Robust Large-Scale Spectrum Auctions against False-Name Bids

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Abstract—Auction is a promising approach for dynamic spectrum access in cognitive radio networks. Existing auction mechanisms are mainly *strategy-proof* to stimulate bidders to reveal their valuations of spectrum truthfully. However, they can suffer significantly from a new cheating pattern, named *false-name bids*, where a bidder can manipulate the auction by submitting bids under multiple fictitious names. We show such false-name bid cheating is easy to make but difficult to detect in dynamic spectrum auctions. To address this issue, we propose ALETHEIA, a novel *flexible, false-name-proof* auction framework for large-scale dynamic spectrum access. ALETHEIA not only guarantees strategy-proofness but also resists false-name bids. Moreover, ALETHEIA enables spectrum reuse across a large number of bidders, to improve spectrum utilization. Following that, we extend ALETHEIA to its general version that supports more practical and flexible auction, where bidders accept the spectrum allocation under their partial satisfactions. Theoretical analysis and simulation results show that ALETHEIA achieves both high spectrum redistribution efficiency and auction efficiency.

Index Terms—Spectrum auctions, false-name-proofness, cognitive radio networks

1 Introduction

1.1 Motivation

Radio spectrum is a critical but scarce resource for wireless communication. With the rapid growth of wireless services and devices, the limited spectrum is draining away, while most licensed spectrum bands (e.g., TV channels) are under-utilized as reported in [2], [16]. To address this dilemma, dynamic spectrum access (DSA) has been proposed based on the advance of cognitive radio (CR) techniques [2], where primary users with licenses can gain financial benefits by leasing their idle spectrum to secondary users without licenses to access, i.e., a win-win situation.

Auctions are the well recognized and *de facto* mechanisms for redistributing spectrum in DSA that can achieve both fairness and allocation efficiency [12]. In auction-based DSA, the spectrum is divided into multiple channels, then the secondary users (referred to as bidders) submit their bids for channels based on the valuation of their short-term local usage, and finally the auction mechanism performed by the primary user (referred to as auctioneer) determines winners as well as their channel allocation and payment. In order to achieve fairness and maximize spectrum utilization, existing spectrum auction designs (e.g., [3], [11], [24], [29]) mainly aim to i) exploit *spectrum reusability*, i.e., a channel can be allocated to multiple bidders as long as the bidders do not interfere with each other, and ii) guarantee *strategy-proofness* (a.k.a. *truthfulness*), i.e., no bidder can improve its own utility by cheating with false valuation, so that each bidder is encouraged to tell the auctioneer its true valuation.

However, the auction manipulation by the bidders can go beyond the cheating with false valuations. As demonstrated in recent studies [6], [8], [19], it is fairly easy for a CR user to generate multiple "names" identified by service-set identifiers (SSIDs). For example, the Atheros chipset supports up to 64 identifiers for one physical device [1]. This can lead to a new cheating pattern named *false-name bids*, where a bidder can submit bids using multiple fictitious names to manipulate the auction results. Unfortunately, due to the open, mobile and ubiquitous nature of CR users, it is prohibitively difficult to detect false identifiers, even using the state-of-the-art authentication methods [6], [8], [19]. A series of questions then naturally arise. What are the consequences of false-name bids for existing spectrum auction mechanisms? Can we design efficient auction mechanisms that are *false-name-proof*, so that each bidder cannot improve its utility by using false-name bids?

1.2 Our Results

To answer the first question, we conduct a broad and deep investigation on several typical strategy-proof spectrum auction mechanisms. For example, we use simulation experiments to examine the effect of false-name cheating to VERITAS [29], a state-of-the-art strategy-proof spectrum auction design. The results show that even a simple pattern of false-name cheating can substantially improve the

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utilities of cheating bidders and reduce the revenue of the auctioneer by 35-40 percent. This highlights the importance of providing false-name-proofness in spectrum auctions. While existing studies have enforced false-name-proofness in auctions for traditional goods (e.g., books and paintings) [13], [20], we show that existing false-name-proof schemes fail when spectrum reusability is embraced. Moreover, it usually results in a low spectrum efficiency.

The above pessimistic results lead us to develop a completely new spectrum auction to resist false-name-bids robustly. In this paper, we propose ALETHEIA, the *first* false-name-proof seal-bid spectrum auction framework for the emerging large-scale DSAs. It is implemented in a price oriented fashion, where the prices of bidders are computed first while winners are then determined independently based on these prices and get corresponding channels in a sequential manner. In this way, it is ensured that the price of buying a bundle of channels is no larger than the sum of prices for buying these channels separately using multiple fictitious names.

Summary of Contributions. Targeting large-scale dynamic spectrum auctions, our work makes three key contributions. First, we show that existing spectrum auction designs are highly vulnerable to false-name bid cheating, especially because false names are easy to form and hard to detect. We find that false-name bids can significantly impair auction revenue. Second, we propose ALETHEIA, a new false-name-proof spectrum auction design for single-minded bidders, who only accept all requested channels or nothing. It guarantees strategy-proofness while resisting false-name bids. ALETHEIA also exploits the spectrum reusability to significantly improve spectrum utilization, while incurring a low computational overhead. Finally, we extend ALETHEIA to support range-request format, where bidders can accept a range of requested channels, by dealing two new essential challenges. The extended design ALETHEIA-RG offers resistance to demand-reduction cheating, which becomes possible in range-based auction. Moreover, the valuation function of each bidder is not in a single step form any more as shown in the single-minded case, and ALETHEIA-RG can support arbitrary step function for various application. It significantly expands the applicable scope of prior work [23], where only step function satisfying the super-additive condition is considered.

2 Preliminaries

2.1 System Model

We consider a cognitive radio network where spectrum is divided into K identical channels of the same bandwidth, denoted as $\mathcal{K} = \{1, \ldots, K\}$ and to be auctioned to N secondary users, denoted as $\mathcal{N} = \{1, \ldots, N\}$. We assume that each bidder $i \in \mathcal{N}$ requests $d_i (0 < d_i \leq K)$ channels, and it has a *valuation* function v_i: $\mathcal{K} \rightarrow \mathbb{R}^+$, which calculates the true valuation (a non-negative value) for the requested channels. Each bidder submits its bid valuation b_i to the auctioneer, with a per-channel bid valuation t_i ($t_i = b_i/d_i$). Note that the bid valuation b_i does not have to be equal to the true valuation $v_i(d_i)$ if manipulating on b_i can make profit.

After collecting all bids and requests that are submitted by all bidders simultaneously, the auctioneer determines the winners from the bidders based on the predefined allocation rules. It then charges each bidder i with a payment denoted as $p_i(b_i, \mathbf{b}_{-i})$, where $\mathbf{b}_{-i}$ denotes the vector including all the bids from b_1 to b_N except b_i. Note that no payment applies to loser i, i.e., $p_i(b_i, \mathbf{b}_{-i}) = 0$. The *utility* of bidder i, denoted by $u_i(b_i, \mathbf{b}_{-i})$, is then defined as the difference between valuation and payment, i.e., $u_i(b_i, \mathbf{b}_{-i}) = v_i(d_i) - p_i(b_i, \mathbf{b}_{-i})$. We simplify notations $v_i(d_i)$, $p_i(b_i, \mathbf{b}_{-i})$, and $u_i(b_i, \mathbf{b}_{-i})$ as v_i, p_i, and u_i respectively, if no confusion is incurred.

As in [9], [22], [29], [30], we use the conflict graph $G(\mathcal{N}, \mathcal{E})$ [9] to capture the interference among bidders, where $\mathcal{E}$ is the collection of all edges. An edge $(i, j) \in \mathcal{E}$ iff bidders i and j interfer with each other when they use a same channel simultaneously. Therefore, a channel can be allocated to multiple bidders as long as no edge exists between any pair of these bidders, which is referred to as *spatial reusability*. Without loss of generality, we assume that the conflict graph is a connected graph. Otherwise, we can perform the auction in each connected component.

When a bidder uses multiple names to submit bids, the auctioneer takes them as if they are from a group of bidders, called *virtual bidders* in this paper. These virtual bidders have the same interference condition of the real bidder, i.e., the real bidder's conflicting neighbors still interfere with these virtual bidders. This is because when a bidder generates multiple names, its geographic information does not change. Moreover, to obtain different channels for transmission, these bidders interfer with each other, i.e., the subgraph consisting of these virtual bidders is a clique.

2.2 Design Targets

The basic target of our auction design is to satisfy *allocation feasibility*.

Definition 1 (Allocation Feasibility). *An allocation $\mathcal{G} = (\mathcal{A}_1, \ldots, \mathcal{A}_N)$, where $\mathcal{A}_i \subset \mathcal{K}$ denotes the set of channels allocated to bidder i, is feasible if $\mathcal{A}_i \cap \mathcal{A}_j = \emptyset$ holds for any $(i, j) \in \mathcal{E}$.*

More importantly, we aim to ensure strategy-proofness and false-name-proofness, that are our primary design targets of the auction mechanisms proposed.

Definition 2 (Strategy-proofness [15], [17]). *An auction mechanism is strategy-proof (or truthful) if for any bidder i and $\mathbf{b}_{-i}$, $u_i(v_i, \mathbf{b}_{-i}) \geq u_i(b_i, \mathbf{b}_{-i})$ holds for any $b_i \neq v_i$.*

Definition 3 (False-name-proofness [21], [26]). *An auction mechanism is false-name-proof if for any bidder i using m false identifiers $i_1, \ldots, i_m$ to participate the auction and any $\mathbf{b}_{-i}$,*

$$u_i(v_i, \mathbf{b}_{-i}) \geq \sum_{j=1}^{m} u_{i_j}(b_{i_j}, \mathbf{b}_{-i} \cup I_{-j}^m),$$

where $I_{-j}^m = \{b_{i_l} : l \in \{1, \ldots, m\}, l \neq j\}$.

Generally speaking, strategy-proofness prohibits improved utility from cheating on bid valuation, while false-name-proofness not only prohibits such a cheating but also discourages bidders to submit false-name bids. Note that false-name-proofness generalizes the concept of strategy-proofness (the case when $m = 1$). In other words, false-name-proofness is a sufficient but in general not a necessary condition of strategy-proofness.

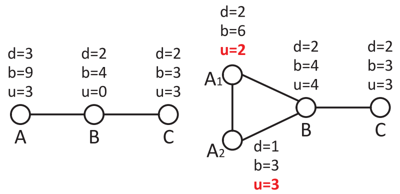


Fig. 1. An example of RF cheating in VERITAS. When bidder A uses two names (A_1 and A_2) to bid, it increases its utility by getting the same number of channels but paying less.

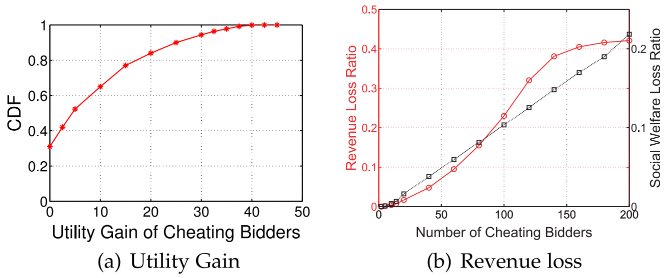


Fig. 2. RF cheating is effective in large-scale spectrum auctions like VERITAS [29]. (a) It can effectively improve bidder utility, giving bidders incentive to cheat. (b) It can significantly impair the revenue when a number of bidders choose to cheat.

3 False-Name Bid Cheating in Spectrum Auctions

In this section, we study the formation and the impact of false-name cheating in the emerging dynamic spectrum auctions. We demonstrate that *a simple form of false-name cheating can effectively raise the cheating bidders' utility and thus degrade the auctioneer's revenue (i.e., the sum of payments of the winners).*

3.1 Methodology

First, we demonstrate that it can be fairly easy to design a false-name cheating pattern in existing strategy-proof spectrum auctions, which can raise bidder's utility effectively. Then, we conduct simulation-based experiments to examine how this pattern of cheating impacts the auction outcomes.

Since a cheating pattern is specific to the auction design, we select VERITAS [29], a famous strategy-proof spectrum auction mechanism, for our case study. Similar works are also done to some other mechanisms, e.g., SMALL [24], which lead to very similar results and are nor included here due to space limitation. For the sake of completeness, we briefly introduce how VERITAS works. In VERITAS, bidders are considered in the descending order of per-channel bid, and if there are enough available channels for a bidder, the bidder will get the requested number of channels with smallest indices. A channel is available to a bidder if it has not been assigned to any other neighboring bidders. To charge a winner i, VERITAS finds its critical neighbor, and then charges i with $d_i \cdot t_j$. If no such a neighbor exists, then there is no charge. A critical bidder c of bidder i is a bidder in $N(i)$ where if i bids lower than c, i will not be allocated, and if i bids higher than c, i will be allocated. $N(i)$ denotes the set of conflicting neighbors of i.

3.2 A Simple Cheating Pattern

We first introduce a very simple false-name cheating pattern in VERITAS named Real-Fake (RF) cheating. It works as follows. A bidder i uses two identifiers, Real and Fake, to bid. Then Real and Fake bid x ($0 < x < d_i$) and $d_i - x$ channels, respectively, with the same per-channel bid t_i. If bidder i can win using a single identifier, it is straightforward to check that it can also win using RF cheating, and achieve the same or higher utility. Fig. 1 shows such an example where higher utility is obtained via RF cheating, where three bidders (A,B, C) competing for three channels. When bidding via a single name, bidder A obtains a utility of three with bidder B as its critical neighbor. However, when bidder A uses two identifiers (A_1 and A_2) to bid, bidder A achieves an improved utility $u_A = u_{A_1} + u_{A_2} = 2 + 3 = 5$ since A_1's critical neighbor is B while A_2 does not have a critical neighbor.

3.3 Impacts of False-Name Bids

We further conduct simulations to examine how RF cheating impairs the auction outcomes. We simulate 1,000 bidders competing for 10 channels in the auction. These bidders are positioned in a 100×100 square and the interference range is set as 1, where each bidder has about three conflict neighbors on average, and thus a high degree of spectrum reuse can be exploited. The request and per-channel bid of each bidder are randomly chosen from integers in $[1, 6]$ and $[1, 10]$, respectively. For RF cheating, the value x is also chosen at random from all possible values.

We run the experiment 100 times. Fig. 2a plots the utility gain of each RF cheating bidder. We observe that nearly 70 percent cheating bidders can gain profit by submitting false-name bids. Fig. 2b plots the performance loss ratio versus the number of cheating bidders, including revenue loss ratio and social welfare ratio. We observe that the revenue loss depends heavily on the number of cheating bidders. When the number of cheating bidders is small, the revenue loss ratio is low. This is because the effect of each RF cheating has a local feature which is inherited from the pricing method of VERITAS. When the number of RF cheating grows, the revenue decreases quickly, and the loss ratio can reach 35-40 percent when more than 150 bidders perform RF cheating.

The above results confirm that the unique requirement of spectrum reuse and the resulting local competition make traditional mechanisms vulnerable to false-name bids. Even simple RF cheating can significantly impair the auction revenue and fairness. This motivates us to design new mechanisms that are robust to the false-name cheating.

4 Challenges

In this section, we discuss the challenges to design false-name-proof spectrum auction mechanisms. We first analyze the classic false-name-proof auctions and articulate their limitations when spectrum reusability is exploited. Then we introduce a simple false-name-proof design with fairly low spectrum reuse, which serves as a baseline for performance comparison.

4.1 False-Name-Proofness versus Spatial Reusability

We study two classic false-name-proof designs, GAL [20] and IR [13] for conventional goods auctions, and show that they cannot even guarantee truthfulness and thus lose

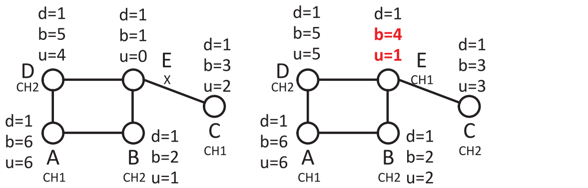


Fig. 3. An illustrative example shows extended GAL is not false-name-proof, because bidder E can improve its utility by raising its bid.

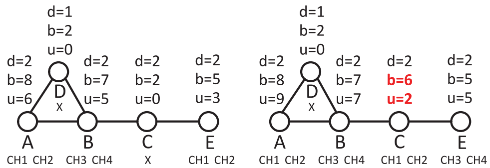


Fig. 4. An illustrative example shows extended IR is not false-name-proof, where bidder C can improve its utility by raising its bid.

false-name-proofness when spatial reusability is enabled in spectrum auctions. One basic rule for extension here is to guarantee that the extended mechanism is equivalent to the original one if all bidders conflict with each other, i.e., the conflict graph is a complete graph.

4.1.1 GAL Auction Design

GAL [20] is a false-name-proof multi-unit auction design using greedy allocation. The basic idea of GAL is similar with the famous k-st auction [12]. Here we extends GAL for spectrum auctions by following the basic idea directly. The allocation and pricing methods can be described as follows.

Allocations.

1) Sort bidders in a descending order by the per-channel bid and set each bidder's available channel set as $\mathcal{K}$.
2) Check these sorted bidders one by one. For each bidder i, if there are at least d_i channels in its available-channel set, it wins and is allocated with the first d_i channels with the lowest indices, each of which is then removed from the available-channel sets of the neighbors of i. Otherwise, bidder i loses.

Pricing. For each winner i, find the neighbor j with highest per-channel bid in its unallocated neighbors. If such neighbor exists, then charge $d_i \cdot t_j$. Otherwise, charge 0.

We prove that this auction is not false-name-proof using a counter example, in which five bidders $(A, B, \ldots, E)$ compete for two channels, as show in Fig. 3. We find out that bidder E will lose with a utility of 0 under truthful bidding, while increasing its utility to 1 if it cheats by raising its bid to 4. In the latter case, bidder E will obtain a channel with a charge of 0. Hence, this mechanism is not strategy-proof and thus not false-name-proof.

4.1.2 IR Auction Design

Iterative Reducing (IR) [13] is another false-name-proof multi-unit mechanism where bidders with largest requests will be considered first. We extend IR by following this idea while considering spatial reusability, leading to the following auction design.

Allocation.

1) Group bidders by their requests d_i and sort these groups in a descending order by d_i. In each group, all bidders are sorted in a descending order by per-channel bid t_i. Initial each bidder's available channel set as $\mathcal{K}$.
2) Sequentially check the ordered groups. For a group, channels are allocated to the bidders sequentially until all bidders in the group win or a bidder loses. In the former case, we continue to check the next group. In the latter case, all the remaining bidders in the group lose and the allocation terminates.

Pricing. If all bidders in a group win, then these bidders are charged 0. Otherwise, each winner i in this group is charged by $d_i * t_j$, where j is the first rejected bidder in the group.

Again, we prove the above mechanism is not false-name-proof, using a counter example given in Fig. 4, where five bidders $A, B, \ldots, E$ are competing for four channels. By the grouping method, bidders A, B, C and E are in group g_1, and bidder D constitutes group g_2. Consider g_1. Bidder C loses and its utility is 0. However, if C cheats by bidding 6, all bidders in g_1 win and thus are charged 0. Therefore, C improves its utility by 2, breaking the strategy-proofness and thus the false-name-proofness.

4.2 A False-Name-Proof Spectrum Auction

The spectrum utilization can be significantly impaired when existing false-name-proof designs are directly applied to spectrum auctions. The mechanism works as follows.

- *Plane Division and Coloring*. Divide the plane into squares with length of the maximal interference radius, and proceed to uniformly color these squares using four colors. The coloring guarantees that, i) each pair of bidders in the same square interfere with each other, ii) bidders in different co-colored squares do not interfere with each other. See Fig. 5 for an illustration.
- *Allocation in Each Box*. Partition all K channels into four subsets, each with $K/4$ channels. Allocate these subsets to the squares, one color relating to an independent subset. In each square, apply the GAL mechanism.

Since the false-name-proofness is guaranteed within each square by the GAL, when a bidder in a box submits false-name bids, the created virtual bidders are all in the same square and thus cannot improve its utility by the GAL. Therefore, the above mechanism is false-name-proof. Nevertheless, the static partition of spectrum among the squares can result in a significant spectrum degradation by a factor up to 4.

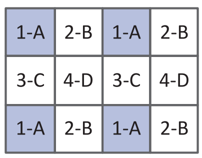


Fig. 5. The plane is divided into squares and colored using 4 colors (indexed from 1 to 4). The channels are divided into 4 subsets (indexed from A to D). Allocation rule is one color relates one subset.

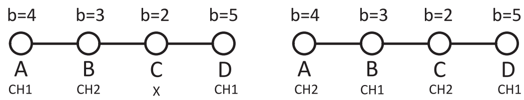


Fig. 6. An illustrative example shows the motivation of using BFS-based ordering method.

5 ALETHEIA

In this section, we introduce the basic design of ALETHEIA, where bidders are assumed to be *single-minded* [13], [20], [29], i.e., a bidder i that requests d_i channels only accepts either all d_i channels or nothing. The extension of ALETHEIA to support range-based requests where bidder i accepts any number of channels between 0 and d_i is proposed in the next section.

5.1 Auction Design

ALETHEIA consists of three steps: (1) order the bidders into a bidder list (Section 5.1.1), (2) compute the price for each bidder (Section 5.1.2), and (3) determine the winners according to the finely computed prices (Section 5.1.3). One example is given in Section 5.1.4 to show how ALETHEIA works.

5.1.1 Bidder Ordering

A fixed order of bidders is critical to satisfying the interference constraints and makes it easier to design an bid-independent pricing rule. To maximize spectrum reusability, we present a novel ordering algorithm based on the Breadth-First-Search (BFS) procedure. When allocating channels to winning bidders, the algorithm selects the requested channels with the lowest indices from the available channel set. Under such strategy, the BFS-based method can help to avoid interference to improve the spectrum reusability. We use an example shown in Fig. 6 to illustrate this, where four bidders compete for two channels and each bidder requests one channel. If we adopt a simple bid-based ordering method, bidder C cannot be satisfied, yet BFS-based method make all bidders satisfied.

The ordered bidder list B is built via constructing a tree described as follows: (1) The bidder with the largest per-channel bid is selected as the root node, and all its conflicting neighbors become its child nodes; (2) For each leaf node, from the one with largest per-channel bid to the lowest one, we add its unincluded conflicting neighbors as its child nodes. The second step iteratively proceeds until all bidders are included in the tree. Note that a bidder's child nodes are ordered in a descending order of per-channel bid from the left to the right.

Finally, list B is obtained by going through the tree layer by layer from the root node and from left to right on each layer. In particular, whenever we visit a new node, we append it at the tail of a FIFO list. The resulting list is B, after we search the whole tree.

5.1.2 Pricing Scheme

With the sorted bidder list B, we use the pricing algorithm (shown in Algorithm 1) to compute the price for each bidder. The price for each bidder i is its request d_i multiplied by the per-channel bid of its *critical bidder*, denoted as $c(i)$. Generally speaking, a bidder i will win when bidding higher than its critical bidder $c(i)$ (*i.e.*, $t_i > t_{c(i)}$), and it will lose when bidding lower than that. As a result, the core procedure of the algorithm is to find the critical bidder for each bidder, described as follows.

Algorithm 1. ALETHEIA-Prices(B)

for $i \in \mathbb{N}$ **do**
  $c(i) = \text{FindCriticalBidder}(B, i)$;
  $p_i = d_i * t_{c(i)}$;
return $\mathbf{p} = (p_1, \ldots, p_N)$;

We use the procedure FindCriticalBidder, given in Algorithm 2, to find the critical bidder for bidder i. In this algorithm we first suppose that d_i channels have been allocated to bidder i, reserving d_i channels for bidder i. It proceeds to allocate channels to other bidders sequentially, and find all of its neighboring bidders that cannot be allocated. The losing neighboring bidder with the largest per-channel bid is i's critical bidder. If all of its neighbors win, then the critical bidder is a *null* bidder, whose per-channel bid equals 0.

Algorithm 2. FindCriticalBidder(B, i)

1 $c(i) \leftarrow null$;
2 $t_{c(i)} = 0$;
3 $\mathcal{A}_{\mathbb{N}(i)} \leftarrow \emptyset$;
4 **for** $k \in \mathcal{N}$ **do**
5   $Avai(k) \leftarrow \mathcal{K}$;
6 $B^{'} \leftarrow B \backslash \{i\}$;
7 **while** $B^{'} \neq \phi$ **do**
8   $j \leftarrow Top(B^{'})$;
9   **if** $|Avai(j)| \geq d_j$ **then**
10   Let $\mathcal{C}$ be the set of d_j channels with lowest indices in $Avai(j)$;
11   **if** $j \notin \mathbb{N}(i)$ || $(j \in \mathbb{N}(i) \&\& |\mathcal{C} \cup \mathcal{A}_{\mathbb{N}(i)}| + d_i \leq K)$ **then**
12       $\mathcal{A}_i \leftarrow C$;
13   **for** $k \in \mathbb{N}(j)$ **do**
14         $Avai(k) \leftarrow Avai(k) - \mathcal{C}$;
15   $B^{'} \leftarrow B^{'} \backslash \{j\}$;
16 **for** $j \in \mathbb{N}(i)$ **do**
17   **if** $A_j = \emptyset$ && $b_j/d_j > t_{c(i)}$ **then**
18     $c(i) = j$;
19     $t_{c(i)} = b_j/d_j$;
20 **return** $c(i)$;

In details, Algorithm 1 sequentially examine each bidder j $(j \neq i)$, where $\mathcal{A}_{\mathbb{N}(i)}$ represents the set of channels that have been allocated to i's neighbors, i.e., $\mathcal{A}_{\mathbb{N}(i)} = \cup_{j \in \mathbb{N}(i)} \mathcal{A}_j$. When there are enough channels for j (line 9), there are two cases to be considered (line 11).

- *Case I*: If j does not belong to $\mathbb{N}(i)$, we assign the d_j channels with the *lowest indices* in $Avai(j)$ to bidder j.
- *Case II*: If j conflicts with i, since we have to reserve d_i channels for i, we thus need to check whether j's allocation would cause i's request not being satisfied. In other words, we need to ensure the relation $|\mathcal{C} \cup \mathcal{A}_{\mathbb{N}(i)}| + d_i \leq K$ holds when allocating $\mathcal{C}$ to bidder j, where $\mathcal{C}$ denotes the channels pre-allocated to bidder j.

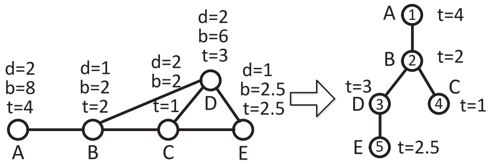


Fig. 7. An illustrative example of ALETHEIA, where three channels (CH1, CH2, and CH3) are auctioned: (left) the conflict graph; (right) the corresponding BFS tree. The index of each bidder in list B is given in the node circle.

After all bidders except i have been considered, we find the losing neighbor j with largest per-channel bid is the critical bidder (lines 17-19).

5.1.3 Allocation Rule

Channel allocation is made by applying Algorithm 3 that sequentially checks all bidders. For each bidder i, the algorithm examines whether its bid valuation is greater than its computed price. If so, we assign d_i channels *with lowest indices* in its available channel set $Avai(i)$ to bidder i. Otherwise, bidder i loses with no charge. In this way, we ensure that no bidder is charged more than bid valuation, to incentivize bidders to participate the auction.

Algorithm 3. ALETHEIA-Allocation(B)

for $i \in \mathcal{N}$ **do**
  $Avai(i) \leftarrow \mathcal{K}$;
while $B \neq \phi$ **do**
  $i \leftarrow Top(B)$;
  if $b_i > p_i$ **then**
    Set $\mathcal{A}_i$ as the set of channels with lowest indices in $Avai(i)$;
    Assign $\mathcal{A}_i$ to bidder i;
    for $j \in \mathbb{N}(i)$ **do**
      $Avai(j) \leftarrow Avai(j) - \mathcal{A}_i$;
  $B \leftarrow B \backslash \{i\}$;

5.1.4 All Together in One Example

Consider an example shown in Fig. 7, where five bidders compete for three channels. The ordered bidder list is also shown in Fig. 7. We use bidder D as an example to find its critical bidder. We sequentially allocate channels to other bidders by reserving two channels for bidder D. Then bidder C and bidder E lose. Since E has higher per-channel bid, it becomes D's critical bidder. Similarly, we can find that $null$, C, D and C are the critical bidders of A, B, C and E, respectively. Therefore, we know bidder C loses and other bidders win by the allocation rule. Bidders A and D win CH1 and CH2, and bidders B and E win CH3.

5.1.5 Discussions on Supporting Different Bid Ranking Metrics

ALETHEIA performs allocation and pricing algorithms based on sorted bidders, where BFS-based sorting method is conducted on bid b_i. It is straightforward to show that ALETHEIA remains false-name-proof when BFS-based method is conducted on a function $f(b_i)$, where $f(b_i)$ is an increasing function of the bid b_i and not affected by the bids of other bidders. Therefore, auctioneers can design different metrics to tune the ALETHEIA allocation algorithm towards desired goals. For instance, to maximize the social welfare by performing the BFS-based sorting method on the descending order of $\frac{b_i}{|N(i)|+1}$ [18], where $N(i)$ denotes the set of conflicting neighbors of bidder i.

5.2 Properties

Now we introduce the key properties of ALETHEIA. The proofs are given the next section. The basic property regarding the correctness of ALETHEIA is that it can always produce a feasible allocation. Due to the limited space of this paper, we omit the proofs here and the detailed proofs can be found in our conference paper [23].

Theorem 1. *ALETHEIA satisfies allocation feasibility, i.e., for any bidder $i \in \mathcal{N}$ with $b_i > p_i$, its request will be satisfied without causing conflicts.*

Next we need to prove that ALETHEIA is false-name-proof, and we first establish the following key lemmas.

Lemma 1. *Give a sorted bidder list B, where bidders i and j conflict with each other and have the same conflicting neighbors except themselves, i.e., $\mathbb{N}(j)\backslash i = \mathbb{N}(i)\backslash j$. If both i and j win in ALETHEIA, their critical bidders have the same per-channel price, i.e., $t_{c(i)} = t_{c(j)}$.*

Lemma 2. *A bidder cannot increase its utility by submitting false-name bids, provided that all other bidders and their bids are the same.*

Lemma 3. *A bidder, using a single name, cannot increase its utility by submitting a cheating bid, provided that all other bidders and bids are the same.*

Theorem 2. *ALETHEIA is false-name-proof.*

Proof. The false-name-proofness of ALETHEIA follows immediately by Lemmas 2 and 3. □

Another property of ALETHEIA is that it incurs a low computational overhead.

Theorem 3. *ALETHEIA runs in $O(N \log N + E + NKE)$, where N, K and E are the number of bidders, auctioned channels and edges in the conflict graph, respectively.*

6 ALETHEIA EXTENSION

6.1 Motivation

The basic design ALETHEIA proposed in the above section only supports all-or-none request, while in practical, bidders may be willing to accept a range of requested channels if it is possible. As a result, to make the auction design more flexible and practical, we extend ALETHEIA to support range-based requests, where a bidder i requesting d_i channels can accept any number of channels from 0 to d_i. We name the enhanced design as ALETHEIA-RG.

New Cheating Pattern. When a request can be partially satisfied, another cheating pattern, named *demand-reduction cheating* [7] arises, which can break the false-name-proofness of ALETHEIA. To see this, we introduce an example in Fig. 8, where there are four bidders (A, B, C, and D) attend the auction to compete for $K = 4$ channels. The bids and demands, together with the conflict graph, are shown at the

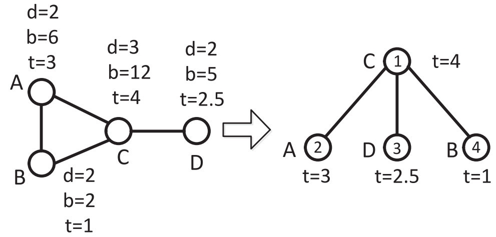


Fig. 8. An illustration of demand reduction cheating, where bidder C can improve its utility when cheating by requesting two channels.

left side of Fig. 8. According to ALETHEIA, bidder C wins and other bidders lose. Bidder C's critical bidder is A, and thus its utility is computed as $12 - 3 * 3 = 3$. Now, suppose bidder C cheats on demand, by submitting $b_i = 8$ to request $d_i = 2$ channels, while other bidders stay unchanged. According to the ALETHEIA, we know only bidder B loses and other bidders win, and C's critical bidder becomes bidder B. In this case, the utility of C becomes $8 - 1 * 2 = 6$. That is to say, bidder C can improve its own utility by reducing the demand.

The emerged new cheating pattern makes designing the extension of ALETHEIA more challenge. In our conference paper [23], the extended mechanism is only suitable for a special case where valuation function of each bidder satisfies the super-additive condition, which is illustrated in the following section. In other words, the extended version in [23] is only suitable for bidders with some limited types of applications like video-streaming. However, in practical systems, valuation functions of bidders can be arbitrary, which makes the conference version of ALETHEIA-RG is no longer suitable. In this section, we resolve this issue by redesigning ALETHEIA-RG. We start to analyze the valuation function of bidders corresponding to different types of applications. Then we design the auction mechanism to address these different cases while addressing the new cheating pattern.

6.2 Valuation for Partial Satisfaction

We now discuss the valuation function $v(d_i)$ of each bidder i who requests d_i channels. Since d_i is a non-negative integer, $v(d_i)$ can be treated as a step function of the demand d_i. In the single-minded case, the function is single-step, while in the range-based requesting model it can include multiple steps.

A common assumption for the valuation function is that the valuation function satisfies *free disposal* [4], based on the fact that bidders are *rational*. In a formal description, free disposal means that, for any $d_i' \geq d_i$, we have $v(d_i) = v(d_i')$, which indicates that when the request of bidder i is completely satisfied, allocating more channels will not improve its utility.

Besides the common assumption on valuation, we need to further discuss different applications with different types of valuation functions. We start from two basic types of valuation functions, *valuation with increasing marginal utility* and *valuation with decreasing marginal utility*, corresponding to two typical applications described as in [5], [22]. The marginal utility of a channel means that an increase in bidder's utility as a result of obtaining one additional channel. For easy description, we denote the width and height of each step for bidder i as d_{i_s} and v_{i_s}, respectively.

- *Type I: Valuation with increasing marginal utility*. See Fig. 9a as an illustration. The marginal utility is the gradient of each step, i.e., v_{i_s}/d_{i_s}, where d_{i_s} is the required number of channels of bidder i, and v_{i_s} is the increase of bidder i's utility for obtaining additional d_{i_s} units. The marginal utility decreases as the number channels increases. In a formal description, we say the valuation function satisfies super-additive, i.e., for any d' and d'' such that $d' + d'' \leq d_i$, we have

$$v_i(d' + d'') \geq v(d') + v(d''). \quad (1)$$

  Super-additive implies that a bidder has higher utility when its request is closer to be fulfilled completely. This type coincides with the scenario where bidders requires higher bandwidth for applications, e.g., live video streaming applications.
- *Type II: Valuation with decreasing marginal utility*. Fig. 9b illustrates the valuation with decreasing marginal utility. Similarly, we say such a valuation function satisfies sub-additive, i.e., for any d' and d'' such that $d' + d'' \leq d_i$, we have

$$v_i(d' + d'') \leq v(d') + v(d''). \quad (2)$$

  Sub-additive implies that when the request of a bidder is partially satisfied, allocating more channels does not significantly increase its utility. This type coincides with the scenario where bidders requires lower bandwidth for applications, e.g., file/text transferring applications.

General Valuation Function. In a general case, the valuation function is an arbitrary step function with multiple

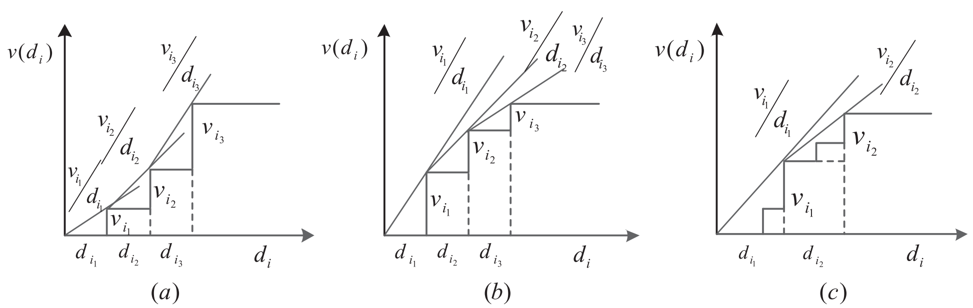


Fig. 9. Valuation type of Bidders. (a) Valuation of increasing marginal utility. (b) Valuation of decreasing marginal utility. (c) General type of valuation function.

steps, neither the increasing type nor the decreasing type. Fortunately, the valuation in a general case can be represented as the type of decreasing marginal utility, following the idea of [20]. The only restriction is that valuation function is non-decreasing, which is quite natural and can be automatically satisfied under the common assumption of free-disposal. In details, the approximation proceeds as follows. For each bidder i, set $d_{i_1} = \sum_{m=1}^{j} d_{i_m}$ and $v_{i_1} = \sum_{m=1}^{j} v_{i_m}$, where $j = argmax_j \frac{\sum_{m=1}^{j} v_{i_m}}{\sum_{m=1}^{j} d_{i_m}}$. This procedure corresponds to find the step where the gradient is maximized, as shown in Fig. 9c. Similarly, we can set $d_{i_2} = \sum_{m=j+1}^{k} d_{i,m}$ and $v_{i_1} = \sum_{m=j+1}^{k} v_{i_m}$, where $k = argmax_k \frac{\sum_{m=j+1}^{k} v_{i_m}}{\sum_{m=j+1}^{k} d_{i_m}}$. The above process is repeated until we set all s steps.

Based on the above discussion, we need only to focus our attention on the two basic types in the following analysis. Note that the single-minded case can be treated as a special case of increasing marginal utility.

6.3 Design of ALETHEIA-RG

Intuitively, for Type I of increasing marginal utility, bidders have no incentive to separately request channels using multiple false names since smaller request always generates lower bid valuation. As a result, we need only to prevent the demand reduction cheating in this case. In contrast, bidders of decreasing marginal utility may have incentive to separately bid for channels using multiple false names.

To overcome the above challenge, we represent each bidder i as s virtual bidders, denoted as $i_1, \ldots, i_s$, each requests d_{i_s} by bidding v_{i_s} (See Fig. 9c). By the assumption of decreasing marginal utility, the per-channel bid $t_{i_s} = v_{i_s}/d_{i_s}$ decreases, i.e., for any k, $t_{i_k} \geq t_{i_{k+1}}$. In addition, these virtual bidders inherit the conflicting conditions of bidder i and conflict with each other. These virtual bidders then participate in the auction on behalf of bidder i. While in the case of increasing marginal utility, bidder i still participates in the auction on its own behalf, requesting $d_i = \sum_{m=1}^{s} d_{i_m}$ channels by bidding $b_i = \sum_{m=1}^{s} b_{i_m}$.

At a high level, ALETHEIA-RG consists of three stages. First, we preprocess bidders as above to obtain the newest bidder list $\tilde{B}$ and the corresponding request list $\tilde{D}$. Second, we apply ALETHEIA to the obtained bidder list and pre-allocate the channels to these winners. Finally, we prevent demand reduction cheating based on the pre-allocation results. The detailed algorithm is given in Algorithm 4.

STAGE 1: Bidders Preprocessing. Bidder i of Type I is treated as a single virtual bidder. The bid and request are $d_i = \sum_{m=1}^{s} d_{i_m}$ and $b_i = \sum_{m=1}^{s} b_{i_m}$, respectively. Bidder i of type II, is represented as multiple virtual bidders as shown above, each virtual bidder s submits $\langle b_{i_s}, d_{i_s} \rangle$. Following that, we use the same BFS procedure in ALETHEIA to sort the processed bidders to obtain the bidder list, denoted as $\tilde{B}$.

STAGE 2: Bidders Pre-Allocation. In this stage, we apply the auction design ALETHEIA on the bidders in $\tilde{B}$, to obtain the pre-allocated channels for each winner. Specifically, for bidder i of Type I, it wins either d_i channels or nothing. For bidder i of Type II, the allocated channels equal the union of allocated channels of its virtual bidders, i.e., $\mathcal{A}_i = \cup_{m=1}^{s} \mathcal{A}_{i_m}$.

Algorithm 4. ALETHEIA-RG

Stage I: Bidders Processing
Construct s bidders $(i_1, \ldots, i_s)$ for bidder i;
Using the BFS procedure to obtain sorted bidder list $\tilde{B}$;
Stage II: Preallocation
ALETHEIA-Prices($\tilde{B}$);
ALETHEIA-Allocation($\tilde{B}$);
Stage III: Prevent Demand-reduction Cheating
for $i = 1$ to N *and i is a winner* **do**
  $\mathcal{A}_i = \cup_{m=1}^{s} \mathcal{A}_{i_m}$;
  $\gamma = |\mathcal{A}_i|$;
  $u_i = temp = v(\gamma) - \sum_{m=1}^{s} p_{i_m}$;
  for $j = |\mathcal{A}_i|$ *to 1* **do**
    Construct bidder i' with $d_{i'} = j$;
    $B' = \tilde{B} \backslash \{i_1, \ldots, i_s\} \cup \{i'\}$;
    //Find critical bidder for i';
    $c(i')$ =FindCriticalBidder(B', i');
    $u_{i'} = v(j) - j * t_{c(i')}$;
    if $u_{i'} > temp$ **then**
      $temp = u_{i'}$;
      $\gamma = j$;
      $p_i = \gamma * t_{c(i')}$;/* determine the final price*/
  Remove the $|\mathcal{A}_i| - \gamma$ channels with largest indices in $\mathcal{A}_i$; /*determine the final allocation*/

STAGE 3: Demand Reduction Cheating Resistance. In this stage, we need to prevent demand reduction cheating based on the pre-allocated results. In particular, after determining the winners in stage II, ALETHEIA-RG needs to check whether demand-reduction cheating is useful. If so, we need to find the actual demand γ for bidder i to maximize its utility, to ensure the false-name-proofness.

ALETHEIA-RG searches all possible demand reduction cheatings, from $|\mathcal{A}_i|$ to 1, to determine the actual demand γ of bidder i where the utility of bidder i is maximized. For easy description, we use identifier i' to substitute bidder i when it chooses demand reduction cheating, with $d' = j$ $(1 \leq j \leq |\mathcal{A}_i|)$. To compute the utility of i', we exclude all virtual bidders of i, i.e., $i_1, \ldots, i_s$, from $\tilde{B}$, and include bidder i'. We apply the procedure FindCriticalBidder to find the critical bidder of i', denoted as $c(i')$. The utility is computed as $u_{i'} = v(j) - j * t_{c(i')}$. This process is repeated until we find the real demand γ when utility is maximal. Finally, we allocate γ channels to bidder i, i.e., we need remove the $|\mathcal{A}_i| - \gamma$ channels with largest indices in $\mathcal{A}_i$. Note that the remaining channels $|\mathcal{A}_i| - \gamma$ are not allocated to other bidders. The final price charging from i becomes $\gamma * t_{c(i')}$.

6.4 Properties with Proofs

Theorem 4. *ALETHEIA-RG satisfies allocation feasibility.*

Proof. ALETHEIA-RG is based on the results of ALETHEIA, and it only decreases the number of allocated channels of each winner in ALETHEIA. Thus, ALETHEIA-RG does not violate the allocation feasibility property. □

Similarly, to prove the false-name-proofness of ALETHEIA-RG, we first establish the following lemmas.

Lemma 4. *For bidder i with valuation of decreasing marginal utility, represented as multiple virtual bidders, the critical bidders of winning virtual bidders have the same per-channel bid price.*

Proof. We know that these virtual bidders share the same conflicting condition of bidder i. Therefore, the lemma holds directly by lemma 1. □

Lemma 5. *A bidder cannot increase its utility by submitting false-name bids, provided that all other bidders and their bids are the same.*

Proof. Similar to Lemma 2, we only need to prove the case of false-name bids using two identifiers, since the case with over two identifiers can be treated in a similar manner. That is, *if bidder i uses two names i^1 and i^2 to participate the auction and obtains x and y channels under the names i^1 and i^2, respectively, then bidder i can obtain a total of $z = x + y$ channels using a single identifier, with a utility that is greater than (or equal to) the sum of that obtained by i^1 and i^2.*

We consider two types of bidders separately.

For the Bidder of Increasing Marginal Utility. When demand reduction cheating is not useful for bidders, the proof is similar to Lemma 2 and thus the claim holds. Therefore, we here consider the case where bidders choose demand-reduction cheating. We first consider the auction when bidder i uses names i^1 and i^2 to bid. For bidder i^1, its utility is maximized by requesting x, i.e., $u_{i^1} = v(x) - x * t_{c(i^1)}$. By ALETHEIA-RG, we know bidder i^1 wins in stage II by requesting x' ($x' > x$) channels. Similarly, bidder i^2 wins in stage II by requesting y' ($y' > y$) channels, with utility $u_{i^2} = v(y) - y * t_{c(i^2)}$. Now we consider the same auction where bidder i using a single name, requesting $x' + y'$ channels. By Lemma 2, we know that i can also win $x' + y'$ channels in state II of ALETHEIA-RG. Now suppose i wins $x + y$ channels in stage III. Because larger demands mean that we need to reserve more channels when computing the charging price, more of its neighbors cannot be allocated, leading to $t_{c(i)} \geq t_{c(i^1)}$ and $t_{c(i)} \geq t_{c(i^2)}$. Combined with (1), we obtain

$$v(x + y) - (x + y) \cdot t_{c(i)} \geq u_{i^1} + u_{i^2}. \tag{3}$$

In other words, if demand reduction cheating is profitable for bidder i, our claim holds by ((3)). If demand reduction cheating is not profitable for bidder i, we have $u_i > v(x + y) - (x + y) \cdot t_{c(i)} \geq u_{i^1} + u_{i^2}$. Again our claim holds.

For Bidder i of Decreasing Marginal Utility. In the absence of demand-reduction cheating, consider the auction where bidder i uses names i^1 and i^2 to bid. Suppose i^1 and i^2 are represented as m and n virtual bidders respectively. By the bidders processing in stage I, we know $t_{i^1_1} \geq \cdots \geq t_{i^1_m}$ and $t_{i^2_1} \geq \cdots \geq t_{i^2_n}$. Assume that the first j bidders of i^1 and the first k bidders of i^2 win. By the pricing rule of ALTHEIA-RG, we know that the per-channel price for charging i^1 is the per-channel bid of critical bidder of $i^{1\prime}$, requesting $x' = \sum_{j=1}^{m} d_{i^1_j}$ in stage III, denoted as $t_{c(i^{1\prime})}$. Similarly, the per-channel price for charging i^2 is $t_{c(i^{2\prime})}$, where $i^{2\prime}$ requests $y' = \sum_{j=1}^{n} d_{i^2_j}$. Now, consider the same auction where bidder i uses a single name to bid, requesting $z' = x' + y'$ channels. According to the allocation rule of ALEHTEIA-RG, bidder i will win and the per-channel price for charging is the per-channel bid of the critical bidder of i' in stage III, denoted as $t_{c(i')}$. Since both i^1 and i^2 win and $z' = x' + y'$, we have $t_{c(i')} = t_{c(i^{1\prime})} = t_{c(i^{2\prime})}$ by Lemma 1. Therefore, the payment is equal to that in the case where bidder i uses false-names.

In the presence of demand-reduction cheating, the derivation is similar to the above deduction and thus is omitted here. □

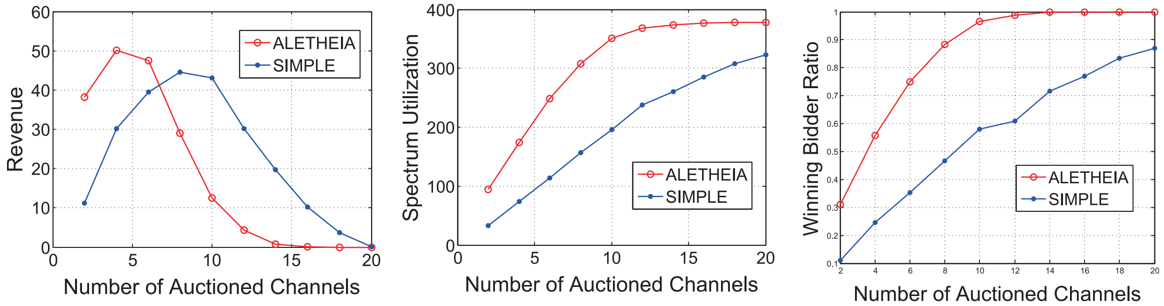
Lemma 6. *A bidder, using a single name, cannot increase its utility by submitting a cheating bid, provided that all other bidders and bids are the same.*

Proof. Since a bidder of increasing marginal utility is processed as a single virtual bidder, its valuation function can be treated as a single step function. In other words, it can be treated as a special case of decreasing marginal utility, i.e., $s = 1$. We therefore consider the bidders of decreasing utility, assuming bidder i is represented as s virtual bidders.

By the bidders processing, we have $t_{i_1} \geq \cdots \geq t_{i_s}$. As we know that these virtual bidders share the same conflict condition with bidder i, bidders with higher per-channel bid will be ranked before that with lower per-channel bid in bidder list $\tilde{B}$. That is, the virtual bidders with higher indices in $\tilde{B}$ will be first allocated. W.l.o.g., assume the first k ($0 \leq k \leq s$) virtual bidders win. Since these virtual bidders share the same root, by ALETHIEA, we have $t_{i_k} = b_{i_k}/d_{i_k} > t_{c(i_k)} \geq t_{i_{k+1}}$. Also by Lemma 4, we have $t_{c(i_1)} = \cdots = t_{c(i_k)}$. Now by ALETHEIA-RG, the per-channel price for charging bidder i is irrelevant to its bid, and per-channel price is equal to $t_{c(i')}$ where bidder i' requests $|\cup_{m=1}^{s} \mathcal{A}_{i_m}|$ channels in stage III. Because larger demands mean more channels should be reserved when computing the charging price, more of its neighbors cannot be allocated with channels, leading to $t_{c(i')} \geq t_{i_1} = \cdots = t_{i_k}$.

In the absence of demand reduction cheating, consider the following cases respectively.

- *Case I: Under-declaring decreases the allocated channels.* Since the charged per-unit price is irrelevant to its bid, i.e., it stays unchanged when it declares. In this case, the utility will decrease since the number of obtained channels decreases.
- *Case II: Under-declaring increases the allocated channels.* This case will not happen, because the virtual bidders with higher per-channel bid will be allocated first, and ALETHEIA-RG never deallocates the allocated channels. Therefore, under-declaring cannot increase the allocated channels.



(a) Revenue (b) Spectrum Utilization (c) Winning Bidder Ratio

Fig. 10. Comparison of ALETHEIA with SIMPLE versus the number of auctioned channels.

- *Case III: Over-declaring decreases the allocated channels.* Since the charged per-channel price stays unchanged when it over-declares its bid, its utility will decreases when the number of allocated channels decreases.
- *Case IV: Over-declaring increases the allocated channels.* Suppose bidder i obtains $\gamma + j$ units in total. We denote the utilities for truth-telling and over-declaring as $u(i, \gamma)$ and $u(i, \gamma + j)$ respectively. According to the method for processing bidders in stage I, we have

$$v(\gamma + j) - v(\gamma) \leq b_{i_{k+1}} * j. \tag{4}$$

Since bidder i_{k+1} is rejected, its per-channel price is lower than or equal to the per-channel price for charging. We have

$$t_{i_{k+1}} \leq t_{c(i_k)} \leq t_{c(i')}. \tag{5}$$

The utility for obtaining $\gamma + j$ channels by paying $t_{c(i')}$ for each channel is $v(j + \gamma) - (j + \gamma) * t_{c(i')}$. Thus we have:

$$\begin{aligned} u(i, j+\gamma) &= v(j+\gamma) - (j+\gamma) * t_{c(i')} \\ &\leq v(j+\gamma) - t_{i_{k+1}} * j - t_{c(i_k)} * \gamma \\ &\leq v(\gamma) - j * t_{c(i_k)} = u(i, j). \end{aligned}$$

The above equation shows that the utility for obtaining j units is larger than or equal to the utility for obtaining $j + \gamma$ units.

In the presence of demand reduction cheating. The proof is similar to the above deduction and thus we omit here. In conclusion, the lemma holds. This completes the proof. □

Theorem 5. *ALETHEIA-RG is false-name-proof.*

Proof. The false-name-proofness of ALETHEIA-RG follows by Lemmas 5 and 6 immediately. □

Theorem 6. *ALETHEIA-RG runs in polynomial complexity of* $O(N\tilde{N}K\log\tilde{N} + N\tilde{N}K^2\tilde{E})$.

Proof. In stage I, the process can be done in time of $O(\tilde{N})$, where $\tilde{N} = |\tilde{B}|$. The process takes $O(\tilde{N}\log\tilde{N} + \tilde{N}K\tilde{E})$ time to run ALETHEIA in stage II, where $\tilde{E}$ denotes the corresponding number of edges. In stage III, for each winner i, we need to run the procedure FindCriticalBidder at most d_i times and thus the procedure of preventing demand reduction cheating takes $N \cdot d_i \cdot O(\tilde{N}\log\tilde{N} + \tilde{N}K\tilde{E})$ for all winners. In total, the ALETHEIA-RG runs in complexity less than $O(N\tilde{N}K\log\tilde{N} + N\tilde{N}K^2\tilde{E})$. □

7 Evaluation

7.1 Simulation Setup

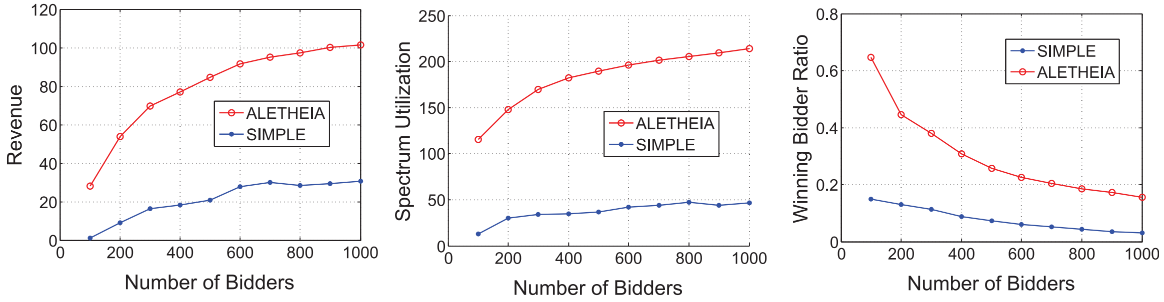
We randomly deploy bidders in a 100×100 square area, and set the interference range as 10. If the distance between any two bidders is less than 10, they interfere with each other when accessing the same channel at the same time. The per-channel bids of bidders are randomly distributed in the range of [0, 1]. We run the simulation 100 times and average the results to get rid of the randomness and observe the general patterns. We use the following metrics to evaluate the performance.

- *Revenue:* The total payments of all winners;
- *Spectrum Utilization:* The sum of allocated channels over all winners;
- *Winning Bidder Ratio:* The ratio of the number of winning bidders to the number of total bidders.

7.2 Performance

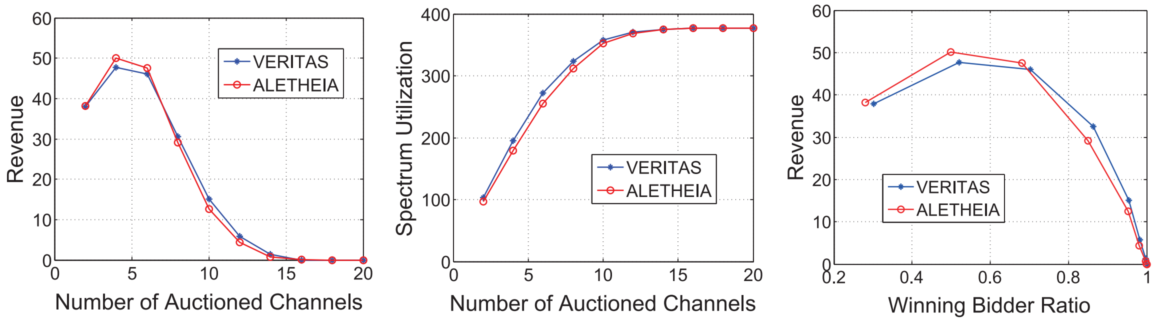
In this section, we compare ALETHEIA with the simple strawman approach proposed in Section 4.2. For ease description, we name it as SIMPLE.

We compare them in two scenarios. First, we set the number of bidders as $N = 300$ and vary the number of auctioned channels. Each bidder requests either 1 or 2 channels. The results are plotted in Fig. 10. ALETHEIA and SIMPLE achieve similar peak revenue when 4 and 8 channels are used, respectively, as illustrated in Figs. 10a. Fig. 10b shows that ALETHEIA significantly improves spectrum utilizations compared to SIMPLE under any number of auctioned channels. Fig. 10c shows that the results of winning bidder ratio. Again, ALETHEIA performs much better. Second, we compare them by varying the number of bidders, setting the default number of auctioned channels as $K = 4$, and the request of each bidder is randomly drawn from set $\{1, 2, 3, 4\}$. The results are shown in Fig. 11. In this case, ALETHEIA significantly improves revenue and spectrum utilization over SIMPLE by up to 300 percent. This is because SIMPLE sacrifices spectrum reuse to maintain false-name-proofness. When the number of bidders grows, the number of allocated



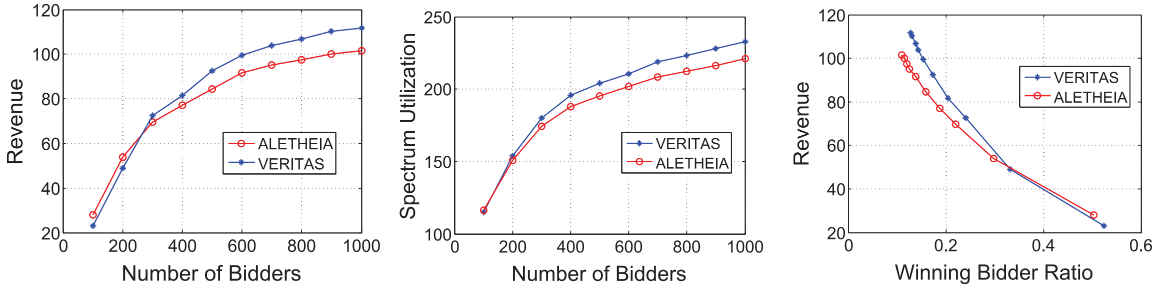
(a) Revenue (b) Spectrum Utilization (c) Winning Bidder Ratio

Fig. 11. Comparison of ALETHEIA with SIMPLE versus the number of bidders.



(a) Revenue (b) Spectrum Utilization (c) Revenue vs. Winning Bidder Ratio

Fig. 12. Comparison of ALETHEIA with VERITAS versus the number of auctioned channels, in terms of revenue, spectrum utilization, and winning bidder ratio.



(a) Revenue (b) Spectrum Utilization (c) Revenue vs. Winning Bidder Ratio

Fig. 13. Comparison of ALETHEIA with VERITAS versus the number of bidders, in terms of revenue, spectrum utilization, and winning bidder ratio.

bidders in each partitioned box in SIMPLE is nearly constant. In contrast, ALETHEIA can accommodate more bidders, i.e., achieving much higher spectrum reuse which can be validated by the result of Fig. 11c. In summary, our mechanism can highly improve the performance in various network settings.

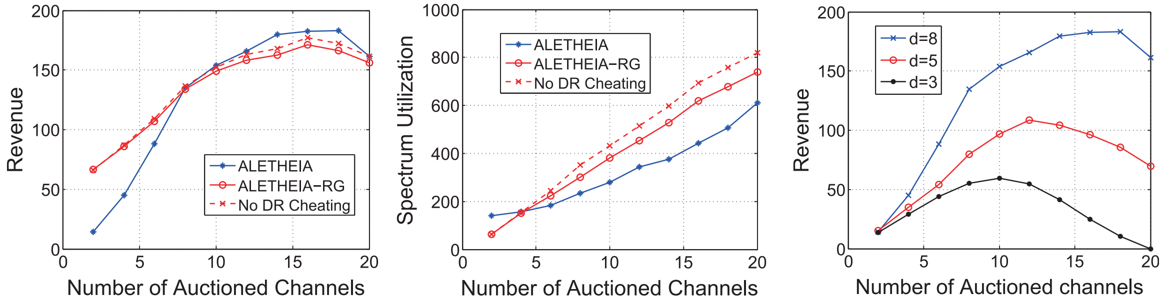
7.3 Cost of False-name-proofness

We also compare ALETHEIA with VERITAS to evaluate the cost of false-name-proofness. Specifically, we try to answer the question: *How much performance would ALETHEIA lose if no bidders submit false-name bids?*

We compare them by vary the number of auctioned channels from 2 to 20 and set the number bidders as 300. The request of each bidder is either 1 or 2. The results are shown in Fig. 12. We can see that ALETHEIA has very similar performance, in terms of both revenue and utilization, as VERITAS. The revenue as a function of winning bidder ratio is plotted in Fig. 13c. In order to guarantee false-name-proofness, ALETHEIA sacrifices part of bidders who have no critical neighbors in VERITAS (as shown in Section 3.1) and thus it performs slightly worse than VERITAS. On the other hand, when the competition between bidders is high (i.e., when the number of auctioned channels is small), ALETHEIA performs slightly better than VERITAS in terms of revenue. This is because ALETHEIA charges by the highest losing neighbor's per-channel bid while VERITAS charges by that of the first losing neighbor. The claim is further confirmed by the results, shown in Fig. 13, where we vary the number of bidders. When the number of bidders increases, the performance gap grows but the gap is no more than 12 percent.

7.4 Impact of Flexible Bidding Patterns

ALETEHIA supports flexible bidding formats, including strict-request and range-request format. We now examine the impact of supporting flexible bidding formats to the auction results. We compare ALTHEIA and ALTHEIA-RG by varying the number of auctioned channels, where the number of bidders is set as $N = 300$ and the request of each



(a) Revenue (b) Spectrum Utilization (c) Impact of d_i

Fig. 14. Evaluate the impact of flexible bidding patterns by comparing ALETHEIA with SIMPLE versus the number of auctioned channels.

bidder is set as $d_i = 10$. We compare the mechanisms in a setting where the valuation function of each bidder has multiple steps. We generate the bid value of each bidder as follows. The request of each bidder d_i is randomly divided into s steps, and the maximal number of steps in an evaluation value is set to 3. For sth step, the bid b_{i_s} is randomly drawn from the range $(0, 1]$.

Figs. 14a and 14b shows the results for comparison. It is observed that the use of range requests increases spectrum utilization and revenue. Fig. 14c shows the revenue as a function of the number of channels auctioned using ALETHEIA-RG, to evaluate the impact of parameter d_i. The results show that a larger request of each bidder will generate higher revenue. In addition, the maximal revenue of ALETHEIA-RG is achieved at different number of auctioned channels when d_i is different. In other words, the optimal number of channels auctioned depends heavily on d_i.

7.5 Computational Cost

In this section, we evaluate the computational cost of the mechanisms by computing the running time. We implement these mechanisms in Windows 7 with Intel Core i5-2520 CPU 2.5 GHz using Matlab 2011b. Fig. 15 shows the results, where we observe that the running time increases as the number of bidders increases. ALETHEIA and VERITAS have the similar cost since they have the same scale of computational complexity. In contrast, to support range-request bidding, ALETHEIA-RG has much more cost to prevent demand-reduction cheating.

7.6 Fairness

In this section, we evaluate the fairness of the proposed mechanisms by quantifying the fairness using Jain's fairness index [10]. The Jain's fairness index is computed as $\frac{1}{N}\sum_{i=1}^{N}\frac{X_i}{X_f}$, where X_i denotes the allocation of bidder i and $X_f = \frac{\sum_{i=1}^{N} X_i^2}{\sum_{i=1}^{N} X_i}$ is the *fair allocation mark*. Thus, each bidder compares its allocation X_i with the amount X_f, and perceives the algorithm as fair or unfair depending upon whether its allocation X_i is more or less than X_f. The overall fairness is the average of *perceived fairness* of total N bidders. The results are shown in Fig. 16, which indicates that ALETHEIA-RG can achieve good performance in terms of fairness, since more bidders can be allocated.

8 Related Work

Spectrum allocation mechanisms have been extensively studied in recent years. A number of auction designs have been proposed to improve spectrum utilization and allocation efficiency. VERITAS [29] is one of the pioneer auction designs with strategy-proofness that exploits the spectrum reusability in radio spectrum. Later, the work is extended to consider double spectrum auctions [30]. Jia et al. [11] and Al-Ayyoub et al. [3] design spectrum auctions to maximize the expected revenue by assuming that the bids of the secondary users follow a certain distribution. SMALL [24] is designed for the scenario where the primary user sets a reserved price for each channel. TRUMP [22] allocates spectrum access rights on the basis of quality-of-service demands. The aforementioned works achieve strategy-proofness under the assumption that each bidder is associated with a unique name. As a result, none of them can resist false-name bid cheating where bidders can improve their utilities by submitting multiple false-name bids

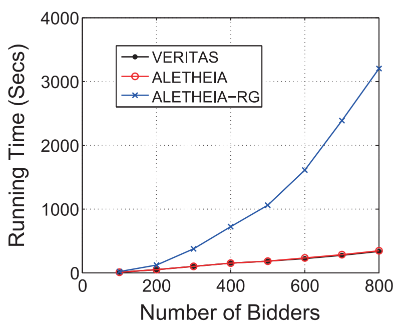


Fig. 15. Running time of the mechanisms.

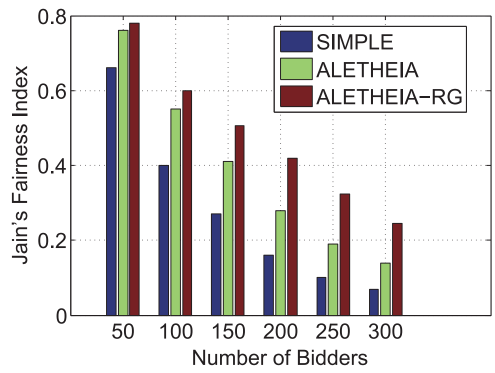


Fig. 16. Evaluate fairness by Jain's fairness index.

simultaneously. Another group of works (e.g., [25], [31]) study the collusion issue among bidders in spectrum auctions. Compared with collusion, while a bidder has to seek out and persuade other bidders to join in collusion, a false-name bid is easier to make since it can be done alone.

With the popularity and success of Internet auctions, false-name bid cheating has attracted more and more research interests. The effects of false-name bids on combinatorial auctions are analyzed in [27]. Following that, a series of false-name-proof mechanisms have been developed for a variety of scenarios. For example, Yokoo et al. [14] design a leveled division set based mechanism for multi-item single-unit auctions and prove its false-name-proofness. In [13], [20], false-name-proof mechanisms have been proposed to address the multi-unit single-item settings. Recently, the work [20] has been extended for double auction mechanisms [28]. All these designs are for traditional goods (e.g., books or paintings). They do not consider the spectrum reusability and cannot deal with the complex inference constraints in spectrum auctions. As a result, when being applied to spectrum auctions, these designs either lose false-name-proofness or create excess interference, as discussed in Section 4.

Different from the existing studies, ALETHEIA not only provides strategy-proofness but also resists false-name bid cheating. To the best of our knowledge, ALETHEIA is the first spectrum auction design that can achieve false-name-proofness. Moreover, the extension of ALETHEIA, named as ALETHEIA-RG, supports range-based request. Note that the conference version of this work has been accepted to ACM MobiHoc'15, and we extend it in this paper mainly by redesigning ALETHEIA-RG to make it be general for various applications.

9 Conclusion

In this paper, we have studied the new type of cheating named false-name bids, in large-scale spectrum auctions. We demonstrated that false-name bid cheating is easy to form in existing strategy-proof spectrum auctions and can severely impair the auction revenue. We further devised ALETHEIA, the first false-name-proof design for spectrum auction that nullifies the possibility of increasing profits by submitting false-name bids. It achieves high spectrum redistribution efficiency and low computational overhead, and is flexible to support diverse request formats of bidders. In our future work, we will analyze how the cheating patterns affect the auction results and solve the topic where bidders are allowed to misreport its total demand and valuation function simultaneously.

Acknowledgments

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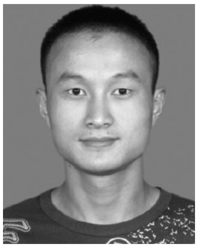

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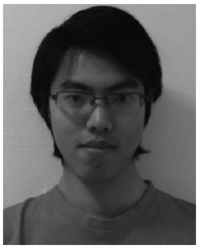

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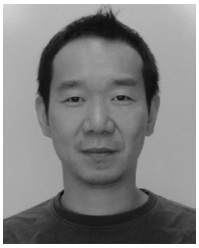

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