; $\beta_1 \leftarrow \phi$; $\beta_2 \leftarrow \phi$
22: **end while**
23: **end**

The β_2 data structure in line 9 captures the set of fresh arrived buyers from all the available buyers in z^b. The *for* loop in line 10 iterates over all the fresh arrived sellers at any instance $t \in T$. In line 11, the valuation component v_i^s of all $z_i \in \beta_1$ is constructed as the product of the bid value of each $z_i \in \beta_1$ and the quality of $z_i \in \beta_1$. In line 13, β_1 holds all the active sellers at time $t \in T$ and the fresh arrived sellers at time $t \in T$. Similarly, β_2 in line 14 captures all the buyers active during time $t \in T$ and the fresh arrived buyers at any instance $t \in T$. In line 15, β_1 is sorted based on the valuation set of the sellers *i.e.* v^s present in β_1.

Algorithm 2 Payment (β_1, β_2)

1: **begin**
2: **for** each $z_i \in \beta_1$ **do**
3:     **if** $a_i == t$ **then**
4:         $\delta_i^s \leftarrow min_\tau\{p_i^s(\tau)\}$
5:     **else**
6:         $\delta_i^s \leftarrow min\{p_i^s(t-1), p_i^s(t)\}$
7:     **end if**
8:     **if** $\delta_i^s > v_i^s$ **then**
9:         $z_i.\delta_i^s \leftarrow \delta_i^s$
10:         $\gamma^s \leftarrow \gamma^s \cup \{z_i.\delta_i^s\}$
11:     **else**:
12:         Seller is priced out
13:     **end if**
14: **end for**
15: **for** each $z_i \in \beta_2$ **do**
16:     **if** $a_i == t$ **then**
17:         $\delta_i^b \leftarrow max_\tau\{p_i^b(\tau)\}$
18:     **else**
19:         $\delta_i^b \leftarrow max\{p_i^b(t-1), p_i^b(t)\}$
20:     **end if**
21:     **if** $\delta_i^b < v_i^b$ **then**
22:         $z_i.\delta_i^b \leftarrow \delta_i^b$
23:         $\gamma^b \leftarrow \gamma^b \cup \{z_i.\delta_i^b\}$
24:     **else**
25:         Buyer is priced out.
26:     **end if**
27: **end for**
28: Allocation(γ^s, γ^b)
29: **end**

In line 16, the buyers in β_2 is sorted based on the valuation set of the buyers *i.e.* v^b present in β_2. In line 17, a call is made to the *payment phase*.

The input to the *payment phase* are: the sorted list of all the sellers present at an instance t *i.e.* β_1, and the sorted list of all the buyers present at an instance t *i.e.* β_2. In line 2 of the *payment phase* the *for* loop iterates over all sellers, $z_i \in \beta_1$. Line 3 checks, the selected seller $z_i \in \beta_1$ is fresh arrival. If the checked condition in line 3, is true then line 4 determines the payment of the selected seller z_i as the minimum of all the payments calculated at each instance $\tau \in [\widehat{a}_i, \widehat{d}_i - k]$. Line 5 takes care of the sellers which are still active. In line 6, the payment of the sellers which are still active is determined as the minimum of all the payments calculated upto the instance $(t-1)$ and the payment calculated at t. Line 8 checks, if the payment of any seller $z_i \in \beta_1$ is greater than the valuation v_i^s of z_i. In line 9, the payment component of z_i is updated with the newly determined payment at line 4 or line 6. In line 10, the γ^s keeps track of all the active sellers $z_i \in \beta_1$. If the condition in line 8 fails, then the sellers are priced out of the market as indicated in line 12 of the *payment phase* of the mechanism. In the priced out case a seller or a buyer can't take part in any of the subsequent auction round, even if his departure time does not expire. In line 15 of the *payment phase* the *for* loop iterates over all buyers, z_i in β_2. Line 16 checks whether the selected buyer $z_i \in \beta_2$ is fresh arrival or not. If the check condition in line 16, is true then line 17 determines the payment of the selected seller z_i as the maximum of all the payments present at any instance τ. Line 18 takes care of the buyers which are still active. In line 19, the payment of the buyers which are still active is determined as the maximum of all the payments upto the instance $(t-1)$ and the payment calculated at t. Line 21 checks, if the payment of any buyer $z_i \in \beta_2$ is less than the valuation v_i^b of z_i. In line 22, the payment component of z_i is updated with the newly determined payment at line 17 or line 19. In line 23, the γ^b keeps track of all the buyers $z_i \in \beta_2$. If the condition in line 21 fails, then the buyers are priced out of the market as indicated in line 25 of the *payment phase*. In line 28, a call is made to the *allocation phase* of the mechanism.

The input to the *allocation phase* are: the set of all active sellers $z_i \in z^s$ denoted as γ^s, and the set of all active buyers $z_i \in z^b$ denoted as γ^b. The output is the winning *seller-buyer* pairs. In line 2 of the *allocation phase* the P_1 and P_2 are set to ϕ. In line 3, γ^s is sorted based on the payment component of the sellers δ^s. Likewise, γ^b is sorted based on the payment component of the buyers δ^b. Line 5 of the *allocation phase* determines the maximum index e that satisfies $\gamma_i^b.\delta_i^b - \gamma_i^s.\delta_i^s \geq 0$. Line 6 of the *allocation phase* iterates over all the winning seller-buyer pair determined by line 5. In Line 7, the P_1 data structure keeps track of the winning sellers.

Algorithm 3 Allocation (γ^s, γ^b)

1: **begin**
2: $P_1 \leftarrow \phi$, $P_2 \leftarrow \phi$
3: $\gamma^s \leftarrow$ Sort_ascend(γ^s,$\gamma^s.\delta^s$)
4: $\gamma^b \leftarrow$ Sort_descend(γ^b,$\gamma^b.\delta^b$)
5: $e^* \leftarrow argmax_e\{\gamma_i^b.\delta_i^b - \gamma_i^s.\delta_i^s \geq 0\}$
6: **for** $i = 1$ to e^* **do**
7: $\quad P_1 = P_1 \cup \{z_i \in \gamma^s\}$
8: $\quad P_2 = P_2 \cup \{z_i \in \gamma^b\}$
9: **end for**
10: $\gamma^s \leftarrow \gamma^s \setminus P_1$
11: $\gamma^b \leftarrow \gamma^b \setminus P_2$
12: **end**

In line 12, The set of available buyers β_1 and set of available sellers β_2 is set to ϕ. After the end of the *allocation phase* the control is transferred to the *payment phase*. As the *payment phase* terminates the control is transferred to the line 18 of the *Main routine* phase. In line 18, the set of initial sellers and set of initial buyers are updated by the still active agents. Line 19 incorporates the new sellers in z^s and line 20 adds the new buyers in z^b.

5.5 Running Time

In the *main routine* of PODA, except the sorting function and the payment function, the total running time can take overall $O(n)$ considering $n \geq m$. The sorting function can take $O(n\log n)$ time. Let us analyse the payment function. In the payment function, calculation of the payment for the sellers and buyers may take $O(k*n*n\log n)$ as, any ith buyer or seller can be aligned with maximum of k slots and for calculating the payment a sorting algorithm may be invoked. For each auction round payment calculation may be done for $O(n)$ number of agents. Hence, this payment calculation will take overall $O(kn^2\log n)$. Except the allocation function other statements may take overall $O(n)$ time. The allocation function can take overall $O(n\log n)$ as sorting is invoked. So, the overall running time of PODA for each auction round is $O(k*n^2\log n)$. If k is constant then it boils down to $O(n^2\log n)$.

5.6 Illustrative Example

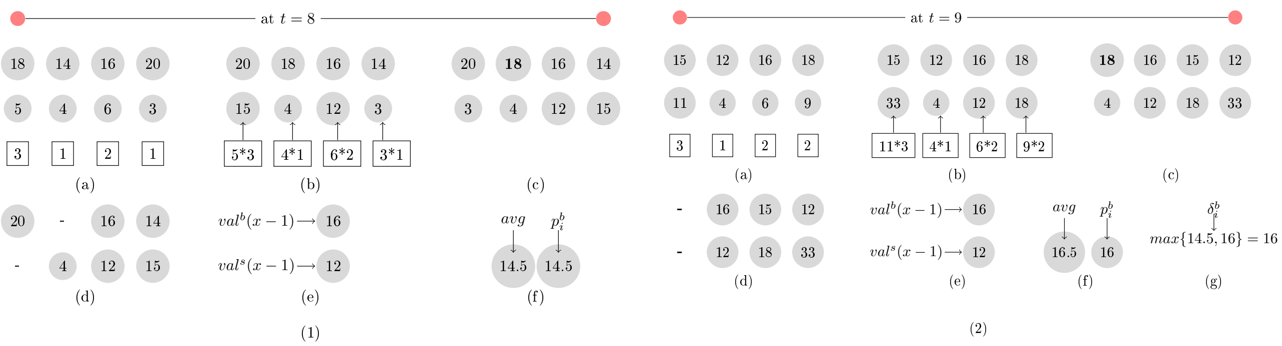

Figure 3. The progress of PODA on the set of $n = 4$ buyers and $n = 4$ sellers at $t = 8$ and $t = 9$. **(1)** The progress of PODA at $t = 8$. **(2)** The progress of PODA at $t = 9$.

The detailed functioning of PODA is illustrated in Figure 3. For understanding purpose, the illustration is done at two different instances *i.e.* at $t = 8$ and at $t = 9$. The number of buyers is $n = 4$ and the number of sellers $n = 4$ as shown in Figure 3(a). The quality of the data q_i provided by each seller i is shown by a value in the rectangular box. In Figure 3.1.(b), the valuation of the sellers is updated by multiplying the quality the sellers to their bid values. In Figure 3.1.(c), following the line 15 and 16 of the *main routine* phase, the buyers and the sellers are sorted based on their valuations. After sorting the buyer, that is present at index 2 with the valuation 18 will be used to demonstrate the payment rule . For agent at index 2, say the arrival time ($\widehat{a}_i = 8$) and the departure time ($\widehat{d}_i = 11$). According to the payment rule, $\widehat{v}^b_2 = 18$ and $\widehat{v}^s_2 = 3$ will be out of the market as shown in Figure 3.1.(d). Based on payment function, the payment calculated at $t = 8$ is 14.5 as shown in Figure 3.1.(f). Similarly, it is shown in Figure 3.2.(f) that the payment at $t = 9$ will be 16. If the agent wins, the final payment is shown in

Figure 3.2.(g). Here, computation is shown for a buyer. Similarly the payment of any arbitrary seller can be computed at $t \in T$. For the case of a seller, the valuation of the ith seller and the bidder with the maximum value will be taken outside the market and then the payment is calculated.

6. Further analysis

Lemma 1. *PODA is budget balanced.*

Proof. The proposed PODA selects the buyer-seller pair only when it satisfies the condition $p_i^b - p_i^s \geq 0$. Taking the summation over all the transactions that are occured, gives the condition $\sum_i p_i^b - \sum_i p_i^s \geq 0$. This is the desirable condition for the budget balanced property. Hence, it is proved that the PODA is *budget balanced*. □

Lemma 2. *PODA is IR.*

Proof. For the losing buyers $u_i^b = 0$. When a buyer remains active in the algorithm, it ensures that $p_i^b \leq b_i^b$ and only the active buyers can win. In this case also, the utility $u_i^b = b_i^b - p_i^b \geq 0$ as $p_i^b \leq b_i^b$. So, the buyer's utility, by the participation, $u_i^b \geq 0$. Similar arguments can be imparted for the sellers also. Hence PODA is IR. □

Theorem 1. *Misreporting a_i does not provide any gain to an agent.*

Proof. Fix b, d, a_{-i}. It is to be noted that due to the realistic misreporting assumption, an agent can misreport his arrival time only within his arrival-departure window.

Let us consider first, that an agent (a buyer) reports his arrival time a_i and in this case his payment p_i is calculated by aligning him in k number of slots. Here, his utility is $u_i = b_i - p_i$. Now consider, he misreports his arrival time as $\widehat{a}_i > a_i$ and $\widehat{a}_i \leq d_i$. Now he will be aligned with k^* number of slots for calculating his payments. As $\widehat{a}_i > a_i$, $k^* > k$ and due to the $max\{p(\cdot)\}$ price function, $p_i^* \geq p_i$. Hence his utility $\widehat{u}_i \leq u_i$ as $b_i - p_i \geq b_i - p_i^*$ with the previous constraints $p_i^* \geq p_i$. Similar arguments can be provided for sellers that they cannot have any gain by misreporting their arrival time. This completes the proof that misreporting a_i is not profitable to the agents. □

Theorem 2. *Misreporting d_i is not profitable for an agent.*

Proof. Fix b, a, d_{-i}. Consider the utility $u_i = b_i - p_i$ when he reports his true departure time d_i. In this case, the number of slots he is aligned with is $l = d_i - k$. Now, if he misreports, by definition, $\widehat{d}_i < d_i$ and $\widehat{d}_i \geq a_i$. As $\widehat{d}_i < d_i$, $l^* = a_i - (\widehat{d}_i - k) > a_i - (d_i - k) = l$. Since $l^* > l$, $p_i^* \geq p_i$. This ensures that $\widehat{u}_i = b_i - p_i^* \leq b_i - p_i = u_i$. Hence no gain is achieved if a buyer misreports his departure time d_i. Similarly, it can be proved that any arbitrary seller can't gain by manipulating his departure time.

It is also observed as well that, if he misreports his departure time, his selection as a winner may be incorporated with more payment than the previous and also he may lose some potential slots where he could win. In either case, he is not gaining. □

Lemma 3. *An winning agent can't gain by manipulating his bid value.*

Proof. **Case 1. Quality Manipulation:** It is to observe that the valuation of an agent $v_i = b_i * q_i$. As the quality is calculated by the third party, it is a public knowledge and can't be manipulated by the agent. However by manipulating the content provided by him, he can lower his quality score. But by the construction of quality score, lowering his quality score means increase the number. In this regard one can manipulate the valuation indirectly by the quality score. Say after manipulation $\widehat{v}_i = b_i * \widehat{q}_i$. If $\widehat{q}_i < q_i$, we can say the ith agent still wins and $\widehat{u}_i = p_i - b_i = u_i$. Now, if $\widehat{q}_i > q_i$, two things can happen he may still win and in this case $\widehat{u}_i = p_i - b_i = u_i$. If he loses, his $\widehat{u}_i = 0 < u_i$. So, by manipulating the quality indirectly, he can't improve his utility, and in another case his utility is less than the utility achieved.

Case 2. We have seen, that lowering the quality an agent can't gain. Now, we have to prove that, by manipulating the bid value, his private information, an agent can't gain. Let us suppose that $\widehat{b}_i^s$ is the manipulated value for any arbitrary seller s_i. If $\widehat{b}_i^s > b_i^s$. Then $\widehat{v}_i^s > v_i^s$. In this situation two things can happen, the seller can still win and then his utility $\widehat{u}_i^s = p_i^s - b_i^s = u_i^s$. However as $\widehat{v}_i^s > v_i^s$, due to the non-decreasing sorting order of the seller, he can lose also. In that respect, $\widehat{u}_i^s = 0 < u_i^s$. so, by misreporting he can't gain if $\widehat{b}_i^s > b_i^s$. If $\widehat{b}_i^s < b_i^s$ he will continue to win, if he was wining with true value, but in this respect two things can happen. First $\widehat{u}_i^s = p_i - b_i^s \geq 0$ and $\widehat{u}_i^s = u_i$ if still $p_i \geq b_i^s$. But in the second case, it may be the situation that $p_i \leq b_i^s$ and for that $\widehat{u}_i^s = p_i - b_i^s \leq 0 < u_i$. Hence by misreporting the bid value a seller can't gain. □

Lemma 4. *A losing seller can gain by manipulating his bid value.*

Proof. If with b_i^s, a seller loses, and reports $\widehat{b}_i^s < b_i^s$ there is a chance that he may win and in that case if $p_i > b_i^s$, then $\widehat{u}_i^s = p_i - b_i^s > 0$ and $\widehat{u}_i^s > u_i = 0$. However, as the $\widehat{q}_i^b = 1$, the losing buyers can't gain by manipulation. □

Theorem 3. *PODA is* partially *truthful.*

Proof. The *partial truthful* nature of the PODA mechanism can be observed with the help of Theorem 1, Theorem 2, and Lemma 3 above. It is shown in Theorem 1, Theorem 2, and Lemma 3 that the agent can't gain by misreporting their arrival time, departure time, and private data (bid values). However by Lemma 4 it is shown that only losing sellers may gain by misreporting their sell-bids. Hence, PODA is *partially truthful*. □

7. Simulations and results

In this section, we compute the efficiency of the PODA via simulations. The experiments are carried out in this section to provide a simulation based on the data (sell-bid and buy-bid) generated using normal distribution. The McAfee's mechanism is considered as a benchmark mechanism. It is to be noted that McAfee's mechanism is not *truthful* and is vulnerable to manipulation in an online environment. In our simulation results, the manipulative nature of McAfee's mechanism can be seen evidently. The experiments are done using Python. Numpy library is used in Python to generate the data.

7.1 Simulation set-up

As shown in Table 1, for the simulation purpose, the nature of both the agents is dynamic. In each iteration, 10 new buyers are added to the list of buyers while the number of new sellers is a random number between 50 to 100. The buy-bids and sell-bids are generated by normal distribution. The buy-bids are in the range 200-250 and the sell-bids are in the range 100-150. The valuation of the buyers and the sellers calculated as $v_i = b_i * q_i$. For the buyers $q_i = 1$ and for the seller there is a quality associated, which is a random number between 1 and 4. The unit of the bid values is \$. The arrival time and departure time of every buyer and seller is also taken into account and they are generated randomly. So, the type of an agent is comprised of four parameters (arrival time, departure time, valuation, and quality).

Table 1. Agent's information

Agents	Distribution	Values in range	Nature
buyers	normal	200-250	dynamic
sellers	normal	100-150	dynamic

7.2 Performance metric

The performance of the PODA mechanism is quantified with three metrics. They are:

- **Payment of the agents:** In this case, how much amount is accumulated by the buyers and the sellers as their payments, are summed up till a particular round $t \in T$. For the buyers it is
$$\sum_{\tau=0}^{t}\sum_{i=0}^{m_\tau} \alpha_i^b. \tag{7.1}$$
This signifies the payment of the so far selected buyers upto the time t. Here m_τ is the numbers of buyers selected in the auction round τ. The total payment of the sellers could be written as:
$$\sum_{\tau=0}^{t}\sum_{i=0}^{m_\tau} \alpha_i^s. \tag{7.2}$$
- **Number of transactions:** In this metric, how many number of seller-buyer pairs are matched so far are summed up to a particular round $t \in T$. In disguise, this metric estimate the social efficiency. By social efficiency we mean, difference between the total number of seller-buyer pairs when every agent reports truthfully and when they are not.

- **Profit of the auctioneer:** The seller-buyer pairs are negotiated by the third party called the auctioneer. The auctioneer, by participating in the auction process, should have some profit. The auctioneer's profit is denoted by:

$$\sum_{\tau=0}^{t}\sum_{i=0}^{m_\tau}(\alpha_i^b-\alpha_i^s). \tag{7.3}$$

In the auction process, in a particular round it may so happen that the payment of an agent is determined by avg. In that case auctioneer may not get any profit i.e. $\alpha_i^b-\alpha_i^s=0$.

7.3 Results and Analysis

Here, we are simulating the PODA mechanism (proposed mechanism) which we are claiming to be truthful (partially) in the online setting The PODA (which will be referred by OM in the figures of the simulation results), will be compared with a benchmark mechanism set by us. In the benchmark mechanism, the payment of the buyers and the sellers are calculated by applying McAfee's idea directly in each round $t \in T$.

Table 2. Description of used notations

Notations	Description
MB	Buyers in McAfee's Mechanism
MS	Sellers in McAfee's Mechanism
OMB	Buyers in Online Mechanism
OMS	Sellers in Online Mechanism
Px	Payment for Normal Distribution with std. dev. x
Tx	Transactions for Normal Distribution with std. dev. x
Ax	Auctioneer's Profit for Normal Distribution with std. dev. x
PxMy	Payment for Normal Distribution with std. dev. x and γ = y%
TxMy	Transactions for Normal Distribution with std. dev. x and γ = y%

In the figures of the simulation results, the benchmark mechanism will be referred by M. However, as the McAfee's idea has been directly adapted in each round, the benchmark mechanism is vulnerable to manipulation i.e. the agents can gain by manipulating the metrics. They can manipulate their buy-bids and sell-bids.

With the simulation set up, several auctions are run in discrete time interval. The simulations are run 100 times and the average results are taken as the representative results.

In the simulation purpose all the agents, may misreport their private data, participating at a particular round $t \in T$ in the benchmark scheme. During the manipulation, the buyers may decrease their bids, and seller may increase their bids by a certain percentage. We set $\gamma = g\%$ of increase or decrease in this simulation, where $g = 30\%$, $g = 40\%$, and $g = 50\%$ are considered. By varying the parameter γ, the PODA and the benchmark mechanism are compared. The simulation is demonstrated with normal distributed valuations with mean

125 for sellers and 225 for buyers and standard deviation 25. The captions of the figures are abbreviated in Table 2.

From Table 2 the buy-bid and sell-bid information along with the variation parameter γ will be clear. Following cases are are considered during the simulations by varying the parameter γ:

Case 1. In this case $\gamma = 0$. It is assumed that, all the agents are declaring their true data. Under this assumption, the benchmark mechanism and the PODA are simulated with the payment, transactions, and the profit of the auctioneer parameters. The truthful nature of the agents can be seen in Figure 4, Figure 5, and Figure 6. In Figure 4, the X-axis is used to represent the number of iterations and Y-axis is used to represent the payment of the agents. The simulation result shown in Figure 4, shows the comparison of the total payment of the winning sellers and buyers using the benchmark mechanism and the PODA mechanism. It is seen in Figure 4 that the payment of buyers in PODA is less than the buyer's payment in benchmark mechanism, as in PODA, many agents may be priced out. Similar nature can be seen for the sellers. In the Figure 5, the X-axis is used to represent the number of iterations and Y-axis is used to represent the number of transactions that are occurring. Here the gap, i.e., the maximum allowable difference of the arrival and departure time of any agent is same for all the agents. It can be seen that the number of transactions is lower in our proposed algorithm since we are not only aligning the agents in the time specified by them but also in the past. Hence, many agents may get priced out and because of that the benchmark scheme will perform better in this case.

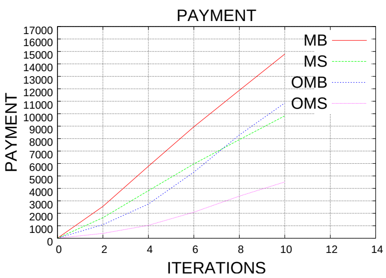

Figure 4. P25

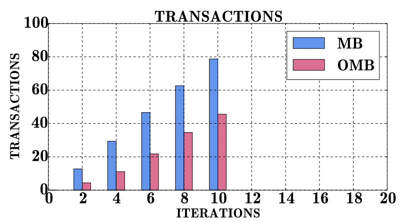

Figure 5. T25

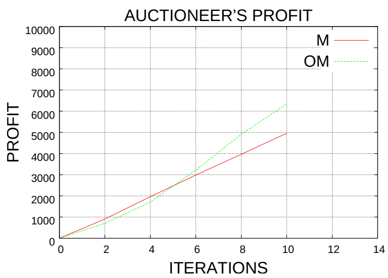

Figure 6. A25

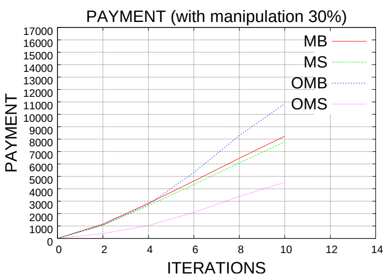

Figure 7. P25M30

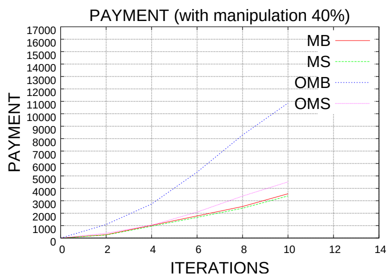

Figure 8. P25M40

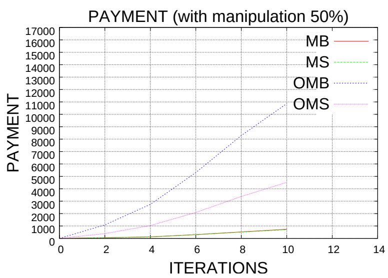

Figure 9. P25M50

In the Figure 6, the X-axis is used to represent the number of iterations and Y-axis is used to represent the auctioneer's profit. As the auctioneer's profit is calculated by $\alpha_i^b - \alpha_i^s$, in both the proposed and the benchmark scheme will provide some profit to the auctioneer. The results is the by-product of Figure 4.

Case 2: Here we vary the parameter γ and the results are demonstrated from Figure 7-Figure 12. The meaning of the X-axis and Y-axis will be same as **Case 1**. It can be seen that the number of transactions and thus payment are decreased when the agents increase (γ). Because of this the performance of the proposed mechanism is better than the performance of the benchmark mechanism. Payment and transactions are shown in the figure. Auctioneer's profit is not shown as that can be deduced from the payments. However, the auctioneer may lose some profit in case of benchmark mechanism.

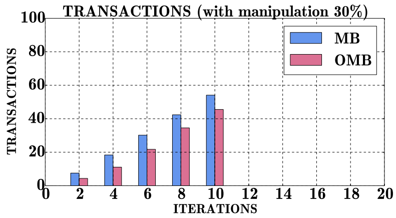

Figure 10. T25M30

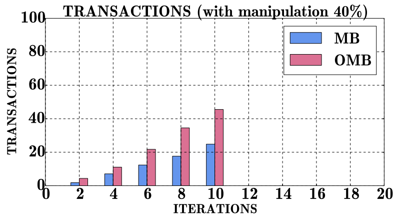

Figure 11. T25M40

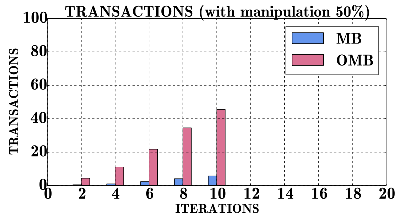

Figure 12. T25M50

8. Conclusions and Future Works

In this paper, an incentive based quality adaptive double auction in an *online* environment for participatory sensing is investigated. This paper introduces a *truthful* mechanism that is termed as PODA and it exhibits *truthfulness* (*partial*), *budget balance*, and *individual rationality*.

With an experimental setup, we evaluate PODA by comparing the payment, transactions, and auctioneer's profit (three parameters set for simulation purpose) against the benchmark mechanism which is vulnerable to manipulation. With the simulation it has been explored that under the vulnerability to manipulation, the PODA is truthful (partial) and performs better than the benchmark mechanism in an online environment for several occasions. However, in some special cases PODA may be manipulative.

The immediate future work is to design truthful budget feasible quality adaptive double auction mechanism in an online environment for PS.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

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