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A Modified Sealed bid Double Auction for Resource Allocation in Device-to-Device Communication

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Abstract—

Device-to-device (D2D) communication serves as a key enabler for increasing demands of high data rates. Many efforts are made to thrive an optimal resource allocation scheme for D2D users. However, there is always a need for a promising scheme for resource allocation with the increasing demands and transforming constraints. In this paper, we propose a truthful sealed bid double auction scheme i.e. Ask Mean Value (AMV) for resource allocation in a single cell where cellular users act as sellers, the D2D users act as buyers and the base station acts as an auctioneer. AMV is a modification of double auction approach that works by taking the mean of the ask values. With sophisticated seller selection, buyer selection and agreement and pricing scheme, the AMV guarantees budget balance, truthfulness and economic efficiency. Moreover, we show the efficiency of AMV over other proposed double auction schemes i.e. TDA and BMV. Further the simulation results reveal that AMV can procure economic efficiency as well as high performance in terms of pricing, number of iterations, seller and buyer satisfaction.

Keywords—Device-to-Device, double auction economic efficiency, sealed bid, truthfulness.

I. INTRODUCTION

The mushroom growth of the D2D users has resulted in the rapid upswing in demand for bandwidth and data rate. Increasing the demand with an effusion of wireless mobile services and number of devices, the existing technology (4G technology) cannot resolve [1]. Additionally, the wireless system designers have been facing the continual rising behest for

ISSN PRINT 2319 1775 Online 2320 7876

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high data rates required by novel wireless applications. As demand for data rate increases, the manufacturers face a conundrum to figure out a way to satisfy this demand with the limited number of available resources. There is finite number of channels at any given time, but they must increase capacity and offer faster data rate to meet user demand. Consequently, it has become the need of the hour to undergo a transition to an upgraded generation of wireless technology i.e. 5G. As a result, more people and more devices in 5G networks will be able to communicate at the same time. The road to 5G runs through 4G wireless infrastructure, and improvements in 4G technologies.

The device-to-device(D2D) communication is one of the most important and enabling technology in 5G networks [2][3]. The D2D communication supports high data rate, low latency and low power consumption compared to cellular communication. It is a way of unmediated communication between mobile terminals which involves dynamic spectrum sharing between D2D devices. An example of a single cell D2D network is shown in Fig. 1. Here the cellular users communicate through the base station which has been shown by solid blue arrows. The transmitter and receiver in D2D mode is shown by solid black arrow. $D2D_{T1}$ and $D2D_{T2}$ are the transmitters and communicate to receivers $D2D_{R1}$ and $D2D_{R2}$ respectively in D2D mode while cellular user CU_1 and CU_2 is communicating with base station in uplink and downlink mode respectively. The dashed blue arrow indicates the channel assignment by BS to the transmitter to proceed the D2D communication with the receiver on this link.

In D2D mode the devices can communicate directly on the D2D link despite being served by the network via base station (BS) [4]. The major advantage of D2D communication in 5G is, there is no need to allocate separate resource block to D2D users. These resource blocks given to the D2D users are shared with the cellular users i.e. it operates in an underlay mode.

ISSN PRINT 2319 1775 Online 2320 7876

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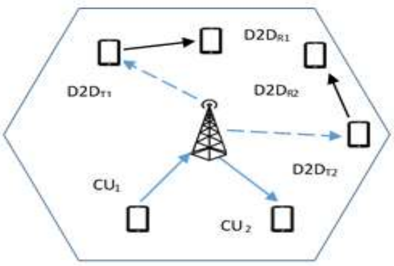

Fig. 1 Device to Device Communication

Consequently, in 5G D2D communication the D2D mode requires half of the resources compared to cellular communication mode.

However, this spectrum (resource blocks) sharing leads to interference among the users sharing same channel. Consequently, spectrum assignment or resource allocation to users insuring minimum interference and high Quality-of-Service, is a challenging and red hot topic [5]. Efficient addressing of the problem of interference management between the users of the underlay D2D enabled cellular network has captivated noteworthy heed in the recent literature. The resource allocation in D2D entails the assignment of a D2D user to proper resource blocks (RBs), which affects the co-channel interference (CCI) from the co-channel cellular user. The base station (BS) is capable of presiding the interference between cellular communication and D2D communication by appropriate power control and resource allocation.

Research work reported in [7][8][9] includes game theoretic methods for resource allocation in device to device communication. It has been observed that these methods give an optimal outcome for individual users but not for system as a whole. The channel will be assigned looking after the SINR demand of the user at that time, but this channel might result in more throughput when allocated to some other user and thus can lead to enhance system throughput. In practical scenario, user transmission and resource allocation is impacted by economic consideration. When we observe D2D scenario from an economic perspective, a market based approach is required for proper utilization of resources available within the network.

Auction theory is a market-based scheme that guarantees proper and efficient utilization of resources. As a result the authors in [10][11] illustrates the work done in auction theory in

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the field wireless networking. Although some auction schemes have been proposed in [10][12][11] in the field of mobile communications but the ones dealing with single auction can lead to the resources unallocated and the ones dealing with double auctions do not satisfy the economic efficiency property of double auction. The economic properties guaranteed by our double auction are necessary for an auction practically.

We propose a modified sealed bid double auction scheme AMV in a single cell, in which D2D users(buyers) can potentially share the resources with the cellular users (sellers) with the help of base station (Auctioneer). Our double auction satisfies the following economic properties i.e. (1) Truthfulness: all the sellers and buyers ask and bid according to their true valuation as this is based on the calculation of SINR values. (2) Budget balance: the auctioneer has no profit no loss. (3) Economic efficiency: the total price for all the sellers is maximum in case of our proposed method.

Contributions: The main contributions of paper are as follows:

- We proposed Typical Double Auction (TDA) for resource allocation. This approach has the application of double auction protocol. It involves selection of lowest ask and highest bid and therefore has inefficient user-buyer pair matching.
- The further improvement of TDA is BMV which has similar cellular user selection as that of TDA but selects the D2D users by taking the mean of their offered bids. However, it still cannot achieve the desired outcome i.e. less iterations and high economic efficiency.
- AMV is the final approach which is an improvement to both TDA and BMV. To the best of our knowledge, AMV is the first modified truthful sealed bid double auction algorithm for D2D communication in a single cell. It works on matching the seller and buyer such that they have to adjust their initial bids and asks by a smaller value.
- AMV is the first algorithm design that satisfies the economic efficiency property of double auction.
- Our scheme is designed such that the devices decide their SINR requirements and then perform the power adjustment to achieve the calculated SINR.

The rest of the paper is organized as follows. We present literature survey in the related work in section II. Section III comprises of the network, system and auction model. The Proposed work is presented in Section IV that describes the auction designs. Section V

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

proofs the economic properties of the proposed double auction scheme and section VI involves simulation settings and results. Section VII concludes the entire proposed approaches.

II. RELATED WORK

Device-to-device communication has become a significant area of interest for the researchers due to the advantages of bypassing the base station and communicating directly to the devices. In the early literature [13] propose to expedite local peer-to-peer communication by a Device-to-Device (D2D) radio that steers as an underlay network to an IMT-Advanced cellular network which facilitates mobile peer-to-peer communication instead of central server based communication for rich multimedia services. The underlay mode of communication has the sharing of the resources between the D2D and the cellular users and an optimal resource sharing is significantly required for achieving higher throughput.

In [14] a resource sharing strategy for the D2D communication underlaying cellular networks is proposed, where multifarious D2D pairs can share sub channels with several cellular users (CUs) and boost the sum rate of D2D pairs while contenting the rate requirements of all CUs. In [15], the authors scrutinized another D2D communication that is based on the statistics of the SINR of all users. In this scheme, SINR behavior is contrived based on the position of the D2D pair. Then method for power control is applied to the D2D communication such that SINR degradation of the cellular link does not fall beyond a certain extent. In [16] the optimal selection of possible resource sharing modes with the cellular network in a single cell is studied. Their proposed method also showed that it entitles a much more authentic device-to-device communication with restrained interference to the cellular network.

Based upon this [17] proposed an optimized resource allocation method that D2D can reuse the resources of more than one cellular user. Later [18] proposes a practical and efficient scheme for generating local awareness of the interference between the cellular and D2D terminals at the base station, which then exploits the multiuser diversity inherent in the cellular network to minimize the interference. In [19] interference using a conflict graph is

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Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

modelled, and methods for computing upper and lower bounds on the optimal throughput for the given network and workload are presented.

In [6] the interference relationships among different D2D and cellular communication links is modelled as a novel interference graph with unique attributes and proposed a corresponding joint resource-allocation scheme that can effectively lead to a near-optimal solution at the base station, with low computational complexity. Various game theoretic methods for resource allocation have also been proposed.[9] proposes resource allocation algorithm and protocol based on the Nash equilibrium derivations.

Auction has been studied in economics in [20][21][22]. Several double auctions have been studied in [22][20][23] but they cannot be directly applied in device to device communication as they fail to address the interference management between the cellular and D2D users. [24] focuses on the bilateral trading mechanism in auctions. Recently it has been used an application in networking problems. For instance, In [11] auction theory has been applied to cooperative communications to either efficiently allocate resources or incentivize wireless devices to participate in cooperative communications. [12] proposes a Vickery-Clarke-Grove (VCG) based mechanism for reverse auction to maximize social welfare and promote hybrid access in femtocell networks.

The authors of [10] proposed a double auction mechanism for trading the resources in frequency domain which satisfies the economic properties like individual rationality, budget balance and truthfulness. However, it doesn't satisfy economic efficiency which is one of the most important properties of a double auction. The above mentioned auction mechanisms are different from our proposed work of modified double auction including the network model, auction model and auction design. Moreover, our double auction mechanism satisfies economic efficiency including budget balance and truthfulness.

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ISSN PRINT 2319 1775 Online 2320 7876

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III. SYSTEM MODEL

In this section, we describe the system model. The system is divided into network model, auction model and economic properties. The network model details about the conditions and assumptions made in our approach while the auction model illustrates about the proposed auction approach. The economic properties details the properties which are satisfied by the proposed auction scheme.

A. Network Model

In this paper, we consider single cell wireless network consisting of a base station, number of cellular users and device to device users as shown in Fig. 2. All the cellular users have been randomly pre-allocated the channels. One cellular user can be allocated only a single channel. These cellular users must have the potential to share this channel among the device to device users. All the device to device users are waiting to get assigned and share some channel. A single device to device user can share a channel with a single cellular user only. When the channel sharing is done, the users experience interference problems due to transmission on the same channel as that of cellular users. To minimize this interference various auction protocols have been described in our auction model.

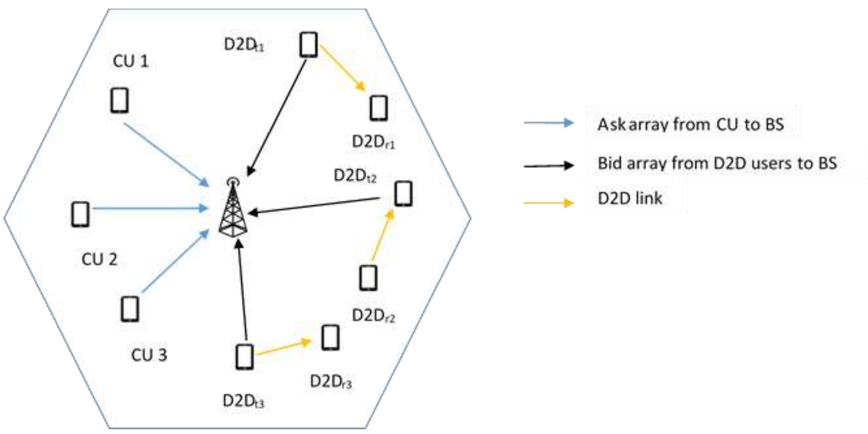

Fig. 2 Network Model

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Auction Model

The AMV is designed by modifying the typical double auction protocol where the cellular users and the device to device user perform the auction according to the modified double auction protocol. The set S denotes the cellular users who are the sellers and want to share the channel they are allocated. The set B denotes the set of device to device users who are the buyers and are eagerly waiting for the channel to get assigned. Each seller contributes a single resource unit by submitting an ask a_i based on the pre-decided minimum requirements. All the asks from the sellers form a vector denoted as, $A = \{a_1, a_2, a_3, ..., a_n\}$.

Being a sealed bid double auction, all the buyers unaware of the asks from the sellers submit their bids. Each buyer submits a vector of bids B to the base station. So bid vector B for buyer i to the base station for n sellers is given by:

$B = \{b_{i1}, b_{i2}, b_{i3}, ..., b_{in}\}$, where b_{ij} denotes the bid value b offered by the buyer i when it shares the channel with seller j. These offered bids are the SINR values calculated as:

$$SINR_{B_{ij}} = \frac{P_I * G_{ir}}{\sigma^2 + \sum_{j \neq i}^{n} G_{jr} * P_j} \qquad (1)$$

G_{ir} → channel gain between the transmitter i and receiver r.

P_i → user i uplink transmission power.

σ^2 → variance of white additive Gaussian Noise Power.

n → total number of users sharing the same channel.

After collecting the ask and the bid values form the all the sellers and buyers respectively, the base station determines the appropriate SINR by applying double auction algorithms (as discussed in auction design later) and then performs the power control to achieve the calculated SINR.

B. *Economic Properties*

Any double auction protocol must follow the following economic properties:

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

1) *Budget Balance:* Budget balace An auction is considered strong budget balanced if the entire transaction is done between the buyers and the sellers and the auctioneer has nothing to gain or to loose i.e.

$$a_i = SINR - \xi \tag{2}$$

$$b_i = SINR + \xi \tag{3}$$

No gain for auctioneer.

2) *Truthfulness:* The proposed double auction follows the dominant strategy incentive compatibility notion of truthfulness which states that any seller or buyer cannot gain over the other players by offering an optimal bid which is different from other players no matter in which manner the ask and bids are done.

3) *Economic Efficiency:* The economic efficiency states states that the summation of all the values should be maximum i.e. after the auction is completed the summation of obtained values should be maximum possible.

$$\sum_{i=1,j=1}^{m,n} b_{ij} \rangle \sum_{i=1,j=1}^{m,n} b_{ij}^{'} \forall b_{ij} b_{ij}^{'} \in B \tag{4}$$

It is noted that an ideal auction design must follow all the double auction properties i.e. individual rationality, Budget balance, Truthfulness, Economic efficiency. But unfortunately no double auction can achieve all the properties simultaneously. So, we tried to optimize our double auction mechanism by satisfying the three properties Budget balance, Truthfulness, Economic efficiency.

IV. PROPOSED WORK

In this section, we illustrate several double auction designs and the basic idea of AMV double auction. Further the AMV double auction algorithm is described and analysed and later explained with the help of an example.

A. *Basic idea*

TDA is the first proposed approach in this paper. It comprises of the sellers i.e. the cellular users who decide minimum SINR requirements which they provide as ask to the base station. Then each buyer i.e. device to device user sends an array of calculated SINR

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

values to the base station. The base station sorts the ask values and selects the lowest ask and then selects the corresponding highest bid value. The base station selects the ask of cellular user k as the lowest ask and then the bids b_{ik} from array of each buyer i will be compared and the highest bid will be selected. This leads to the formation of seller and buyer pair which goes on bargaining to reach to a final bid value. Although this algorithm strictly follows double auction protocol but it lacks auction efficiency as the lastly paired seller-buyer pairs have vast difference in their offered values which increases the number of iterations to reach to some finalized value.

An improvement to this is BMV algorithm that takes the mean of the bid values and chooses the bid which is closest to the mean value. But unfortunately this also does not solve the mentioned problem to a great extent. We show this problem in the example using the tabular results later.

As a more optimized strategy we propose the AMV algorithm which conquers the drawbacks in the above algorithms by taking the ask values in a different sequence. This algorithm does not propose to sort the ask values but it takes the mean value of asks and selects the ask which is closest to the mean value. This approach pairs the seller and buyer such that they do not have much difference between their initial ask/bid values and the finalized values. Thereby, comparatively reducing the number of iterations to reach to a mutually agreed bid value.

In the next section we show the design and algorithms of various auction schemes comprising of TDA, BMV, and AMV auction algorithms.

B. *Auction Design*

The simplest auction design is TDA algorithm. It deals with making the seller - buyer pairs and then perform bargaining by adding and subtracting ξ from the bid and ask values respectively. ξ is mathematically expressed according to the following equation:

$$\xi = \frac{c}{1 + e^{\Delta a / T}} \tag{5}$$

T → evolution parameter (here assumed constant

c → constant

$\Delta a \rightarrow a_0^r - avg\{p^1, p^2, p^3, \ldots, p^{r-1}\}$

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

This is based on the simple double auction protocol. It finds

Algorithm1 Typical Double Auction Algorithm

```
1: for k = 0 to N-1 do
2:      find index i corresponding to minimum ask value
3:      minask = A[i]
4:      A[i] = 0
5:      find the maximum bid corresponding to seller i.
bid = max(B[j][i]) // assuming there are j bidders
6:      while bid < minask
7:            bid = bid + ξ
8:            ask = ask – ξ
9:      end while
10:     final bid value for seller i and bidder j = bid
11: end for
```

the lowest ask value(minask) among the values asked by the sellers and stores the value and the seller's index(i). Assuming j number of bidders, it then compares the bid values of all the bidders B[j][i] corresponding to the stored seller's index i to find the maximum bid value (max(B[i][j]). So seller (with lowest ask value) and buyer (with highest bid value) forms a pair. Now bargaining between the minask and bid takes place by adding ξ to the bid and subtracting ξ from the minask till bid $\geq$ minask.

We then present the BMV algorithm for double auction which is similar to TDA but the only difference is the bidder with the bid closest to the mean value of the bids is chosen to pair up with the seller. This mean value is the mean of all the bids by j number of bidders corresponding to seller i which can be mathematically expressed as:

$$Mean(B[i][j]) = \frac{B[1][i] + B[2][i] + \ldots.. + B[j][i]}{j} \quad (6)$$

The bargaining process between ask and bid values after their selection remains same as that of TDA algorithm.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Algorithm 2 Bid Mean Value Algorithm

```
for k = 0 to N-1 do
    find index i corresponding to minimum ask value
    minask = A[i]
    A[i] = 0
    bid=Closest(Mean(B[j][i]))        //find the closest bid value to the mean bid value
    while bid< minask
        bid = bid + ξ
        ask = ask – ξ
    end while
    final bid value for seller i and bidder j = bid
end for
```

We now illustrate the details of the finally proposed AMV algorithm which comprises of three steps including seller selection, bidder selection and Agreement and pricing.

1) *Step 1-Seller Selection:* In this algorithm the base station selects the sellers not in the order of ascending ask values but the selection of sellers occurs according to closest mean ask value i.e. the mean value of all the asks by the sellers (taking part in the present round) is calculated then the seller having the ask value closest to this mean value is chosen as the winner. In the proposed algorithm the Mean (all asks in round k) gives the mean value of the asks of all the sellers taking part in current round k and the Closest(Mean()) gives the index of ask i which is closest to the calculated mean value.

2) *Step 2-Bidder selection:* Assuming that j number of bidders are participating in auction, then the maximum bid value corresponding to the winning seller is selected and the bidder having the maximum bid value is selected as the winner among the bidders.

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3) *Step 3-Agreement and Pricing*: The agreement in this algorithm occurs by the seller bringing down the ask value and the buyer bringing up the bid value till bid ≥ ask. This agreement is a bargaining procedure which happens among the winner seller and the winner buyer. The seller goes on decreasing his ask and the buyer goes on increasing his bid by subtracting and adding ξ respectively. The pricing happens as follows:

$$bid = bid + \xi \tag{7}$$

$$ask = ask - \xi \tag{8}$$

Whenever the bid becomes more than the ask then the agreement takes place i.e. the seller and the buyer gets agreed to the final bid price as shown in Algorithm 3. This algorithm gets repeated for all the sellers and the final bid price has the least difference form the initial ask and initial bid values.

Algorithm 3 Ask Mean Value Algorithm

1: for k = 0 to N-1 do
2: find the index i of the ask which is closest to mean value of all the asks in round k.
i = Closest[Mean(all asks in round k)]
3: minask = A[i]
4: A[i] = 0
5: find the maximum bid corresponding to seller i.
bid = max(B[j][i]) // assuming there are j bidders
6: while bid< minask
7: bid = bid + ξ
8: ask = ask – ξ
9: end while
10: final bid value for seller i and bidder j = bid
11: end for

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

C. *Illustrative Example*

We give an illustrative example to show the working process of TDA, BMV, AMV algorithms for better understanding. We consider 5 sellers and 5 buyers and one base station which acts as an auctioneer. All the sellers and buyers ask and bid truthfully in this double auction. Figure 2 shows sellers, bidders, ask array and the bid array. The asks by the sellers are denoted here as ask array such that ask by seller k is Ask[k] and the bids are denoted here as Bids array such that the bid by bidder i for seller j is denoted by B[i][j]. The bidder i sends a bid array B[i][], such that it has the bids for all the sellers. So each row in 2-D array B[][] corresponds to a bidder whereas columns denote for which seller the bidder is bidding.

1) *TDA:* As described in algorithm 1, the first seller chosen is seller 5 and corresponding to this the bidder will be chosen from all the values in B[i][5] where i = 1 to 5. So the bidder chosen is bidder 5 with highest ask for seller 5.

Now the bargaining happens and the agreement value is 0.903 which required 3 iterations as shown in Table 1.

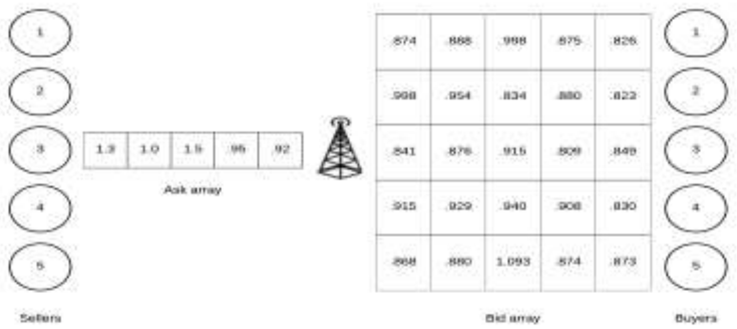

Fig. 3 Bidding in proposed auction scheme

1) *BMV:* As described in algorithm 2, the first seller chosen is seller 5 as it has the lowest ask value. Then the mean of the bid values corresponding to this seller is calculated i.e. $(\sum_{i=1}^{5} B[i][5])\ /\ 5$, then the bid value closest to this mean value is chosen i.e. bidder 3 is chosen. Similarly, this process repeats for other sellers and we get the results stated in Table

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

2. This algorithm also suffers from the problem of high number of iterations i.e. the paired seller and buyer has more difference in their initial ask and bid values.

AMV: As described in algorithm 3, the first seller chosen which has the closest value to the calculated mean value is seller 2, corresponding to which the bidder 2 is selected. Now as observed from Table 3, the number of iterations are lesser (51) and the total finalized prices are higher (5.206).

TABLE I. TDA

Round	**Matched Pairs**	**Number of iterations required to achieve finalized bid**	**Finalized Price/Bid**
1	$S_5 - B_5$	3	.903
2	$S_4 - B_4$	3	.938
3	$S_2 - B_2$	3	.984
4	$S_1 - B_1$	22	1.094
5	$S_3 - B_3$	30	1.215
TOTAL		61	5.134

TABLE II. BMV

Round	**Matched Pairs**	**Number of iterations required to achieve finalized bid**	**Finalized Price/Bid**
1	$S_5 - B_3$	4	.889
2	$S_4 - B_5$	4	.914
3	$S_2 - B_1$	6	.948
4	$S_1 - B_4$	20	1.115
5	$S_3 - B_2$	34	1.174
TOTAL		64	5.04

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

TABLE III. AMV

Round	Matched Pairs	Number of iterations required to achieve finalized bid	Finalized Price/Bid
1	$S_2 - B_2$	3	.984
2	$S_1 - B_4$	20	1.115
3	$S_4 - B_1$	4	.915
4	$S_3 - B_5$	21	1.303
5	$S_5 - B_3$	4	.889
TOTAL		52	5.206

V. ECONOMIC ANALYSIS

In this section, we prove the economic properties that our double auction satisfies i.e. budget-balance, truthfulness, economic efficiency.

Theorem 1: AMV is budget-balanced.

Proof: According to Algorithm 3, if a_i and b_i are the final ask and bid and B_{ij} denotes the final price on which the agreement is done between the seller j and buyer i then they are mathematically expressed as

$$a_i = SINR - \xi$$

$$b_i = SINR + \xi$$

$B_{ij} = b_i \geq b_0$ and $a_i \leq a_0$ but $b_i \geq a_i \geq b_0$ for all sellers and buyers which denotes $\sum B_{ij}$ is a non-negative profit for all the sellers and buyers and the auctioneer is at no profit no loss condition. Also the number of sellers is same as the number of buyers $|S_{win}^{ch}| = |B_{win}^{ch}|$ i.e. the number of winning sellers and winning buyers is equal because one D2D user can be

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assigned shared channel with one D2D user only. The profit of D2D users is the gain in SINR obtained by the difference between the finalized price and the initial bid $|B_{win}^{ch}|B_{ij} - |B_{win}^{ch}|b_i \geq 0$ .While the profit of cellular users is expressed as $\sum |S_{win}^{ch}|a_{ij} \geq |S_{win}^{ch}|B_{ij} \geq |S_{win}^{ch}|b_i|$ i.e. $\sum |S_{win}^{ch}|a_{ij} - |S_{win}^{ch}|B_{ij} - |S_{win}^{ch}|b_i| \geq 0$. So the overall profit for both the cellular and D2D user is no less than 0.

Lemma 1 Given a_i be the ask and b_i be the bid such that $a_i > b_i$.

Proof: Since $a_i > b_i$ the finalized price is calculated according to algorithm 3. Suppose B_{ij} is the finalized price then the profit is expressed as $\sum |S_{win}^{ch}|a_{ij} - |S_{win}^{ch}|B_{ij} - |S_{win}^{ch}|b_i| \geq 0$ which is no less than 0. Thus the algorithm is budget balanced in this case.

Lemma 2 Given a_i be the ask and b_i be the bid such that $a_i \leq b_i$.

Proof: Since $a_i \leq b_i$, the finalized price will be b_i so the profit for cellular user is $|S_{win}^{ch}|b_i - |S_{win}^{ch}|a_i \geq 0$ while the profit for D2D user is 0 in this case so the overall profit in this case is no less than 0 and the auctioneer is at no profit no loss condition.

Theorem 2: AMV is truthful for sellers.

Proof: Given a_i be the initial ask and b_i be the bid value then the seller has SINR requirement as the initial ask which it sends to the base station as a sealed bid. No seller i is aware about the ask of seller j i.e. a_i. Thus there is a single strategy of seller i to ask for i and it cannot differ it's ask (before getting matched to a seller) to any other value $a_i + \Delta$ such that this Δ depends on the ask a_i .Thus AMV is truthful for sellers.

Theorem 3: AMV is truthful for buyers.

Proof: Given a_i be the initial ask and b_i be the bid value then any buyer bids according to (1). This is the calculated SINR offered by a buyer to the sellers and it therefore can't differ it's offered bid before it gets matched to a seller. So, $b_i \neq b_i + \Delta$ where $\Delta \in |b_j - b_i|$. This Δ is the change that a non-truthful buyer can make in it's offered bid seeing the bid b_j of buyer j, such that $b_i \geq b_j$ Thus AMV is truthful for buyers.

Theorem 4: AMV is economically efficient.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Proof: Given b_{ij} is the bid by buyer i for seller j then the final price will be based on two cases.

Lemma 1: When $a_i \leq b_{ij}$

Proof: When $a_i \leq b_{ij}$ then the finalized price will be b_{ij} . So, $\sum_{i=0,j=0}^{m,n} b_{ij}^{'} = \sum_{i=0,j=0}^{m,n} b_{ij}$ which is maximum price a seller j can get from buyer i. Since the bid exceeds the ask, so the price which is more than the ask is always satisfactory for the sellers.

Lemma 2: When $a_i \rangle b_j$

Proof: When $a_i \rangle b_j$, the finalized price will be calculated such that $a_i - \xi \leq b_i + \xi$. On reaching this condition the bid $b_i^{'} = b_i + \xi$ is the finalized price . So

$$b_i^{'} \geq b_i \forall i \in S, B$$

$$\sum_{i=0,j=0}^{m,n} b_{ij}^{'} \geq \sum_{i=0,j=0}^{m,n} b_{ij}$$

So, the total finalized price i.e. $\sum_{i=0,j=0}^{m,n} b_{ij}^{'}$ is always maximum than what sellers could have got initially with the initially offered bids. Moreover, AMV gives maximum value for $\sum_{i=0,j=0}^{m,n} b_{ij}^{'}$ in comparison with other algorithms like TDA and BMV. This can be proved with the calculated values in Table 1,2,3. Also Section VI describes the economic efficiency of AMV in Fig 9.

VI. PERFORMANCE EVALUATION

In this section we illustrate the simulation results and settings under different algorithms illustrated above.

A. *Simulation Settings*

In this simulation the sellers, buyers and the base station is randomly distributed in the cell. We have considered a single cell scenario in the cellular network. Also the following metrics have been described and evaluated in the simulation results:

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1) Price in terms of the finalized SINR value to which both the seller-buyer got agreed.
2) Iterations required is the number of times both the sellers and the buyers adjusted their values to come to an agreement.
3) Economic Efficiency is the summation of the finalized prices for all the buyers in an algorithm.
4) Seller satisfaction is the difference between the initial ask and the agreed price. It increases as the difference decreases.
5) Buyer satisfaction is the difference between the agreed price and the initial bid. It increases as the difference decreases.

B. Simulation Results

Here we consider the constant c as 0.02 and T as 1 to calculate ξ while bargaining in the algorithms. Fig. 4, Fig. 5, Fig. 6 gives the initial bid, initial ask and the mutually agreed value i.e. the finalized price for different seller buyer pairs for TDA, BMV, and AMV respectively. The given graphs, illustrates the variation of finalized price with initial ask and bid. These graphs undergo rise and fall according to the initial biddings made by the users.

In Fig. 4 the difference in the initial bid and finalized price as well as the initial ask and the finalized price is more. This states that both the buyer as well as the seller need to adjust their initial biddings by a big measure. This will certainly involve more number of iterations. Also there is great difference in the adjustments made by buyer and seller i.e. sometimes buyer has to adjust much more than seller to come to finalized price or vice-versa. Here, In pair 1 seller adjusts comparatively lesser than the buyer. That means buyer has to pay considerably higher amount. So, it will greatly impact buyer satisfaction.

Fig. 5 illustrates BMV, this shows comparatively less difference between the initial biddings and the finalized price for some seller-buyer pairs. However, it shows large difference for some seller-buyer pairs (here pair1 and 3), while pair 2, 4, 5 has very less difference. This results in the increase in number of iterations (for pair 1 and 3) to come to an agreement on a finalized price, while pair 2, 4, 5 has least number of iterations. For seller-buyer pair 1 and pair 4, the buyer has to adjust lesser but the seller faces great decline in adjusting it's initial ask value to finalized value. This is not desirable as both the seller and buyer should adjust nearly equally to come to a finalized price. This problem is almost sorted in AMV as shown by Fig. 6.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

It is clear that in Fig. 6 there is least difference between the initially selected ask and the bid and therefore the final price also makes the least difference from the ask and the bid. This symbolizes that both the seller and the

buyer need to adjust their values by a significantly lesser amount than that of TDA and BMV. Moreover, both the seller and buyers adjust almost equally to come to a finalized price.

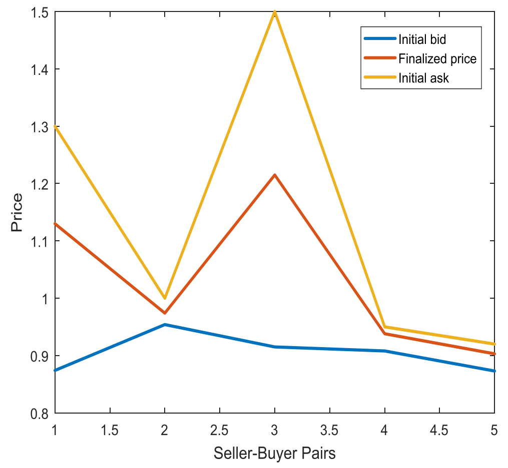

Fig. 4 TDA

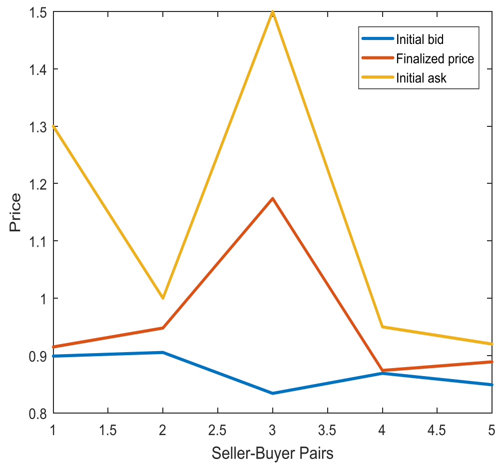

Fig. 5 BMV

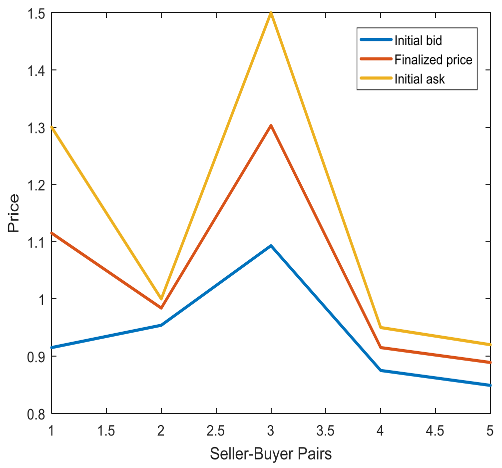

Fig. 6 AMV

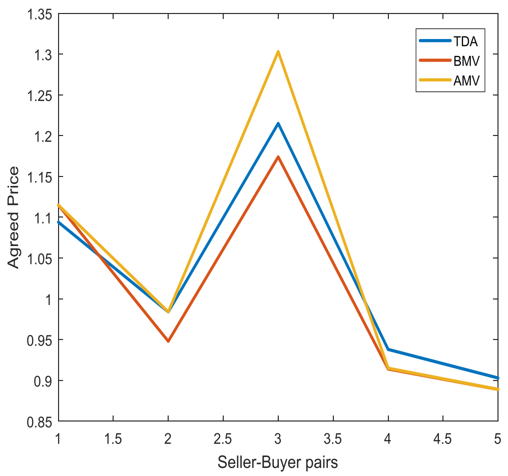

Fig. 7 Finally Agreed Prices

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The Economic Efficiency can be seen from Fig. 7 and Fig. 10. Fig. 7 gives the comparison of the finalized prices in TDA, BMV and AMV. It is clear that AMV gives the highest prices in comparison to other algorithms. Therefore, the summation of all the finalized prices for all seller-buyer pairs is maximum in AMV algorithm (i.e. 5.206) as shown in Fig. 10. Therefore, AMV is economically efficient double auction algorithm.

We show the iterations required to come finalized values in different algorithms in Fig. 8. This shows that the iterations for AMV (52) are comparatively lesser than that of TDA (61) and BMV (64). We show it more precisely with the help of Fig. 9, which gives the comparison of number of iterations required for finalizing value between different seller-buyer pairs in different rounds in all the three algorithms. We see that the highest number of iterations did not exceed 21 while in other algorithms they are 30(in TDA) and 34(in BMV). We also see that as we proceed towards the last rounds the iterations go on increasing, this is due to the inappropriate matching of seller buyer pairs which have great difference in their initial ask and bids. Thereby increasing the number of iterations for mutual settlement.

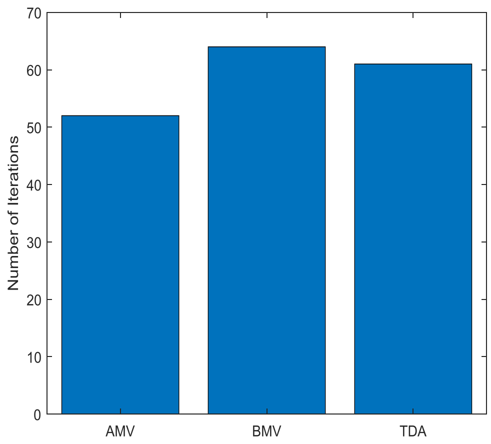

Fig. 8 Iterations required for mutual agreement

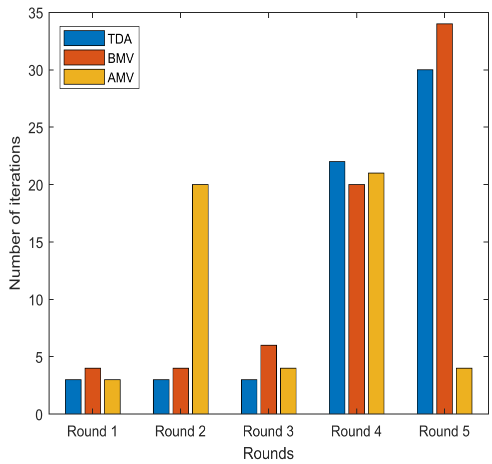

Fig. 9 Iterations required per round

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We show seller and buyer satisfaction in Fig. 11, Fig. 12 and Fig. 13. Fig. 11 illustrates that the difference between the initial ask by the seller and the final price is less in AMV on an average. Lesser difference guarantees more satisfaction. Similarly, in Fig. 12 difference between initial bid and final price is shown. Although for buyer 4 and 5 the difference is bit high but it gets compensated in the overall difference i.e. the total difference in AMV is comparatively much lesser than other algorithms as shown in Fig. 13. Since the total difference is comparatively much lesser for sellers and buyers therefore the seller satisfaction and the buyer satisfaction is highest in AMV.

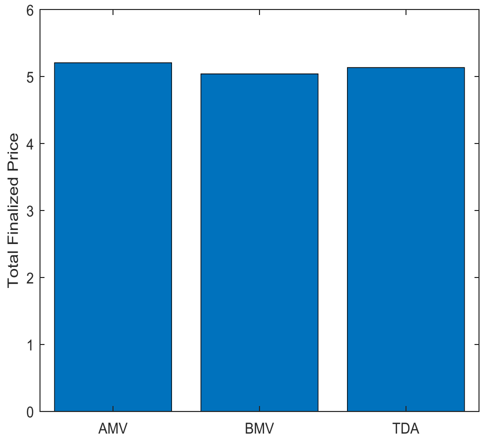

Fig. 10 Economic Efficiency

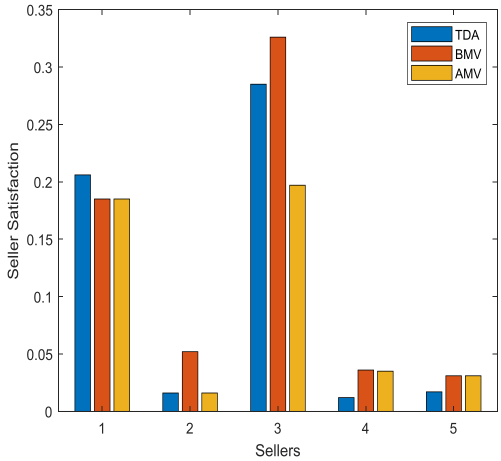

Fig. 11 Seller Satisfaction

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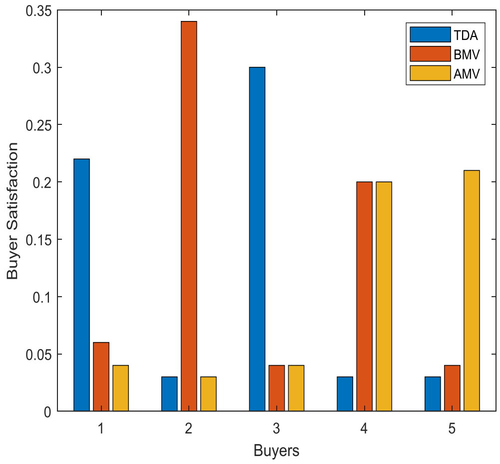

Fig. 12 Buyer Satisfaction

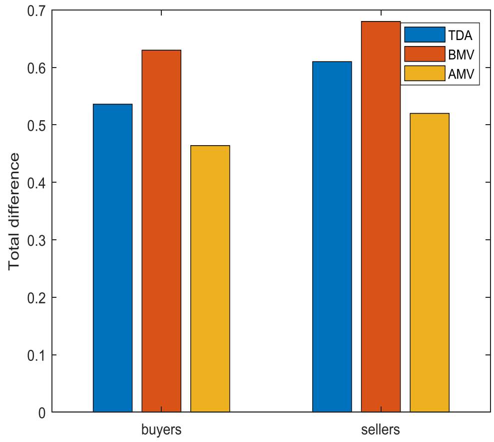

Fig. 13 Total Satisfaction

CONCLUSION

In this paper, we show a truthful sealed bid double auction between the cellular users who act as sellers and the D2D users who act as buyers and the base station acts as auctioneer. The sellers are waiting to share the channel and buyers are waiting to access the channel for communication in a single cell. We propose TDA, BMV, and AMV algorithms for double auctions. TDA is the basic double auction approach and BMV is modified approach of TDA. Further extension and the improved version of these schemes is AMV. The AMV algorithm satisfies maximum properties of a double auction including truthfulness, Budget balance and economic efficiency. The simulation results show that the AMV auction scheme is economically efficient in terms of the final agreed price and can achieve high seller and buyer satisfaction.

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