Spectrum Auctions Under Physical Interference Model

Yuhui Zhang, *Student Member, IEEE*, Dejun Yang, *Member, IEEE*, Jian Lin, *Student Member, IEEE*, Ming Li, *Student Member, IEEE*, Guoliang Xue, *Fellow, IEEE*, Jian Tang, *Senior Member, IEEE*, and Lei Xie, *Member, IEEE*

***Abstract*—Spectrum auctions provide a platform for licensed spectrum users to share their underutilized spectrum with unlicensed users. Existing spectrum auctions either adopt the protocol interference model to characterize interference relationship as binary relationship or only lease channels that are not used by the primary user (PU) to secondary users (SUs). In this paper, we design spectrum auctions under the physical interference model, which allow PU and SUs to transmit simultaneously. Specifically, we consider both single-minded and multi-minded cases, and design auctions SPA-S and SPA-M, respectively. We prove that both auctions are truthful, individually rational, and computationally efficient. Extensive simulation results demonstrate that, these designed auctions achieve higher spectrum utilization, buyer satisfaction ratio, and revenue than a representative existing spectrum auction adapted for the physical interference model.**

***Index Terms*—Cognitive radio ad hoc networks, dynamic spectrum access, spectrum auction, physical interference model, game theory.**

I. Introduction

Spectrum is a critical yet scarce resource due to the substantial growth of wireless technology and applications. Unused spectrum has become the darling of innovation, and its allocation has yielded many economic benefits and technological gains. Indeed, the Federal Communications Commission (FCC) and its counterparts across the world have released licenses of unused spectrum and collected billions of dollars in the past decade.

Fundamentally different from conventional goods, spectrum is reusable, which is referred to as *spatial reusability*. Users can share the same channel as long as they can transmit signals simultaneously without disrupting each other's transmission. Allowing spectrum to be shared by multiple users can significantly improve the spectrum utilization efficiency. In cognitive radio networks (CRNs), there are two types of users: 1) primary users (PUs) who are spectrum license holders; 2) secondary users (SUs) who do not own any licensed channel but are willing to pay for the usage in the short term. Therefore, the PUs may be motivated to open up their underutilized spectrum for sharing with SUs, so that they may make profit by leasing access to spectrum resources.

When the spatial reusability of the spectrum is considered, one arising challenge is to characterize the interference among users in CRNs. In the literature, two main interference models have been proposed [7]: the *protocol interference model* and the *physical interference model*. Next we shall explain these two models in detail.

1) Protocol Interference Model [7]: When two users transmit using the same channel simultaneously, one user interferes with the other if the other user's receiver is within the interference range of its transmitter. A transmitter's interference range depends on its transmission power. Usually, a conflict graph is used to model the interference relationship under the protocol interference model. In this graph, each node represents a user, and an edge exists between two nodes, if one user interferes with the other, thus they cannot share the same channel. For example, Figure 1 shows a wireless network under the protocol interference model (Figure 1(a)) and the corresponding conflict graph (Figure 1(b)). We show the interference ranges of five links in Figure 1(a). According to Figure 1(b), Links 2, 4 and 5 can share a channel simultaneously. But in practice, the accumulated interference from Links 4 and 5 may fail Link 2's transmission. Unfortunately, a conflict graph only reflects the interference relationship between any two links, but does not precisely express the interference relationship between one link and a set of other links. This simplified model abstracts away the accumulative nature of interference. Even if a transmitter far away from a receiver may not corrupt the transmission, the accumulated interference from several such nodes could still generate enough interference to prevent the receiver from successfully decoding the received message.

2) Physical Interference Model [7]: The physical interference model considers the accumulative nature of interference. In this model, the success of signal transmission is determined by the Signal-to-Interference-plus-Noise Ratio (SINR) at the receiver. Therefore, this model is also known as SINR model.

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Y. Zhang, D. Yang, J. Lin, and M. Li are with the Colorado School of Mines, Golden, CO 80401 USA (e-mail: yuhzhang@mines.edu; djyang@mines.edu; jilin@mines.edu; mili@mines.edu).

G. Xue is with Arizona State University, Tempe, AZ 85287 USA (e-mail: xue@asu.edu).

J. Tang is with Syracuse University, Syracuse, NY 13244 USA (e-mail: jtang02@syr.edu).

L. Xie is with the State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210023, China (e-mail: lxie@nju.edu.cn).

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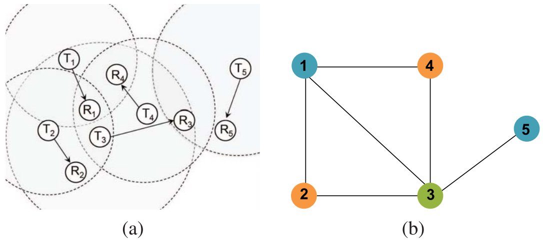


Fig. 1. Protocol interference model. (a) Interference range. (b) Conflict graph.

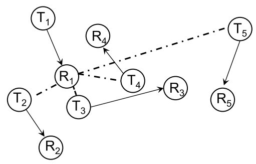


Fig. 2. Physical interference model.

Let $\mathcal{T}$ be a set of transmitters that simultaneously transmit over a certain channel. Then the SINR of Link (T_i, R_i) can be computed by

$$SINR_i = \frac{\frac{P_i}{d(T_i,R_i)^\alpha}}{\sum_{T_j \in \mathcal{T} \wedge T_j \neq T_i} \frac{P_j}{d(T_j,R_i)^\alpha} + N_0}, \tag{1}$$

where P_i is the transmission power of T_i, $d(T_j, R_i)$ is the maximum of 1 and the Euclidean distance from transmitter T_j to receiver R_i, α is the path loss exponent with value between 2 and 6 usually, and N_0 is the ambient noise power level. If $SINR_i$ is no less than the threshold β_i, the signal transmission is considered successful for the corresponding receiver, and it is considered unsuccessful otherwise. Figure 2 shows the same wireless network as in Figure 1, under the SINR model. For example, Link (T_1, R_1) receives interference from all other links. Then the transmission from T_1 is successfully received by R_1 if

$$\frac{\frac{P_1}{d(T_1,R_1)^\alpha}}{\sum_{T_j \in \mathcal{T} \wedge T_j \neq T_1} \frac{P_j}{d(T_j,R_1)^\alpha} + N_0} \geq \beta_1, \tag{2}$$

where β_1 is the threshold. Compared with the protocol interference model, the physical model has been recognized as a more realistic model in wireless communications.

Most of the existing spectrum auctions adopt the protocol interference model and thus simplify channel allocation by grouping users according to the derived conflict graphs. The foundation of these auctions is the assumption that the interference between any two users can be modeled as binary relationship. But in practice for wireless networks, a conflict graph may cause issues. On one hand, since the interference from other users is accumulative, the resulting channel allocation may not guarantee successful transmission for every user. On the other hand, a conflict graph constructed to consider the accumulated interference may eliminate potential sharing between users and thus lead to low channel utilization. For example, in Figure 1(a) Links 3 and 5 may share the same channel. In this paper, we design spectrum auctions under the *physical interference model*, which characterizes interference relationship more closely to reality. In our designed spectrum auctions, we iteratively assign users to channels in a greedy manner. In each iteration, we select a user who is willing to pay a high payment for each channel and is highly resistant to interference. For each winning user, we calculate its critical value [12] (defined in Section IV-C) as its payment.

The main contributions of this paper are:

- To the best of our knowledge, we are the first to design spectrum auctions, which allow the PU and SUs to share channels simultaneously under the physical interference model. In our model, the PU and SUs can be general star networks instead of single links.
- For SUs, we consider both single-minded and multi-minded cases. In the single-minded case, an SU only accepts the number of channels as it requests; in the multi-minded case, an SU accepts any number of channels no more than it requests. We design corresponding spectrum auctions, SPA-S and SPA-M, for these two cases, respectively.
- We rigorously prove both SPA-S and SPA-M are truthful, individually rational, and computationally efficient.

The remainder of the paper is organized as follows. In Section II, we give a brief review of existing spectrum auctions in the literature. In Section III, we formally describe the CRN model as well as the auction formulation. We present our designed auction SPA-S in the single-minded case, and analyze its properties in Section IV. Then we design SPA-M, which supports the multi-minded case in Section V. We evaluate the performance of SPA-S and SPA-M by comparing them with existing auctions in Section VI and conclude this paper in Section VII.

II. Related Work

As pioneers in spectrum auction design, Zhou *et al.* [25] proposed VERITAS under the protocol model, the first truthful auction considering the spectrum reusability and computation efficiency. In [9], based on the concept of virtual valuation, Jia *et al.* designed an exponential time VCG-based auction to maximize the expected revenue. Along this line, Al-Ayyoub and Gupta [1] designed a polynomial time spectrum auction that yields approximated expected revenue. Wu and Vaidya [18] designed SMALL to guarantee that the owner's utility is non-negative in the scenario where the owner of the spectrum has a reserved price for each of the channels. Following the same design methodology, Wei *et al.* [15] designed SHIELD that improves spectrum utilization and buyer satisfaction compared with VERITAS and SMALL. Inspired by the group-buying service on the Internet, Lin *et al.* [11] designed a three-state auction, called TASG that allows a leader in each group to conduct an outer auction for aggregating the bids within the group. Along this line, Yang *et al.* [21] designed TRUBA that significantly increases the revenue. Gopinathan and Li [6] studied spectrum auctions with prior-free setting and designed a truthful auction to approximately maximize the revenue.

TRUST [26] is the first truthful double auction designed for spectrum trading. Feng *et al.* [5] extended to heterogeneous spectrum auctions and designed TAHES. In [13], a double truthful auction, called DOTA, was proposed to allow each user to bid for more than one channel. Considering the fact that secondary users may join the network in an online fashion, Wang *et al.* [14] designed TODA. Yang *et al.* [22] proposed PROMISE for maximizing the profit without the knowledge of the users valuation distribution.

In the scenario of the physical interference model, Kakhbod *et al.* [10] developed a truthful auction for dividing a spectrum channel into several small channels with less bandwidth, where all transmitters power levels are fixed homogeneously. In [2], a truthful single auction was studied by Bae *et al.* where a sequential auction (an auction with multiple rounds) was used to reach a pure strategy equilibrium. Huang *et al.* [8] also introduced a truthful auction-based spectrum sharing mechanism where a group of users compete for a spectrum channel under different definitions of their utilities. Zhang *et al.* proposed TSA [23], a framework for truthful double auctions under the physical interference model with power control. To the best of our knowledge, there is no truthful auction that allows the primary user and secondary users to share channels simultaneously under the physical interference model.

III. Network Model and Auction Formulation

In this section, we describe our network model and formulate the process of channel leasing as a spectrum auction.

A. Cognitive Radio Network Model

We consider a cognitive radio network consisting of one primary user (PU), e.g., TV broadcaster, and a set $\mathcal{S} = \{S_1, S_2, \ldots, S_n\}$ of n secondary users (SUs), e.g., wireless local area networks or cellular networks. The PU owns m *homogeneous* channels $\mathcal{C} = \{c_1, c_2, \ldots, c_m\}$, and is willing to lease them for profit. The channels are assumed to be orthogonal, which means that there is no interference among users using different channels. Let P_0 denote the transmission power of the PU's transmitter, e.g., TV tower, denoted by T_0. SUs do not have licensed spectrum channels, but are willing to pay for channels from the PU in the short term.

Most of the existing spectrum auctions model an SU as a transmitter-receiver pair. However, an SU consisting of one transmitter and multiple (rather than one) receivers is also common in reality, e.g., a cell phone tower and cell phones in the corresponding cell. The receivers associated with the same transmitter can receive signals simultaneously from their corresponding transmitter without interrupting each other. In our model, each $S_i \in \mathcal{S}$ consists of one transmitter T_i, e.g., access point and a set $\mathcal{R}_i = \{R_i^1, R_i^2, \ldots, R_i^{r_i}\}$ of r_i receivers, e.g., wireless clients. All the receivers can decode signals from T_i successfully and simultaneously. Let P_i denote the transmission power of T_i. We can achieve spatial reuse by leasing the channel to multiple SUs, if they can transmit simultaneously. After channel allocation, let G_k be the group of SUs assigned to channel c_k.

We allow the PU and SUs to transmit signals over the same channels simultaneously. Let $\mathcal{C}_0 \subseteq \mathcal{C}$ represent the channels that the PU is currently using. To protect the transmission of the PU from being interrupted by the transmissions of SUs, the FCC proposed a metric, named Interference Temperature Limit (ITL) [4], which sets the maximum cumulative amount of interference that can be tolerated at the certain locations. Let $\mathcal{L} = \{l_1, l_2, \ldots, l_h\}$ denote the locations where the PU measures ITL. We use γ_j to represent PU's tolerated ITL at location l_j. With this setting, the PU can lease its channels to SUs as long as the transmissions of them do not cause more interference than γ_j, for any $l_j \in \mathcal{L}$. The ITL constraints can be represented by

$$\mathbb{1}_{\mathcal{C}_0}(c_k) \sum_{S_i \in G_k} \frac{P_i}{d(T_i, l_j)^\alpha} \le \gamma_j, \forall l_j \in \mathcal{L}, \forall c_k \in \mathcal{C}, \tag{3}$$

where $\mathbb{1}_{\mathcal{C}_0}(c_k)$ is an indicator function defined as

$$\mathbb{1}_{\mathcal{C}_0}(c_k) = \begin{cases} 1, & c_k \in \mathcal{C}_0, \\ 0, & c_k \notin \mathcal{C}_0, \end{cases} \tag{4}$$

$d(T_i, l_j)$ is the maximum of 1 and the Euclidean distance from transmitter T_i to location l_j, and α is the path loss exponent with value between 2 and 6 usually.

To closely characterize the interference relationship among the SUs in G_k, we adopt the physical interference model (a.k.a. SINR model). In this model, a receiver R_i^r can decode signals successfully from its corresponding transmitter T_i if and only if its Signal-to-Interference-plus-Noise Ratio (SINR) [7] is no less than a threshold β_i. In this system, the interference on a receiver of S_i might come from both the PU and other SUs sharing the same channel c_k with S_i. Therefore, $\forall R_i^r \in \mathcal{R}_i$ the SINR is

$$SINR(R_i^r) = \frac{\frac{P_i}{d(T_i, R_i^r)^\alpha}}{\frac{\mathbb{1}_{\mathcal{C}_0}(c_k) P_0}{d(T_0, R_i^r)^\alpha} + \sum_{S_i \neq S_j \in G_k} \frac{P_j}{d(T_j, R_i^r)^\alpha} + N_0}, \tag{5}$$

where $\mathbb{1}_{\mathcal{C}_0}(c_k)$ is defined in (4), and N_0 is the ambient noise power level. Then the transmission from T_i is successfully received by all S_i's receivers if

$$\min_{R_i^r \in \mathcal{R}_i} \frac{\frac{P_i}{d(T_i, R_i^r)^\alpha}}{\frac{\mathbb{1}_{\mathcal{C}_0}(c_k) P_0}{d(T_0, R_i^r)^\alpha} + \sum_{S_i \neq S_j \in G_k} \frac{P_j}{d(T_j, R_i^r)^\alpha} + N_0} \ge \beta_i. \tag{6}$$

We assume that Condition (6) is satisfied for any S_i when it solely occupies a channel. Otherwise we can discard it before our proposed auctions.

Before we formally describe our auctions, we introduce the following definitions: *SU Tolerance* [20] and *Feasible Group*.

Definition 1 (SU Tolerance): The tolerance τ_i indicates how much interference S_i can endure before its SINR value falls below the threshold β_i. It can be calculated by

$$\tau_i = \frac{\min_{R_i^r \in \mathcal{R}_i} \frac{P_i}{d(T_i, R_i^r)^\alpha}}{\beta_i} - N_0. \tag{7}$$

Definition 2 (Feasible Group): A group G_k of SUs is *feasible* with respect to S_i if, after the addition of S_i to the group, Condition (6) is satisfied for $\forall S_j \in G_k \cup \{S_i\}$ and Condition (3) is satisfied for the PU.

TABLE I
NOTATIONS

Notation	Meaning
$\mathcal{C}$	A set of channels contributed by the seller
$\mathcal{C}_0$	A set of channels being used by the seller, $\mathcal{C}_0 \subseteq \mathcal{C}$
d_i	The number of channels requested by S_i
b_i	The maximum price S_i is willing to pay for one channel
v_i	S_i's private per-channel valuation
p_i	The total price charged to S_i
u_i	S_i's utility

B. Auction Formulation

We formulate the process of leasing channels in cognitive radio networks as a spectrum auction. In this auction, the PU is the seller and SUs are buyers. Throughout the rest of this paper, we use PU and seller, and SU and buyer interchangeably. The seller contributes a set of channels $\mathcal{C}$ and is using channels in $\mathcal{C}_0 \subseteq \mathcal{C}$. Each buyer S_i requests d_i channels and holds a private per-channel valuation $v_i \geq 0$ for leasing a channel. We consider two cases for buyers: 1) *single-minded case*, where a buyer accepts either d_i channels or 0 channel; 2) *multi-minded case*, where a buyer accepts any x_i channels if $0 \leq x_i \leq d_i$. In this paper, we design spectrum auctions for both cases.

Both spectrum auctions work as follows: Each buyer submits a per-channel bid $b_i \geq 0$ as the maximum amount that it would pay for a channel and its number of requested channels at the beginning. After collecting the bids and requests from all buyers, we decide the channel allocation and winning buyers. We also compute the payment p_i for each buyer S_i.

The utility of S_i is defined as follows:

$$u_i = \begin{cases} v_i x_i - p_i, & \text{if } S_i \text{ wins,} \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

where $x_i = d_i$ for the single-minded case, and $0 \leq x_i \leq d_i$ for the multi-minded case. Table I lists the important notations.

Note that the *homogeneous* model can be generalized to the *heterogeneous* model with minor modification. In the heterogeneous case, a secondary user can have different valuations and submit bids separately for different channels. In this case we run our designed spectrum auction for each channel.

C. Desired Properties

There are three desired properties for an auction to satisfy:

- *Truthfulness:* an auction is truthful if each buyer obtains the highest utility by biding its true valuation of the resource.
- *Individual Rationality:* an auction is individually rational if all buyers have non-negative utilities by revealing their true valuations.
- *Computational Efficiency:* an auction is computationally efficient if it can be conducted within polynomial time.

The goal of this paper is to design spectrum auctions that maximize the total number of winners, while guaranteeing the three desired properties. However, it has been proved that the problem of maximizing the number of SUs sharing one channel with the PU is NP-hard in [3]. Since our problem without considering the economic properties is a generalized version of the problem in [3], we claim that our problem is NP-hard as well. Guaranteeing the economic properties makes it more challenging to design approximation algorithms. Therefore, we focus on fast heuristic algorithms that can be deployed in practice and yet assure the spectrum auctions the economic properties. Further theoretical analysis of the approximation ratio and designing approximation algorithms will be our future work directions.

Algorithm 1: SPA-S-Allocation ($\mathcal{S}$)

Sort all SUs in a non-increasing order based on $\tilde{b}_i$ and get a sorted list $\mathbb{S} : \mathbb{S}_1, \mathbb{S}_2, \mathbb{S}_3, \ldots, \mathbb{S}_n$;
for $k \leftarrow 1$ **to** m **do** $G_k \leftarrow \emptyset$;
for $i \leftarrow 1$ **to** n **do**
    for $k \leftarrow 1$ **to** m **do** Initialize f_{ik} by (9), $a_{ik} \leftarrow 0$;
    if $\sum_{k=1}^{m} f_{ik} \geq d_i$ **then**
        for $k \leftarrow 1$ **to** m **do**
            if $f_{ik} = 1$ **and** $\sum_{k=1}^{m} a_{ik} < d_i$ **then**
                $a_{ik} \leftarrow 1$, $G_k \leftarrow G_k \cup \{\mathbb{S}_i\}$;
            end
        end
    end
end
$\mathcal{G} \leftarrow \{G_1, G_2, \ldots, G_m\}$;
return $\mathcal{G}$

IV. AUCTION DESIGN FOR SINGLE-MINDED CASE

In this section, we introduce the basic design of a **SP**ectrum **A**uction under the physical interference model, named SPA-S, where buyers are single-minded, i.e., a buyer S_i that requests d_i channels only accepts either all d_i channels or none.

A. High-Level Description

SPA-S consists of two stages: channel allocation and pricing. The channel allocation stage sorts buyers based on both their bids and tolerances. Then for each buyer we check the feasibility of each of m channels sequentially and assign this buyer to the first d_i feasible channels. If there exist d_i feasible channels, this buyer is considered as a winner, otherwise a loser. In the pricing stage, we determine the payment for each winner, which is its critical value. We present the detailed algorithms in the following two subsections.

B. Channel Allocation

Intuitively, when we choose a buyer to allocate a channel, the one with a large per-channel bid and high tolerance is preferred. In other words, this buyer is willing to pay more for each channel and more resistant to interference. This property is best characterized by the product: $\tilde{b}_i = b_i \tau_i$. Note that we choose the product of b_i and τ_i, because both factors are equally essential but maybe in different orders of magnitude.

In the stage of channel allocation as shown in Algorithm 1, we sort all SUs and allocate SUs sequentially from $\mathbb{S}_1$ to $\mathbb{S}_n$. For each buyer $\mathbb{S}_i$, the algorithm checks whether G_k is feasible

Algorithm 2: SPA-S-Pricing ($\mathbb{S}$, $\mathcal{G}$)

for $i \leftarrow 1$ **to** n **do** $p_i \leftarrow 0$;
$\mathcal{W} \leftarrow \bigcup_{G_k \in \mathcal{G}} G_k$;
for $\mathbb{S}_i \in \mathcal{W}$ **do**
  $\mathbb{S}^{[-i]} \leftarrow \mathbb{S} \setminus \{\mathbb{S}_i\}$;
  for $k \leftarrow 1$ **to** m **do** $G_k \leftarrow \emptyset$; Initialize f_{ik} by (9);
  for $q \leftarrow 1$ **to** $n-1$ **do**
    for $k \leftarrow 1$ **to** m **do** Initialize f_{qk} by (9), $a_{qk} \leftarrow 0$;
    if $\sum_{k=1}^{m} f_{qk} \geq d_q$ **then**
      for $k \leftarrow 1$ **to** m **do**
        if $f_{qk} = 1$ **and** $\sum_{k=1}^{m} a_{qk} < d_q$ **then**
          $a_{qk} \leftarrow 1$, $G_k \leftarrow G_k \cup \{\mathbb{S}_q^{[-i]}\}$;
          if *G_k is infeasible to $\mathbb{S}_i$* **then**
            $f_{ik} \leftarrow 0$;
            if $\sum_{k=1}^{m} f_{ik} < d_i$ **then** $p_i \leftarrow \frac{d_i \tilde{b}_q}{\tau_i}$;
          end
        end
      end
    end
    if $p_i > 0$ **then** break;
  end
end
return $\{p_1, p_2, \ldots, p_n\}$

Algorithm 3: SPA-M-Allocation ($\mathcal{S}$)

1 Sort all SUs in a non-increasing order based on $\tilde{b}_i$ and get a sorted list $\mathbb{S} : \mathbb{S}_1, \mathbb{S}_2, \mathbb{S}_3, \ldots, \mathbb{S}_n$;
2 **for** $k \leftarrow 1$ **to** m **do** $G_k \leftarrow \emptyset$;
3 **for** $i \leftarrow 1$ **to** n **do**
4   **for** $k \leftarrow 1$ **to** m **do** Initialize f_{ik} by (9), $a_{ik} \leftarrow 0$;
5   **for** $k \leftarrow 1$ **to** m **do**
6   **if** $f_{ik} = 1$ **and** $\sum_{k=1}^{m} a_{ik} < d_i$ **then**
7       $a_{ik} \leftarrow 1$, $G_k \leftarrow G_k \cup \{\mathbb{S}_i\}$;
8   **end**
9   **end**
10   $x_i \leftarrow \sum_{k=1}^{m} a_{ik}$;
11 **end**
12 $\mathcal{G} \leftarrow \{G_1, G_2, \ldots, G_m\}$;
13 **return** $\mathcal{G}$

to $\mathbb{S}_i$ for $1 \leq k \leq m$. We use a binary variable f_{ik} to represent the feasibility status for $\mathbb{S}_i$, defined as:

$$f_{ik} = \begin{cases} 1, & \text{if } G_k \text{ is feasible to } \mathbb{S}_i, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

The algorithm assigns $\mathbb{S}_i$ to the first d_i feasible channels if available. We use another binary variable a_{ik} to denote the allocation status for $\mathbb{S}_i$. If c_k is allocated to $\mathbb{S}_i$, then $a_{ik} = 1$; otherwise 0. If there are less than d_i feasible channels to $\mathbb{S}_i$, the algorithm assigns $\mathbb{S}_i$ nothing.

C. Pricing

With each buyer either assigned d_i channels or nothing, next we need to compute their payments. To maintain truthfulness, we find each winning buyer its critical value [12].

Definition 3 (Critical Value): The critical value is the value such that a buyer will win when bidding higher than this value and lose when bidding lower than it.

We calculate each winning buyer's critical value based on the following concept.

Definition 4 (Critical SU): A critical SU of a winning buyer S_i is an SU whose selection ahead of S_i decreases the number of feasible channels to S_i that is already no more than the number of channels allocated to S_i in the channel allocation stage.

According to the definitions of critical value and critical SU, the critical value of each winning buyer is calculated based on its first critical SU. Thus it suffices to find the first critical SU of each winning buyer. Algorithm 2 illustrates the payment computation for all buyers. The basic idea is that for each winner $\mathbb{S}_i \in \mathcal{W}$, we first take $\mathbb{S}_i$ out of the sorted list $\mathbb{S}$ and get a sorted list $\mathbb{S}^{[-i]}$ consisting of the remaining buyers. Then we allocate channels to the remaining buyers. Each time when assigning a channel to a remaining buyer, check the feasibility of this channel to $\mathbb{S}_i$. When we find the first $\mathbb{S}_q^{[-i]}$, who makes $\mathbb{S}_i$'s request unsatisfiable, this SU is considered to be $\mathbb{S}_i$'s first critical SU, and its corresponding $\frac{\tilde{b}_q}{\tau_i}$ is $\mathbb{S}_i$'s critical value. If we cannot find the critical value for $\mathbb{S}_i$, the payment is 0.

D. Analysis

We prove that SPA-S satisfies the desired properties defined in Section III. The proof can be found in [24].

Theorem 1: SPA-S is truthful, individually rational, and computationally efficient.

V. Auction Design for Multi-Minded Case

In this section, we design a spectrum auction, called SPA-M, for the multi-minded case, where S_i requests d_i channels but accepts any number of channels between 0 and d_i.

A. Channel Allocation

The channel allocation stage is presented in Algorithm 3. Compared to the channel allocation stage in the single-minded case, when the number of feasible channels for $\mathbb{S}_i$ is no more than d_i, we allocate if there is any available. We use x_i to denote the number of channels allocated to $\mathbb{S}_i$ in Line 9.

B. Pricing

In this section, we describe the pricing stage for the multi-minded case, illustrated in Algorithm 4. The payment calculation for each winner is based on the critical SUs.

The fundamental difference from the pricing stage for the single-minded case is that now a buyer accepts any x_i channels between 0 and d_i. Different bids may result in different numbers of allocated channels. Thus the payment cannot be calculated solely based on a single value as in the single-minded case, where a winner will become a loser if it bids below its critical value. In the multi-minded case, bidding below the critical value of a channel, a winner will lose this

Algorithm 4: SPA-M-Pricing ($\mathbb{S}$, $\mathcal{G}$)

for $i \leftarrow 1$ **to** n **do** $p_i \leftarrow 0,\ Q_i \leftarrow \emptyset,\ \ x_i \leftarrow \sum_{k=1}^{m} a_{ik}$;
$\mathcal{W} \leftarrow \bigcup_{G_k \in \mathcal{G}} G_k$;
for $\mathbb{S}_i \in \mathcal{W}$ **do**
  $\mathbb{S}^{[-i]} \leftarrow \mathbb{S} \setminus \{\mathbb{S}_i\}$;
  for $k \leftarrow 1$ **to** m **do** $G_k \leftarrow \emptyset$; Initialize f_{ik} by (9);
  for $q \leftarrow 1$ **to** $n-1$ **do**
    for $k \leftarrow 1$ **to** m **do** Initialize f_{qk} by (9), $a_{qk} \leftarrow 0$;
    for $k \leftarrow 1$ **to** m **do**
      if $f_{qk} = 1$ **and** $\sum_{k=1}^{m} a_{qk} < d_q$ **then**
        $a_{qk} \leftarrow 1,\ G_k \leftarrow G_k \cup \{\mathbb{S}_q^{[-i]}\}$;
        if $f_{ik} = 1$ **and** *G_k is infeasible to $\mathbb{S}_i$* **then**
          $f_{ik} \leftarrow 0$;
          if $\sum_{k=1}^{m} f_{ik} < x_i$ **then** $p_i \leftarrow p_i + \frac{\tilde{b}_q}{\tau_i}$;
        end
      end
    end
  end
end
return $\{p_1, p_2, \ldots, p_n\}$

channel. Therefore, a winner should be charged separately on each individual allocated channel.

Algorithm 4 illustrates the pricing stage for all buyers. The basic idea is that for each winner $\mathbb{S}_i \in \mathcal{W}$, we first take $\mathbb{S}_i$ out of the sorted list $\mathbb{S}$ and get a sorted list $\mathbb{S}^{[-i]}$ consisting of the remaining buyers. Then we allocate channels to the remaining buyers, similar to what we did in the channel allocation stage. The difference is that each time when assigning a channel to a remaining buyer $\mathbb{S}_q^{[-i]}$, we check the feasibility of this channel to $\mathbb{S}_i$. If the selection of $\mathbb{S}_q^{[-i]}$ makes this channel infeasible to $\mathbb{S}_i$, and the number of feasible channels of $\mathbb{S}_i$ is no more than x_i, then $\mathbb{S}_q^{[-i]}$ is a critical SU of $\mathbb{S}_i$, and the corresponding $\frac{\tilde{b}_q}{\tau_i}$ is the payment of $\mathbb{S}_i$ for one of its allocated channels. The total payment is the sum of payments for all its allocated channels.

C. Analysis

We prove that SPA-M satisfies the desired properties.
SPA-M

Theorem 2: is truthful, individually rational, and computationally efficient.

Proof: It is not intuitive to prove this lemma using the critical value as we did in Lemma 1, because the payment calculated in the pricing stage is the summation of multiple values. Thus we prove truthfulness using its definition.

Recall that x_i is the number of channels allocated to S_i in the channel allocation stage. In the pricing stage, when the number of remaining feasible channels to S_i is no more than x_i, we find a critical SU of S_i every time one channel becomes infeasible to it. Let Q_i denote the set of S_i's critical SUs found in all iterations. Thus we have $|Q i| = x_i$. Since multiple channels may correspond to the same critical SU, Q_i might be a multiset.

Assume for each buyer S_i, it wins x_i' channels and pays p_i' by bidding b_i', and it wins x_i'' channels and pays p_i'' by bidding $b_i'' < b_i'$. We first prove that the following statement holds:

$$\left(x_i' - x_i''\right)b_i'' \le p_i' - p_i'' \le \left(x_i' - x_i''\right)b_i'. \tag{10}$$

Let $\mathbb{S}'$ and $\mathbb{S}''$ be the sorted lists when S_i bids b_i' and b_i'', respectively. With $b_i'' < b_i'$, we have $\tilde{b}_i'' < \tilde{b}_i'$ since τ_i is the same. Therefore S_i's position in $\mathbb{S}'$ is ahead of that in $\mathbb{S}''$. Because S_i wins x_i'' channels by bidding b_i'', there are at least x_i'' feasible channels for S_i when it is considered according to $\mathbb{S}''$. This implies there are also at least x_i'' feasible channels for S_i when it is considered according to $\mathbb{S}'$. Thus $x_i' \ge x_i''$.

Let Q_i' and Q_i'' be the sets of S_i's critical SUs, when S_i bids b_i' and b_i'', respectively. Thus $|Q_i'| = x_i'$ and $|Q''_i| = x_i''$. Because the critical SUs of S_i are ranked after S_i, we have $\frac{\tilde{b}_q}{\tau_i} \le b_i', \forall S_q \in Q_i'$. Similarly, we have $\frac{\tilde{b}_q}{\tau_i} \le b_i'', \forall S_q \in Q_i''$. For each critical SU in Q_i'', it makes one channel infeasible to S_i. Thus it also makes one channel infeasible to S_i, when S_i is considered according to $\mathbb{S}'$. Thus we have $Q_i'' \subseteq Q_i'$. Since $p_i' = \sum_{S_q \in Q_i'} \frac{\tilde{b}_q}{\tau_i}$ and $p_i'' = \sum_{S_q \in Q_i''} \frac{\tilde{b}_q}{\tau_i}$, we have $p_i' - p_i'' = \sum_{S_q \in Q'_i \setminus Q''_i} \frac{\tilde{b}_q}{\tau_i}$. Because the ranking of each critical SU in $Q_i' \setminus Q_i''$ is ahead of S_i in $\mathbb{S}''$ and after S_i in $\mathbb{S}'$, we have $b_i'' \le \frac{\tilde{b}_q}{\tau_i} \le b_i', \forall S_q \in Q_i' \setminus Q_i''$. Since $|Q_i' \setminus Q_i''| = x_i' - x_i''$, we have $(x_i' - x_i'')b_i'' \le \sum_{S_q \in Q_i' \setminus Q_i''} \frac{\tilde{b}_q}{\tau_i} \le (x_i' - x_i'')b_i'$. This proves (10).

In the following, we prove that SPA-M is truthful, i.e., $u_i^v \ge u_i^b, \forall S_i \in \mathcal{S}$, where u_i^v and u_i^b represent the utilities when S_i bids v_i and $b_i \neq v_i$, respectively. Based on (8), the utilities are calculated as follows: $u_i^v = v_i x_i^v - p_i^v$, $u_i^b = v_i x_i^b - p_i^b$. Thus we have:

$$u_i^v - u_i^b = v_i x_i^v - v_i x_i^b - p_i^v + p_i^b \tag{11}$$

We consider the following two cases separately:

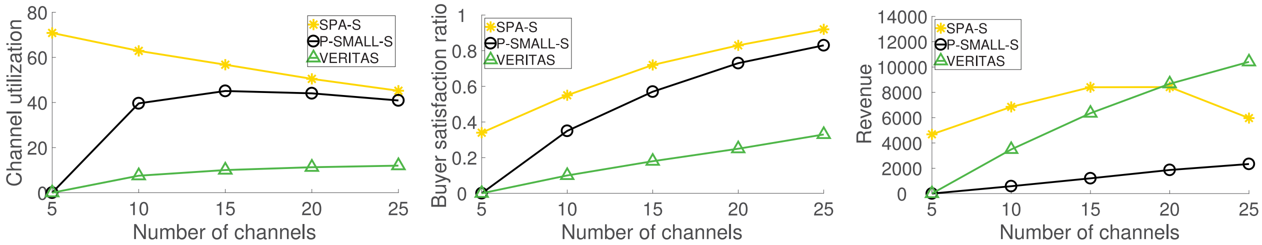
- *Case 1: $b_i > v_i$*
  We rearrange (11) and have $u_i^v - u_i^b = (p_i^b - p_i^v) - (x_i^b - x_i^v)v_i$. According to the first inequality in (10), $(x_i^b - x_i^v)v_i \le p_i^b - p_i^v$, thus $u_i^v - u_i^b \ge 0$.
- *Case 2: $b_i < v_i$*
  Similar as Case 1, we have $u_i^v - u_i^b = (x_i^v - x_i^b)v_i - (p_i^v - p_i^b)$. According to the second inequality in (10), $p_i^v - p_i^b \le (x_i^v - x_i^b)v_i$, thus $u_i^v - u_i^b \ge 0$.

Thus $u_i^v \ge u_i^b, \forall S_i \in \mathcal{S}$. SPA-M is truthful.

Assume that each buyer S_i bids truthfully, i.e., $b_i = v_i$. For all losers, $u_i = 0$. For each winning buyer S_i, we have $p_i = \sum_{S_q \in Q_i} \frac{\tilde{b}_q}{\tau_i}$ and $|Q_i| = x_i$. Because S_i's critical SUs are ranked after it in the sorted list $\mathbb{S}$, we have $\frac{\tilde{b}_q}{\tau_i} \le b_i, \forall S_q \in Q_i$. Thus $p_i \le b_i x_i = v_i x_i$. Therefore $u_i = v_i x_i - p_i \ge 0$.

Thus, $u_i \ge 0, \forall S_i \in \mathcal{S}$. SPA-M is individually rational.

We now analyze the running time of SPA-M. To allocate x_i channels to a buyer S_i, Algorithm 3 needs to examine at most m channels. This process takes $O((m+n)n)$ time for n buyers. Algorithm 4's complexity only comes from the processes of initialization and checking feasibility for S_q, which is $O((m+n)n)$ for each buyer. In total, the overall time complexity of SPA-M is $O((m+n)n^2)$. ■



(a) (b) (c)

Fig. 3. Impact of m on SPA-S, P-SMALL-S and VERITAS. (a) Channel utilization. (b) Buyer satisfaction ratio. (c) Revenue.

VI. Performance Evaluation

A. Evaluation Setup

First, we investigate the advantages of physical interference model by comparing SPA-S and SPA-M with VERITAS and Range-VERITAS [25] for single-minded and multi-minded cases, respectively. Theses two auctions form groups during channel allocation as SPA-S and SPA-M but were designed under the protocol interference model. Then we examine the channel allocation mechanisms in SPA-S and SPA-M by comparing them with an existing spectrum auction. Most of the known prior works [11], [15], [18], [21] form groups before channel allocation to achieve spatial reusability, according to the given conflict graphs under the protocol interference model. As we surveyed in Section **II**, there is no existing auction under the physical interference model. However, they can be modified to adopt the physical interference model by forming groups under SINR constraints, as Zhang *et al.* [23] did in TSA. Note that the existing spectrum auctions do not allow SUs to share channels with the PU. In our evaluation, we choose SMALL [18], which is most related to our auctions. Since the stage of group formation in SMALL must be bid-independent, we implemented an effective heuristic algorithm for link scheduling in [19] to group SUs. We name the modified SMALL as **P-SMALL-S** and **P-SMALL-M**, for single-minded and multi-minded cases, respectively.

Based on the parameters pertaining to cellular networks, we randomly distributed the PU and SUs in a 100,000 by 100,000 meters square area, which is roughly the size of the Los Angeles metropolitan area [17]. The length of links depends on the radius of the cells in cellular networks, which may vary from 1,000 to 30,000 meters [16]. Thus, all the links, including both the PU links and SU links, were uniformly randomly generated in length between 1,000 and l_{max}, where l_{max} varied from 5,000 to 10,000. The transmitter of PU was placed in the center of the square region. We set the transmission power $P_i = 20$ watts for all $i \in \{0, 1, \ldots, n\}$, since the typical transmission power of a cellular base station is from a few watts to 100 watts, which is the maximum power required by FCC. In addition, we have the path loss exponent $\alpha = 4$, background noise $N_0 = 10^{-16}$, and the SINR threshold $\beta = 16$. We assume that the values of all SUs are distributed uniformly at random over $(0, 100]$, and each buyer requests at most 3 channels. All the results were averaged over 1000 runs for each configuration of the parameters.

We use the following three performance metrics.

- *Channel Utilization:* Average number of buyers allocated to each channel.
- *Buyer Satisfaction Ratio:* The percentage of buyers who win at least one channel.
- *Revenue:* The total payment from all the winning buyers.

In our evaluation, we show the impact of the number of SUs (n), the number of total channels (m) and the number of channels used by the PU (d_0) on different spectrum auctions in terms of the above three metrics. For the impact of n, we vary it from 50 to 1000 with an increment of 100, while fixing $m = 10$ and $d_0 = 5$. For the impact of m, we vary it from 5 to 25 with an increment of 5, while fixing $n = 500$ and $d_0 = 5$. For the impact of d_0, we vary it from 5 to 10 with an increment of 1, while fixing $m = 10$ and $n = 500$.

In the multi-minded case, a buyer accepts any number of channels no greater than it requests. Specifically we are interested in the distribution of the winners' allocated-to-requested ratio: the number of allocated channel over the number of requested channels of each buyer. In our evaluation, we show the distribution of the winners' allocated-to-requested ratio by fixing $m = 10$, $n = 500$ and $d_0 = 5$.

B. Evaluation Results and Analysis

Figure 3 shows the impact of m on the channel utilization, buyer satisfaction ratio and revenue of SPA-S, P-SMALL-S and VERITAS. Figure 3(a) shows the impact of m on the channel utilization. We observe that SPA-S outperforms P-SMALL-S and VERITAS. The reason is that P-SMALL-S and VERITAS do not allow the PU to share channels with SUs, P-SMALL-S always sacrifices one SU in each group, and VERITAS is designed under the physical interference model that characterizes the interference relationship among users as binary, which leads to low channel capacity. When there are more channels, SPA-S and P-SMALL-S gradually result in less channel utilization because the competition among SUs is no longer intense. In addition, we notice that the channel utilization of P-SMALL-S and VERITAS increase when m changes from 5 to 10. Because the PU uses 5 channels, which cannot be shared with SUs in P-SMALL-S, and the channel utilization is 0 when $m = 5$. That is also the reason that VERITAS's channels utilization grows with more channels. In Figure 3(b), the satisfaction ratio of SPA-S and P-SMALL-S increase with m and stay at a steady level nearly 100% when there are enough channels for almost all SUs. We also observe that SPA-S

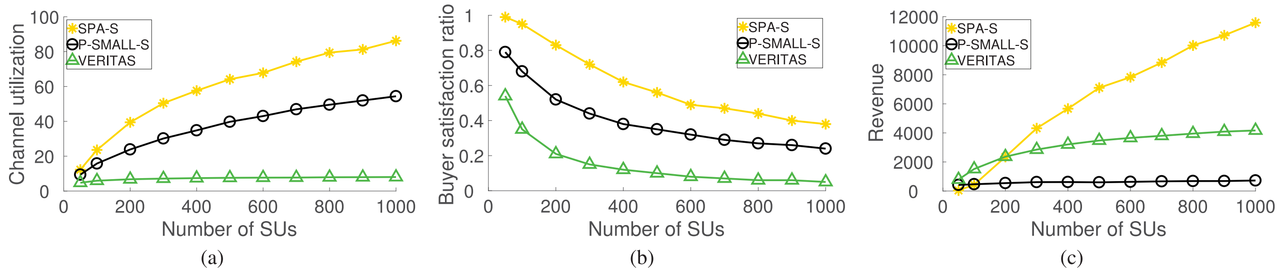


Fig. 4. Impact of n on SPA-S, P-SMALL-S and VERITAS. (a) Channel utilization. (b) Buyer satisfaction ratio. (c) Revenue.

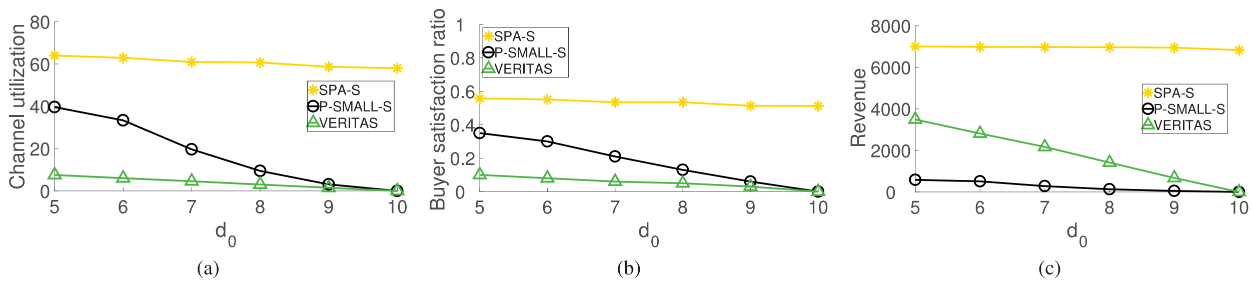


Fig. 5. Impact of d_0 on SPA-S, P-SMALL-S and VERITAS. (a) Channel utilization. (b) Buyer satisfaction ratio. (c) Revenue.

performs better than P-SMALL-S and VERITAS, especially with fewer channels, because P-SMALL-S and VERITAS do not allow the PU to share channels with SUs. In addition, P-SMALL-S can never achieve 100% satisfaction ratio, because it always sacrifices one SU in each group to guarantee truthfulness; VERITAS has the lowest satisfaction ratio due to the low channel capacity. From Figure 3(c) we observe that the revenue of P-SMALL-S grows when there are more channels, but converges after the saturation of the market. On the other hand, the revenue of SPA-S increases at the beginning and then falls down when m is above 20. The essential reason is that, with more channels, the competition among SUs is no longer intense, which leads to zero payments for some winners in SPA-S; but a winner's payment in P-SMALL-S is determined by the minimum bid in the group and is always greater than 0. However, the revenue of VERITAS is higher than SPA-S with more than 20 channels, because the low channel utilization results in intense competition, and the critical value of a winner becomes higher.

Figure 4 shows the impact of n on the channel utilization, buyer satisfaction ratio and revenue of SPA-S, P-SMALL-S and VERITAS. Figure 4(a) illustrates the channel utilization when more SUs join the auctions. The average number of SUs in each channel in SPA-S increases gradually at first and then remains at a level around 80 due to the saturation of the market. P-SMALL-S has lower channel utilization due to the sacrifice rule. In addition, VERITAS has the lowest channel utilization, because it is designed under the physical interference model. From Figure 4(b), we observe that, initially the satisfaction ratio is nearly 100% in SPA-S, because most SUs are winners. However, P-SMALL-S cannot achieve 100% satisfaction ratio due to its sacrifice rule. VERITAS's satisfaction ratio is the lowest because the physical interference model results in low channel capacity. The common trend is when there are more SUs, higher percentage of them cannot

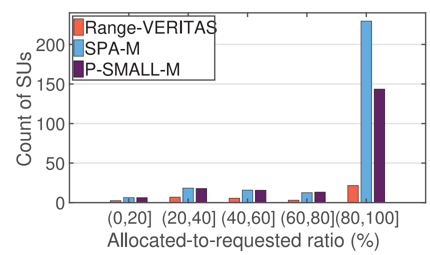
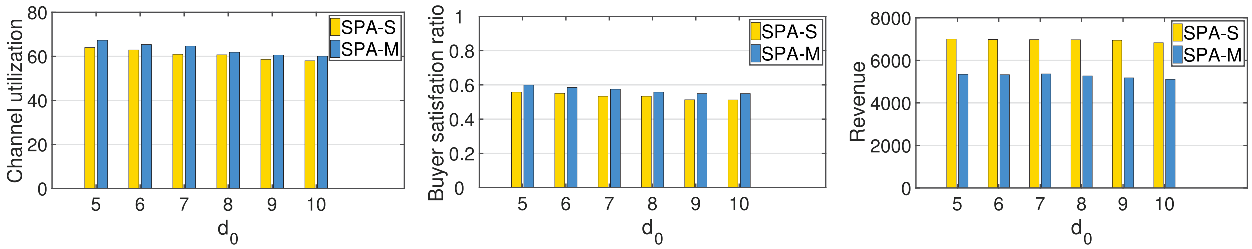


Fig. 6. Distribution of allocated-to-requested ratio.

be winners. Thus the satisfaction ratio drops for all auctions. In Figure 4(c), the competition between SUs becomes more intense with more SUs involved. Consequently, winners' critical values are higher, and the revenue increases in SPA-S and VERITAS. Similarly, the competition between groups in P-SMALL-S grows with more SUs, thus the seller receives more revenue. However, the payment rule in P-SMALL-S inhibits noticeable revenue growth.

Figure 5 compares these auctions in terms of the three metrics, when d_0 varies. We observe that with more channels used by the PU, the performance of SPA-S decreases slightly. This is because the PU is guaranteed to be able to transmit signals successfully, and fewer SUs can be allocated to the channels that are used by the PU as a result. Whereas, P-SMALL-S decreases significantly in all three metrics, because the PU cannot share channels with SUs in P-SMALL-S. Moreover, VERITAS's channel utilization and buyer satisfaction ratio are not very high due to the low channel capacity, and its revenue falls down when PU uses more channels.

For the impact of n, m and d_0 on SPA-M, P-SMALL-M and Range-VERITAS in terms of all three metrics, we have similar observations as in Figures 3, 4 and 5, which can be explained in the same way.



(a) (b) (c)

Fig. 7. Comparing SPA-S and SPA-M. (a) Channel utilization. (b) Buyer satisfaction ratio. (c) Revenue.

Figure 6 illustrates the distribution of winners' allocated-to-requested ratio in SPA-M, P-SMALL-M and Range-VERITAS. We observe that most winners received more than 80% of the requested channels in all auctions. In SPA-M, more winners have the allocated-to-requested ratio higher than 80%, because SPA-M offers higher channel utilization compared with P-SMALL-M and Range-VERITAS.

We are also curious about the performance of spectrum auctions with different SUs cases, thus we compare SPA-S and SPA-M in terms of the above three metrics. Note that we have similar observations, when n, m or d_0 varies. Thus we only show the impact of d_0 in Figure 7 for illustration. We notice that SPA-M achieves higher channel utilization and buyer satisfaction ratio than SPA-S, while SPA-S has higher revenue. Because in SPA-M, the channel allocation is more flexible — SUs accept a portion of their requested channels, which leads to higher buyer satisfaction ratio and channel utilization. On the other hand, the payments in SPA-M are calculated based on multiple critical SUs, while the payments in SPA-S are calculated based on the first critical SU. With the same input, the first critical SU has the highest ranking position among all critical SUs for any winning SU, and this results in higher per-channel payment in SPA-S than SPA-M. Therefore, the revenue in SPA-S is higher than that in SPA-M.

VII. Conclusion

In this paper, we studied the design of spectrum auctions which allow the primary and secondary users to share channels simultaneously under the physical interference model. For secondary users, we considered both single-minded and multi-minded cases. The difference between these two cases is whether a secondary user accepts a portion of its requested channels. We proposed SPA-S and SPA-M for these two cases, respectively. We analyzed both SPA-S and SPA-M and proved these auctions satisfy truthfulness, individual rationality, and computational efficiency. Further performance evaluation indicates SPA-S and SPA-M achieve better channel utilization and buyer satisfaction ratio compared with VERITAS [25] and SMALL [18] adapted for the physical interference model.

Acknowledgment

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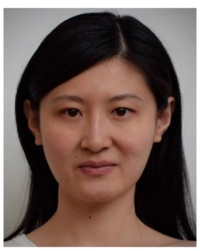
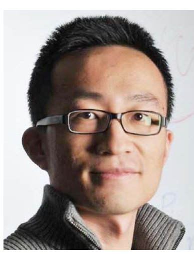


Yuhui Zhang (S'16) received the B.S. degree in applied chemistry from Sun Yat-sen University, Guangzhou, China, in 2011, and the M.S. degree in computer science from the Colorado School of Mines, Golden, CO, USA, in 2016.

She is currently pursuing the Ph.D. degree in computer science with the Colorado School of Mines. Her main research interests lie in the areas of game theory, location privacy, and crowdsourcing.



Dejun Yang (M'13) received the B.S. degree in computer science from Peking University, Beijing, China, in 2007 and the Ph.D. degree in computer science from Arizona State University, Tempe, AZ, USA, in 2013.

He is currently the Ben L. Fryrear Assistant Professor of computer science with the Colorado School of Mines, Golden, CO, USA. His research interests include economic and optimization approaches to networks, crowdsourcing, smart grid, and security and privacy.

Prof. Yang was a recipient of the best paper awards at the IEEE GLOBECOM in 2015, the IEEE International Conference on Mobile Ad hoc and Sensor Systems in 2011, and the IEEE ICC in 2011 and 2012, as well as the Best Paper Award Runner-up at the IEEE International Conference on Network Protocols in 2010. He has served as a Technical Program Committee Member for many conferences, including the IEEE International Conference on Computer Communications, IEEE Conference on Communications and Network Security, the IEEE International Conference on Communications, and the IEEE Global Communications Conference.

Jian Lin (S'15) received the B.S. and M.S. degrees in computer science from Southwest Jiaotong University, Chengdu China, in 2011 and 2014, respectively.

He is currently pursuing the Ph.D. degree in computer science with the Colorado School of Mines, Golden, CO, USA. His research interests include economic and optimization approaches to networks, mobile crowdsensing, and mobile computing.

Ming Li (S'15) received the B.S. degree in geochemistry from Peking University, Beijing, China, in 2013 and the M.S. degree in computer science from the Colorado School of Mines, Golden, CO, USA, in 2015.

She is currently pursuing the Ph.D. degree with Colorado School of Mines. Her main research interests include game theory, contract theory, crowdsourcing, smartphone-based sensing systems, and visible light communication technologies.

Guoliang Xue (M'96–SM'99–F'11) received the B.S. degree in mathematics and the M.S. degree in operations research from Qufu Normal University, Qufu, China, in 1981 and 1984, respectively, and the Ph.D. degree in computer science from the University of Minnesota, Minneapolis, MN, USA, in 1991.

He is a Professor of computer science and engineering with Arizona State University, Tempe, AZ, USA. His research interests span the areas of quality of service provisioning, network security and privacy, crowdsourcing and network economics, RFID systems and Internet of Things, smart city and smart grids. He has published over 280 papers in these areas, many of which in top conferences such as IEEE International ICNP, INFOCOM, ACM Conference on Mobile Computing and Networking, ACM International Symposium on Mobile Ad Hoc Networking and Computing, Network and Distributed System Security Symposium, and top journals such as the IEEE/ACM TRANSACTIONS ON NETWORKING, the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, and the IEEE TRANSACTIONS ON MOBILE COMPUTING. He was a Keynote Speaker at IEEE Conference on Local Computer Networks in 2011 and International Conference on Computing, Networking and Communication in 2014. He was a TPC Co-Chair of INFOCOM in 2010 and a General Co-Chair of CNS in 2014.

Prof. Xue is the Elected Vice President of the IEEE Communications Society for Conferences from 2016 to 2017. He has served on the TPC of many conferences, including ACM Conference on Computer and Communications Security, MobiHoc, ICNP, and INFOCOM. He served on the editorial board of the IEEE/ACM TRANSACTIONS ON NETWORKING and the *Computer Networks* Journal. He serves as the Area Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, overseeing 13 editors in the Wireless Networking area.

Jian Tang (M'06–SM'13) received the Ph.D. degree in computer science from Arizona State University in 2006.

He is currently a Professor with the Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY, USA. His research interests lie in the areas of wireless networking, deep learning, big data, and cloud computing.

Dr. Tang was a recipient of NSF CAREER Award in 2009, the 2016 Best Vehicular Electronics Paper Award from IEEE Vehicular Technology Society, and the best paper awards from ICC in 2014 and GLOBECOM in 2015. He has published over 100 papers in premier journals and conferences. He has been an Editor for the IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING since 2017, the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS since 2016, the IEEE INTERNET OF THINGS JOURNAL since 2013, and the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY from 2010 to 2017. He served as a TPC Co-Chair for IEEE International Conference on Internet of Things in 2015 and ICNC in 2016.

Lei Xie (M'10) received the B.S. and Ph.D. degrees in computer science from Nanjing University, China, in 2004 and 2010, respectively.

He is currently an Associate Professor with the Department of Computer Science and Technology, Nanjing University.

Prof. Xie has published over 50 papers in TMC, the IEEE TRANSACTION ON PARALLEL AND DISTRIBUTED SYSTEMS, ACM International Joint Conference on Pervasive and Ubiquitous Computing, ACM MobiHoc, IEEE INFOCOM, and IEEE ICNP.