TAHES: A Truthful Double Auction Mechanism for Heterogeneous Spectrums

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***Abstract*—Auction is widely applied in wireless communication for spectrum allocation. Most of prior works have assumed that all spectrums are identical. In reality, however, spectrums provided by different owners have distinctive characteristics in both spacial and frequency domains. Spectrum availability also varies in different geo-locations. Furthermore, frequency diversity may cause non-identical conflict relationships among spectrum buyers since different frequencies have distinct communication ranges. Under such a scenario, existing spectrum auction schemes cannot provide truthfulness or efficiency. In this paper, we propose a Truthful double Auction mechanism for HEterogeneous Spectrum, called TAHES, which allows buyers to explicitly express their personalized preferences for heterogeneous spectrums and also addresses the problem of interference graph variation. We prove that TAHES has nice economic properties including truthfulness, individual rationality and budget balance. Results from extensive simulation studies demonstrate the truthfulness, effectiveness and efficiency of TAHES.**

***Index Terms*—Spectrum auction, double auction, TV white space, truthfulness.**

I. Introduction

SPECTRUM is a valuable resource for wireless communication [1]. Ever-increasing wireless traffic demand (propelled by the rapid development of smart devices and 3G technology) has contributed to the spectrum crisis. However, measurement results have shown that spectrum utilization is highly dynamic in different geo-locations[2]. In some places, spectrums may be under-utilized and are usually referred to as "white spaces". More efficient utilization of white spaces of different frequencies is considered to be a potential solution for the next generation of wireless networking.

A promising way to better utilize white spaces is to enable spectrum owners to lease their spectrums to secondary service providers in the geo-locations where the primary users will not suffer interference. In return, the spectrum owners can get paid from secondary service providers. One company, SpectrumBridge[3] has already launched an online platform called SpecEx to allow spectrum owners to sell their unused spectrums to potential buyers. With an entirely new business model, spectrums from multiple sellers reside in different frequency bands and have various availabilities in different locations. Also, spectrum buyers may express different preferences for different spectrums. Another interesting aspect of this scenario is the reusability of the spectrum. Two buyers that are far enough away from each other may reuse the same spectrum concurrently.

The problem of spectrum redistribution between multiple spectrum owners and multiple secondary service providers can be modeled as a *single round multi-item double auction*. In our case, the spectrum owners are the sellers; the secondary service providers are the buyers; the spectrums are the goods. The auctioneer can be a third party providing the auction platform such as SpectrumBridge or regulators such as FCC.

Although auction has been widely applied to spectrum allocation in wireless communication, no existing double auction schemes[8]-[13] can be directly applied to our scenario. There are three major challenges in our problem. The first challenge is the spatial heterogeneity of spectrum. Spectrums offered by different spectrum owners are available to different buyers. However, existing works[8]-[13] consider only the scenario where all spectrums are available to all buyers. The second challenge comes together with frequency heterogeneity and spectrum reusability. The spectrums may reside in various frequency bands. The communication range of low frequency band is larger than that of high frequency band. In this case, the interference relationships between different buyers can be different in different bands. However, existing works considering spectrum reusability[12][13] usually assume the same conflict relationship among all buyers throughout all frequencies. The third challenge comes from the auction mechanism design. A well designed auction scheme should preserve the most critical property: *Truthfulness* (or strategy-proofness). A truthful auction incites all bidders to voluntarily reveal their true valuation for the items they are bidding. By valuation, we mean that the true value of the spectrum to the bidders. For the spectrum buyers, its true valuation can be obtained via the evaluation of the spectrum capacity or availability. In a truthful auction, the auctioned items are finally assigned to bidders who value it the most. Unfortunately, with heterogenous items, the truthfulness cannot be guaranteed when simply applying existing schemes. Besides truthfulness, several other properties are also desirable: i) *Individual rationality*: The utility of both buyers and sellers is enhanced because of the auction; ii) *Budget balance*: The net profit of the auctioneer is non-negative; and iii) *System Efficiency*: The total valuation of all the bidders is optimized, e.g the total utility of all buyers and sellers in this paper.

In this paper, we propose TAHES, a **T**ruthful double

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Auction scheme for **HE**terogeneous **S**pectrum, to address the above-mentioned challenges. TAHES groups spectrum buyers according to their non-identical conflict relationships in heterogeneous spectrums to explore spectrum reusability. To guarantee truthfulness, TAHES employs a matching procedure between buyer groups and sellers. A novel pricing scheme is also integrated into TAHES to improve the system efficiency. In summary, the main contributions of the paper are as follows:

- To the best of our knowledge, TAHES is the first double auction mechanism for heterogeneous spectrum transactions, allowing buyers to express diversified preferences for spectrums of difference frequencies.
- TAHES improves spectrum utilization by taking into consideration of the spectrum reusability. As far as we know, TAHES is the first auction mechanism that can deal with the problem of interference graph variation caused by spectrum frequency heterogeneity.
- TAHES ensures that bidding truthfully is the dominant strategy for all bidders. Despite this, TAHES also conforms with individual rationality and budget balance.

The rest of the paper is organized as follows. Section II presents the auction model of heterogeneous spectrum trading and then sets the design objectives for the proposed auction mechanism. In section III, challenges in heterogeneous auction design are further explained. We give detailed description of TAHES in section IV. Simulation results are given in section V. We discuss related works in Section VI and summarize the entire work in Section VII.

II. Model Description and Design Targets

In this section, we first formulate the problem of heterogeneous spectrum exchange between spectrum owners and service providers as a double auction. Then, we overview ideal economic properties of an auction mechanism and state our auction design target.

A. Problem Formulation

We consider the scenario where N secondary service providers trying to purchase spectrum resources from M spectrum owners. A single-round double auction consists of M seller and N buyers is held to serve this purpose. Let $S = \{s_1, s_2, \cdots, s_M\}$ denotes the set of sellers and $W = \{w_1, w_2, \cdots, w_N\}$ denotes the set of buyers. A third-party acts as the auctioneer and decides the winning bidders and the payment. For simplicity, here, we assume each seller contributes one distinct channel and each buyer would like to purchase one channel. The case that each buyer contributes multiple channels and one buyer can obtain multiple channels will be left as our future work. The buyers have different valuations for the channels. Therefore, the buyers' bids are channel-specific. We also assume that the maximum power levels of all buyers are the same across all channels. We assume that the auction is sealed-bid, private and collusion-free. In other words, in the auction, all bidders simultaneously submit sealed bids so that no bidder knows any other participants' bids. In addition, we assume that bidders do not collude with each other to improve the utility of the coalitional group.

We use C_i to denote the bid of s_i. $C = (C_1, C_2, \cdots, C_M)$ is the bid matrix of all sellers and C_{-i} denotes the bid matrix with s_i's bid removed. We use b_i^j to denote the bid of w_i for seller s_j's channel. $B_i = (b_i^1, b_i^2, \cdots, b_i^M)$ is the bid vector of w_i. $B = (B_1, B_2, \cdots, B_N)$ is the bid matrix of all buyers. Let B_{-i} denote the bid matrix with buyer w_i's bid B_i excluded. The true valuation of s_i for its channel is V_i^s and the true valuation of w_i for seller s_j's channel is v_i^j. $V_i^w = (v_i^1, v_i^2, \cdots, v_i^M)$ is the valuation vector of buyer w_i. If s_j's channel is unavailable to w_i, v_i^j is zero. The true valuation of both buyers and sellers may or may not be equal to their bids. In the auction, the auctioneer determines the payment P_i^s for seller s_i and the price p_i^w that buyer w_i should pay. P_i^s and p_i^w are not necessarily equal.

Therefore, the utility of the seller s_i is defined as:

$$U_i^s = \begin{cases} P_i^s - V_i^s, & \text{if } s_i \text{ wins} \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

Similarly, the utility of buyer w_i is defined as:

$$u_i^w = \begin{cases} v_i^{\theta(i)} - p_i^w, & \text{if } w_i \text{ wins} \\ 0, & \text{Otherwise} \end{cases} \tag{2}$$

in which $\theta(i)$ is the channel that w_i wins.

B. Design Target

According to [7][28], truthfulness, budget balance and system efficiency cannot be achieved in any double auction at the same time, even without the consideration of individual rationality. In our scenario, we need to warrant that spectrum owners have the incentive to lease their spectrum and also the third party (spectrum transaction platform, government) is willing to participate as an auctioneer. Therefore, in this paper, we set our design target as achieving truthfulness, individual rationality and budget balance, which are also selected by many existing double auctions[13][28]:

- *Truthfulness*. Neither buyers nor sellers can get higher utility by misreporting their true valuation, i.e., $C_j \neq V_j^s$ or $B_i \neq V_i^w$.
- *Individual rationality*. A winning seller is paid more than its bid and a winning buyer pays less than its bid.
- *Budget balance*. The auctioneer's profit is non-negative. This profit equals to the price paid by the buyers minus the payment to the sellers.

III. Challenges of Heterogeneous Spectrum Auction Design

In this section, we briefly illustrate the challenges of designing a truthful auction mechanism for heterogeneous spectrum. We will first introduce the heterogeneous nature of spectrum. Then we show that existing mechanisms are unsuccessful in meeting our design targets when directly applied to heterogeneous spectrum auction.

A. Spatial Heterogeneity

Spatial heterogeneity means that spectrum availability varies in different locations. For example, one TV channel is available only if there are no nearby TV stations or wireless microphones occupying the same channel.

Traditional auction design involving spectrum reusability usually groups buyers by finding independent sets on their

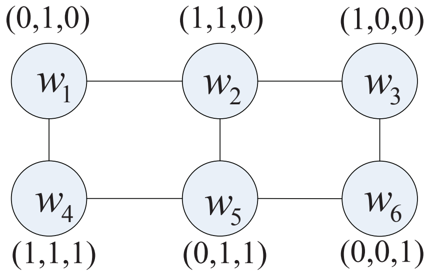

Fig. 1: No channels are commonly available for buyers in both buyer groups: $\{w_1, w_3, w_5\}$ or $\{w_2, w_4, w_6\}$.

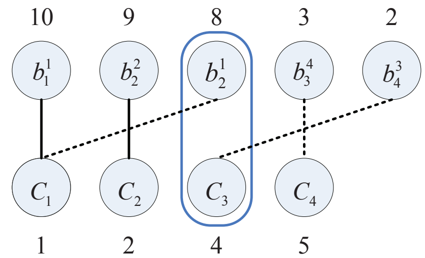

Fig. 2: Buyer b_2 can manipulate its non-winning bid to increase the utility.

interference graph (or conflict graphs) [22], and then set the group bid according to the minimum bid in the group [12][13]. However, if two buyers with no common available channels are grouped together, the group bid should be 0 for all channels and this group can never win in the auction. Take the scenario in Fig. 1 for example. There are 6 buyers: $w_1 - w_6$ and three channels: 1-3. Two nodes with an edge between them are mutually conflict. The bid vectors are also depicted along with each buyer. For example, only channel 2 is available for buyer w_1, so only its bid for channel 2 is not 0.

In this example, by finding the maximal independent sets in the interference graph, the 6 buyers can be grouped into two groups, $\{w_1, w_3, w_5\}$ and $\{w_2, w_4, w_6\}$, respectively. However, there is no common available channel for all users in either group. For example, in the group $\{w_1, w_3, w_5\}$, channel 2 is the only common available channel for the two users w_1 and w_5, but it is not available for w_3.

B. Frequency Heterogeneity

Frequency heterogeneity means that different frequencies have different transmission ranges. According to the propagation model recommended by ITU[14], the center frequency of one spectrum band can impact the path loss between two nodes:

$$L = 10 \log f^2 + \gamma \log d + P_f(n) - 28 \qquad (3)$$

where L is the total path loss in decibel(dB), f is the frequency of transmission in megahertz(MHz), d is the distance in meter(m), γ is the distance power loss coefficient and $P_f(n)$ is the floor loss penetration factor. In our model, the spectrums offered by spectrum owners may consist of a wide range of frequencies. For example, in the German spectrum auction held in 2010, the highest frequency (2.6GHz) was more than three times higher than the lowest frequency (800MHz)[16]. This caused a more than 10dB path loss difference at the same distance between the two. This huge gap leads to non-identical interference relationships among spectrum buyers on different channels. However, based on our knowledge, no existing auction schemes address non-uniform interference relationships among buyers caused by frequency heterogeneity.

C. Market Manipulation

In a double auction for homogeneous items, the two well-known auction algorithms VCG[4]-[6] and McAfee[15] can both ensure truthfulness. However, truthfulness cannot be guaranteed if we directly apply these algorithms to heterogeneous items.

In the McAfee double auction, the auctioneer sorts the buyers' bids in non-increasing order and the sellers' bids in non-decreasing order: $b_{i_1}^{j_1} \geq b_{i_2}^{j_2} \geq \cdots \geq b_{i_{N\times M}}^{j_{N\times M}}$ and $C_{i_1} \leq C_{i_2} \leq \cdots \leq C_{i_M}$. Then the auctioneer finds the largest k such that $b_{i_k}^{j_k} \geq C_{j_k}$. The McAfee scheme discards $(b_{i_k}^{j_k}, C_{j_k})$ which is the least profitable transaction and sets the uniform price for buyers to be $b_{i_k}^{j_k}$ and the uniform payment for sellers to be C_{j_k}. In a double auction for heterogeneous items, although one buyer can win at most one item, it can manipulate its bids to achieve higher utility.

In Fig. 2, there are four buyers among which buyer w_2 has two non-zero bids b_2^2 and b_2^1. Both the buyers and sellers' bids have been sorted according to the McAfee mechanism. We can see that the index of the least profitable transaction marked by the blue frame is $k = 3$. So the price charged for the winning group is $b_2^1 = 8$. If the buyer w_2 lowers its bid for seller s_1 to make $b_2^1 < 8$, say $\widetilde{b}_2^1 = 7$, this misconduct will not change the results of the auction, but can contort the price from 8 to 7. As a result, the utility of w_2 can be increased.

Since the VCG double auction uses a similar way to determine winners and prices, it suffers the same defect. Moreover, the VGC scheme also fails to achieve the budget balance[13][28].

IV. Auction Design: TAHES

In this section, we propose TAHES, a **T**ruthful double **A**uction for **HE**terogeneous **S**pectrum.

A. Overview

To handle both spectrum heterogeneity and spectrum reusability, we design three key steps in TAHES:

(1) Buyer Grouping:

Spectrum can be reused by non-conflict buyers in different locations. By non-conflict, we mean that when two buyers w_i and w_j use the same channel h, they are out of $h's$ interference range of each other. However, the conflict relationships between one pair of buyers are non-identical in different frequencies. In this step, the auctioneer uses a grouping algorithm considering non-identical interference graphs to form non-conflict buyer groups so that the buyers in the same group can purchase the same channel. Our buyer grouping algorithm is bid-independent. The input of the grouping algorithm is the channel availability information of each buyer. This kind of

Algorithm 1 Buyer-Grouping(A, E, H)

```
1: // L represents the set of grouped buyers
2: L = ∅, G = ∅, F = ∅;
3: while L ≠ W do
4:     for all h_i ∈ H do
5:         Candidate buyers to be grouped: Q = ∅;
6:         Q = {w_k | A_{k,i} = 1 ∧ w_k ∉ L};
7:         Find independent set IS_i on buyer set Q based on
           E_i;
8:     end for
9:     Find IS_i, such that EFF(IS_i) is maximized;
10:    g = {w_j | w_j ∈ IS_i};
11:    L = L ⋃ {w_j | w_j ∈ IS_i};
12:    f = {h_j | h_j ∈ H ∧ R(h_j) <= R(h_i)};
13:    G = G ⋃ g, F = F ⋃ f;
14: end while
15: return (G, F);
```

information can be calculated according to the path loss model given the locations of buyers and sellers or can be obtained from a geo-location database[17]. We assume the auctioneer can get such location information of all the buyers and sellers. The bid-independent property of the grouping algorithm is critical to ensure truthfulness in the auction[13].

(2) Matching:

After the first step, each buyer group may still purchase channels from multiple sellers if the buyers in a group have more than one common channels. While indeed, each group can at most win one channel. We have shown that only one bid in a bid vector should be kept non-zero for further winner determination. Otherwise, the auction can be vulnerable to market manipulation. Some buyers can strategically change some of their bids to lower the group bids so that they can change the price they need to pay and increase their utility. In this matching step, the auctioneer chooses one conventional matching algorithm to match each buyer group to only one seller based only on the channel availability for each group. Therefore, the matching step is also bid-independent.

(3) Winner Determination and Pricing:

After buyer grouping and matching, the remaining problem of winner determination and pricing are similar to that in the McAfee double auction design. However, since each buyer group in our problem is matched to one seller, if we directly use the k'th pair of buyer group and seller to determine the winners, the number of winning bidding pairs may be small. So we enhance the McAfee mechanism by taking into consideration of the matching results.

B. Auction Procedure

TAHES comprises the following steps:

1) Buyer Grouping: Suppose the set of channels from sellers is $H = \{h_1, h_2, \cdots, h_M\}$. h_i's communication range which is defined as the transmission range under the maximum allowed power level on channel h_i is denoted as $R(h_i)$. We assume the maximum allowed power on all channels for all buyers are the same. Without loss of generality, we assume $R(h_1) \leq R(h_2) \leq \cdots \leq R(h_M)$. Let $A = \{a_{i,j} | a_{i,j} \in \{0, 1\}\}_{N\times M}$, an N by M matrix, represent the buyers' channel availability. $a_{i,j} = 1$ means that channel h_j is available for buyer w_i. Let $E = \{e_{i,j,k} | e_{i,j,k} \in \{0, 1\}\}_{M\times N\times N}$, an M by N by N matrix, represent the conflict relationships between buyers in each channel. $e_{i,j,k} = 1$ means that buyers w_j and w_k are conflict in h_i.

In this step, the inputs are A and E, which are both bid-independent. After grouping, we get a set of l ($l \leq N$) buyer groups denoted as $G = \{g_1, g_2, \cdots, g_l\}$ and the corresponding candidate channel set for each group denoted as $F = \{f_1, f_2, \cdots, f_l\}$. f_i contains the channels that g_i can purchase, which is assigned by the auctioneer. G and F are the outputs of the grouping algorithm. The grouping algorithm should satisfy the following constraints:

Common Channel Existence Constraint: There exists at least one channel that is available for all buyers in the same group.

$$\forall g_i, \exists h_j, s.t. \forall w_k \in g_i \Rightarrow h_j \in f_i \wedge A_{k,j} = 1 \quad (4)$$

Interference Free Constraint: Any two buyers in the same group do not mutually interfering with each other in any channel in the candidate channel set.

$$\forall w_j, w_k \in g_i, \forall h_l \in f_i \wedge A_{j,l} = A_{k,l} = 1 \Rightarrow E_{l,j,k} = 0 \quad (5)$$

The grouping algorithm first finds an independent set of buyers in each channel. Then it selects one such set with maximum *Grouping Efficiency* and continues to find the next group until all buyers are classified into one group. The efficiency of each group relates to the group size and the channel communication range. Suppose the independent set found on channel h_i is IS_i, we define efficiency as:

$$EFF(IS_i) = |IS_i| \times R(h_i) - \alpha \cdot V(G, h_i) \quad (6)$$

where $V(G, h_i)$ indicates the number of groups already formed according to the independent set on the interference graph of h_i. From this definition, we can see that we prefer to group buyers on a channel with a larger communication range. This is because if IS_i is an independent set of the conflict graph of channel h_i, it is also an independent set of the conflict graph of any channel $h_j (j < i)$. We also prefer to group buyers into various channels since one channel can only be sold to one buyer group. We can set the parameter α to be very large, e.g $N \times R(h_M)$, to ensure an even distribution of groups on all channels. We will evaluate various $EFF(\cdot)$ in Section V.

The grouping procedure is shown in Algorithm 1.

In Algorithm 1, we can use any existing algorithms to find independent sets, for example, the algorithms described in [20]. From the procedure of Algorithm 1, it is obvious that all buyers in IS_i have a common available channel h_i. And from line 12, we can see that the grouping algorithm only considers the candidate channels with a smaller or equal communication range of h_i. Therefore, the grouping results G and F also satisfy the Interference Free Constraint.

Theorem 1. *The buyer groups and candidate channel sets returned by Algorithm 1 satisfy the Common Channel Existence Constraint and the Interference Free Constraint.* □

Algorithm 2 Buyer-Group-Matching(G, F, S)

```
// Let Δ be an |G| by |S| matrix representing the weighted adjacent matrix between G and S
Δ = {0}_{M×N};
for all g_x ∈ G, s_y ∈ S do
    if δ_x^y > 0 and h_y ∈ f_x then Δ_{x,y} = Δ_{y,x} = |g_x|;
end for
(G_C, S_C, σ) = MATCH(X, Y, Δ);
return (G_C, S_C, σ);
```

2) *Matching:* After step 1, we have formed a group set G. Suppose the number of buyers in group g_i is n_i and the group bid vector is $\delta_i = (\delta_i^1, \delta_i^2, \cdots, \delta_i^M)$. We follow the idea in [13] and assigned the group bid to be the minimum bid times the group size as:

$$\delta_i^j = \min\{b_k^j | w_k \in g_i\} \cdot n_i \tag{7}$$

Here, we can imagine each buyer group as one *super buyer*. In δ_i, there may be more than one non-zero entry. If not well designed, the auction may be untruthful, as shown in Section III-C. Such a type of market manipulation is caused by the multiple non-zero group bids. To tackle this challenge, in TAHES, we apply a channel matching scheme to match one buyer group to an identical seller. We call the results after matching the candidate winning group set G_C and candidate winning sellers set S_C. The matching procedure is shown in Algorithm 2.

In this algorithm, σ records the matching result. For example, $\sigma(g_x) = s_y$ indicates that buyer group g_x is assigned to seller s_y. $MATCH(X, Y, \Delta)$ matches nodes set X to Y with weighted edges in Δ. It can be any matching algorithm for bipartite graphs specified by the auctioneer, for example, maximum matching[18] or maximum weighted matching[19]. This matching step here is also independent both the buyers and sellers' bids.

3) *Winner Determination and Pricing:* In the winner-determination and pricing stage, we need to consider the matching results from the second step. Here, we can directly apply the pricing mechanism used in McAfee here. However, the winner determination algorithm in McAfee may reduce the number of winning pairs and thus decrease the system efficiency. Therefore, instead of directly using the buyer group-seller pair (g_{i_k}, s_{j_k}) to determine winners, we make one step further. Observed that there may be multiple equal g_{i_k}, s_{j_k} pairs, the auction outcome may be affected by the order of bids after sorting. So we check all the possible orders of bids equal to g_{i_k} or s_{j_k} and choose the one with the maximum matchings. The detailed algorithm is shown in Algorithm 3.

In line 6, the algorithm finds all group bids equal to $\delta_{i_k}^{\sigma(i_k)}$, and stores them in the set Λ_k^W. Actually, the order of group bids in Λ_k^W can be arbitrary. Similarly, Λ_k^S contains all sellers with bids equal to C_k. In line 9, the algorithm checks all the combinations of possible orders of groups in Λ_k^W and sellers in Λ_k^S to determine the number of matchings that can be achieved. The algorithm finally finds the maximum number of matchings for the given winner candidate sets G_C, S_C. $M(X, Y)$ denotes the set of matching induced by X and Y. From line 13 to line 18, the algorithm calculates the price for each buyer and the payment for each seller. $\tau(\cdot)$ is the mapping function from the indices of buyers to the indices of the groups they belong to. The group price is shared by all the members in that group.

Algorithm 3 Winner-Determination-and-Pricing(G_C, S_C, σ)

```
1: G_W = ∅, S_W = ∅; // The set of winning groups and sellers
2: Construct X = {g_{i_1}, g_{i_2}, ···, g_{i_l}}, such that δ_{i_1}^{σ(i_1)} ≥ δ_{i_2}^{σ(i_2)} ≥ ··· ≥ δ_{i_l}^{σ(i_l)};
3: Construct Y = {s_{j_1}, s_{j_2}, ···, s_{j_M}}, such that C_{j_1} ≤ C_{j_2} ≤ ··· ≤ C_{j_M};
4: Find the largest k, s.t. δ_{i_k}^{σ(i_k)} ≥ C_{j_k};
5: if k < 2 then return (G_W, S_W, 0, 0);
6: Find the groups Λ_k^W, s.t. ∀g_x ∈ Λ_k^W, δ_{i_k}^{σ(i_k)} = δ_x^{σ(x)};
7: Find the sellers Λ_k^S, s.t.∀s_y ∈ Λ_k^S, C_{j_k} = C_y;
8: // Let X_i be the sublist of the first i groups in X, Y_j be the sublist of the first j sellers in Y
9: Find X_k, Y_k, s.t. |M(X_{k−1}, Y_{k−1})| is maximal, where g_i ∈ Λ_k^W and s_j ∈ Λ_k^S can be in any orders;
10: // Determine the winning groups and sellers
11: p^w = δ_{i_k}^{σ(i_k)}, P^s = C_{j_k}, G_W = {g_x|∀g_x ∈ M(X_{k−1}, Y_{k−1})}, S_W = {s_y|∀s ∈ M(X_{k−1}, Y_{k−1})};
12: // Determine the price and payment
13: for all Buyer w_i ∈ W do
14:     if g_{τ(i)} ∈ G_W then p_i^w = p^w/n_{τ(i)};
15: end for
16: for all Seller s_j ∈ S do
17:     if s_j ∈ S_W then P_j^s = P^s;
18: end for
19: return (G_W, S_W, P^S, p^w);
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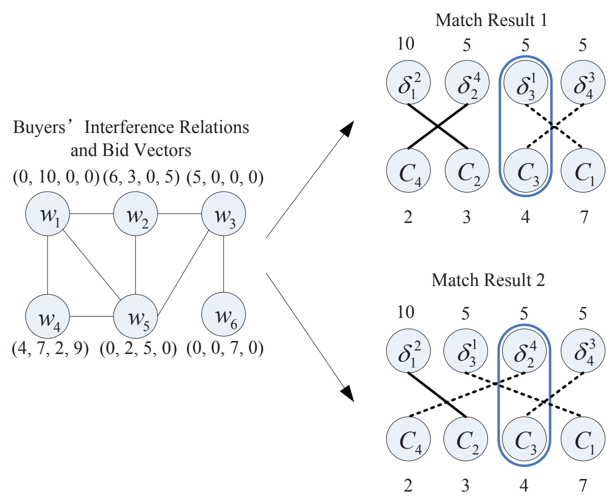


Fig. 3: An illustrative example with six buyers.

C. Illustrative Example

Fig. 3 shows a scenario with 6 buyers and 4 sellers. The bid vectors and buyers' conflict relationships are shown in Fig. 3. For the sake of simplicity, here we assume their conflict relationships are the same across all channels. The sellers' bids are: $s_1 = 7$, $s_2 = 3$, $s_3 = 4$ and $s_4 = 2$.

After buyer grouping, the buyers form 4 groups with group bids shown in Table I. The bids in bold font are chosen after the matching step. We can see that, there are three candidate

TABLE I: Members and bids of four buyer groups.

groups	s_1	s_2	s_3	s_4
$g_1 = \{w_1\}$	0	**10**	0	0
$g_2 = \{w_2, w_4\}$	4	3	0	**5**
$g_3 = \{w_3\}$	**5**	0	0	0
$g_4 = \{w_5, w_6\}$	0	0	**5**	0

bids with the same value 5. In the winner-determination and pricing step, after sorting all the bids, according to Algorithm 3, in our scenario, $k = 3$, $\Lambda_k^W = \{g_2, g_3, g_4\}$, $\Lambda_k^S = \{s_3\}$. Then the algorithm checks all possible orders of groups in Λ_k^W and orders of sellers in Λ_k^S to determine the winners. When g_2 orders first in Λ_k^W, there are two successful matchings, as shown in Matching Result 1. Otherwise, there can only be one successful matching. One of such cases is shown in Matching Result 2. Therefore, we will use the order in Matching Result 1 as the auction result. The price for one winning group $p^w = \delta_3^1 = 5$, the payment for the winning seller $P^s = C_3 = 4$. The price for winners g_2 and g_4 will be shared by the members in these two groups. Therefore, $p_2^w = p_4^w = p_5^w = p_6^w = 2.5$, $p_1^w = p_3^w = 5$. The profit the auctioneer makes is $2\times(5-4) = 2$.

D. Proofs of Economic Properties

In this section, we prove that TAHES is individually rational, budget-balanced and truthful.

Theorem 2. *TAHES is individually rational.* □

Proof: For each buyer w_i in winning group g_k:

$$p_i^w = \frac{p^w}{n_k} \le \frac{\delta_k^{\sigma(k)}}{n_k} \le \frac{n_k \cdot b_i^{\sigma(k)}}{n_k} = b_i^{\sigma(k)}$$

For each winning seller s_j: $P_j^s \ge C_k \ge P^s$ ■

Theorem 3. *TAHES is budget-balanced.* □

Proof: According to the sorting in the winner determination algorithm, we have $p^w \ge P^s$ and $|G_W| = |S_W|$, therefore the budget for the auctioneer is: $|G_W| \times p^w - |S_W| \times P^s \ge 0$ ■

Theorem 4. *TAHES is truthful.* □

To prove Theorem 4, we first show that the auction result for buyer w_i is only related to the bid $w_i^{\theta(i)}$ ($\theta(i)$ is the channel that w_i wins, $\theta(i) = \sigma(\tau(i))$). Then we show that the winner determination is monotonic and the pricing is bid-independent, such that for any buyer w_i or seller s_j, it cannot increase its utility by bidding untruthfully.

Lemma 5. *The auction result only depends on the buyers' bids for the assigned channel after channel matching.* □

Proof: Both the grouping and matching step are bid-independent. After grouping, buyer w_i is in group $g_{\tau(i)}$. After the matching step, only the group bid $g_{\tau(i)}^{\theta(i)}$ is considered in the winning determination and pricing procedure. $g_{\tau(i)}^{\theta(i)}$ is only related with buyer bid $s_i^{\theta(i)}$. ■

In the following, we will consider only $s_i^{\theta(i)}$ for buyer w_i.

Lemma 6. *The position of k remains the same for all combinations of orders of Λ_k^W and Λ_k^S.*

Proof: Since the group bids of groups in set Λ_k^W are equal and the seller bids of sellers in set Λ_k^S are also equal. The order of elements in Λ_k^W and Λ_k^S do not change k. ■

Lemma 7. *Given B_{-i}, if buyer w_i wins in the auction, it also wins by bidding $\widetilde{b_i}^{\theta(i)} > b_i^{\theta(i)}$.* □

Proof: Case 1: if $b_i^{\theta(i)} > \delta_{\tau(i)}^{\theta(i)}$, $\widetilde{b_i}^{\theta(i)}$ will not change $\delta_{\tau(i)}^{\theta(i)}$. Case 2: if $b_i^{\theta(i)} = \delta_{\tau(i)}^{\theta(i)}$, $\delta_{\tau(i)}^{\theta(i)}$ can only be increased for $\widetilde{b_i}^{\theta(i)}$. Since the channel matching is independent of bids, the buyer group $g_{\tau(i)}$ will also be matched to the same seller. As the group bid increased, during the winning determination stage, the buyer group $g_{\tau(i)}$ matching to $s_{\theta(i)}$ can still wins the auction. ■

Lemma 8. *Given C_{-j}, if seller s_j wins in the auction, it also wins by bidding $\widetilde{C}_j < C_j$.* □

Proof: Since the channel matching is independent of bids, the seller s_j should be matched to the same buyer group when bidding lower. Since its bid is decreased, during the winning determination stage, the buyer group $g_{\sigma^{-1}(j)}$ matching to s_j can still win. ■

Lemma 9. *Given B_{-i}, if buyer w_i wins the auction by bidding $\widetilde{b_i}^{\theta(i)}$ and $b_i^{\theta(i)}$, the prices charged to w_i are the same.* □

Proof: According to Lemma 6 and 7, increasing a winning buyer's bid will not change the auction results. It will not change k. Since the price is only dependent on k, the prices charged are the same. ■

Lemma 10. *Given C_{-j}, if buyer s_j wins the auction by bidding $\widetilde{C}_j$ and C_j, the payment paid to s_j are the same.* □

Proof: According to Lemma 6 and 8, decreasing a winning seller's bid will not change the auction results or k. Similarly with Lemma 9, the prices charged are the same. ■

Lemma 11. *TAHES is truthful for buyers.* □

Proof: We need to prove that no buyer b_i can increase its utility by bidding untruthfully, that is, when bidding $\widetilde{b_i}^{\theta(i)} \neq b_i^{\theta(i)}$, $\widetilde{u}_i^w < u_i^w$.

Case 1: $\widetilde{u}_i^w = u_i^w = 0$.

Case 2: $\widetilde{u}_i^w = 0$, $u_i^w > 0$.

Case 3: According to Lemma 7, it happens only when $\widetilde{b}_i^s > v_i^{\theta(i)}$. Since w_i wins the auction by bidding higher, w_i should have offered the lowest bid in the group $g_{\tau(i)}$ when bidding truthfully. As a result, $\delta_{\tau(i)}^{\theta(i)} = n_{\tau(i)} \cdot v_i^{\theta(i)}$. Since w_i wins when bidding untruthfully and loses when bidding truthfully, its group bid should satisfy the following condition: $\widetilde{\delta}_{\tau(i)}^{\theta(i)} \ge \widetilde{\delta}_x^{\sigma(x)} \ge \delta_{\tau(i)}^{\theta(i)}$. Here we suppose (x, y) are the boundary in the auction result. The price paid by w_i when bidding untruthfully is $p_i^w = \widetilde{\delta}_x^{\sigma(x)}/n_{\tau(i)} \ge \delta_{\tau(i)}^{\theta(i)}/n_{\tau(i)} = v_i^{\theta(i)}$. Therefore, $\widetilde{u}_i^w < 0 = u_i^w$.

Case 4: According to Lemma 9, $\widetilde{u}_i^w = u_i^w > 0$

According to Lemma 5, a buyer cannot improve its utility by submitting any bid vector other than its true valuation vector. ■

Similarly, we can prove the following lemma on the truthfulness for sellers.

TABLE II: TAHES is truthful.

Buyer			
M	$U_T^w > U_U^w$	$U_T^w = U_U^w$	$U_T^w < U_U^w$
5	0.9%	99.1%	0%
10	0.4%	99.6%	0%
15	0.4%	99.6%	0%
Seller			
M	$U_T^s > U_U^s$	$U_T^s = U_U^s$	$U_T^s < U_U^s$
5	7.3%	92.7%	0%
10	11.2%	88.8%	0%
15	10.6%	89.4%	0%

Lemma 12. *TAHES is truthful for sellers.* □

Proof of Theorem 4: Lemma 11 and Lemma 12 together prove that TAHES is truthful. ■

V. Numerical Results

In this section, we use simulation to evaluate the performance of TAHES. We first verify the truthfulness of TAHES. Then we study the economic impact on the system efficiency.

A. Simulation Settings

In the simulation, buyers are randomly distributed in a 400×400 square. There are 5-30 spectrum sellers. The radio interference range spans from 20 to 100 in most cases. Each seller has its own base stations in the same area, therefore, the channel is only available to buyers when there is no primary base station nearby. The number of base stations of one seller can be from 2 to 5.

We assume, in the auction, the buyers' bids are randomly distributed over $[0, V_{MAX})$ where V_{MAX} can be within the range of [4, 10]. If the channel is not available for the buyer, the bid is 0. The sellers' bids are randomly distributed over $[2, 2 \times V_{MAX})$. Due to spectrum reusability, sellers may expect its channel to be sold to more than one buyers, so we set the sellers' bids higher. We set $V_{MAX} = 6$ as a default. We use Maximum Matching[18] as a the default in both Algorithm 2 and 3. In our simulation, all the results are averaged over 200 runs.

The metrics evaluated in the simulation are as follows:

- Number of successful transactions.
- Buyer satisfaction ratio: percentage of buyers that can get one channel.
- Average group size.

The first two metrics together determine the system performance of the auction. The third one reflects the effectiveness of the grouping algorithm.

B. Truthfulness of TAHES

To show the truthfulness of TAHES, we fix the number of buyers at 50. The number of sellers can be 5, 10 and 15. In each run, we randomly sample 3 buyers and 3 sellers and compare their utilities when bidding truthfully or untruthfully.

The results are shown in Table II, in which U_T^w (U_U^w) means the utility when a buyer is bidding truthfully(untruthfully) and U_T^s (U_U^s) means the utility when a seller is bidding truthfully(untruthfully). We observe i) the utility of one buyer or seller when bidding truthfully is always higher than that when bidding untruthfully, and ii) the utilities of one buyer when bidding truthfully or untruthfully are the same for most of the time. The first observation verifies the truthfulness of TAHES for both the buyers and sellers. The reason for the second phenomenon is that one buyer can hardly change the group utility by changing its bid.

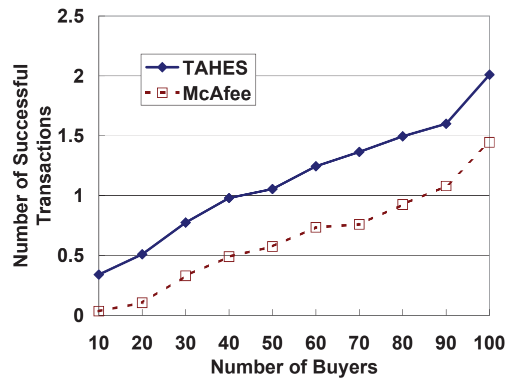


Fig. 4: Comparison between TAHES and McAfee.

C. Impact on System Performance

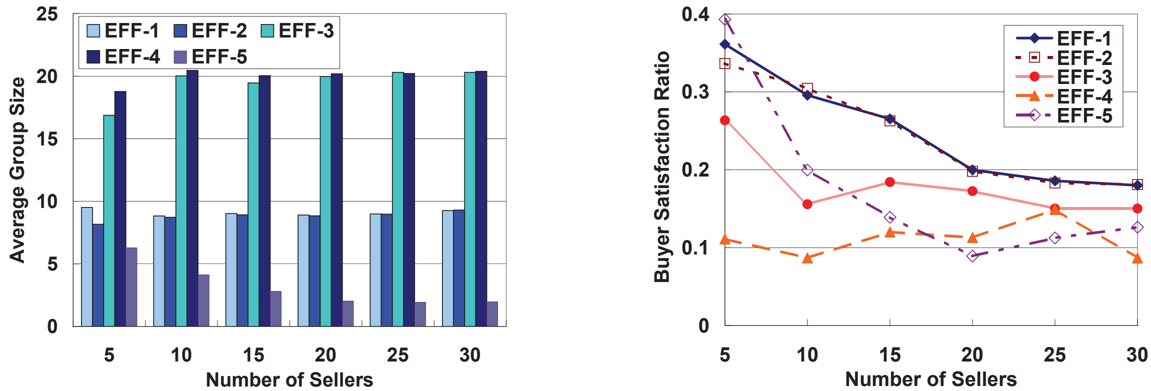
In this section, we evaluate the system performance of TAHES based on two metrics: number of successful transactions and buyer satisfaction ratio.

1) Impact of the Winner Determination Algorithm: The winner determination algorithm used in TAHES finds an optimal order to determine winners, while the mechanism of McAfee fails to consider the matching between buyer groups and sellers. In another words, the McAfee mechanism algorithm just consider one possible order of bids. In the simulation, we fix $M = 10$ and vary the buyer number N. Fig. 4 shows the number of successful transactions provided by both TAHES and McAfee. In all node densities, TAHES provides 30% more transactions than McAfee. In this sense, our winner determination algorithm has traded the time complexity for the system efficiency.

$$\begin{cases} EFF-1 & = & |IS_i| \times R(h_i) - \alpha \cdot V(G, h_i) \\ EFF-2 & = & |IS_i| \times R(h_i) \\ EFF-3 & = & |IS_i| - \alpha \cdot V(G, h_i) \\ EFF-4 & = & |IS_i| \\ EFF-5 & = & \begin{cases} \text{EFF-1}, & \text{if } |IS_i| \le N/M \\ 0, & \text{otherwise} \end{cases} \end{cases} \quad (8)$$

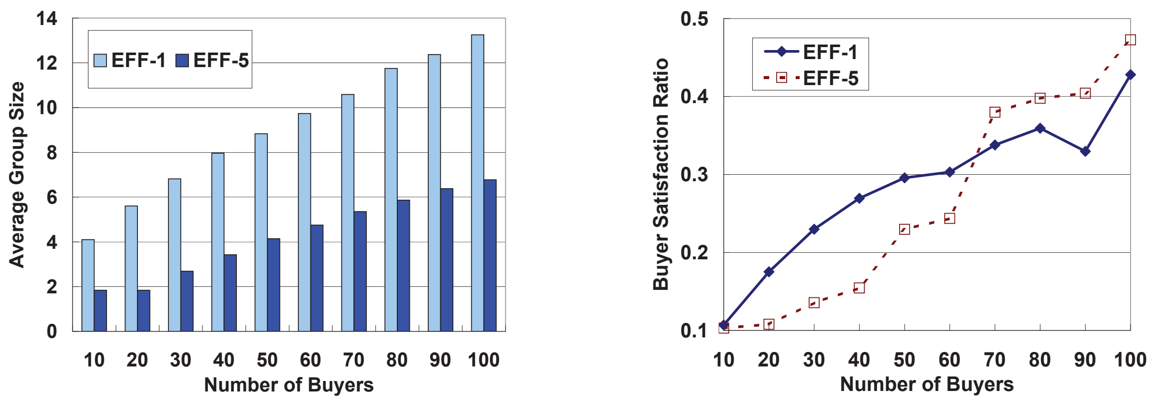
2) Impact of the Grouping Function $EFF(\cdot)$: In the buyer grouping step, we have used the idea of *grouping efficiency* to determine which buyers are grouped on which channel first. Other than the one used in our algorithm, there may be some other choices shown in Equ. 8:

EFF-1 is the one used as our default efficiency function. α is set to $N \times R(h_M)$. Among the five functions, EFF-1, EFF-3, EFF-5 try to distribute buyer groups evenly to different sellers. EFF-1 and EFF-2 both consider group size and channel interference range and prefer to group buyers



(a) Group Size (b) Buyer Satisfaction Ratio

Fig. 5: Comparison of different grouping criterions.



(a) Group Size (b) Buyer Satisfaction Ratio

Fig. 6: Comparison between EFF-1 and EFF-5 in different node densities.

under the channel with the longer range. The first four function are independent of seller number and they use maximum independent set of buyers as groups. On the other hand, EFF-5 limits the size of a group to be no more than N/M. Therefore, the number of groups obtained from EFF-5 is comparable with the number of sellers.

Fig. 5 shows the results under various M when $N = 50$. In Fig. 5a, EFF-1 and EFF-2 have smaller group size compared with EFF-3 and EFF-4. This is because the channel with the larger interference range may have more conflict neighbors, the group size of the channel with the larger interference range is expected to be smaller. As the group size increases, the total number of groups decreases, since the groups are matched to one dedicated seller, therefore, fewer groups can win and the buyer satisfaction ratio may decrease. However, the group size obtained from EFF-5 is too small. Although more groups win, the total number of winning buyers is still low. Fig. 5b shows this situation.

Fig. 6 compares EFF-1 and EFF-5 in different node densities when $M = 10$. We can see from Fig. 6a, the group size by EFF-5 is much smaller than that of EFF-1 and is always below N/M. Interestingly, when the number of sellers is larger than 60, the efficiency provided by EFF-5 outperforms that of EFF-1. We guess there may be an optimal group size setting in different settings of M and N. We will further explore this issue in our future works.

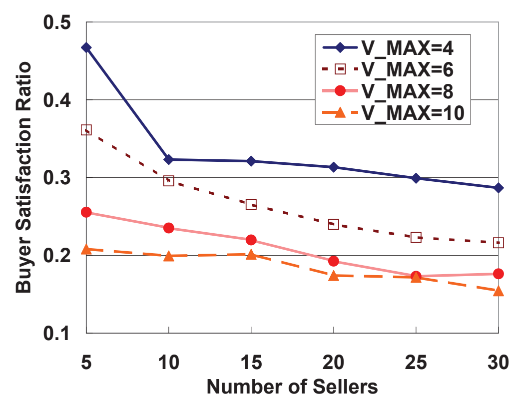


Fig. 7: Comparison of group size and buyer satisfaction ratio under different bid distributions.

3) Impact of the Bid Distribution: In previous simulations, we fix V_{MAX} to be 6. Here we vary V_{MAX} from 4 to 10 while $N = 50$. Fig. 7 illustrates the buyer satisfaction ratio in different V_{MAX}. With higher V_{MAX}, the expected value of buyer's valuation is higher. However, since the group bid is

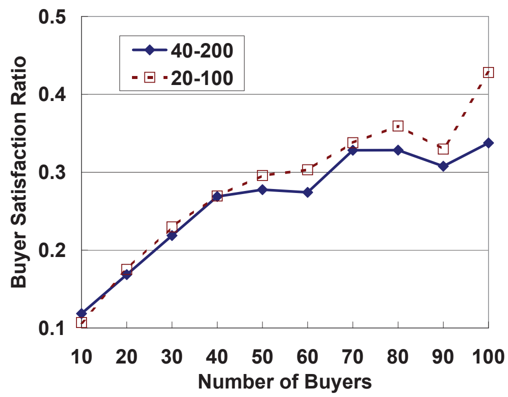


Fig. 8: The impact of communication range.

determined by the minimum bid in the group, whose expected value does not increase at the same speed as V_{MAX}. Therefore, we can observe that the buyer satisfaction ratio has decreased for larger V_{MAX}.

4) Impact of the Communication Range: To evaluate the impact of the communication range to the auction result, we change the span of channels' communication from [20-100] to [40-200]. We fix the seller number $M = 10$. Fig. 8 shows the satisfaction ratios. With a larger communication range, the degree of spatial reuse decreases, so we can observe that the span [20-100] provides a higher buyer satisfaction ratio compared with that of [40-200].

VI. Related Works

Auction has been extensively studied in the scope of spectrum allocation[8]-[13][21]-[27]. However, most existing works failed to consider spectrums as non-identical items. In [13], Zhou and Zheng first address spectrum reusability in their auction design: TRUST. In [12], the authors also consider spectrum reusability for buyers, and they assume buyers can have multiple radios. Recently, in [27], Dong *et al.* address the spectrum reusability in a time-frequency division manner and model the problem as a combinatorial auction. The proposed TAHES scheme also considers spectrum reusability, moreover, TAHES can tackle the case when spectrums are heterogeneous.

In [23], an auction design for heterogeneous TV white space spectrums is proposed. In that paper, the spectrum allocation problem has been defined as an optimization problem where maximum payoff of the central trading entity (called spectrum broker) is the optimization goal. However, [23] is not a double auction scheme and its design goal is different from TAHES. Recently, in [28], Yang *et al.* proposed a double auction design for cooperative communications with heterogeneous relay selections. However, there is no reusability in their scenario.

Different from our single-round auction model, there have also been works considering spectrum auction in an online fashion[21][24]. In an online spectrum auction, buyers may arrive at different times and they can request the spectrum for a particular duration. However, existing online double auction schemes consider only homogeneous spectrum.

VII. Conclusions

In this paper, we have designed TAHES, a truthful double auction scheme for heterogeneous spectrum. TAHES allows multiple spectrum owners with available spectrums in different locations and different frequency bands to participate in the spectrum leasing to secondary service providers. TAHES increases spectrum utilization through spectrum reuse. Carefully designed TAHES can not only solve unique challenges caused by spectrum heterogeneity but also preserve nice economic properties: Truthfulness, Budget Balance and Individual Rationality. With mathematical analysis and extensive simulations, we have shown that TAHES can achieve all required properties and provides higher system efficiency compared with traditional double auction schemes.

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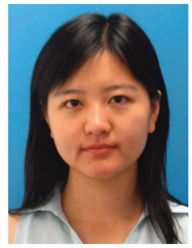

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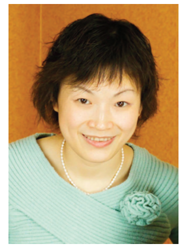

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