Auction-based Spectrum Sharing in Multi-Channel Cognitive Radio Networks with Heterogeneous Users

by

Changyan Yi

A Thesis submitted to the Faculty of Graduate Studies of
The University of Manitoba
in Partial Fulfilment of the Requirements for the degree of

Master of Science

Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg

Abstract

Dynamic spectrum access based on cognitive radio has been regarded as a prospective solution to improve spectrum utilization for wireless communications. By considering the allocation efficiency, fairness, and economic incentives, spectrum marketing has been attracting more and more attentions in recent years. In this thesis, we focus on one of the most effective spectrum marketing methods, i.e., auction approach, in multi-channel cognitive radio networks. After presenting some fundamentals and related works, we begin our discussion in a recall-based auction system where buyers have various service requirements and the seller could recall some sold items after the auction to deal with a sudden increase of its own demand. Both single-winner and multi-winner auctions are designed and analyzed. In addition, we also consider the heterogeneity of radio resource sellers and formulate a framework of combinatorial spectrum auction. With theoretical analyses and simulation results, we show that our proposed algorithms can improve spectrum utilization while satisfy the heterogeneous requirements of different wireless users.

Acknowledgements

This thesis would not have been accomplished without the help of so many people in different ways. First of all, I would like to express my deepest gratitude to my advisor Prof. Jun Cai for his continual support of my master study, for his patience, motivation, energy and immense knowledge. Dr. Cai taught me how to question thoughts and express ideas. I have been fortunate to have an advisor who gave me the freedom to explore on my own and meanwhile his guidance helped me in all the time of research and writing of this thesis. In addition, I greatly appreciate his understanding and encouragement which boosted my enthusiasm towards wireless communications and all related theoretic research works.

Besides, I would like to thank the rest of my thesis committee: Prof. Attahiru S. Alfa and Prof. Qingjin Peng for their insightful comments and helpful suggestions. I would also thank all the professors in the department of Electrical and Computer Engineering and the other departments at the University of Manitoba for their well-taught lectures and invaluable guidance.

My sincere thanks also goes to all my colleagues in the Robert Alan Kennedy Communication Lab. Thanks to Hong Zhang, Suren Tharanga, Shiwei Huang, Huijin Cao, Hongqiao Tian, Aditya Kedia and all the other friends for all our stimulating discussions in research and boundless friendship during the past two years.

Last but not the least, I would like to thank my family for supporting me spiritually throughout my life.

Contents

List of Figures

Chapter 1

Introduction

1.1 Background and Motivations

Generally speaking, radio spectrum refers to the frequency range from 3 kHz to 300 GHz that is used for wireless communications. Signal interference was once considered as the main issue of spectrum allocation. Specifically, interference can occur when multiple radios are transmitted simultaneously over the same frequency. Hence, traditional spectrum management is required to statically assign exclusive spectrum bands to different wireless users to avoid potential interference. Since 1930s, spectrum was assigned through administrative licensing by governments. For example, Federal Communications Commission (FCC) in U.S. adopts the command-and-control management approach so that the regulator (FCC) is acted as a centralized authority to determine the spectrum usage and grant license to authorized parties to use them [1]. Such allocation pattern is normally static in both temporal and spatial dimensions. In other words, spectrum licenses are valid for ages (usually decades) and for large geographical areas (country wide). This command-and-control based management framework can ensure exclusive spectrum usages, and thus guarantee interference free communications. However, it has been argued as an artifact of outdated technologies due to its simpleness and inflexibility. Moreover, as claimed in the report [2] of FCC in 2002, the licensed spectrum are utilized 15 to 85 percent with a high variance in time. With dramatically growing demand of spectrum for new wireless devices and applications, current fixed spectrum assignment policy has imposed significant restrictions on spectrum utilization efficiency which leads to a serious issue, called spectrum scarcity. Therefore, it is imperative to exploit under-utilized spectrum in a more intelligent and flexible way [3]. To achieve this goal, dynamic spectrum access based on cognitive radio (CR) has been proposed as a prospective solution which allows unlicensed wireless users to opportunistically access the licensed spectrum on the premise that the services of authorized users are not degraded because of interference [4–6].

The concept of CR was first presented by Joseph Mitola III in 1998. It was a novel technique in wireless communications, which was later defined in [3] as follows: "Cognitive Radio is an intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations by adjusting the transmission parameters (e.g. frequency band, modulation mode, and transmit power) in real-time." The main functions of traditional CR include spectrum sensing, spectrum management, and spectrum mobility. Through spectrum sensing, cognitive radio users (also called, secondary users) detect the information of licensed spectrum (e.g. the gain and the activities of primary users who own the spectrum). During the spectrum management, sensing information is collected and used for making decisions on spectrum access. If the radio environment changes, cognitive radio users could change the frequency of operation by the function of spectrum mobility.

However, CR based on spectrum sensing [7–9] has two inherent limitations which have been realized to be crucial and restricted for implementing dynamic spectrum sharing: i) Primary users (PUs) are pre-assumed to be unconscious of secondary users' (SUs') sensing activities so that they have no countermeasures even their interests are harmed. For example, SUs may violate PUs' interference tolerances due to misdetection. Since perfect sensing is impossible in practice, mitigating interference and impairments to PUs is always challenging. ii) Second, the development of spectrum sharing requires the cooperation of

PUs since most of spectrum bands have already been sold to them. Intuitively, if adopting CR can only increase the spectrum utilization and flexibility (which are mainly benefited for SUs), self-interested PUs would not vote for CR because their spectrum usages have been guaranteed through licenses and they may even feel unfair against unpaid SUs.

For the reasons stated above, CR based on spectrum marketing [10] has attracted more and more attentions in recent years. Compared to sensing-based CR, PUs could take initiative in spectrum marketing by deciding the quantity of spectrum to be leased so as to maximize their utilities within their interference tolerance. Moreover, instead of free sharing based on sensing, PUs could charge SUs for dynamically using licensed spectrum for original license costs and possible performance degradation. Thus, marketing-based CR can not only enhance the spectrum efficiency, but also provide economic incentive for PUs to participate in dynamic spectrum access.

In spectrum marketing, auction-based method [11] is a natural way in constructing economic model and are widely discussed in literatures [12–16] since it can better depict the behaviors of self-serving users and can take into consideration both the individual utility and social welfare of the system. A comprehensive literature review of auction-based dynamic spectrum access schemes are presented in Chapter 2.

The motivation of this thesis is mainly concentrated on the following two aspects:

First, most works in literature assumed that the auctioned channels are occupied exclusively by the winning SU(s). Such assumption imposes a dilemma for the PUs to either auction idle channels and get auction revenue at the risk of a sudden increase of demand from themselves, or reserve spectrum uneconomically. To address this issue, in Chapter 3, we introduce the idea of recall-based dynamic spectrum auction in which PUs are always granted highest channel access priority so that auctioned channels could be recalled if necessary. Moreover, the potential heterogeneity of SUs in terms of spectrum demand and stability requirements, is also taken into account in our designed auction framework.

Second, according to the definition of CR, SUs are flexible to access the spectrum which may belong to different networks or primary specctrum operators (PO), e.g., TV band and Global System for Mobile Communications (GSM), and it is common that each PO may have more than one channel for sharing. Moreover, each PO may have different per channel bandwidth (e.g., the channel bandwidths are 6 MHz and 200 KHz for TV band and GSM, respectively) so that each SU may need to request different number of channels from each PO so as to satisfy its spectrum demand. In Chapter 4, we design a new spectrum auction algorithm with the consideration of all these heterogeneities.

1.2 Summary of Contributions

The contribution of this thesis are summarized as follows:

In Chapter 3, multi-item recall-based spectrum auction is addressed in a CR network consisting of one primary base station (PBS) and multiple SUs. Each SU has heterogeneous quality of service (QoS) requirements in terms of spectrum demands and spectrum stability requirements. We begin our discussion with single winner auction and then extend it to the case with multiple winners. In both scenarios, SUs determine their bids based on both the auction information from the PBS and their own spectrum demands and stability requirements. For the single winner auction, the second-price sealed-bid (SPSB) model [17] is adopted, while in the multi-winner auction, Vickrey-Clarke-Groves (VCG) mechanism [18] is applied as the payment function to match the requirements of combinatorial auction [19,20]. In both cases, we redefine the private valuation of spectrum for each SU and redesign the optimal strategies for both SUs and the PBS. For multi-winner auction, a new channel recall scheme is also proposed to achieve fairness among multiple SUs. Both analytical and simulation results are provided to show that the proposed spectrum auction algorithm can improve the channel utilization, while guaranteeing SUs' heterogeneous QoS requirements. This work has contributed to a journal paper, which has already been accepted by IEEE Transaction on Vehicular Technology.

In Chapter 4, a new spectrum auction mechanism for a CR network with multiple primary spectrum owners (POs) and multiple SUs is proposed. Each PO has multiple channels to sell, while each SU can access multiple licensed channels to satisfy its specific spectrum demand. Because of the consideration of multichannel CR networks, the spectrum allocation problem is formulated as a combinatorial auction where all users bid for bundles of resources. Through the auction, each PO sells a number of channels within its providing; while each SU buys sufficient number of channels to satisfy its spectrum demand if winning, or buys nothing if losing. In addition, the heterogeneity of channels' bandwidth is also taken into account. We formulate such auction framework as a multiple multidimensional knapsack problem (MMKP) and derive the upper bound via surrogate relaxation. Moreover, we present a polynomial-time approximation algorithm to derive a sub-optimal allocation and adopt a tailored "Vickrey-like" pricing mechanism in payment design. Theoretical analysis prove that our auction algorithm is economically robust in terms of incentive compatibility and individual rationality. Numerical results show that the spectrum allocation efficiency could be enhanced compared to counterparts. To our best knowledge, we are the first to design such combinatorial spectrum auction framework among multiple POs and SUs with consideration on heterogeneity of different POs' channel bandwidth. This work has contributed to a conference paper, which has been accepted by IEEE International Conference on Communications (ICC' 2014).

1.3 Outline of the Thesis

The rest of the thesis is organized as follows. Chapter 2 introduces some fundamentals and related works that are relevant to our research. Motivated by the limits of existing auction-based spectrum sharing approaches in CR networks, recall-based single-winner auction (RSSA) and multiple-winner auction (RMSA) algorithms are proposed and analyzed theoretically and numerically in Chapter 3. In Chapter 4, a combinatorial spectrum auction with consideration on sellers' heterogeneities is studied. Finally, Chapter 5 presents a brief conclusion of this thesis and summarizes some possible extensions as our future works.

Chapter 2

Fundamentals and Related Works

In this chapter, fundamental knowledge and related literatures are presented as the basis for future reference. We first provide an overview of cognitive radio networks (CRNs) including its architecture and functions, dynamic spectrum access and research challenges. After that, some basic elements and properties of auction theory are introduced along with three auction mechanisms in terms of second-price sealed-bid (SPSB) mechanism, Vickrey-Clarke-Groves (VCG) mechanism and Lehmann-O'Callaghan-Shoham (LOS) mechanism. As one of the most effective spectrum marketing methods, spectrum auction has been widely discussed in wireless communication networks. Thus, we also provide a comprehensive literature review for most of recent researches on spectrum auctions.

2.1 Overview of Cognitive Radio Networks

Cognitive radio (CR) pioneered by Joseph Mitola III from software defined radio (SDR) was originally considered as a strengthened SDR with artificial intelligence [21]. With such concept, CR was imagined to be capable of sensing the radio environment and reacting accordingly. FCC endorsed the idea of CR shortly and provided a more explicit definition [2]: CRs are radios which could opportunistically use licensed bands under the restriction of interference temperature of primary users (PUs).

In recent years, CR has been studied widely and deeply in telecommunication researches. It is regarded as the key enabling technology of dynamic spectrum access to address the issues, such as spectrum scarcity, inefficiency and inflexibility. Formally, CR has two main characteristics as defined in [3]:

- *Cognitive capability*: Cognitive users could identify the portions of unused spectrum through real-time interaction with radio environment. CR enables the opportunistic usage of temporally unused spectrum (also referred as *spectrum hole*) among SUs without interfering licensed users. A simple illustration is shown in Fig. 2.1 [22].

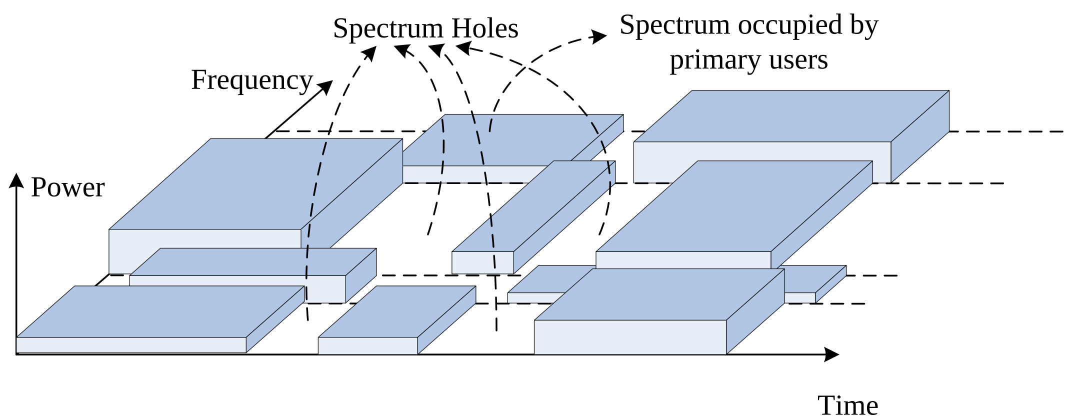

Figure 2.1: Illustration of spectrum holes

- *Reconfigurability*: CR users could transmit and receive on various radio frequencies of wide spectrum bands, and apply different access technologies through software reconfiguration.

The primary objectives of CR networks are: i) facilitating efficient spectrum utilization in a fair-minded way; and ii) providing highly reliable communications for all users in networks.

2.1.1 Architecture and Functions of Cognitive Radio Networks

The components of the CR networks architecture can be classified in two categories [6]: *primary networks* and *secondary networks*.

The primary networks are existing networks for PUs to operate on specific licensed spectrum bands. If primary networks have infrastructure, primary base stations are equipped to control the spectrum usage of PUs. Since PUs are always granted higher spectrum access priority, the primary networks should not be affected by SUs' activities.

The secondary networks have no license for spectrum usage. Thus, additional functions are required for SUs to dynamically share the licensed spectrum bands. They can also be equipped with secondary base stations to dynamically allocate the spectrum resources among SUs.

Though CR networks have a lot of similarities with traditional wireless networks, its spectrum access manner and resource allocation scheme make them different. Specifically, in overlay spectrum sharing, SUs cannot access the same spectrum bands which have already been occupied by PUs; or in underlay spectrum sharing, the interference introduced by SUs should be not larger than the tolerance of PUs. Therefore, the activities of PUs may have severe impact on the spectrum usage of SUs. First, spectrum availability for SUs may be varied due to the random activities of PUs, which is known as spectrum variability. Second, SUs operated in different primary networks may access spectrum with different qualities, bandwidths, and availabilities. Such issue is called spectrum heterogeneity.

In order to support intelligent and efficient spectrum management, CR has the following four main functions:

- *Spectrum sensing*: Since SUs can only access unused spectrum of SUs, CR is required to monitor the licensed spectrum and detect the spectrum holes through periodically sensing.

- *Spectrum decision*: The information collected from spectrum sensing is used to make spectrum allocation decisions. Such decisions are made by optimizing some desired performance (e.g. total throughput of SUs) under the constraints of spectrum availabilities and interference limits.

- *Spectrum access*: After a decision has been made, spectrum holes might be accessed by multiple SUs. In order to avoid possible collisions with licensed users and other unlicensed users, a cognitive medium access control (MAC) protocol should be applied in the spectrum access.

- *Spectrum mobility*: In CR networks, SUs are considered as visitors to temporally/dynamically access the unused licensed spectrum. Thus, if a PU returns and starts accessing a channel which is currently occupying by a SU, the SU needs to vacate the channel and may continue its transmission on another idle channel.

The relationships of the above four functions is demonstrated in Fig. 2.2 [23].

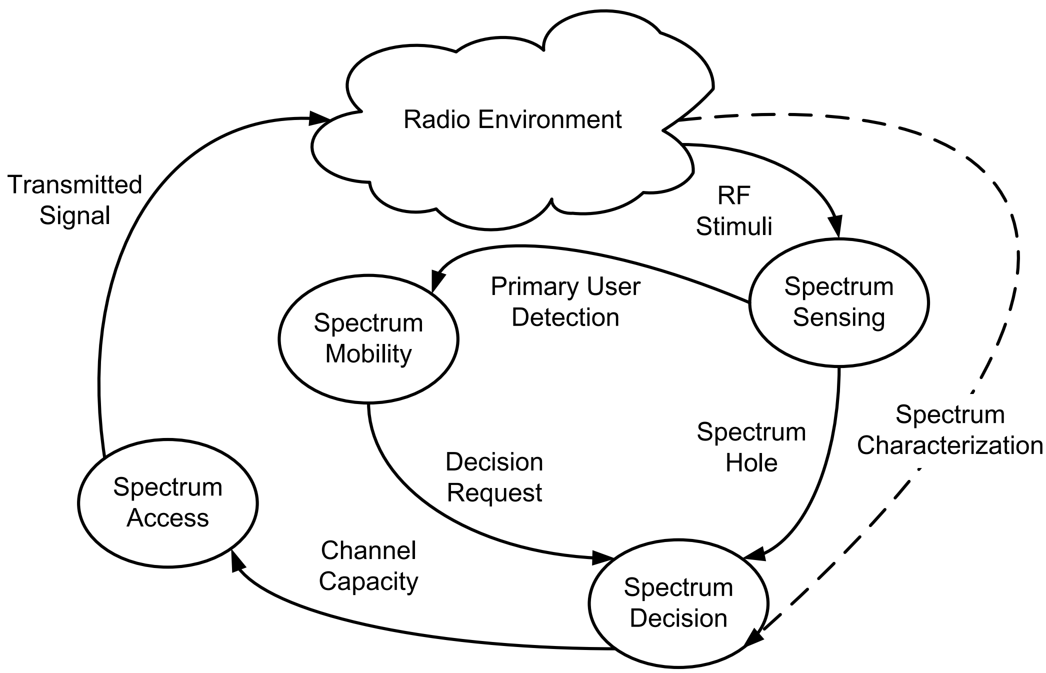

Figure 2.2: Cognitive radio cycle

2.1.2 Dynamic Spectrum Access

Cognitive radio is certainly considered as a prospective approach to realize dynamic spectrum access (DSA). In [24], DSA is defined as a mechanism to adjust the spectrum usage dynamically towards the changes of radio environment (e.g., channel availability) , objective (e.g., type of application), and external constraints (e.g., radio propagation and operational policy). There are three major categories of DSA [5], called, dynamic exclusive use model, open sharing model and hierarchical access model, as shown in Fig. 2.3.

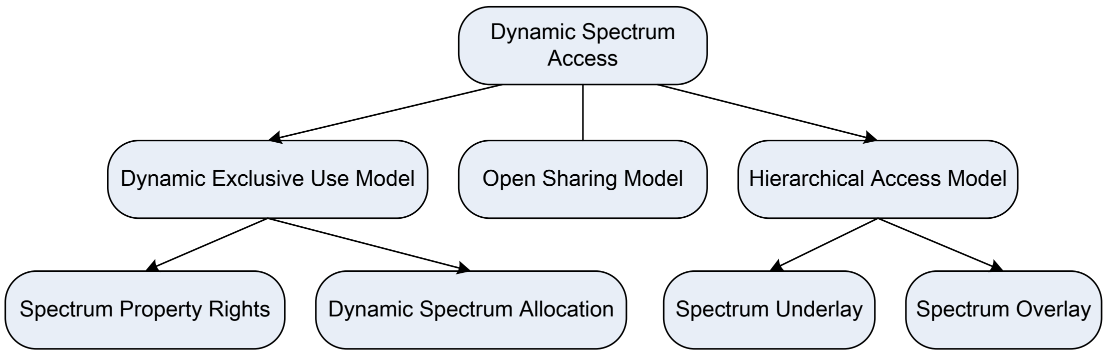

Figure 2.3: Categories of dynamic spectrum access

Dynamic exclusive use model maintains the basic structure of current spectrum regulation policy, while introduces flexibility to improve spectrum efficiency. There are two approaches proposed under this model, i.e., spectrum property rights [25] and dynamic spectrum allocation [26]. The former approach is the primitive of spectrum marketing. It enables the licensed holders to lease and trade spectrum by using freely determined technology. The second approach was first raised by European DRiVE project [26], which aims to dynamically assign the spectrum by exploiting spatial and temporal statistics. It improves the spectrum utilization because the allocation varies much faster than the current policy.

In open sharing model [27], all users are treated as peers for sharing a specific spectral band. The sharing strategies under this management model have been investigated in both centralized [28] and distributed [29] patterns.

Hierarchical access model allows SUs to access unused licensed spectrum while limiting the interference introduced to PUs. Two approaches have been considered: spectrum underlay and spectrum overlay. The underlay approach is based on a worst-assumption that PUs transmit all the time. Thus, it constraints the transmission power of SUs so as to make the noise perceived by PUs less than a certain threshold. The advantage of this approach is that it does not need to detect and exploit spectrum holes. Unlike spectrum underlay, overlay sharing requires SUs to identify and use the idle spectrum defined in space, time and frequency. However, it does not necessarily impose limits on SUs' transmission power.

2.1.3 Research Challenges in Cognitive Radio Networks

In this section, we list some major research challenges for CR.

- *Spectrum sensing*: In traditional CR, spectrum sensing is identified as a key function to avoid collisions and interference with PUs. Reliable sensing is based on the information of modulation type, power, and frequency of PUs, and it is commonly considered as a detection problem. Existed research works mainly focused on two techniques: *energy detection* [30] and *feature detection* [31]. If sufficient information cannot be obtained by CR, energy detection is the optimal choice. However, its performance is susceptible to uncertainty in noise power. Furthermore, since energy detector cannot differentiate signal types, false alarms trigged by unintended signals are easy to be generated. In contrast, feature detection is more robust by analyzing the spectral cyclostationarity of signals. However, it is computationally complicated and requires extremely long observation time. Therefore, it is still a challenge to design a sensing technique which could accurately detect weak primary signals while maintain low computation complexity and low cost to implement.

- *Advanced spectrum management*: CR could significantly improve spectrum utilization by enabling SUs to dynamically access spectrum holes. A critical challenge for CR is the implementation of an efficient medium access control (MAC) mechanism which could adaptively allocate transmission powers and frequencies among SUs according to the radio environment.

- *Economic incentive and rationality*: Different with conventional wireless networks, the presence of user priority (i.e., primary and secondary) in CR networks introduces some unique design challenges. One main challenge is to provide sufficient economic incentive for PUs to participate in spectrum sharing. In addition, ensuring economic rationality and fairness in secondary networks is also necessary.

- *Transmission security*: With increasing attention over past few years on wireless system security and survivability, it is essential for researchers to notice that distributed intelligent networks (e.g., CR networks) offer benefit and high possibility for potential attacks [32]. As a basic requirement for reliable communications, providing secure transmissions in CR networks is a crucial issue.

- *Cross-layer design*: Due to the flexibility of CR, the designed cross layer algorithms should be adapted to changes in physical link quality, radio interference, radio node density, network topology and traffic demands. Moreover, spectrum handoff and mobility management in CR also add new challenges to cross-layer design, especially when the quality of service (QoS) needs to be guaranteed.

- *Hardware and software architecture*: As an extension of software-defined radio, CR aims to transmit and receive signals over various radio environments and communication devices. CR makes decisions based on performance measurements including frequency, power, antenna, transmitter bandwidth, modulation and coding schemes etc. Thus, it requires a robust and reconfigurable hardware and software architecture.

2.2 Auction Theory

An auction is a process of resource allocation and price discovery on the basis of bids from participants. As an applied branch of economics, auction theory aims to study how people behave in markets and researches the outputs and economic properties of auction [33]. Design of an auction should take into account the efficiency of the auction, optimal and equilibrium bidding strategies, and auction revenue comparison. Auction theory is also used as a theoretical tool to guide the implementation of real-world auctions, e.g., for the privatisation of public-sector companies or the usage of spectrum in telecommunications [34]. Auctions have also been widely used as mechanisms for multi-agent interaction, job assignment and resource allocation.

There are numerous forms of auction, however they all satisfy two conditions [35]: i) They can be applied to sell any item, thus are universal; ii) Outcomes of auctions are independent of bidders' identities, i.e., auctions are anonymous.

2.2.1 Basic Elements of an Auction

The basic concept of auctions can be stated as a process of buying/selling commodities or services. Generally, an auction consists of the following basic elements:

- *Bidder*: The one who wants to buy commodities in auctions is regarded as a bidder. In literature, *buyer* is also commonly used as a synonym for *bidder*. For wireless communications, bidders are users who are eager to obtain radio resources for their own transmissions through pricing competitions with other users.

- *Seller*: As another kind of players in the auction, sellers own commodities and are willing to sell them for potential economic profits. In spectrum auctions, sellers could be any spectrum holder, e.g., the regulator (FCC) and a primary license owner.

- *Auctioneer*: An auctioneer acts as an intermediate agent and a central controller who hosts and runs auction processes between sellers' and bidders' sides. In general, auctioneers could be non-profit entities, third-party brokers or even the sellers themselves. For instance, a base station or an access point in wireless networks can conduct its own radio resource auctions.

- *Commodity*: Commodities are also known as goods in the market which could be traded between sellers and buyers. In radio resource auctions, such commodity can be spectrum bandwidth, licenses of spectrum, and time periods.

- *Valuation*: Valuations represent the monetary evaluation of assets. Every bidder should have its own valuation towards its demand. However, different bidders may have different valuations for the same commodity due to their personal preferences. A valuation can be *private* which means that bidders do not know the others' valuations, or *public* so that its valuation is known to the others.

- *Price*: During an auction, a seller can submit an *ask* to indicate an asking price on its selling commodity. Sometimes, asking prices are not necessary (i.e., equal zero), e.g., spectrum of PUs may have no value if it remains idle. On the other hand, a buyer can submit a *bid* to inform the bidding price for its demanded commodity. A *hammer price* is determined by the auctioneer, indicating the payments of bidders and earnings of sellers.

2.2.2 Some Typical Categorizations of Auctions

In fact, a lot of auction designs have been proposed in theoretical researches and applied in practical markets. Here, we summarized some typical categorizations that are widely discussed in literature [11]:

- *Forward or reverse*: In forward auctions, bidders/buyers bid and compete for getting commodities from seller(s), as shown in Fig. 2.4. On contrast, in reverse auctions, sellers compete for selling commodities to buyer(s), as shown in Fig. 2.5.

- *Single-sided or double-sided*: Single-sided auction refers to the case with only buyers or sellers competing in the auction (Fig. 2.4 and Fig. 2.5). If competitions exist in both sellers' and buyers' sides, the auction is formulated as double-sided (Fig. 2.6).

- *Open-cry or sealed-bid*: In an open-cry auction, buyers report their bids publicly so that every buyer knows the bids from others. However, buyers can submit their bids secretly to the auctioneer in sealed-bid auction.

- *Single-item or multi-item*: Intuitively, buyers can only bid and demand one commodity in single-item auction at a time, while they can bid for multiple commodities in a multi-item auction.

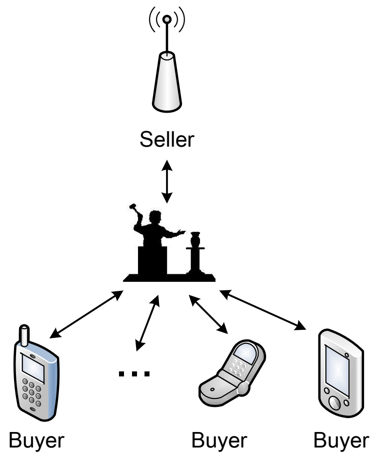

Figure 2.4: Forward auction with a single seller.

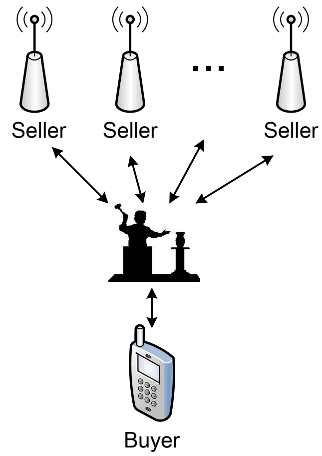

Figure 2.5: Reverse auction with a single buyer.

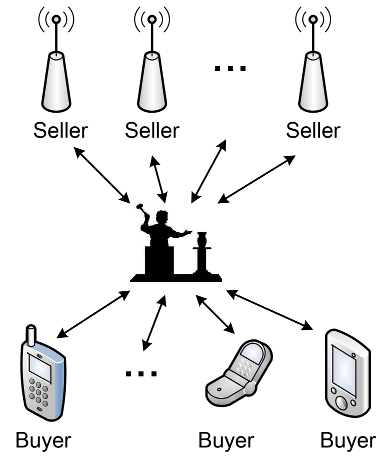

Figure 2.6: Double auction with multiple sellers and buyers.

2.2.3 Required Economic Properties

In this section, we review some important solution concepts in auction theory and mechanism design. First, we recall the definition of *dominant strategy*:

Definition 2.2.1 (Dominant strategy [36,37]). *A dominant strategy of a player is one that maximizes its utility regardless of other plays' strategies. Specifically, a_i is the dominant strategy for player i if its utility u_i cannot be improved for any $a_i' \neq a_i$, and any strategy profile of the other players a_{-i}, i.e.,*

$$u_i(a_i, a_{-i}) \geq u_i(a_i', a_{-i}) \tag{2.1}$$

Before introducing the definition of *Strategy-proof auction*, we define *direct-revelation* first. In a mechanism with direct-revelation, the only available actions to players are to make claims about their preferences. In auction design, the strategy of a buyer is reporting a bid based on its actual valuation. Hence, an auction with direct-revelation is strategy proof if it satisfies two conditions, i.e., *incentive compatibility* and *individual rationality*.

- *Incentive compatibility*: An auction is incentive compatible if no matter how other players bid, no buyer or seller could improve its own utility by bidding untruthfully (bidding price does not equal the buyer's valuation or the asking price does not equal the seller's valuation).

- *Individual Rationality*: An auction is individual rational if no winning buyer pays more than its bid (In addition, if there is a competition among sellers, no winning seller is paid less than its asking price).

Truthfulness is essential to resist market manipulation and ensure auction fairness and efficiency [14]. In untruthful auctions, selfish bidders might be able to manipulate their bids to game the system and obtain outcomes that favor themselves but hurt the others. In truthful auctions, the dominant strategy for bidders is to bid truthfully so that the possibility of market manipulation and the overhead of strategizing over others are eliminated. Individual rationality guarantees non-negative utilities for all players who behave truthfully and provides them incentives to participate in the auction.

The formal definition of strategy-proof mechanism is stated as follows:

Definition 2.2.2 (**Strategy-proof auction [18]**). *An auction with direct-revelation is strategy proof if the dominant-strategy equilibrium for all players is to report truthful information.*

2.2.4 SPSB mechanism

Second-price sealed-bid (SPSB) auction mechanism is also well known as Vickrey auction mechanism [38] which was first proposed by the Nobel prize winner Dr. William Vickrey in 1961. With this mechanism, bidders are asked to submit sealed bids $b_1, \ldots, b_n$. The bidder who bids highest wins (i.e., it is awarded the commodity), while pays the amount of the second highest bid.

Let v_i and b_i be the value and bid of bidder i in the auction, respectively. The utility of bidder i is

$$u_i = \begin{cases} v_i - \max_{j \neq i} b_j & \text{if } b_i > \max_{j \neq i} b_j \\ 0 & \text{if } b_i < \max_{j \neq i} b_j \end{cases} \tag{2.2}$$

It is also assume that if there is a tie, i.e., $b_i = \max_{j \neq i} b_j$, the commodity goes to each winning bidder with equal probability. Since SPSB apparently guarantees individual rationality through its payment rule, only the incentive compatibility remains to be examined.

Proposition 2.2.1. *In SPSB mechanism, it is a dominant strategy for each bidder i to bid according to $b_i = v_i$.*

Proof. We first consider overbidding ($b_i > v_i$). If $\max_{j \neq i} b_j < v_i$, the bidder would win the auction with a truthful bid as well as an overbid. The bidding price does not change its obtained utility in this case. If $\max_{j \neq i} b_j > v_i$, the bidder would lose in either way so that the strategies have equal utilities at the end. If $b_i > \max_{j \neq i} b_j > v_i$, then only the strategy of overbidding would win the auction. However, the utility would be negative for the strategy of overbidding because they paid more than their valuations, while the utility for a truthful bid would be zero. Thus the strategy of overbidding is dominated by the strategy of truthful bidding. A similar argument shows that it is not profitable to bid less than v_i. In conclusion, truthful bidding dominates the other possible strategies (underbidding and overbidding), thus it is an optimal strategy in SPSB mechanism. $\square$

In fact, the truthful equilibrium described in Proposition 2.2.1 is the unique symmetric Bayesian Nash equilibrium of the second price auction [34].

2.2.5 VCG mechanism

Vickrey-Clarke-Groves (VCG) [38–40] mechanism is a more general version of Vickrey auction mechanism. VCG mechanism aims to assign commodities in a socially optimal manner. This system charges each individual the harm they cause to other bidders [17] and ensures that the optimal strategy for each bidder is to bid its true valuations. It is also a generalization of Vickrey auction for multiple-item combinatorial auctions [41].

In order to specify VCG mechanism, we first go through some features of combinatorial auction. Considering a set $\mathcal{S}$ of multiple selling goods, we call a subset $\mathcal{T} \subseteq \mathcal{S}$ of goods as a *bundle*. The valuation v_i of each bidder i is a function of its demanding bundle $\mathcal{T}_i$, thus it can be also denoted as $v_i(\mathcal{T}_i)$. Different from the single-item auction, there can be multiple winners in a combinatorial auction and the outcome is to decide whether allocate $\mathcal{T} \subseteq \mathcal{S}$ to bidder i such that bundles given to all the winners are disjoint (no good can be assigned to multiple winners). In addition, winners can be charged by different payments in combinatorial auctions. For simple clarification, we assume quasilinear utilities [42] in the following discussions.

VCG mechanism is stated as follows:

(1) Each bidder i submits a bid $b_i(\mathcal{T}_i)$ for its demanding bundle $\mathcal{T}_i \subseteq \mathcal{S}$. Note that, for truthful bidding, $b_i(\mathcal{T}_i) = v_i(\mathcal{T}_i)$.

(2) The auctioneer determines a feasible allocation and a winners-assignment that maximize the total bidding price from all winners. Consider an auction with n bidders and let a decision variable $x_i = 0$ or 1 indicate losing or winning of bidder i. For all feasible allocations $\{x_i\}_{i=1}^n$ (feasible means that for any two winners $i \neq j$, $\mathcal{T}_i \cap \mathcal{T}_j = \emptyset$), our objective is
$$\max_{\{x_i\}_{i=1,\ldots,n}} \sum_{i=1}^{n} b_i(\mathcal{T}_i) \cdot x_i \tag{2.3}$$

(3) With the optimal winner allocation $\{x_i^*\}_{i=1}^n$, charge each bidder i an appropriate price p_i which is calculated as
$$p_i = \left(\max_{\{x_j\}_{j\neq i}} \sum_{j\neq i} b_j(\mathcal{T}_j) \cdot x_j \right) - \sum_{j\neq i} b_j(\mathcal{T}_j) \cdot x_j^* \tag{2.4}$$
where the first term is the maximum-possible surplus if we ignore the bid from player i and optimize only for $n-1$ other players. Note that this term can be obtained from step (2) by deleting i's bid from the input. The second term collects all the winning

bids from the optimal allocation $\{x_i^*\}_{i=1}^n$ except for bidder i. Thus, the payment for bidder i reflects the damage caused to other players by i's presence.

Proposition 2.2.2. *The VCG mechanism is economically efficient which means that, if all players bid truthfully, then the VCG mechanism outputs an allocation that maximizes* $\sum_{i=1}^n v_i(\mathcal{T}_i) \cdot x_i$ *over all feasible allocations.*

Proof. It can be directly observed from step (2) of the mechanism. □

Proposition 2.2.3 (Individual rationality). *The utility of any truthful bidder in the VCG mechanism is always non-negative.*

Proof. Given (2.4), we can first simply add and subtract $b_i(\mathcal{T}_i) \cdot x_i^*$ so that p_i can be also expressed as

$$p_i = b_i(\mathcal{T}_i) \cdot x_i^* - \left[\sum_{j=1}^n b_j(\mathcal{T}_j) \cdot x_j^* - \left(\max_{\{x_j\}_{j \neq i}} \sum_{j \neq i} b_j(\mathcal{T}_j) \cdot x_j \right) \right] \tag{2.5}$$

Thus, the proposition is equivalent to show that the discount term in (2.5) is non-negative. It holds since adding an extra bidder can only increase the maximum achievable surplus (i.e., it only increase the number of possible feasible allocations). □

Proposition 2.2.4 (Incentive compatibility). *For every bidder i, even if the player knows the full bids of all other bidders, bidder i maximizes its utility by bidding truthfully, i.e,* $b_i(\mathcal{T}_i) = v_i(\mathcal{T}_i)$.

Proof. The core idea of VCG mechanism is to charge p_i independent of b_i. A long technical proof of the incentive compatibility can be found in [17, 18, 38] □

2.2.6 LOS mechanism

Since winner determination (WD) problems in multi-item combinatorial auctions are normally Non-deterministic Polynomial-time (NP) hard, a lot of approximate WD algorithms have been proposed recently. However, VCG mechanism is incompatible with approximate

WD algorithms [35]. Therefore, we introduce the Lehmann-O'Callaghan-Shoham (LOS) [43] mechanism which consists of a LOS WD algorithm and a truthful payment scheme.

Consider an auction with a single seller who owns m goods and n bidders, each has a bid $(\mathcal{T}_i, b_i)$, where $\mathcal{T}_i$ and b_i represent the request bundle and bidding price, respectively. The procedure of *LOS algorithm* is summarized as follows:

i) Reindex the bids so that

$$\frac{b_1}{\sqrt{|\mathcal{T}_1|}} \geq \frac{b_2}{\sqrt{|\mathcal{T}_2|}} \geq \cdots \geq \frac{b_n}{\sqrt{|\mathcal{T}_n|}} \tag{2.6}$$

ii) For $i = 1, 2, \ldots, n$: if no items of $\mathcal{T}_i$ have already been assigned to a previous player, set $x_i = 1$ to indicate that bidder i is a winner; otherwise, set $x_i = 0$ to indicate that bidder i loses the auction.

Proposition 2.2.5. *The LOS algorithm is a $\sqrt{m}$-approximation algorithm for the WD problem [43].*

Proof. Let $X \subseteq \{1, 2, \ldots, n\}$ and $X^* \subseteq \{1, 2, \ldots, n\}$ denote the set of winners granted by the LOS greedy algorithm and the optimal WD, respectively. We need to prove that

$$\sum_{i^* \in X^*} b_{i^*} \leq \sqrt{m} \cdot \sum_{i \in X} b_i \tag{2.7}$$

We say that a bid $i \in X$ *blocks* a bid $i^* \in X^*$ if $T_i \cap T_{i^*} \neq \emptyset$. For a bid $i \in X$, let $F_i \subseteq X^*$ denote the bids of X^* first blocked by i. There are two key points. First, suppose $i^* \in F_i$ is first blocked by $i \in X$. Then, when the greedy algorithm chose to grant the bid i, the bid i^* was not yet blocked and was a viable alternative; by (2.6), we must have

$$\frac{b_i}{\sqrt{|\mathcal{T}_i|}} \geq \frac{b_{i^*}}{\sqrt{|\mathcal{T}_{i^*}|}} \tag{2.8}$$

whenever $i^* \in F_i$. The second key point is that each optimal bid $i^* \in X^*$ lies in precisely one set F_i. Thus, the F_i is a partition of X^*; in particular,

$$\sum_{i^* \in X^*} b_{i^*} = \sum_{i \in X} \sum_{i^* \in F_i} b_{i^*} \tag{2.9}$$

This fact allows us to consider each bid separately and then combine those results to obtain the global bound (2.7). Summing all $i^* \in F_i$ in (2.8) together, we have

$$\sum_{i^* \in F_i} b_{i^*} \leq \frac{b_i}{\sqrt{|\mathcal{T}_i|}} \sum_{i^* \in F_i} \sqrt{|\mathcal{T}_{i^*}|} \tag{2.10}$$

Since all bids of F_i were simultaneously granted by the optimal solution, they must be disjoint and thus

$$\sum_{i^* \in F_i} |\mathcal{T}_{i^*}| \leq m \tag{2.11}$$

According to Cauchy-Schwarz inequality and (2.10), we have

$$\sum_{i^* \in F_i} b_{i^*} \leq \frac{b_i}{\sqrt{|\mathcal{T}_i|}} \sum_{i^* \in F_i} \sqrt{\frac{m}{|F_i|}} = \sqrt{m} \cdot \frac{b_i}{\sqrt{|\mathcal{T}_i|}} \sqrt{|F_i|} \tag{2.12}$$

Since the bid i blocks all the bids of F_i, and bids of F_i are disjoint, we have $|F_i| \leq |\mathcal{T}_i|$, which implies that

$$\sum_{i^* \in F_i} b_{i^*} \leq \sqrt{m} \cdot b_i \tag{2.13}$$

Finally, summing over all $i \in X$ and applying (2.9), we can observe that the inequality (2.7) holds. □

The basic idea of the LOS pricing scheme is to charge prices that are "Vickrey-like". Before presenting the pricing scheme, we introduce the definition of *u-blocks*.

Definition 2.2.3. *Suppose that bidder i was granted by the LOS algorithm while j was denied. The bid i u-blocks the bidder j if, the bidder j could be granted after deleting the bidder i from the input.*

In LOS pricing scheme, a winning bidder will be charged according to the highest-value bid that it *u-blocks*. Specifically, it can be summarized as follows:

- If bidder i loses or it wins but *u-blocks* no other bid, then its payment is 0.

- If bidder i is granted its demand $\mathcal{T}_i$ and let $(\mathcal{T}_j, b_j)$ be the first bid in the LOS ordering that i's bid *u-blocks*, the payment p_i of bidder i is set as

$$p_i = \frac{b_j}{\sqrt{|\mathcal{T}_j|}} \cdot \sqrt{|\mathcal{T}_i|} \tag{2.14}$$

Proposition 2.2.6 (Individual rationality). *Truthful bidders always obtain non-negative utilities in the LOS mechanism.*

Proof. Let $(\mathcal{T}_j, b_j)$ be the first bid that $(\mathcal{T}_i, b_i)$ u-blocks. With the LOS ordering, we must have

$$\frac{b_i}{\sqrt{|\mathcal{T}_i|}} \geq \frac{b_j}{\sqrt{|\mathcal{T}_j|}} \tag{2.15}$$

Thus, the payment calculation always produce $p_i \leq b_i$, as desired. □

Proposition 2.2.7 (Incentive compatibility). *The LOS mechanism is incentive compatible.*

Proof. This property is not that obvious, however [43] provided a comprehensive and profound proof for the strategyproofness. □

2.3 Auction-based Spectrum Access in Wireless Networks

Since radio resource auction in wireless communications (including CR) has been researched for decades, a general survey on auction-based spectrum access in wireless networks is presented in this section. To facilitate reading, we classify the existing spectrum auction approaches in three groups in terms of auction with single seller, multiple sellers and online fashion.

1) Spectrum Auction with Single Seller: In this kind of auction, there is no competition at sellers' side, thus it is also referred as single-sided auction. Moreover, the role of auctioneer can also be integrated in the seller since the only seller owns and conducts auction of its radio resource(s) among multiple buyers.

The authors in [15] proposed two auction mechanisms for receiving power allocation, so as to achieve social optimality and fairness in underlay spectrum sharing. A real-time spectrum auction framework was formulated in [16] where interference constraints were modeled by linear programming, and the maximum revenue was generated by optimally selecting market clearing price. In [44], the authors considered to accommodate multiple secondary users in one band and presented a novel multi-winner spectrum auction which was proved to be strategy-proof. All these works only considered the scenario that the seller has one item (channel) to auction.

However, auctions for a single item may not be efficient and practical in wireless systems such as CR networks which have multiple radio resources (e.g., channels) for allocation. In [45] and [46], the multi-item allocation process was modeled as a knapsack problem to maximize the seller's auction revenue. The available resources of the seller was considered as the "knapsack", while the requests of buyers were treated as "items" and the volume/size of a request was the number of its demanded resources. The authors in [47] introduced an integrated contract and auction design so as to maximize PU's expected profit under stochastic network environment. A strategy-proof spectrum auction mechanism was presented in [48] with consideration of multi-band spectrum buyers. A novel auction algorithm for subchannel allocation was proposed in [49] which focused on designing the valuation function to express the buyers' willingness of receiving the requested subchannel. Specifically, the function was defined as the gap between the user's transmission rate over the requested subchannel and the maximum transmission rate over any other subchannels.

2) Spectrum Auction with Multiple Sellers: As illustrated in Fig. 2.6, double spectrum auction is a way to assign multiple radio resources from multiple sellers to multiple buyers. Both sellers and buyers submit their prices (i.e., asks/bids) for trading resources. Normally, a centralized controller is needed to act as the auctioneer who is responsible for collecting auction information and matching asks and bids.

The authors in [14] proposed a general framework for truthful double spectrum auctions, where multiple parties can trade spectrum based on their individual needs. [50] presented a set of new spectrum double auctions that were specifically designed for local spectrum markets. In [51], a truthful double auction mechanism was studied for heterogeneous spectrums where the distinctive characteristics in both spacial and frequency domains were considered. In [52], the authors investigated a discriminating pricing double spectrum auction where bidders were charged of different prices for the same item they purchased. Most of the aforementioned double spectrum auctions presumed single-item (single-channel) or homogeneous demands from all buyers so that the assignment problem could be simplified to a one-one matching problem between sellers and buyers.

In reality, it is common for wireless users to request multiple heterogeneous number of items (or channels) especially in multimedia communication scenarios [48, 53, 54]. To meet this practical requirements, [48] proposed a sealed bid reserve auction mechanism for multi-radio spectrum allocation. [53] discussed a strategy-proof combinatorial auction for heterogeneous channel allocation with channel spatial reusability. The authors in [54] studied a cooperation-based dynamic leasing mechanism via multi-winner auction over multiple available spectrum bands. [55] presented a framework for multi-channel spectrum auction where both primary users and secondary users are required to trade multiple items.

3) Online Spectrum Auction: Traditionally, auctions are processed in an offline pattern, i.e., the auctioneer collects all the bidding information at the beginning and makes decisions only at a certain time. Recently, spectrum auction has also been studied by considering potential temporal reusability and online spectrum auctions have attracted more and more attention. In an online manner, buyers submit bids for resources at any time, while the auctioneer makes allocation decisions immediately without the information of future bids.

In [56], the authors proposed a truthful online spectrum auction framework that distributes spectrum efficiently by exploring both spatial and time reusability while resisting bidders from misreporting their bids and time reports. [57] considered an online spectrum allocation that took both spectrum uncertainty and sensing accuracy into account. It studied the social welfare maximization problem for serving secondary users with various delay tolerance and compared the performance of online algorithm with optimal offline allocation. Besides, [58] investigated a truthful mechanism for expiring spectrum sharing in CR networks where the property of collusion-resistance was proved in details. [59] presented a semi-truthful online frequency allocation method and analytically proved that the competitive ratios of their methods were within small constant factors of the optimal method.

Furthermore, double-sided online spectrum auctions were studied in [60] and [61]. The authors in [60] proposed an auction mechanism where sellers submited their asks only before the auction starts, and bids of buyers arrived by based on Poisson distribution. [61] extended the work of [60] to a strategyproof online spectrum admission where all distribution parameters of random processes are unknown for the auctioneer.

Different from all existing works, in this thesis, we focus on the heterogeneities of different users in multichannel spectrum auctions, including the heterogeneous wireless service requirements of secondary users, various number of auctioned channels and different per channel bandwidths of primary users. We propose new spectrum auction frameworks and algorithms in Chapter 3 and Chapter 4 to address these issues.

Chapter 3

Multi-channel Auction for Recall-based Cognitive Radio Networks with Multiple Heterogeneous Secondary Users

In this chapter, we consider a spectrum auction system among heterogeneous secondary users (SUs) with various quality of service (QoS) requirements and a recall-based primary base station (PBS) which could recall channels after auction to deal with a sudden increase of its own demand. Beginning with proposing a Recall-based Single-winner Spectrum Auction (RSSA) algorithm, we further extend our work to allow multiple winners in order to improve the spectrum utilization, and propose a Recall-based Multiple-winner Spectrum Auction (RMSA) algorithm. A combinatorial auction model is then formulated and Vickrey-Clarke-Groves (VCG) mechanism is applied in the payment function. Moreover, the proposed RMSA algorithm focuses on a fair spectrum allocation among heterogeneous SUs and the increase of the PBS's auction revenue. Both theoretical and simulation results show that the proposed spectrum auction algorithm can improve the spectrum utilization with guarantees on SUs' heterogeneous QoS requirements.

3.1 System Model

Consider a CR network with N SUs who opportunistically access the unused channels of a PBS. The PBS owns total C units of homogenous and undivided channels. Assume that each PU only requires one channel and the PUs with channel demands would generate a queue at the PBS. We further assume that all PUs obey the first-come-first-served (FCFS) rule. If all available channels have been fully occupied, newly arrived PUs have to wait in the queue. The PUs arrive at the PBS following a Poisson process with arrival rate λ so that the interarrival times are independent and identically distributed (i.i.d.) random variables with an exponential distribution. Furthermore, assume that the PUs' channel occupancy time are also i.i.d. exponential random variables with service rate μ. Thus, the channel service of PUs could be considered as a $M/M/m$ queueing system as shown in Fig. 3.1, where M refers to "Markov process" and m denotes the number of channels for PUs. A channel is considered as "idle" if it was not occupied by any PU, otherwise it is "busy". Note that, SUs have no information about PUs' random activities.

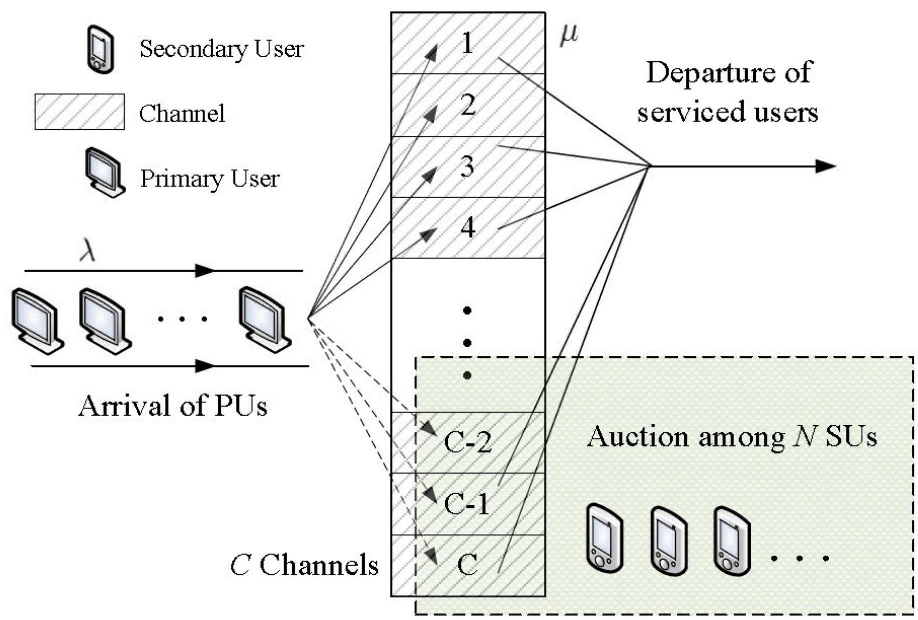

Figure 3.1: The system model of recall-based spectrum auction

The PBS leases certain number of channels to SUs, and at the same time provides its PUs with a QoS guarantee. In this paper, we let the mean waiting time in the queue be and

Table 3.1: IMPORTANT NOTATIONS IN THIS CHAPTER

Notation	Meaning
m	number of channels needed by the PUs
M_w	mean waiting time of PUs in the queue
C	total number of channels owned by the PBS
C_a	number of auctioned channels
C_r	maximum number of channels recalled
$C_{r,a}$	actual number of channels recalled
C_i	number of channels SU i demands
$C_{r,i}$	actual number of channels recalled from SU i
ρ_i	risk factor of SU i in single-winner auction
θ_i	spectrum stability factor of SU i in multiple-winner auction

as the measure of the QoS for PUs [62]. Specifically, we suppose that the mean waiting time of PUs, M_w, cannot be greater than a certain threshold γ. Due to the randomness of PUs' arrivals, if the PBS decides to auction some unused channels for economic revenue from SUs, it may suffer a risk that there are no enough channels to deal with a sudden increase of PUs' spectrum demands. By considering the higher priority of PUs in this paper, we allow spectrum recall for the PBS, i.e., the PBS could recall some channels from the winning SU(s) in order to satisfy its own PUs' demands when necessary. In this way, the newly arrived PUs need to wait if and only if there is no idle channels in the PBS and no more channels can be recalled. Recalled channels will not be returned to SUs till next round of auction. Of course, the auction winner(s) will get corresponding compensation if their channels were recalled by the PBS.

Different from traditional works, in this chapter, SUs are heterogeneous in spectrum demands and stability requirements. Furthermore, we assume that each SU works on an integral number of licensed channels. Such assumption is commonly employed in the literature, such as [63] which considered the application of Microsoft KNOWS prototype [64]. Let SU i have a spectrum demand C_i and a value V_i for C_i channels. Each SU submits a sealed bid b_i according to its demand to maximize its expected utility.

The auction is carried out frame by frame and each frame has a length of T. We limit our discussion to small region networks [12], i.e., all SUs are located within the interference range of each other, so that no spectrum reuse among SUs within a frame is considered. We further let SUs be risk neutral. At the beginning of each T, there is a small period $\Delta T \ll T$ used for channel auction. Unlike [13], we focus on the utilities of SUs and consider the spectrum allocation among multiple heterogeneous SUs.

For convenience, Table 3.1 lists some important notations used in this chapter.

3.2 Recall-based Single-Winner Spectrum Auction

In this section, a Recall-based Single-winner Spectrum Auction (RSSA) algorithm is proposed. The valuation function of SUs is first defined and the second-price sealed-bid auction (SPSB) model is applied as the payment rule. After that, optimal strategies for both SUs and the PBS are analyzed.

3.2.1 Private Values of SUs

Without the use of recall-based PBS, the private value of SU i, $v_i(C_i)$, should increase with the number of demanded channels, C_i. Since SU i, if winning the auction, exclusively occupies the channels, it could transmit at any available power level without interfering with others. Thus, similar to [65] and [13], in this chapter, we define the private value of SU i equals the Shannon capacity it could achieve by obtaining C_i channels, i.e.,

$$v_i(C_i) = C_i B \log_2 \left(1 + \frac{P_t}{n_0 C_i B}\right), \qquad C_i \geq 0 \tag{3.1}$$

where B is the bandwidth per channel, P_t denotes the unified transmit power of all SUs and n_0 indicates the spectral density of noise.

Now, let's consider the situation with a recall-based PBS. In this case, the PBS first divides C channels into two categories (C_a, $C - C_a$) at the beginning of each auction. C_a channels are auctioned while the remaining $C - C_a$ channels are reserved for its PUs. For the purpose of protecting its own PUs, the PBS also determines C_r, the maximum number of channels which can be recalled. In other words, the PBS has at most $C - C_a + C_r$

channels for PUs in the following frame in order to guarantee the average waiting time of the system would not be greater than the threshold γ. Obviously, C_r should be less than or equal to C_a.

Apparently, for any SU i, its utility would not decrease with the channel recall if $C_i \leq C_a - C_r$. It means that even under the maximum channel recalls, there is no effect on SU i if it wins the auction. However, if $C_a - C_r < C_i \leq C_a$, the channel recall by the PBS introduces a reduction on the utility of winning SU i. It is not difficult to find that under the worst case, the maximum number of recalled channels from SU i equals $C_i - (C_a - C_r)$. In order to reflect the effects on SUs due to channel recalls, a particular parameter ρ ($0 \leq \rho \leq 1$), called the risk factor, is introduced. Hence, if $C_a - C_r < C_i$, the benefit of SU i to obtain C_i channels in the recall-based system can be defined as

$$v_i'(C_i) = \left[1 - \frac{C_i - (C_a - C_r)}{C_i}(1 - \rho_i)\right] \times C_i B \log_2\left(1 + \frac{P_t}{n_0 C_i B}\right) \tag{3.2}$$

In (3.2), $[C_i - (C_a - C_r)]/C_i$ represents the maximum channel recall ratio on the only winner SU i. Obviously, $v_i'(C_i)$ is a decreasing function of C_r, which matches the intuition that the more channels the PBS declares to recall, the lower private values SUs may have. The parameter ρ_i is used to reflect different attitudes from SUs towards the potential channel recall. SU with larger ρ is more willing to take risk in this recall-based system and has less concern about the channel recall. Note that ρ is a system factor and cannot be changed by SUs arbitrarily. In fact, such factor heavily depends on the SU's traffic type and the QoS requirements.

Based on the above discussions, we can define single-minded secondary users in the single-winner spectrum auction with different private value functions.

Definition 3.2.1. *For C homogeneous channels and SU i with valuation $v(C_i)$, the SU i is single-minded if there is a number of auctioned channels C_a and a number of maximum recalled channels C_r such that,*

$$V_i = \begin{cases} v_i(C_i), & \text{if} \quad 0 \leq C_i \leq C_a - C_r \qquad \text{(3.3a)} \\ v_i'(C_i), & \text{if} \quad C_a - C_r < C_i \leq C_a \qquad \text{(3.3b)} \end{cases}$$

Note that, it is meaningless to report a demand $C_i > C_a$ since the request of SU i can never be satisfied. Hence, we assume all demands from SUs are bounded by C_a. Then, from SU's perspective, there are two distinct outcomes: i) it gets all channels it demands, i.e., C_i, and does not need to worry about the channel recall; ii) it gets all channels it demands but evaluates C_i with consideration of channel recalls.

3.2.2 Optimal Strategies in RSSA

Since all bids are sealed, SU i does not know the bids from others. But it is natural for all SUs and the PBS to know that all bids follow the same valuation function defined in (3.3) except their private information. We further assume that no SU would misreport their channel requests C_i. Such assumption is widely used in the auction with heterogeneous bidding requests [48,55]. If the PBS only allows one winner, no matter how much channels are demanded from each SU, all C_a channels are auctioned to the single winner. Thus, the PBS could simply consider the auction including same-demand SUs, even though each SU may have its specific demand and valuation.

Optimal Strategy of SUs

According to the SPSB auction that highest bidder wins the auction but pays the second highest bid, the optimal strategy for each bidder is to bid the true valuation of its demanded objects [17], i.e.,

$$b_i^{single} = V_i \tag{3.4}$$

Similar to the private valuation function in (3.3), SU i has two outcomes of bids according to the values of C_i, C_a and C_r. In the first condition, $b_i^{single} = C_i B \log_2(1 + P_t/n_0 C_i B)$, and the channel recall has no impact on SU i. In this case, the bid is monotonically increased with its spectrum demand C_i. In the second condition, $b_i^{single} = \{1 - (1-\rho_i)[C_i - (C_a - C_r)]/C_i\} C_i B \log_2(1 + P_t/n_0 C_i B)$, and the channel recall would affect the service of SU i. In this case, the bid varies with SU's spectrum demand C_i, the maximum recall ratio on SU i and its risk factor ρ_i. The bid would increase as ρ_i increases. That is to say, SU which is not much concerned on the impact of channel recall so as having a larger ρ would bid higher in the auction.

Auction information broadcast by the PBS

In recall-based spectrum auction, SU i with highest bidding price wins the auction and pays the second highest bid, i.e., b_{2nd}. During $[\Delta T, T]$, the PBS recalls $C_{r,a}$ channels after the auction and the actual number of channels recalled from SU i is $C_{r,i}$. Note that for winner SU i, its demand should be less than the total number of auctioned channels, i.e., $0 < C_i \leq C_a$. Thus,

$$C_{r,i} = \begin{cases} 0, & \text{if} \quad C_i \leq C_a - C_{r,a} \quad (3.5a) \\ C_i - (C_a - C_{r,a}), & \text{if} \quad C_i > C_a - C_{r,a} \quad (3.5b) \end{cases}$$

Hence, the PBS compensates $C_{r,i}b_{2nd}/C_i$ back to the winning SU. Then, the final auction revenue of the PBS can be expressed as

$$R_a^{single} = \frac{C_i - C_{r,i}}{C_i} b_{2nd} \tag{3.6}$$

Since the PUs' QoS would be always protected because of the spectrum recall, we have

$$\max_{C_a} U_{PBS} = \max_{C_a} R_a^{single} \tag{3.7}$$

where U_{PBS} denotes the utility of the PBS.

Therefore, the optimal strategy for the PBS is to choose the highest bid and maximize its auction revenue. Since C_i is bounded by C_a, and relaxing C_a always produce a non-decreasing R_a^{single}, C_a should be as large as possible, or in other words, the PBS should auction all its idle channels at the beginning of each frame.

In fact, the maximum number of recalled channel, C_r, can also be determined given $M_w \leq \gamma$. According to $M/M/m$ queue [66] with the arrival rate λ and the service rate μ, the minimum number of channels needed by the PUs, m, can be obtained by

$$M_w = \frac{\mathcal{Q}(m, G)}{\mu(m - G)} \leq \gamma \tag{3.8}$$

where $G = \lambda/\mu$ and $\mathcal{Q}(m, G)$ is the queueing probability which equals

$$\mathcal{Q}(m, G) = \frac{G^m/m!}{[(m - G)/m] \sum_{r=0}^{m-1} (G^r/r!) + G^m/m!} \tag{3.9}$$

Suppose $C \geq m$. Thus, in order to guarantee the QoS of PUs, the minimum number of total reserved channels at the PBS should satisfy the condition that $m \leq (C - C_a) + C_r$ or $C_r \geq m - (C - C_a)$. In addition, C_r should not be greater than the number of auctioned channels. Therefore, C_r should be ranged as $C_a \geq C_r \geq m-(C-C_a)$. Since the derivation of m has guaranteed the QoS of PUs, the PBS has no intension to reserve more channels, i.e., $C_r = m - (C - C_a)$.

However, the PBS may cheat in the auction if and only if its utility can be improved. According to the discussions above, the PBS may benefit by misreporting the amount of auctioned channels, $C_a' > C_a$ or misreporting the maximum amount of recalled channels, $C_r' < C_r$. Intuitively, the latter kind of cheating is much more harmful and possible to happen in practice since reporting $C_a' > C_a$ would be immediately realized by the winning SU at the beginning of each auction frame, however, misreporting $C_r' < C_r$ might only be discovered at the end of each frame.

An Amendment to the SUs' Private Value

As mentioned that the PBS may use mendacious information for more revenue. Specifically, given a constant C_a, a smaller C_r declared by the PBS indicates more available spectrum for SUs. As a result, SUs will bid higher values according to (3.3). However, if the practical quantity of recalled channels is larger than C_r at the end of the auction, SUs will suffer a loss. They will notice that the PBS cheat them by broadcasting untruthful auction information in order to gain more auction revenue.

For protecting SUs in repeated auction, we allow SU i to add a belief index $\varphi_i \leq 1$ to its valuation function which denotes its belief on the truthfulness of the PBS. A small value of φ_i implies that SU i lacks trust on the PBS. With φ_i, the private value function of SU i can be modified as

$$V_i' = \varphi_i \cdot V_i \tag{3.10}$$

At the end of the $(m-1)$-th auction, SU i updates its belief index from $\varphi_i(m-1)$ to $\varphi_i(m)$ for the coming m-th auction following Algorithm 1. In repeated games, trigger strategy is widely adopted for punishing possible strategies deviations [67]. In our problem, the update rule of φ can be designed as the SUs' trigger strategy for punishing the PBS's untruthful behaviors, which is explained as follows.

Algorithm 1 Update Rule of Belief Index

if $C_{r,a}(m) > C_r(m)$ **then**
    $\varphi(m+1) = \kappa\varphi(m)$;
else if $C_{r,a}(m-k) < C_r(m-k)$, $k = 0, 1, \ldots, \Delta m - 1$ **then**
    $\varphi(m+1) = \varphi_0$;
else
    $\varphi(m+1) = \varphi(m)$;
end if

In the Algorithm 1, $C_{r,a}(m)$ is the practical amount of channels recalled in m-th round of auction and $\varphi_{(}m)$ is the SU's belief index in the m-th round. $\varphi_0 = 1$ is the initial value of belief index which means that SU i trusts the PBS. $\kappa < 1$ is set to be a discount ratio. SUs will decrease their belief index in the next round if they notice that they have been cheated. Moreover, this reduction will be kept for Δm rounds after the PBS's rehabilitation (i.e., recall less channels than C_r). In other words, one time deception causes Δm times punishment.

3.2.3 Time-line of RSSA Algorithm

The detailed time-line of the proposed RSSA algorithm is listed as follows.

- At the beginning of each frame, the PBS broadcasts the auction information including the number of auctioned channels C_a and the maximal recalls C_r based on its current service state. The settings of C_a and C_r can be found in Section 3.2.2.

- Each SU i receives the auction information and sets up a value V_i based on its own spectrum demand C_i, risk factor ρ_i and the maximum channel recall ratio on itself, i.e., $[C_i - (C_a - C_r)]/C_i$. Then, SUs submit sealed bids and their specific demands to the PBS.

- The PBS determines the only winner by selecting the SU with highest bidding price and charges it with the second highest bid b_{2nd}.

- After the auction, the PBS can recall channels from the winning SU i if necessary to satisfy its own sudden increase of spectrum demand. At the end of T, the PBS refunds SU i with $C_{r,i}b_{2nd}/C_i$.

3.3 Recall-based Multiple-Winner Spectrum Auction

Since the demand of each SU i, C_i, is independent of the number of auctioned channels C_a, it is very likely that the auctioned channels C_a cannot be fully utilized by one winning SU. Thus, the auction revenue could be enhanced if the PBS picks more than a single winner. However, the allowance of multiple winners makes the spectrum auction become a more complicated combinatorial auction problem.

In the payment design of the proposed RMSA algorithm, VCG mechanism is adopted. Though VCG mechanism cannot guarantee the maximum auction revenue for the PBS [41], it is the basic payment mechanism in combinatorial auction which can ensure efficiency, incentive compatibility and individual rationality. Note that revenue-maximizing combinatorial auction mechanism or any approximating auction mechanism, such as virtual valuation combinatorial auctions (VVCA) [68] or LOS mechanism [43], can also be applied in our proposed scheme.

3.3.1 Strategy of SUs in RMSA

Without channel recall, the private value on channel demand C_i of SU i in multiple-winner auction is the same as that in (3.1), i.e., $v_i(C_i) = C_i B \log_2 (1 + P_t/n_0 C_i B)$ for $C_i \geq 0$.

With channel recall, the PBS needs to announce C_a and C_r at the beginning of each frame. Different from the single winner case where each SU could figure out the maximum number of channels recalled from itself if it won the auction, such information is not available in multi-winner auction because the number of channels recalled from a winning SU is not only determined by its own demand, but also the demands of other winners.

Let $W \subseteq \{1, 2, \ldots, N\}$ be the set of winners. Different from single winner case, since the auctioned channels C_a may not be fully utilized by winners in W, the maximum channel recall ratio on W equals

$$\chi^{multiple} = \frac{C_r - (C_a - \sum_{i \in W} C_i)}{C_a} \tag{3.11}$$

Same as RSSA algorithm, each SU needs to evaluate its private value towards its spectrum demand based on $\chi^{multiple}$. However, term $(C_a - \sum_{i \in W} C_i)$ is unpredictable since W cannot be determined before the auction. We approximate $\chi^{multiple}$ as C_r/C_a.

Similar to the risk factor in RSSA algorithm, we define $\theta \in [0, 1]$ as SU's spectrum stability factor in its private value function definition. Though θ_i also reflects the attitude of SU i towards channel recall, the physical meaning of θ in RMSA is different from ρ in RSSA. In single winner case, since the maximum channel recall ratio on the single winner can be determined before auction, the spectrum stability is only determined by the activity of PUs. However, in multi-winner case, since the maximum channel recall ratio can only be determined at the system level, i.e., C_r/C_a, rather than each winner, the spectrum stability factor may affect both the winner determination and the channel recall ratio on each winner.

The definition of single-minded SUs in RMSA algorithm is given in the following.

Definition 3.3.1. *For C homogeneous channels and SU i with valuation V_i, SU i is single-minded if there exist a number of auctioned channels C_a and a number of maximum recall*

C_r *such that:*

$$V_i = v_i''(C_i) = \left[1 - \frac{C_r}{C_a}(1-\theta_i)\right] \times v_i(C_i), \quad \textit{if} \quad 0 \le C_i \le C_a \tag{3.12}$$

Thus, from the perspective of SU i, it gets channels it demands, however multiplies a channel stability ratio to its valuation. Similar as RSSA algorithm, the larger C_r the PBS declares, the lower private values SUs may have. Moreover, SUs with different spectrum demand and stability factor would also lead to different private values. Larger θ_i indicates that SU i could be provided a more stable service so as to gain higher utility. Note again that θ is also predetermined by the system depending on SUs' traffic types and transmission requirements, and cannot be changed arbitrarily by SUs.

In the design of payment function, VCG mechanism requires that all bidders only know their own private values for their demands and each of them has a quasi-linear utility function. Since SU i could determine its valuation of the bundle of channels C_i when they receive the announcement of C_a and C_r, we prove the quasi-linearity of our utility function in the following proposition.

Proposition 3.3.1. *For SU $i \in \{1, 2, \ldots, N\}$ with particular spectrum demand C_i and spectrum stability requirement factor θ_i, $u_i = V_i - t_i$ is a quasi-linear utility function, where t_i denotes the payment of SU i in the auction.*

Proof. In order to prove that $u_i = V_i - t_i$ is a quasi-linear utility function, we only need to prove that V_i is a concave function of channel demand C_i [17]. Recall that $V_i = [1 - (C_r/C_a)(1-\theta_i)]C_i B \log_2(1 + P_t/(n_0 C_i B))$, if $0 \le C_i \le C_a$. Since the ratio caused by channel recall, $1 - (C_r/C_a)(1-\theta_i)$, is not varied with C_i, the concavity and convexity of V_i only depends on the formula of Shannon capacity. In fact, it can be directly proved that the capacity $C_i B \log_2(1 + P_t/(n_0 C_i B))$ is an increasing, concave function of bandwidth $C_i B$ [69]. Thus, V_i is a concave function of C_i and u_i is a quasi-linear utility. $\square$

According to VCG mechanism, truthful bidding maximizes any player's utility regardless of other players' choices [17]. Hence, all the SUs would truthfully bid in the spectrum auction by honestly telling the PBS their private values and their demands, i.e.,

$$b_i^{multiple} = V_i \tag{3.13}$$

3.3.2 Actions of the PBS in RMSA

Similar to the analysis in Section 3.2.2 for determining C_a and C_r in RSSA algorithm, the PBS would auction all its idle channels and announce a maximum recall quantity C_r based on PUs' QoS requirement (For simplicity, we assume that the PBS in RMSA would be always truthful, otherwise, similar amendment as in Section 3.2.2 can also be applied here). In this section, we focus on the winner determination of combinatorial auction and the payment charged for each winner. Furthermore, a new channel recall scheme is proposed to achieve some level of fairness in spectrum sharing among heterogeneous SUs.

Winner Determination and Payment Design

In our system, each SU tells the PBS its sealed bid and specific spectrum demand. The PBS determines the winners by solving the following optimization problem.

Given the bid $B = \{b_1, b_2, \ldots, b_N\}$ and spectrum demand $\{C_1, C_2, \ldots, C_N\}$, the PBS determines the winners such that,

$$\max_{\{x_i\}, \forall i \in N} \; P_B^C = \sum_{i=1}^{N} b_i x_i \tag{3.14}$$

$$s.t. \quad \sum_{i=1}^{N} C_i x_i \leq C_a$$

where

$$x_i = \begin{cases} 1, & \text{if SU } i \text{ is the winner of the auction;} \\ 0, & \text{otherwise.} \end{cases}$$

The optimization problem (3.14) aims to find the set of winners $W = \{i | x_i = 1, \forall i \in N\}$ such that the sum of their bids received by the PBS could be maximized under the constraint that their total spectrum demand is less than or equal to the number of auctioned channels C_a. Furthermore, since we assume that SUs are single-minded so that SU i can either get all spectrum it demands or nothing, the maximization problem (3.14) is actually a 0-1 single knapsack problem which can be solved to optimality in pseudo-polynomial time by using dynamic programming or branch and bound algorithm [70,71]. Note that the availability of optimal solution to (3.14) guarantees the feasibility of VCG payment rule.

After deciding the set of winners, the PBS charges the winning SUs according to the VCG mechanism. The payment of SU i is

$$t_i = P^{C}_{B\backslash\{b_i\}} - P^{C\backslash\{C_i\}}_{B\backslash\{b_i\}} \tag{3.15}$$

where $P^{C}_{B\backslash\{b_i\}}$ denotes the maximum welfare if SU i does not participate in the auction and $P^{C\backslash\{C_i\}}_{B\backslash\{b_i\}}$ denotes the maximum welfare if SU i does not participate and it takes out its winning C_i channels from the total C channels in the auction. The details of payment rule in VCG mechanism can be found in Chapter 2 of this thesis or [17].

Channel Recall Scheme

The VCG payment mechanism is actually designed for buyers with fixed private values. But in our system model, the utilities of winning SUs may decrease after the auction because of channel recalls. It provides us an incentive to design a new spectrum recall allocation in our RMSA algorithm.

For explanation purpose, we first introduce a simple definition of fairness index.

Definition 3.3.2 (Min-max fairness). *For each winner $i \in W$, if the actual number of channels recalled on SU i is less than its spectrum demand, i.e. $C_{r,i} < C_i$, we define a resource allocation index as*

$$f_i = \frac{C_i - C_{r,i}}{t_i} \tag{3.16}$$

where $C_i - C_{r,i}$ indicates the actual number of channels SU i obtained and t_i is the payment. Given $f_i,\ i \in W$, a Min-max fairness index can be defined as

$$I_{min-max} = \frac{min\{f_i\}}{max\{f_i\}},\ \ i \in \{i | i \in W, C_{r,i} < C_i\} \tag{3.17}$$

Obviously, according to the definition shown above, the spectrum allocation is more fair when $I_{min-max}$ tends to 1.

Proposition 3.3.2. *The VCG mechanism is unfair under the situation that multiple homogeneous channels are auctioned among SUs with different stability requirement and a same recall ratio $C_{r,a}/C_a$ on multiple winners is applied.*

Proof. Consider the system with only two winners, SUs i, j, both of which have same spectrum demands, i.e., $C_i = C_j$. According to (3.12), the difference of their private values only depends on the spectrum stability factor θ. Assume that $\theta_i > \theta_j$. Then, SU i has a larger private value than SU j, which leads to a larger bid, i.e, $b_i > b_j$. With the VCG mechanism of item allocation and payment design, it is easy to find that SU i and SU j will get the same number of channels, but with $t_i > t_j$. Since the recall ratio is the same on both SUs i and j, i.e., $C_{r,a}/C_a$, the fairness index can be calculated as

$$I = \frac{f_i}{f_j} = \frac{C_i(1 - C_{r,a}/C_a)}{t_i} \times \frac{t_j}{C_j(1 - C_{r,a}/C_a)} = \frac{t_j}{t_i} \tag{3.18}$$

Thus, this scheme is not fair, especially for the case that $t_i \gg t_j$ when $\theta_i \gg \theta_j$. □

Proposition 3.3.2 indicates that applying same recall ratio on multiple winners is not reasonable for SUs with different spectrum stability factors.

In addition, the channel recall may also affect the auction revenue of the PBS. According to the VCG mechanism, channel recalls will be evenly distributed among winning SUs. The recall compensation equals the product of actual spectrum recall ratio and the sum of payments gained from winners, i.e., $C_{r,a}/C_a \times \sum_{i \in W} t_i$. Thus, the revenue of PBS can be written as

$$R_{a1}^{multiple} = \left(1 - \frac{C_{r,a}}{C_a}\right) \sum_{i \in W} t_i \tag{3.19}$$

Obviously, the PBS could get more profit and decrease the compensation by recalling more channels from the winners with low payments.

Based on the above analysis, we propose a simple but effective channel recall scheme as follows:

Assume during $t \in [\Delta T, T]$, the winning SU $i \in W$ uses C_i channels, and totally $\sum_{i \in W} C_i$ channels are used by SUs. The PBS could recall channels one by one when necessary. Since the PBS knows the payment of each SU and the details of auction mechanism, it can figure out the unit price of each channel. Thus, the channel with lower price has the higher priority to be recalled and the unused channels would be recalled in the first place. At the end of T, the PBS refunds winning SU i with $t_i \times C_{r,i}/C_i$, where $C_{r,i}$ denotes the number of channels which are actually recalled from SU i. Note that $C_{r,i}$ is heterogeneous for each winner and it is likely that $C_{r,i} = 0$ for the winner with high unit price for each channel, whereas the channels may be completely recalled for the winner with low unit price.

3.3.3 Time-line of RMSA Algorithm

We summarize the time-line of the proposed RMSA algorithm as follows.

- The PBS broadcasts the auction information including C_a and C_r at the beginning of each frame.
- Each SU i receives the auction information and sets up a value V_i based on its own spectrum demand C_i, stability factor θ_i and the channel recall ratio C_r/C_a. Then, SUs submit sealed bids and their specific spectrum demands to the PBS.
- The PBS determines the winner by solving the optimization problem in (3.14) and charges the winner SU $i \in W$ based on the VCG payment rule in (3.15).
- After the auction, the PBS can recall channels one by one to meet its own sudden increase of spectrum demand. The channel recall follows the scheme proposed in Section 3.3.2. At the end of T, the PBS refunds each winner SU i with $t_i \times C_{r,i}/C_i$.

Note that although the proposed RMSA algorithm follows the basic idea of recall-based dynamic spectrum auction [13], the system model under our consideration is more general by considering heterogeneous SUs' requirements, multi-item auction and multiple winners.

3.4 Performance Analyses

In this section, economic properties of proposed auction algorithms are analyzed in terms of PBS's auction revenue and SUs' utilities.

3.4.1 Auction revenue of the PBS

Since the PBS has the ability of channel recall, the PUs' service would be completely protected. In addition, since PUs always have higher priority to access the channels, the PBS takes no risk on its own QoS degradation but only benefits from dynamic spectrum auction. Hence, we focus on analyzing the auction revenue of the PBS only.

In our system model, the arrival of PUs follows Poisson process and spectrum auction is carried out by the PBS frame by frame. We use $u(r)$ to represent the number of PUs who are in service at the end of rth frame. Obviously, $u(r)$ also indicates the number of busy channels at the beginning of frame $r+1$. With our proposed auction algorithm, the number of auctioned channels at the beginning of rth frame is $C_a = C - u(r-1)$. In addition, the actual number of channels recalled during the rth frame is $C_{r,a} = u(r) - u(r-1) + d(r)$, where $d(r)$ denotes the number of all departures during that period. Note that only $u(r-1)$ is known by the PBS at the beginning of the rth frame, while $u(r)$ and $d(r)$ are unknown.

For single-winner auction with channel recall, the winner determination would be optimal only if the winner i^* satisfies:

$$i^* = \arg\max_i \frac{C_i - C_{r,i}}{C_i} \times b'_i \tag{3.20}$$

where

$$b'_i = v'_i(C_i, C_{r,i}) = \left[1 - \frac{C_i - (C_a - C_{r,i})}{C_i}(1-\rho_i)\right] v_i(C_i) \tag{3.21}$$

Note that (3.21) is formulated based on the assumption that the accurate amount of channel recall, $C_{r,i}$, is known at the beginning of the auction. Obviously, the bidding pattern and winner determination in RSSA might be suboptimal compared to the above case with complete information, since $C_{r,i}$ is actually unknown at the beginning of auction with unknown $C_{r,a}$. Such deficit of Vickrey auction payment rule on the auction revenue in recall-based systems will be presented numerically by the simulation in Section 3.5.

This shortage also exists in multiple-winner auction under VCG mechanism. In fact, the winner determination and spectrum allocation should satisfy the following conditions. Given the bid $B = \{b_1'', \ldots, b_i'', \ldots, b_N''\}$, where $b_i'' = v_i(C_i)$, and spectrum demand $\{C_1, C_2, \ldots, C_N\}$, the winner in set $W^* = \{i | x_i = 1, \forall i \in N\}$ should satisfy:

$$\begin{aligned} \max_{\{x_i\}, \forall i \in N} \ P_B^C &= \sum_{i=1}^{N} b_i'' x_i \\ s.t. \quad \sum_{i=1}^{N} C_i x_i &\leq C_a - C_{r,a} \\ x_i &= 0/1, \qquad \forall i \in \{1, 2, \ldots, N\}. \end{aligned} \tag{3.22}$$

For the same reason that $C_{r,a}$ is unknown at the beginning of auction, it is impossible for the PBS to find the optimal decision and SUs will not bid non-recall valuations.

We now analyze the effects of the proposed channel recall scheme on the utility of the PBS. After receiving the payments from the winners in W, the PBS rearrange the payments according to an increasing order of the unit price per channel. Let the payment set as $T = \{t^1, t^2, \ldots, t^m\}$, where m is the number of elements in W, and C_{t^i} be the demand of SU who paid t^i. If SU j^* who paid t^{j^*} is the last one in W whose channel will be completely recalled, j^* can be found as

$$j^* = \arg\min_j \left(\sum_{k=1}^{j} t^k + \frac{C_{r,a} - \sum_{k=1}^{j} C_{t^k}}{C_{t^{j+1}}} \times t^{j+1} \right) \tag{3.23}$$

Therefore, the auction revenue of the PBS can be expressed as

$$R_{a2}^{multiple} = \sum_{i \in W} t_i - \left(\sum_{k=1}^{j^*} t^k + \frac{C_{r,a} - \sum_{k=1}^{j^*} C_{t^k}}{C_{t^{j^*+1}}} t^{j^*+1}\right) \tag{3.24}$$

We can evaluate the difference with respect to (3.19) as

$$\begin{aligned}
\Delta &= R_{a2}^{multiple} - R_{a1}^{multiple} \qquad (3.25)\\
&= \sum_{i\in W} t_i - (\sum_{k=1}^{j^*} t^k + \frac{C_{r,a} - \sum_{k=1}^{j^*} C_{t^k}}{C_{t^{j^*+1}}} t^{j^*+1}) - (1 - \frac{C_{r,a}}{C_a}) \sum_{i\in W} t_i\\
&= -(\sum_{k=1}^{j^*} t^k + \frac{C_{r,a} - \sum_{k=1}^{j^*} C_{t^k}}{C_{t^{j^*+1}}} t^{j^*+1}) + \frac{C_{r,a}}{C_a} \sum_{i\in W} t_i\\
&= -(\sum_{k=1}^{j^*} t^k + \frac{C_{r,a} - \sum_{k=1}^{j^*} C_{t^k}}{C_{t^{j^*+1}}} t^{j^*+1}) + \frac{C_{r,a}}{C_a} \sum_{k=1}^{m} t^k
\end{aligned}$$

Let $\delta_1 = \frac{C_{r,a}}{C_a} \sum_{k=1}^{m} t^k$, which indicates the compensation in the auction with evenly distributed channel recall ratio; while $\delta_2 = \sum_{k=1}^{j^*} t^k + \frac{C_{r,a} - \sum_{k=1}^{j^*} C_{t^k}}{C_{t^{j^*+1}}} t^{j^*+1}$, which represent the compensation in the auction with the proposed channel recall scheme. Since j^* could minimize the compensation in T as presented in (3.23), thus $\Delta = \delta_1 - \delta_2 \geq 0$. Therefore, VCG mechanism with the proposed channel recall scheme could improve the auction revenue of the PBS.

3.4.2 Analysis on the SUs' utilities

Each SU's utility equals the difference between its gain and payment. At the beginning of the auction, SU i evaluates C_i channels based on the auction information. However, winning SU i may not obtain C_i channels due to the potential channel recall. Therefore, we need to investigate the relation between SU's utility and its private information. Moreover, in order to satisfy the heterogeneous requirements of SUs and provide them a fair spectrum allocation in multi-winner auction, we need to prove that any SU with higher spectrum stability factor which results in a higher bid for a unit of spectrum can be guaranteed with a more stable service by the PBS.

SUs' Utilities in RSSA algorithm

Consider the case without channel recall first. With the SPSB rule, the highest bidder wins, but the price paid is the second highest bid [17]. Thus, the expected utility for SU i is

$$U_i = (V_i - b_{2nd})\text{Pr.}\left\{b_i > \max_{j \neq i} b_j\right\} \tag{3.26}$$

where $V_i - b_{2nd}$ is its net utility and Pr.$\{b_i > \max_{j\neq i} b_j\}$ is its winning probability.

For the system with channel recall, two cases need to be considered.

- Case 1: $0 \leq C_i \leq C_a - C_{r,a}$. The actual gain of SU i is same as (3.1), i.e., $G_i = v_i(C_i)$.

- Case 2: $C_a - C_{r,a} < C_i \leq C_a$. The actual gain G_i' can be obtained by (3.2), except that the amount of obtained channels C_i is replaced by $C_i - C_{r,i}$, i.e.,

$$G_i' = \left[1 - \frac{C_i - (C_a - C_r)}{C_i}(1 - \rho_i)\right](C_i - C_{r,i})B\log_2\left(\frac{P_t}{n_0(C_i - C_{r,i})B}\right) \tag{3.27}$$

Then, we can derive the expected utility for SU i in the recall-based system as

$$U_i^{single} = \begin{cases} (G_i - b_{2nd})\text{Pr.}\{b_i > \max_{j\neq i} b_j\} & 0 \leq C_i \leq C_a - C_{r,a} \\ (G_i' - (1 - \frac{C_{r,i}}{C_i})b_{2nd})\text{Pr.}\{b_i > \max_{j\neq i} b_j\} & C_a - C_{r,a} < C_i \leq C_a \end{cases}$$

Apparently, the SUs' utilities are different because of the SUs' heterogeneous requirements.

Lemma 3.4.1. *In RSSA algorithm, the utility of SU i is not monotonically increased with its spectrum demand C_i.*

Proof. Apparently, U_i^{single} is monotonically increased with C_i in case 1. However, this property would not be maintained when C_i continues to increase. Since SU$_i$ in case 1 can fully utilize C_i channels, but SU i in case 2 is affected by channel recall, U_i^{single} has a sudden decrease when C_i reach the threshold $C_a - C_{r,a}$. Therefore, the utility of SU i cannot consecutively increase with C_i from 0 to C_a. $\square$

The following Lemma shows the impact on SUs' utilities caused by their different risk factors.

Lemma 3.4.2. *In RSSA algorithm, SU with larger value of risk factor ρ has better utility than the SU with a smaller one.*

Proof. Obviously, the gain or the bid of SU i in both case 1 and case 2 would be increased with ρ_i, i.e., $\partial G_i/\partial \rho_i > 0$ and $\partial G_i'/\partial \rho_i > 0$, and ρ_i has nothing to do with the compensation. Thus, we have

$$\frac{\partial U_i^{single}}{\partial \rho_i} \geq 0 \tag{3.28}$$

Moreover, Pr.$\{b_i > \max_{j \neq i} b_j\}$ would also be enhanced when ρ_i is larger. Therefore, SU with larger risk factor ρ could be provided a higher chance to win the auction. □

With the above lemmas, we conclude the advantage of RSSA algorithm in the following theorem.

Theorem 3.4.1. *The RSSA algorithm can provide economic incentive for all the SUs to participate in the auction since their utilities are always non-negative and their heterogeneous requirements could be satisfied when they win the competition.*

Proof. Since second price sealed-bid auction is a mechanism which could ensure incentive compatibility and individual rationality to all the players [17], we have $U_i^{single} > 0$ when SU$_i$ wins the auction and $U_i^{single} = 0$, otherwise. Moreover, all SUs are assumed to truthfully report their channel demands. With the help of Lemma 3.4.1 and 3.4.2, we can prove that the utility of SU is strictly related to how much it concerns for channel recall but not its channel demand. Hence, all the SUs would follow the rules in the auction. □

SUs' Utilities in RMSA algorithm

In multiple-winner auction, the private value model is symmetric since the valuation function of each winner is the same as (3.12), except the private information. Without the consideration of channel recall, we have

$$U_i' = (V_i - t_i)\text{Pr.}\{i \in W\} \tag{3.29}$$

where $V_i - t_i$ is its net utility and Pr.$\{i \in W\}$ is its winning probability in the knapsack problem of (3.14).

Similarly, with channel recall, according to the valuation function in (3.12), the gain of winning SU i is

$$G_i'' = \left[1 - \frac{C_r}{C_a}(1-\theta_i)\right](C_i - C_{r,i})B\log_2\left(\frac{P_t}{n_0 C_i B}\right) \tag{3.30}$$

Therefore, the expected utility in recall-based multiple-winner spectrum auction can be formulated as

$$U_i^{multiple} = \left[G_i'' - (1 - \frac{C_{r,i}}{C_i})t_i\right]\text{Pr.}\{i \in W\} \tag{3.31}$$

Note that the actual recall quantity on SU i, $C_{r,i}$, is determined by the channel recall scheme.

Lemma 3.4.3. *In RMSA algorithm, the utility of SU i can only be ameliorated with the increase of stability factor θ_i.*

Proof. Obviously, the utility of SU i has no monotonicity with the change of C_i since the number of recalls on SU i, $C_{r,i}$, also increases with the demand C_i. However, $C_{r,i}$ will decrease with the increase of θ_i because of the proposed channel recall scheme. That means $\frac{\partial C_{r,i}}{\partial \theta_i} < 0$. Thus,

$$\frac{\partial G_i''}{\partial \theta_i} = \left[1 - \frac{C_r}{C_a}(1-\theta_i) - \frac{\partial C_{r,i}}{\partial \theta_i} + \frac{C_r}{C_a}(C_i - C_{r,i})\right]B\log_2(1 + \frac{P_t}{n_0(C_i - C_{r,i})B}) > 0 \tag{3.32}$$

Though the compensation $\frac{C_{r,i}}{C_i}t_i$ would be monotonically decreased with θ_i, this decrease is less than the increase of G_i'' since the payment is always less than the gain to ensure non-negative utility. Thus,

$$\frac{\partial U_i^{multiple}}{\partial \theta_i} \geq 0 \tag{3.33}$$

Moreover, the increase of θ_i will also result in the enhancement of Pr.$\{i \in W\}$. That means, SU i with larger θ_i has higher probability to win in the auction and the quantity of recall $C_{r,i}$ will decrease. In other words, the spectrum occupied by SU i with larger θ_i is more stable. $\square$

Based on Lemma 3.4.3, we summarize the benefit of RMSA algorithm in the following theorem.

Theorem 3.4.2. *The RMSA algorithm can provide economic incentive for all the SUs to participate in the auction since their utilities are non-negative and the algorithm also ensures a fair spectrum allocation by considering the heterogeneous requirements of SUs.*

Proof. VCG mechanism employed in the algorithm is incentively compatible for all the players. Moreover, the payment scheme can also ensure non-negative utility and maximize the social welfare [17]. According to our designed channel recall scheme, SU with larger stability factor is granted a more stable spectrum environment. The assumption of single-minded SUs and Lemma 3.4.3 demonstrate that SUs' heterogeneous requirements can be satisfied with our auction model. $\square$

3.5 Simulation Results

In this section, we conduct simulations to evaluate our proposed RSSA and RMSA algorithms. With the use of recall-based PBS model, the performance in terms of auction revenue and SUs' utilities are presented.

3.5.1 Simulation Scenario

Consider a CR network with a PBS and N heterogeneous SUs. PUs' arrival rate $\lambda = 2$ and channel service rate $\mu = 0.1$. The threshold γ is set to be $6.25 \times 10^{-4}s$, and the PBS owns $C = 36$ channels to satisfy the inequality (3.8). The length of each frame $T = 6s$, so that the average number of PUs arrive in one minute is 20 and the mean time of service for each

PU is $60s$. These settings are commonly used in the design of the mobile base station [13]. Furthermore, $B = 10^5 Hz$, $n_0 = 2 \times 10^{-10} W/Hz$ and $Pt = 0.01W$. Note that the number of SUs N, spectrum demands C_i and factors ρ_i, θ_i for each SU i are varied according to the evaluation scenarios.

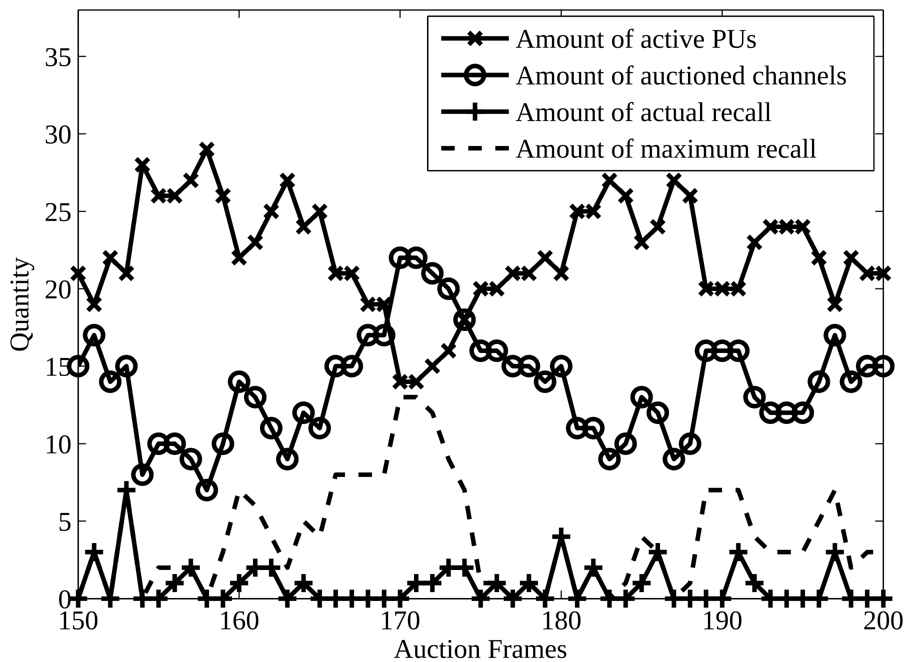

Figure 3.2: State information of the PBS in different auction frames

Fig. 3.2 shows the PBS's state information (the number of "idle" and "busy" channels) at each frame. For each frame, the number of active PUs can be determined by the parameters of queueing system. Since the PBS auctions all the idle channels, the number of auctioned channels is increased when the number of PUs decreases. Moreover, the increase of recall quantity also leads to a decrease on the number of auctioned channels. Since the PBS is truthful in the long-term auction, it is shown that the announced number of maximum recall is always larger than the number of actual recalls. All rest simulation results are based on the state information shown in this figure.

3.5.2 Performance of RSSA algorithm

In Fig. 3.3, the auction revenue of the PBS is compared between optimal winner determination as described in (3.20) and our proposed RSSA algorithm. Intuitively, small-scale network has higher probability of coincidence that the optimal determination is the same as the decision made by our single-winner auction. Therefore, we consider a relatively large network with $N = 50$ SUs in this simulation. Moreover, the demand of each SU is selected randomly from integers 0 to 15 and risk factor is chosen randomly in $[0, 1]$. Fig. 3.3 shows that the curve of the PBS's auction revenue obtained by our proposed single-winner auction algorithm is close to the one with optimal winner determination. It indicates that our algorithm can achieve close to optimal performance for the PBS.

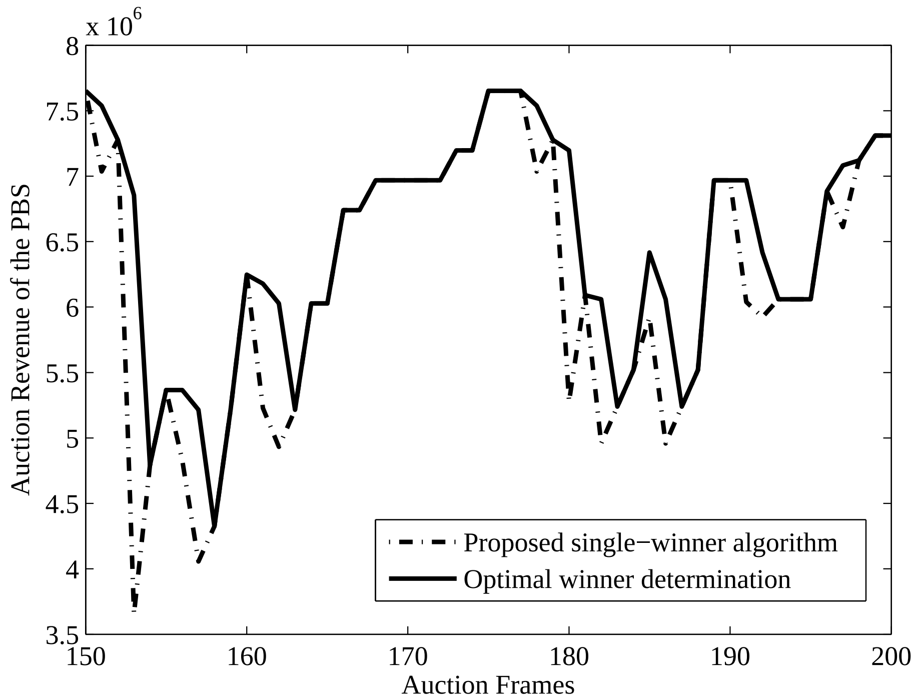

Figure 3.3: The auction revenue of the PBS in RSSA ($N = 50$)

In order to demonstrate the superiority of enabling spectrum recall, we compare the utilities of PBS with and without recall. Here, the PBS's utility function is defined as [72]:

$$\begin{aligned} U_{PBS} &= R_a + R_s - U_{punish} \\ &= \begin{cases} R_a + \omega_s C_s - \omega_p \frac{C_v - C_s}{C_s}, & \text{if } C_v \geq C_s \\ R_a + \omega_s C_v - \omega_p \frac{C_s - C_v}{C_s}, & \text{if } C_v < C_s \end{cases} \end{aligned} \tag{3.34}$$

where R_a denotes the auction revenue, R_s denotes the revenue from its own users' service, and U_{punish} is a punishment term, which represents the loss due to excessive or insufficient channel reservation. ω_s and ω_p indicate average revenue per PU and the weight index of punishment, respectively. C_v denotes the amount of channel reservation by the PBS before the auction and C_s denotes the actual demand of PBS's own users. In the simulation, we set $\omega_s = \omega_p = 10^6$. In Fig. 3.4, it can be seen that the PBS has lower and more fluctuating utility without recall, which clearly illustrates the improvement by using recall-based PBS system.

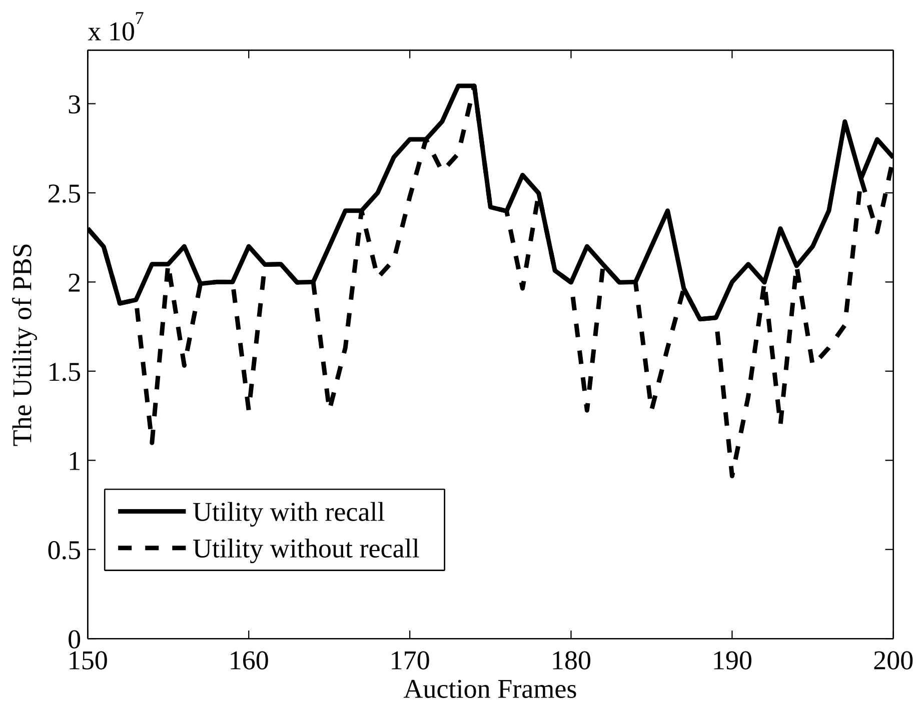

Figure 3.4: The utility of the PBS in recall-based system ($N = 50$)

As proofs for Lemma 3.4.1 and Lemma 3.4.2, we examine the impacts on a specific

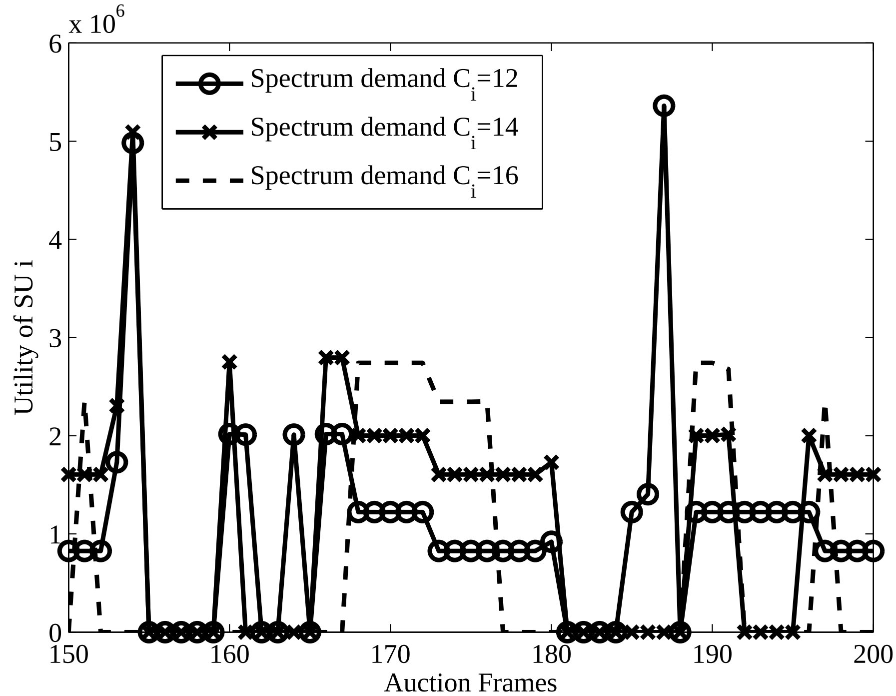

Figure 3.5: The utility of SU i with different spectrum demand in RSSA ($N = 10$)

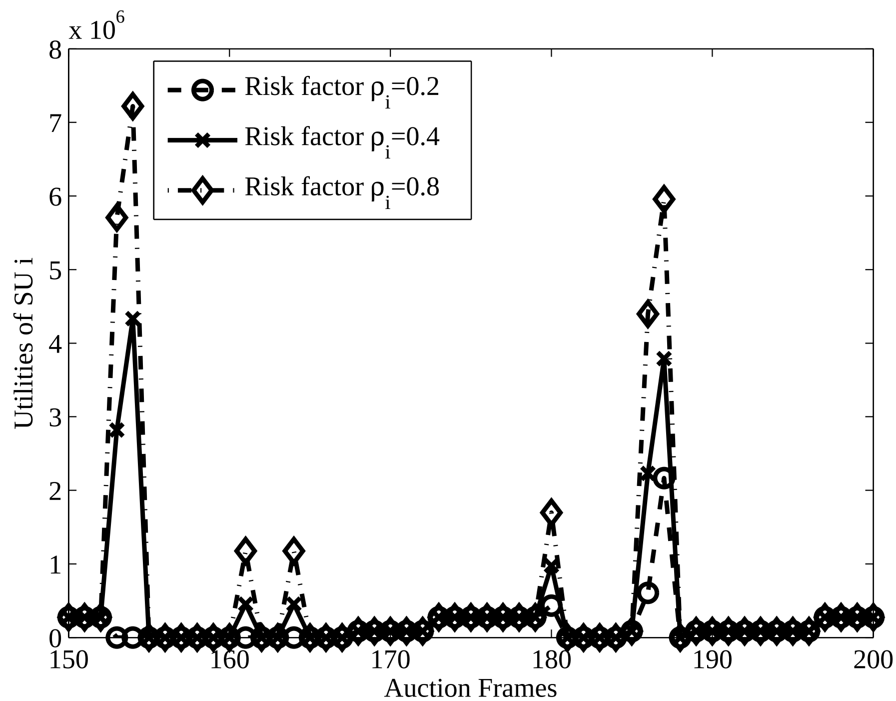

Figure 3.6: The utility of SU i with different risk factors in RSSA ($N = 10$)

SU's utility by changing its spectrum demand C_i and risk factor ρ_i in Fig. 3.5 and Fig. 3.6, respectively. For simplicity, $N = 10$ SUs are considered and we further assume that all SUs except SU i have a fixed spectrum demand 10 and risk factor 0.3. Fig. 3.5 demonstrates that larger spectrum demand cannot provide higher utility on SU i. Furthermore, it is also shown in the figure that larger C_i leads to a higher probability of zero utility for SU i. That means the winning probability will decrease when C_i increases. However, SU i can benefit when its risk factor is larger. As shown in Fig. 3.6 when C_i is fixed to 12, the utility of SU i is monotonically increased with ρ_i varied from 0.2 to 0.8. Moreover, larger ρ_i also results in higher winning probability. In summary, the utility of SU i only depends on its risk factor.

3.5.3 Performance of RMSA algorithm

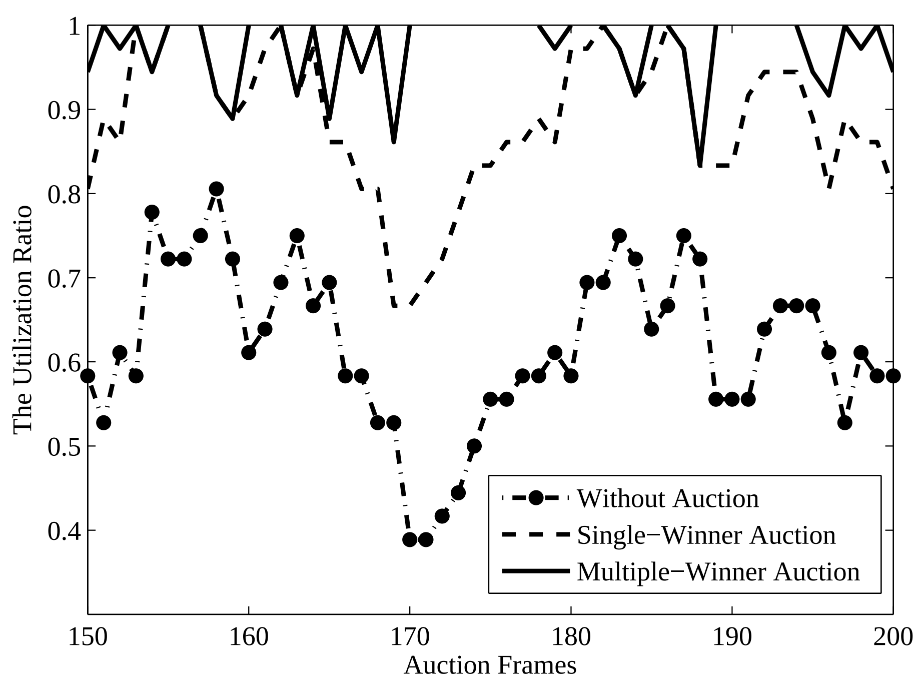

Figure 3.7: Comparison of spectrum utilization between single and multiple winner auctions ($N = 10$)

Fig. 3.7 exhibits the comparison of channel utilization ratio between single winner auction and multi-winner auction. The demand of each SU ($N = 10$) is selected randomly from integer 0 to 10 and ρ, θ are chosen randomly in $[0, 1]$. In addition, the ratio without auction is also presented, which is only determined by the number of active PUs. The figure shows that auction with multiple winners has higher spectrum utilization than single winner auction, and this ratio almost reaches 100%.

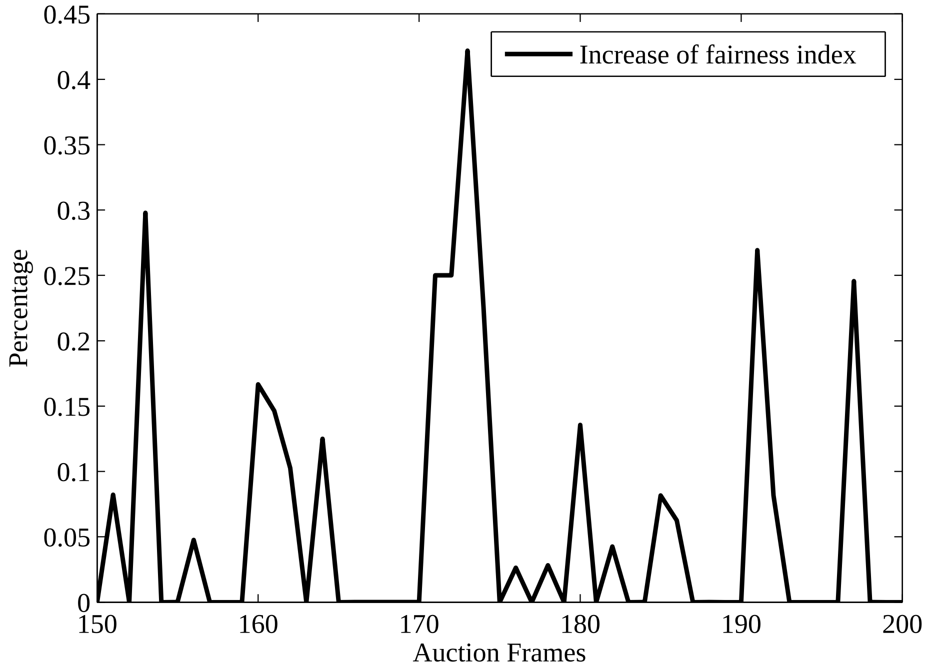

Figure 3.8: The improvement on fairness by using proposed channel recall scheme

The percentage increase of Min-max fairness index by applying our proposed channel recall scheme is shown in Fig. 3.8. Compare our scheme with evenly distributed channel recall ratio, the fairness index is enhanced up to more than 40%. During some periods, e.g. $165T - 170T$, there is no improvements of fairness. The reason is that the number of channel recalls is zero as shown in Fig. 3.2. Thus, we can conclude that the proposed channel recall scheme in RMSA algorithm is more fair and suitable for recall-based spectrum auction mechanism.

We further examine the relation between SU's utility and its private information in multiple-winner case as discussed in Lemma 3.4.3. For simplicity, we only consider $N = 4$ SUs. We focus on the utility of a specific SU i by varying its spectrum demand and stability

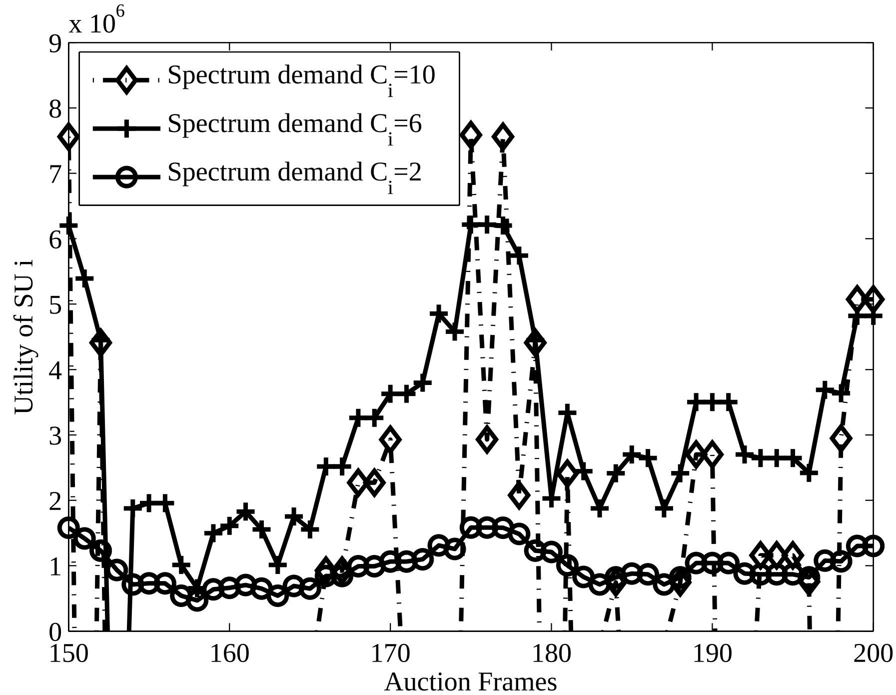

Figure 3.9: The utility of SU i with different spectrum demands in RMSA

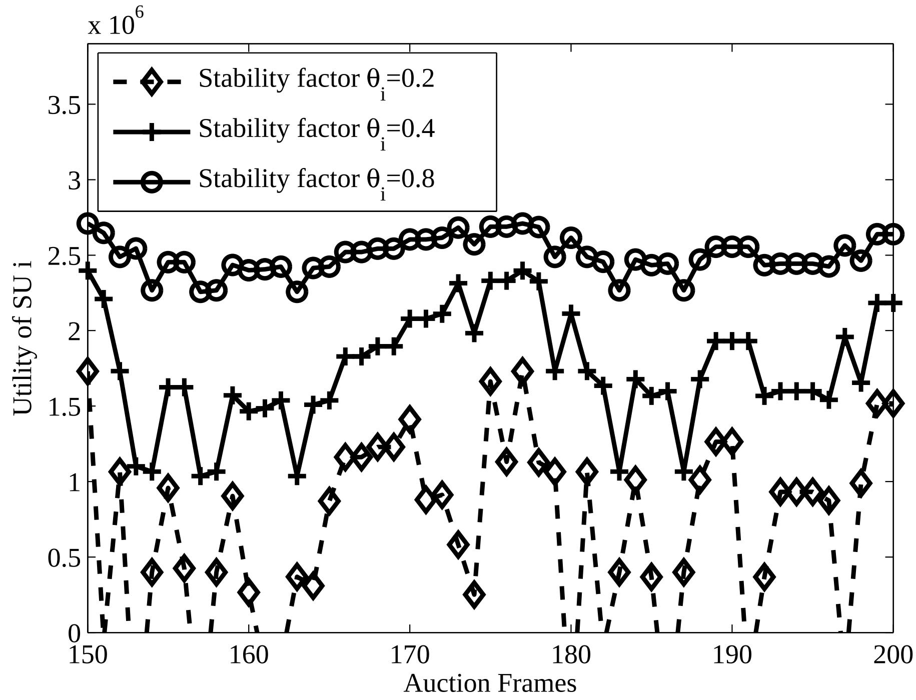

Figure 3.10: The utility of SU i with different stability factors in RMSA

factor, while fixing other SUs with spectrum demand 5 and stability factor $\theta = 0.2$. Fig. 3.9 shows that a larger spectrum demand cannot ensure a higher utility. Moreover, the utility is more unstable for the case with larger C_i because the actual recall quantity on SU i will also increase. Furthermore, since the winner determination is a knapsack problem, smaller spectrum demand guarantees a higher winning probability.

With $C_i = 5$, we change the stability factor of SU i, θ_i, to show the effect on its utility in Fig. 3.10. When $\theta = 0.2$, all the SUs in this auction are homogeneous with same spectrum demands and stability factor. Thus, the utility is highly fluctuated. Apparently, the spectrum can be more stable when θ_i continues to increase. The reason is that larger θ_i indicates higher payment for each channel, so that the actual recall ratio on SU i will decrease because of our proposed channel recall scheme. Moreover, Fig. 3.10 justifies that the SU's utility is monotonically increased with its stability factor. Therefore, it provides incentive compatibility for heterogeneous SUs to participate in this multi-winner spectrum auction since their different QoS requirements can be satisfied.

Chapter 4

Combinatorial Spectrum Auction with Multiple Heterogeneous Sellers in Cognitive Radio Networks

In this chapter, we propose a new combinatorial spectrum auction framework for the scenarios that each primary spectrum owner (PO) has multiple channels to sell and each secondary user (SU) demands multiple channels. Moreover, the heterogeneity in terms of POs' channel bandwidths and SUs' demands is also considered. The winner determination problem (WDP) in the proposed auction framework is formulated as a multiple multidimensional knapsack problem (MMKP). Both an upper bound and an approximation algorithm with polynomial time are developed. A tailored pricing mechanism is adopted in the payment design to ensure truthfulness and individual rationality. Numerical results show that our proposed auction algorithm can improve the spectrum allocation efficiency compared to counterparts.

4.1 System Model

Consider a CR network consisting of m primary spectrum owners (POs) and n secondary users (SUs). There is a non-profit central entity in the network, called *spectrum auctioneer*, who is responsible to run the auction, determine the winners, optimally assign the resources, and charge the payments. Each PO has a set of channels to serve its subscribed primary users (PUs). If at some time there are idle channels available, POs could allow the SUs to access these channels in order to obtain some extra profits. For each round of auction, let the number of auctioned channels provided by PO j be c_j. We assume that channels owned by the same PO are identical, whereas channels from different POs may be different in terms of channel bandwidth. Fig. 4.1 shows an example of this model.

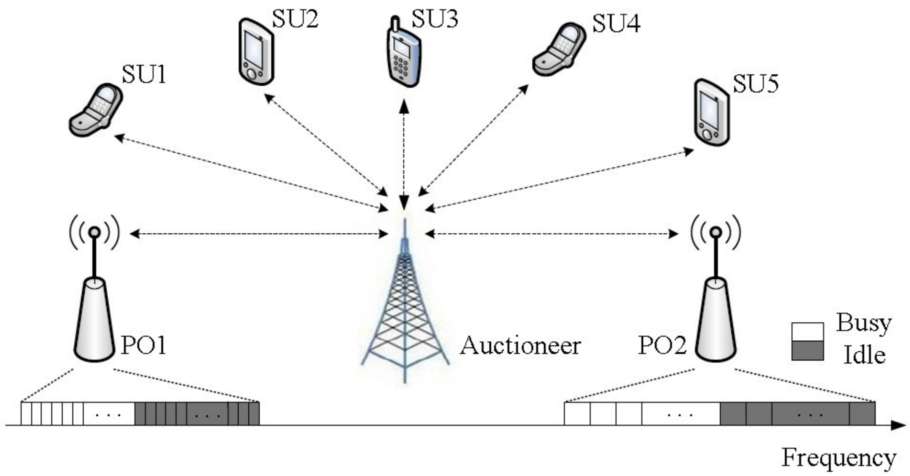

Figure 4.1: An example to illustrate the auction with heterogeneity among POs

All the SUs are within their interference ranges so that one channel cannot be accessed by multiple SUs simultaneously [12]. Each SU is allowed to access multiple channels to satisfy its specific spectrum demand. Since it is difficult for a radio device to employ multiple discontinuous spectrum bands from different spectrum operators [12, 63], we assume that each SU can only access the channels from the same PO.

At the beginning of the auction, each PO submits the number of auctioned channels and per channel bandwidth to the *spectrum auctioneer*. At the same time, each SU sends out its private information, including its specific spectrum demand and its bidding price. The auctioneer collects all these sealed-bid information and determines an optimal allocation scheme which leads to a social optimality. In addition, the auctioneer calculates the payments and payoffs for SUs and POs, respectively.

4.2 Combinatorial Spectrum Auction

In this section, the proposed combinatorial spectrum auction is discussed in details. We first formulate an optimization problem for spectrum allocation. After solving this optimization problem, a tailored pricing mechanism is designed as the payment function. At last, economic properties of the proposed auction are analyzed.

4.2.1 Winner Determination Problem (WDP)

Define a set of POs, $\mathcal{M}$, with $|\mathcal{M}| = m$. In order to represent the potential difference of the auctioned channels in terms of quantity and bandwidth, the auctioned channels are expressed by the following two vectors as

$$\boldsymbol{C} = (c_1, c_2, \ldots, c_j, \ldots, c_m) \tag{4.1}$$

$$\boldsymbol{BW} = (\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_j, \ldots, \hat{b}_m) \tag{4.2}$$

where $c_j \in Z^+$ indicates the number of auctioned channels from PO j and $\hat{b}_j \in R$ represents the bandwidth of PO j's channels.

Similarly, define a set of SUs, $\mathcal{N}$, with $|\mathcal{N}| = n$. Each SU has a specific spectrum demand, $d_i \in R$, $i = 1, \ldots, n$, and a private valuation for its demand, v_i, $i = 1, \ldots, n$. Note that d_i is only determined by SU i without consideration on channels' bandwidths of POs. Without loss of generality, let v_i be equal to the Shannon capacity SU i could achieve over d_i spectrum bandwidth as

$$v_i = d_i \log(1 + \beta_i) \tag{4.3}$$

where β_i is the signal-to-noise ratio (SNR), which is supposed to be a constant for SU i.

Obviously, in the formulated auction, there are m sellers (POs) and each seller has multiple goods (channels). Only SUs are bidders and the set of bid bundles is $\boldsymbol{B} = \{B_1, \ldots, B_i, \ldots, B_n\}$. Each bid B_i is specified as a 3-tuple $(d_i, p_i, \boldsymbol{w_i})$, where

- $d_i \in R$ is the spectrum demand of bidder i.
- $p_i \in R$ is the amount that the bidder is willing to pay for d_i. For truthful auction, the bidding price equals the true valuation, i.e., $p_i = v_i$.
- $\boldsymbol{w_i} = (w_{i1}, w_{i2}, \ldots, w_{ij}, \ldots, w_{im})$ with $\boldsymbol{w_i} \in Z^m$: w_{ij} is the number of channels SU i requested from PO j, which can be expressed as

$$w_{ij} = \left\lceil \frac{d_i}{\hat{b}_j} \right\rceil \tag{4.4}$$

  Note that $\boldsymbol{w_i}$ is actually calculated and automatically added into B_i by the *auctioneer* since each SU has no information about $\boldsymbol{BW}$.

After receiving $\boldsymbol{C}$, $\boldsymbol{BW}$, and $\boldsymbol{B}$, the *spectrum auctioneer* formulates an optimization problem as follows to determine the winners in order to maximize the social welfare, i.e., the total bidding price.

$\underline{\mathcal{P}1:}$

$$\max\ z = \sum_{j=1}^{m} \sum_{i=1}^{n} p_i x_{ij} \tag{4.5}$$

$$s.t \qquad \sum_{i=1}^{n} w_{ij} x_{ij} \leq c_j, \quad \forall j \in M, \tag{4.6}$$

$$\sum_{j=1}^{m} x_{ij} \leq 1, \qquad \forall i \in N, \tag{4.7}$$

$$x_{ij} \in \{0, 1\} \qquad \forall j \in M,\ \forall i \in N. \tag{4.8}$$

where

$$x_{ij} = \begin{cases} 1, & \text{if SU } i \text{ is allocated to PO } j \\ 0, & \text{otherwise.} \end{cases}$$

The first constraint means that for all SUs allocated to PO j, their total demands should be less than the number of channels PO j can offer. The second constraint limits each SU to access channels from no more than one PO. Apparently, $\mathcal{P}1$ is a binary integer programming (BIP) problem which is known to be NP-hard. If we consider POs as knapsacks and SUs as items, such an optimization problem can be treated as a 0-1 multiple multidimensional knapsack problem (MMKP). However, unfortunately, such MMKP is still NP-hard. In the next subsections, we will derive the upper bound of $\mathcal{P}1$ and propose a polynomial-time approximation algorithm.

4.2.2 Upper bound

Notice that the complexity of $\mathcal{P}1$ results from the fact that for a given channel demand, the number of channels requested from each PO is different. Thus, to easy the solution, we relax constraint (4.6) by allowing SUs to access fractional number of channels as

$$\sum_{i=1}^{n} d_i x_{ij} \leq c_j \hat{b}_j, \quad \forall j \in M, \tag{4.9}$$

With this relaxation, spectrum demand from each SU i keeps same to any PO so that $\mathcal{P}1$ is reduced to a multiple knapsack problem (MKP). In the following, we derive the upper bound of the MKP by using surrogate relaxation.

Define $(\pi_1, \ldots, \pi_m)$ as positive multipliers. The surrogate relaxed MKP can be written as $\underline{\mathcal{P}2:}$

$$\max \quad up(z) = \sum_{j=1}^{m} \sum_{i=1}^{n} p_i x_{ij} \tag{4.10}$$

$$s.t \qquad \sum_{j=1}^{m} \pi_j \sum_{i=1}^{n} d_i x_{ij} \leq \sum_{j=1}^{m} \pi_j c_j \hat{b}_j, \quad \forall j \in M, \tag{4.11}$$

$$\sum_{j=1}^{m} x_{ij} \leq 1, \qquad \forall i \in N, \tag{4.12}$$

$$x_{ij} \in \{0, 1\} \qquad \forall j \in M, \ \forall i \in N. \tag{4.13}$$

where the optimal choice of multipliers π_j should make the objective function in (4.10) minimized and hence obtain the tightest upper bound of MKP. For $\mathcal{P}2$, we have the following theorem, which has been proved in [70].

Theorem 4.2.1. *For any instance of MKP, the optimal choice of multipliers for surrogated relaxed MKP is $\pi_j = \xi$ for all $j \in M$, where ξ could be any positive constant.*

With this choice of π_j, $j \in M$, the formulated surrogate relaxed MKP becomes a general 0-1 single knapsack problem as

$\underline{\mathcal{P}3:}$

$$\max \quad up(z) = \sum_{i=1}^{n} p_i \cdot x'_i \tag{4.14}$$

$$s.t \quad \sum_{i=1}^{n} d_i x'_i \leq \sum_{j=1}^{m} c_j \hat{b}_j, \quad \forall j \in M, \tag{4.15}$$

$$x'_i \in \{0, 1\} \qquad \forall i \in N. \tag{4.16}$$

where the binary variable $x'_i = \sum_{j=1}^{m} x_{ij}$ indicates whether SU i wins the auction and $\sum_{j=1}^{m} c_j \hat{b}_j$ could be regarded as the total amount of spectrum that all POs can provide.

With these relaxations, the upper bound of $\mathcal{P}1$ can be obtained by solving the single knapsack problem $\mathcal{P}3$ by dynamic programming [71]. Although with the upper bound, we can derive the optimal solution of $\mathcal{P}1$ by applying the Branch & Bound technique [73], the high computational complexity involving in this procedure makes the solution infeasible for practical applications. In the following subsection, we proposed an approximation algorithm with polynomial solution time.

4.2.3 Polynomial-time Approximation Algorithm

Inspired by the approximation algorithm for MKP in [70], we propose a new approximation algorithm for solving MMKP in polynomial time. Note that, different from MKP, the weight of an item in MMKP depends on which knapsack it is assigned to. Thus, we redesign the algorithm by considering various channels demands on different POs from each SU.

After receiving all the bids, the *spectrum auctioneer* first sorts the SUs based on a decreasing order of $\frac{p_i}{\sqrt{d_i}}$[1], $i = 1, \ldots, n$, and POs according to an increasing order of the amount of auctioned spectrum, $c_j\hat{b}_j$, $j = 1, \ldots, m$, i.e.,

$$\frac{p_1}{\sqrt{d_1}} \geq \frac{p_2}{\sqrt{d_2}} \geq \ldots \geq \frac{p_i}{\sqrt{d_i}} \geq \ldots \geq \frac{p_n}{\sqrt{d_n}} \tag{4.17}$$

$$c_1 b_1 \leq c_2 b_2 \leq \ldots \leq c_j b_j \leq \ldots \leq c_m b_m \tag{4.18}$$

Note that in (4.17) and (4.18), the indices of SUs and POs have been rearranged and all the following searching procedure will follow this order.

We first derive an initial feasible solution by using the algorithm as shown in Algorithm 2. Define z as the overall bidding price of the auction winners, $\overline{c_j}$ as the remaining capacity (in terms of the number of channels) of knapsack (PO) j, $j = 1, \ldots, m$, and e_i as the status indicator of SU i , where

$$e_i = \begin{cases} 0, & \text{if SU } i \text{ is currently unallocated} \\ \text{index of the PO it is allocated to,} & \text{otherwise} \end{cases}$$

Algorithm 2 Initial Solution

$z = 0$;
for $i = 1$ to n **do**
    $e_i = 0$;
end for
for $j = 1$ to m **do**
    $\overline{c_j} = c_j$;
    call Greedy;
end for

The proposed algorithm considers the POs one by one. For each PO j, it calls the Greedy procedure, as shown in Algorithm 3, to allocate the channels to the unallocated SUs one by one unless the remaining capacity is smaller than the request from the SU. For each feasible allocation, the algorithm updates the following parameters as $e_i = j$,

[1] Although, it is more straightforward to make the order based on the unit bidding price, i.e., $\frac{p_i}{d_i}$, proposition 2.2.5 and [43] has proved that ordering bids with $\frac{p_j}{\sqrt{d_j}}$ can produce a solution with better performance in approximation ratio.

$\overline{c_j} = \overline{c_j} - w_{ij}$, and $z = z + p_i$.

Algorithm 3 Greedy

input: n, p_i, w_{ij}, z, e_i, j, $\overline{c_j}$;
output: z, e_i;
for $i = 1$ to n **do**
  if $e_i = 0$ **and** $w_{ij} \leq \overline{c_j}$ **then**
    $e_i = j$, $\overline{c_j} = \overline{c_j} - w_{ij}$, $z = z + p_i$;
  end if
end for

After that, we will improve the derived initial solution based on the idea of local exchanges. The improvement consists of three processes, i.e., rearrangement, interchange and replacement, as shown in Algorithms 4, 5, and 6, respectively.

- *Rearrangement*

  Consider all SUs with $e_i > 0$ according to the increasing order of $\frac{p_i}{\sqrt{d_i}}$. We rearrange these SUs one by one to the next available PO with sufficient remaining capacity in a cyclic manner. Note that, with rearrangement, the SUs with less demand may be assigned to the PO with small residual capacities so that more capacity in the current PO may be available to unallocated SUs. After rearrangement for all allocated SUs, greedy algorithm in Algorithm 3 will be recalled for all unallocated SUs.

- *Interchange*

  Interchange process considers all pairs of allocated SUs and, if possible, interchanges their PO assignment whenever doing so allows insertion of an unallocated SU to one of the knapsacks (POs). Through this algorithm, social welfare (the value of z) can be enhanced since the number of winning SUs would be increased.

- *Replacement*

  This process aims to replace any already allocated SU by one or more unallocated SUs so that the total profit is increased.

Algorithm 4 Rearrangement

$z = 0$;
for $j = 1$ to m **do**
  $\overline{c_j} = c_j$;
end for
$j = 1$;
for $i = n$ to 1 **do**
  if $e_i > 0$ **then**
    let l be the first index in $\{j, \dots, m\} \cup \{1, \dots, j-1\}$ such that $w_{il} \leq \overline{c_j}$;
    if no such l **then**
      $e_i = 0$
    else
      $e_i = l$, $\overline{c_l} = \overline{c_l} - w_{il}$, $z = z + p_i$;
      if $l < m$ **then**
        $j = l + 1$
      else
        $j = 1$;
      end if
    end if
  end if
end for
for $j = 1$ to m **do**
  call Greedy;
end for

Algorithm 5 Interchange

for $i = 1$ to n **do**
  if $e_i > 0$ **then**
    for $k = i + 1$ to n **do**
      if $0 < e_k \neq e_i$ **then**
        $h = \arg\max\{d_i, d_k\}$, $l = \arg\min\{d_i, d_k\}$;
        $d = d_h - d_l$;
        if $\lceil d/b_{e_l} \rceil \leq \overline{c_{e_l}}$ **and** $\overline{c_{e_h}} + \lceil d/b_{e_h} \rceil \geq \min\{w_{e_h u} | e_u = 0\}$ **then**
          $t = \arg\max_u\{p_u : e_u = 0 \text{ and } w_{e_h u} \leq \overline{c_{e_h}} + \lceil d/b_{e_h} \rceil\}$, $\overline{c_{e_h}} = \overline{c_{e_h}} + \lceil d/b_{e_h} \rceil - w_{e_h t}$, $\overline{c_{e_l}} = \overline{c_{e_l}} - \lceil d/b_{e_l} \rceil$, $e_t = e_h$, $e_h = e_l$, $e_l = e_t$, $z = z + p_t$;
        end if
      end if
    end for
  end if
end for

Obviously, by sequentially executing Algorithms 4 to 6, the initial greedy solution can be improved. Apparently, Algorithm 3 (Greedy) takes $O(n)$ time for at most $|\mathcal{N}|$ iterations.

Algorithm 6 Replacement

for $i = n$ to 1 **do**
  if $e_i > 0$ **then**
    $\overline{c} = \overline{c_{e_i}} + w_{e_i i}$, $Y = \emptyset$;
    for $k = 1$ to n **do**
      if $e_k = 0$ and $w_{e_i k} \leq \overline{c}$ **then**
        $Y = Y \cup \{k\}$, $\overline{c} = \overline{c} - w_{e_i k}$;
      end if
    end for
    if $\sum_{k \in Y} p_k > p_i$ **then**
      for each $k \in Y$ **do**
        $e_k = e_i$;
      end for
      $\overline{c_{e_i}} = \overline{c}$, $e_i = 0$, $z = z + \sum_{k \in Y} p_k - p_i$;
    end if
  end if
end for

Algorithms 2 and 4 call the Greedy process for m times so that in the worst case, $O(mn)$ operations are needed. The complexity of Algorithm 5 is $O(n^2)$ due to the updating of $\min\{w_{y_h u} | y_u = 0\}$ and the search for t. In addition, Algorithm 6 requires no more than $O(mn)$ operations. In conclusion, no step of our proposed approximation algorithm needs more than $O(n^2)$ time. Thus, the proposed approximation solution for $\mathcal{P}1$ can be achieved in a polynomial time.

4.2.4 Payment Rule

In this section, we aim to extend our algorithm to a strategy-proof auction mechanism by charging suitable prices. Note that the well-known Vickrey-Clarke-Groves (VCG) payment rule is inapplicable with approximate WDP algorithm [35]. Thus, we adopt the idea of *LOS pricing shceme* [43] which is to charge prices that are "Vickrey-like". Specifically, the payment of each winning SU should be a function of the highest-value bid that its bid *blocks*.

Definition 4.2.1 (blocks). *Suppose SU i with bid B_i won by the WDP algorithm while bids in set $\boldsymbol{B_{i^-}}$ were denied. The bid B_i* blocks *$\boldsymbol{B_{i^-}}$ if after removing SU i from bidders' set,* *all bids in $\boldsymbol{B}_{\boldsymbol{i}^-}$ would be granted.*

Based on this definition, our method calculates the payment of each SU i by distinguishing two cases:

- If SU i loses in the auction or it wins but *blocks* no other bid (i.e., $\boldsymbol{B}_{\boldsymbol{i}^-} = \emptyset$), then its payment is 0.
- If SU i is granted its demand d_i and $\boldsymbol{B}_{\boldsymbol{i}^-} \neq \emptyset$, the payment q_i of SU i is set as

$$q_i = \sqrt{d_i} \times \max_{k \in \boldsymbol{B}_{\boldsymbol{i}^-}} \left(\frac{p_k}{\sqrt{d_k}} \right) \tag{4.19}$$

After deciding the charges from all the winning SUs, the *spectrum broker* is also responsible to determine the payoffs to each PO based on the number of SUs allocated to it. The income of PO j, $\mathcal{I}_j$, can be easily derived as

$$\mathcal{I}_j = \sum_{i=1}^{n} x_{ij} q_i \tag{4.20}$$

4.2.5 Economic Properties

In this section, we prove that our proposed combinatorial spectrum auction framework is economically robust with individual rationality and incentive compatibility.

Theorem 4.2.2. *The proposed auction framework is individually rational for all truthful bidders (i.e., $p_i = v_i$), which means that all SUs would be guaranteed with non-negative utilities.*

Proof. The utility of SU i is zero if it loses the auction. Otherwise, the utility of winning SU i is calculated as

$$\begin{aligned} u_i &= v_i - q_i \\ &= p_i - \sqrt{d_i} \times \max_{k \in \boldsymbol{B}_{\boldsymbol{i}^-}} \left(\frac{p_k}{\sqrt{d_k}} \right) \\ &= \left[\frac{p_i}{\sqrt{d_i}} - \max_{k \in \boldsymbol{B}_{\boldsymbol{i}^-}} \left(\frac{p_k}{\sqrt{d_k}} \right) \right] \times \sqrt{d_i} \geq 0 \end{aligned} \tag{4.21}$$

The above inequality holds since SU i is a winner and thus $\frac{p_i}{\sqrt{d_i}} \geq \max_{k \in \boldsymbol{B}_{\boldsymbol{i}-}}(\frac{p_k}{\sqrt{d_k}})$ according to Definition 4.2.1. Hence, the payment scheme ensures non-negative utilities for SUs with truthful bidding information. $\square$

Theorem 4.2.3. *The proposed auction framework is incentive compatible, which means that no SU would expect a higher utility by untruthfully bidding.*

Proof. In order to prove this theorem, we need to go through two different cases:

- SU i wins the auction and gets utility $u_i \geq 0$ when bidding truthfully. In this situation, if SU i bids untruthfully ($p_i' \neq v_i$), there would be two possible outcomes, i.e., i) SU i loses the auction and gets $u_i = 0$; ii) SU i keeps winning and its utility becomes

$$\begin{aligned} \widehat{u_i} &= v_i - q_i' \\ &= v_i - \sqrt{d_i} \times \max_{k \in \boldsymbol{B}_{\boldsymbol{i}-}} \left(\frac{p_k}{\sqrt{d_k}} \right) = u_i \end{aligned} \tag{4.22}$$

- SU i loses the auction when bidding truthfully and get utility $u_i = 0$. Its utility would be changed only if SU i wins with a higher untruthful bid. Let p_i and p_i' denote truthful bidding and untruthful bidding, respectively. We have $\frac{p_i'}{\sqrt{d_i}} \geq \max_{k \in \boldsymbol{B'}_{\boldsymbol{i}-}}(\frac{p_k}{\sqrt{d_k}}) \geq \frac{p_i}{\sqrt{d_i}}$, otherwise SU i still cannot win the auction. In this case, its utility can be proved to be non-positive as

$$\begin{aligned} \widehat{u_i} &= v_i - q_i' \\ &= v_i - \sqrt{d_i} \times \max_{k \in \boldsymbol{B'}_{\boldsymbol{i}-}} \left(\frac{p_k}{\sqrt{d_k}} \right) \\ &\leq v_i - \sqrt{d_i} \times \frac{p_i}{\sqrt{d_i}} \\ &= v_i - p_i = 0 \end{aligned} \tag{4.23}$$

Therefore, SU i cannot increase its utility by bidding any other value than v_i. In other words, bidding truthfully is a dominant strategy for each buyer. $\square$

4.3 Numerical Results

In this section, we conduct simulations to evaluate the proposed auction algorithm in the scenario with multiple heterogeneous POs (both the number of auctioned channels and per channel bandwidth are different) and multiple SUs with different spectrum demands. For comparison purpose, the pure allocation (PA) is also simulated as the benchmark, which iteratively selects the unallocated SU with largest spectrum demand and assign it to POs regardless of its bidding price.

The considered CR network consists of 100 SUs and the number of POs varies from 5 to 50. For each PO j, $\forall j \in M$, the number of auctioned channels it offers is randomly selected in $[10, 20]$ Chs, and its channel bandwidth is randomly chosen in $[5, 20]$ MHz. For each SU i, $\forall i \in N$, its spectrum demand is determined randomly in $[50, 200]$ MHz, while its SNR β_i is random in $[100, 200]$. All results are based on the average over 1000 runs.

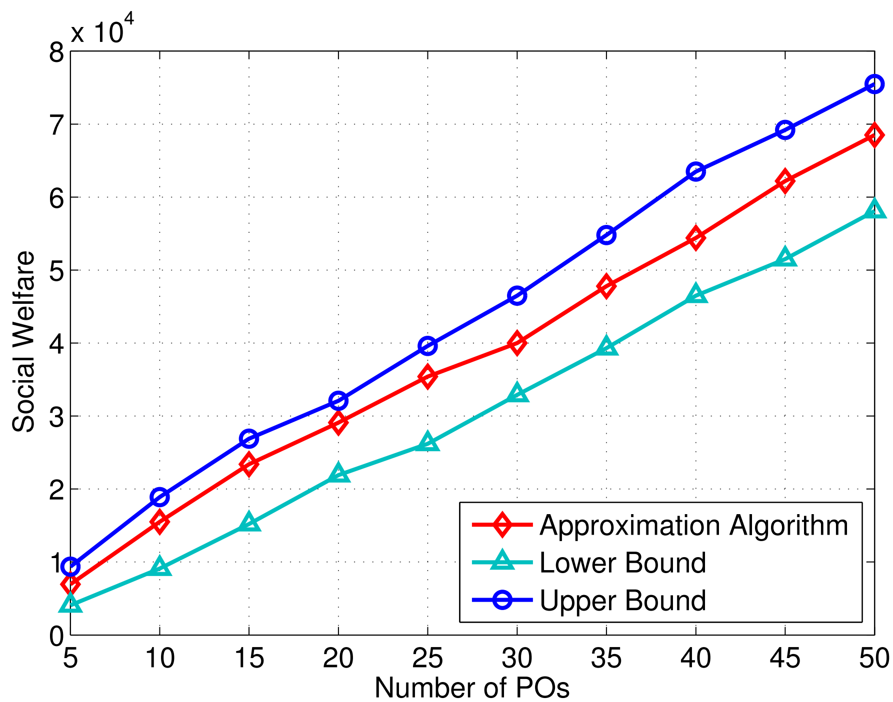

Figure 4.2: Performance of the proposed algorithms on WDP

Fig. 4.2 shows the social welfare with different solution algorithms to WDP. The upper bound is achieved by surrogate relaxation and lower bound is calculated according to the greedy algorithm. It shows that the proposed approximation algorithm can improve the initial result (by greedy algorithm) to a certain extent. Moreover, the curve of approximation algorithm is considerably close to the upper bound. Since the optimal solution cannot be obtained in polynomial-time and the approximation algorithm has demonstrated its sub-optimality in WDP, the proposed algorithm is more suitable for practical applications.

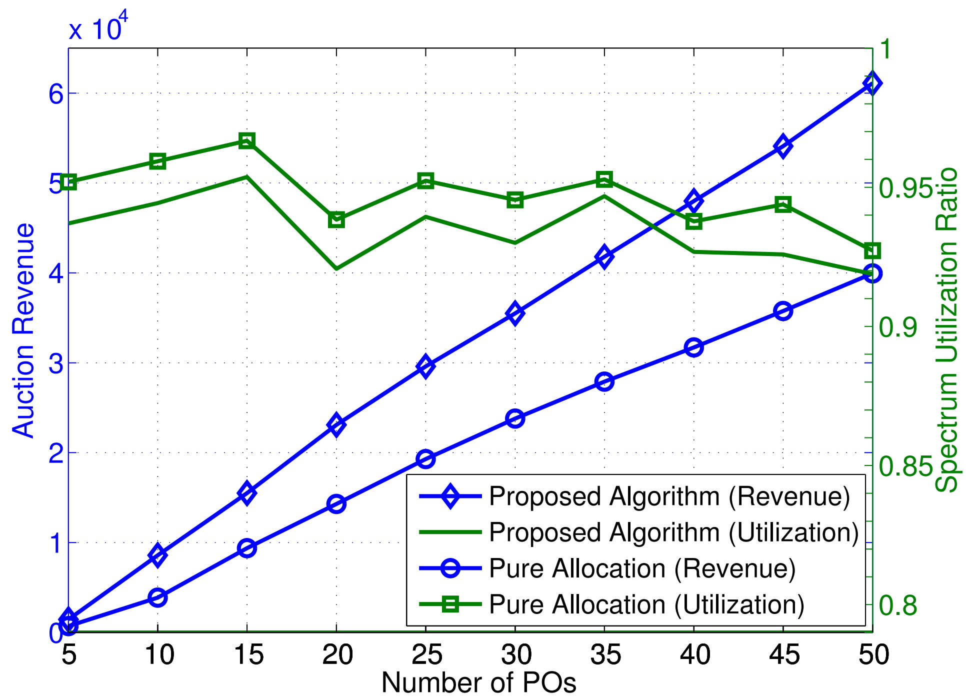

Figure 4.3: Performance on auction revenue and spectrum utilization

Compared with PA, Fig. 4.3 shows that our proposed algorithm could achieve much larger auction revenue. As a tradeoff, spectrum utilization ratio of PA is higher since it only aims to increase the allocation efficiency. However, with the consideration of heterogeneous channel bandwidth, the decrease of our proposed algorithm on spectrum utilization (at most 2.06%) is relatively small compare to the increase on auction revenue (averaged to 66.36%).

We further compare the buyers' satisfaction (number of winning SUs/number of total SUs) achieved by our proposed algorithm with the PA, as shown in Fig. 4.4. From the figure, we can figure out that a higher buyers' satisfaction ratio can be achieved by our proposed algorithm. Or, in other words, more SUs could be satisfied. It is because in our algorithm, SUs with small demands but high unit bidding prices would receive more attention.

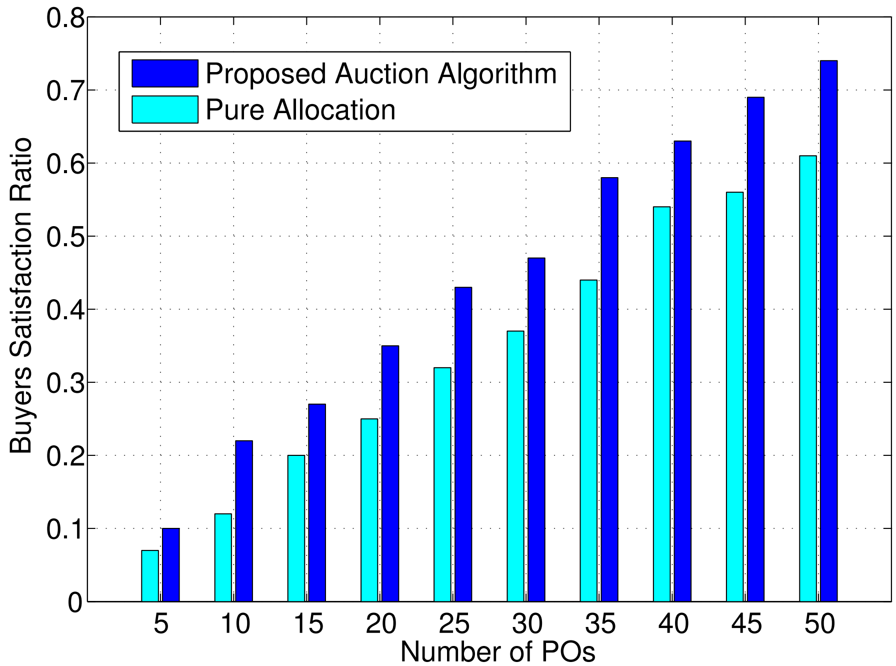

Figure 4.4: Comparison on buyers satisfaction ratio

Chapter 5

Conclusions and Future Works

5.1 Conclusion and Comments

In this thesis, the architecture, functions and development of CR networks are reviewed. More specifically, we focus on dynamic spectrum access and illustrate the research challenges in current CR design. In order to encourage all wireless users to participate in dynamic spectrum sharing, auction-based economical approaches are studied as our main contributions. In Chapter 2, some fundamental knowledge of auction theory and a comprehensive literature survey of existing spectrum auction algorithms are provided.

In Chapter 3, a recall-based spectrum auction among multiple heterogeneous secondary users (SUs) has been discussed. Both single winner and multiple winners cases are considered. In order to meet SUs' requirements on spectrum demands and stability, we propose new private valuation functions for single-minded SUs, and design RSSA and RMSA algorithms along with a new channel recall scheme. Theoretical and simulation results show that our proposed spectrum auction algorithm can improve the auction revenue of the primary base station and can enhance spectrum efficiency by adopting multiple winners. Moreover, SUs' heterogeneous quality of service requirements can be satisfied, which provides economic incentive for all the users to participate in the spectrum auction.

In Chapter 4, a new spectrum auction framework is proposed for CR networks with multiple multichannel primary spectrum owners (POs), heterogeneous POs' channel bandwidths, and multiple SUs. We formulate the winner determination problem (WDP) in the proposed auction frame as a multiple multidimensional knapsack problem (MMKP) and derive the upper bound through surrogate relaxation. An approximation algorithm is further proposed to solve the WDP in polynomial time. By adopting a "Vickrey-like" mechanism, we prove that such auction algorithm is economically robust. Numerical results indicate that our proposed auction algorithm could enhance the spectrum allocation efficiency in terms of auction revenue and buyers' satisfaction ratio.

5.2 Future Works

In our recall-based spectrum auction design, primary users (PUs) are always guaranteed with highest channel access priority. Thus, the primary base station (PBS) runs the auction with complete protection of PUs' QoS requirements. When demands of PUs raise, the PBS has no choice but finding a channel (e.g., through recall). However, if the PBS can tolerate some performance degradation to PUs, the amount of channel recall would become a strategy of the PBS and a multi-stage game has to be studied. For instance, we can allow each SU to strategize over a payment reduction, while the PBS calculates the best channel recall quantity based on the sub-game equilibrium of SUs.

Furthermore, we may consider multiple PBSs in our recall-based auction framework. Intuitively, the competition becomes two-sided and the idea of double auction may be appropriate for such scenario. In addition, we assume that the quality of channels are homogeneous which may not be feasible in practice. Considering potential channel heterogeneity would also change the basic auction model. For example, in our combinatorial spectrum auction design, the channel heterogeneity would definitely lead to various signal-to-noise (SNR) ratios and thus, makes the bidding price different for different POs' channels. In this case, WDP would be even more complicated than a MMKP.

Unlike conventional commodities, spectrum in wireless networks has its own characteristic that it can be reused. From sellers' side, spectrum auction can be processed separately in seller-defined geographic regions. Since spectrum can be regarded as a local resource and leased to wireless users who are within the coverage, spectrum sellers may declare different auction area and runs its auction locally, which is also referred as a local market. On the other hand, spectrum buyers can also reuse spectrum in either spatial or time domain, i.e., wireless users who are not interfered with each other can access a same channel simultaneously.

Reference

[1] J. Peha, "Spectrum management policy options," *Communications Surveys Tutorials, IEEE*, vol. 1, no. 1, pp. 2–8, 1998.

[2] P. Kolodzy and I. Avoidance, "Spectrum policy task force," *Federal Commun. Comm., Washington, DC, Rep. ET Docket*, no. 02-135, 2002.

[3] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201–220, Feb 2005.

[4] J. Peha, "Sharing spectrum through spectrum policy reform and cognitive radio," *Proceedings of the IEEE*, vol. 97, no. 4, pp. 708–719, April 2009.

[5] Q. Zhao and B. Sadler, "A survey of dynamic spectrum access," *Signal Processing Magazine, IEEE*, vol. 24, no. 3, pp. 79–89, May 2007.

[6] I. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *Communications Magazine, IEEE*, vol. 46, no. 4, pp. 40–48, 2008.

[7] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *Communications Surveys Tutorials, IEEE*, vol. 11, no. 1, pp. 116–130, 2009.

[8] A. Ghasemi and E. Sousa, "Spectrum sensing in cognitive radio networks: requirements, challenges and design trade-offs," *Communications Magazine, IEEE*, vol. 46, no. 4, pp. 32–39, April 2008.

[9] W. Wang, J. Cai, A. S. Alfa, A. C. Soong, and S. Li, "Adaptive dual-radio spectrum-sensing scheme in cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 13, no. 14, pp. 1247–1262, 2013.

[10] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey," *Comput. Netw.*, vol. 50, no. 13, pp. 2127–2159, Sep. 2006.

[11] Y. Zhang, C. Lee, D. Niyato, and P. Wang, "Auction approaches for resource allocation in wireless systems: A survey," *Communications Surveys Tutorials, IEEE*, vol. 15, no. 3, pp. 1020–1041, 2013.

[12] L. Gao, Y. Xu, and X. Wang, "MAP: Multiauctioneer progressive auction for dynamic spectrum access," *Mobile Computing, IEEE Transactions on*, vol. 10, no. 8, pp. 1144–1161, 2011.

[13] G. Wu, P. Ren, and Q. Du, "Recall-based dynamic spectrum auction with the protection of primary users," *Selected Areas in Communications, IEEE Journal on*, vol. 30, no. 10, pp. 2070–2081, November 2012.

[14] X. Zhou and H. Zheng, "TRUST: A general framework for truthful double spectrum auctions," in *INFOCOM 2009, IEEE*, April 2009, pp. 999–1007.

[15] J. Huang, R. A. Berry, and M. L. Honig, "Auction-based spectrum sharing," *Mob. Netw. Appl.*, vol. 11, no. 3, pp. 405–418, Jun. 2006.

[16] S. Gandhi, C. Buragohain, L. Cao, H. Zheng, and S. Suri, "A general framework for wireless spectrum auctions," in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, 2007, pp. 22–33.

[17] V. Krishna, *Auction Theory*. Academic Press, Mar. 2002.

[18] N. Nisan, *Algorithmic game theory*. Cambridge University Press, 2007.

[19] Y. Cai, C. Daskalakis, and S. M. Weinberg, "Optimal multi-dimensional mechanism design: Reducing revenue to welfare maximization," *Foundations of Computer Science, IEEE Annual Symposium on*, vol. 0, pp. 130–139, 2012.

[20] T. Sandholm, "Algorithm for optimal winner determination in combinatorial auctions," *Artif. Intell.*, vol. 135, no. 1-2, pp. 1–54, Feb. 2002.

[21] J. Mitola and J. Maguire, G.Q., "Cognitive radio: making software radios more personal," *Personal Communications, IEEE*, vol. 6, no. 4, pp. 13–18, Aug 1999.

[22] E. Hossain, D. Niyato, and Z. Han, *Dynamic spectrum access and management in cognitive radio networks*. Cambridge University Press, 2009.

[23] I. F. Akyildiz, W.-Y. Lee, and K. R. Chowdhury, "Crahns: Cognitive radio ad hoc networks," *Ad Hoc Netw.*, vol. 7, no. 5, pp. 810–836, Jul. 2009.

[24] R. Venkatesha Prasad, P. Pawelczak, J. Hoffmeyer, and H. Berger, "Cognitive functionality in next generation wireless networks: standardization efforts," *Communications Magazine, IEEE*, vol. 46, no. 4, pp. 72–78, April 2008.

[25] D. Hatfield and P. Weiser, "Property rights in spectrum: taking the next step," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 43–55.

[26] L. Xu, R. Tonjes, T. Paila, W. Hansmann, M. Frank, and M. Albrecht, "Drive-ing to the internet: Dynamic radio for ip services in vehicular environments," in *Local Computer Networks, 2000. Proceedings. 25th Annual IEEE Conference on*, 2000, pp. 281–289.

[27] W. Lehr and J. Crowcroft, "Managing shared access to a spectrum commons," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 420–444.

[28] O. Ileri, D. Samardzija, and N. Mandayam, "Demand responsive pricing and competitive spectrum allocation via a spectrum server," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 194–202.

[29] R. Etkin, A. Parekh, and D. Tse, "Spectrum sharing for unlicensed bands," *Selected Areas in Communications, IEEE Journal on*, vol. 25, no. 3, pp. 517–528, April 2007.

[30] Y.-C. Liang, Y. Zeng, E. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 4, pp. 1326–1337, April 2008.

[31] P. Sutton, K. Nolan, and L. Doyle, "Cyclostationary signatures in practical cognitive radio applications," *Selected Areas in Communications, IEEE Journal on*, vol. 26, no. 1, pp. 13–24, Jan 2008.

[32] B. Kasiri, J. Cai, A. Alfa, and W. Wang, "A distributed cooperative attack on the multi-channel spectrum sensing: A coalitional game study," in *Global Telecommunications Conference (GLOBECOM 2011), 2011 IEEE*, Dec 2011, pp. 1–5.

[33] R. A. Feldman and R. Mehra, "Auctions: theory and applications," *Staff Papers-International Monetary Fund*, pp. 485–511, 1993.

[34] P. Klemperer, "Auction theory: A guide to the literature," *Journal of economic surveys*, vol. 13, no. 3, pp. 227–286, 1999.

[35] N. Nisan and A. Ronen, "Computationally feasible vcg mechanisms," *J. Artif. Int. Res.*, vol. 29, pp. 19–47, 2007.

[36] M. J. Osborne and A. Rubinstein, *A course in game theory*. MIT press, 1994.

[37] R. B. Myerson, *Game theory*. Harvard university press, 2013.

[38] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *The Journal of finance*, vol. 16, no. 1, pp. 8–37, 1961.

[39] E. H. Clarke, "Multipart pricing of public goods," *Public choice*, vol. 11, no. 1, pp. 17–33, 1971.

[40] T. Groves, "Incentives in teams," *Econometrica: Journal of the Econometric Society*, pp. 617–631, 1973.

[41] D. Porter, S. Rassenti, A. Roopnarine, and V. Smith, "Combinatorial auction design," *Proceedings of the National Academy of Sciences*, vol. 100, no. 19, pp. 11 153–11 157, 2003.

[42] D. M. Kreps, *A course in microeconomic theory*. Harvester Wheatsheaf New York, 1990.

[43] D. Lehmann, L. I. Oćallaghan, and Y. Shoham, "Truth revelation in approximately efficient combinatorial auctions," *J. ACM*, vol. 49, no. 5, pp. 577–602, Sep. 2002.

[44] Y. Wu, B. Wang, K. Liu, and T. Clancy, "A scalable collusion-resistant multi-winner cognitive spectrum auction game," *Communications, IEEE Transactions on*, vol. 57, no. 12, pp. 3805–3816, 2009.

[45] S. Sengupta and M. Chatterjee, "Designing auction mechanisms for dynamic spectrum access," *Mob. Netw. Appl.*, vol. 13, no. 5, pp. 498–515, Oct. 2008.

[46] ——, "An economic framework for dynamic spectrum access and service pricing," *Networking, IEEE/ACM Transactions on*, vol. 17, no. 4, pp. 1200–1213, Aug 2009.

[47] L. Gao, J. Huang, Y.-J. Chen, and B. Shou, "An integrated contract and auction design for secondary spectrum trading," *Selected Areas in Communications, IEEE Journal on*, vol. 31, no. 3, pp. 581–592, 2013.

[48] F. Wu and N. Vaidya, "A strategy-proof radio spectrum auction mechanism in noncooperative wireless networks," *Mobile Computing, IEEE Transactions on*, vol. 12, no. 5, pp. 885–894, 2013.

[49] S. wook Han and Y. Han, "A competitive fair subchannel allocation for ofdma system using an auction algorithm," in *Vehicular Technology Conference, 2007. VTC-2007 Fall. 2007 IEEE 66th*, Sept 2007, pp. 1787–1791.

[50] W. Wang, B. Li, and B. Liang, "District: Embracing local markets in truthful spectrum double auctions," in *Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2011 8th Annual IEEE Communications Society Conference on*, 2011, pp. 521–529.

[51] X. Feng, Y. Chen, J. Zhang, Q. Zhang, and B. Li, "TAHES: A truthful double auction mechanism for heterogeneous spectrums," *Wireless Communications, IEEE Transactions on*, vol. 11, no. 11, pp. 4038–4047, 2012.

[52] L. Xiang, G. Sun, J. Liu, X. Wang, and L. Li, "A discriminatory pricing double auction for spectrum allocation," in *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, 2012, pp. 1473–1477.

[53] Z. Zheng, F. Wu, and G. Chen, "SMASHER: a strategy-proof combinatorial auction mechanism for heterogeneous channel redistribution," in *Proceedings of the fourteenth ACM international symposium on Mobile ad hoc networking and computing*, ser. MobiHoc '13, 2013, pp. 305–308.

[54] H.-J. Lim, M.-G. Song, and G.-H. Im, "Cooperation-based dynamic spectrum leasing via multi-winner auction of multiple bands," *Communications, IEEE Transactions on*, vol. 61, no. 4, pp. 1254–1263, 2013.

[55] Z. Chen, H. Huang, Y. e Sun, and L. Huang, "True-MCSA: A framework for truthful double multi-channel spectrum auctions," *Wireless Communications, IEEE Transactions on*, vol. 12, no. 8, pp. 3838–3850, August 2013.

[56] L. Deek, X. Zhou, K. Almeroth, and H. Zheng, "To preempt or not: Tackling bid and time-based cheating in online spectrum auctions," in *INFOCOM, 2011 Proceedings IEEE*, April 2011, pp. 2219–2227.

[57] S. Li, Z. Zheng, E. Ekici, and N. Shroff, "Maximizing social welfare in operator-based cognitive radio networks under spectrum uncertainty and sensing inaccuracy," in *INFOCOM, 2013 Proceedings IEEE*, April 2013, pp. 953–961.

[58] S. Sodagari, A. Attar, and S. Bilen, "On a truthful mechanism for expiring spectrum sharing in cognitive radio networks," *Selected Areas in Communications, IEEE Journal on*, vol. 29, no. 4, pp. 856–865, April 2011.

[59] P. Xu and M. Li, "TOFU: Semi-truthful online frequency allocation mechanism for wireless networks," *Networking, IEEE/ACM Transactions on*, vol. 19, no. 2, pp. 433–446, April 2011.

[60] S. Wang, P. Xu, X. Xu, S. Tang, X. Li, and X. Liu, "Toda: Truthful online double auction for spectrum allocation in wireless networks," in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, April 2010, pp. 1–10.

[61] P. Xu, S. Wang, and M. Li, "SALSA: Strategyproof online spectrum admissions for wireless networks," *Computers, IEEE Transactions on*, vol. 59, no. 12, pp. 1691–1702, Dec 2010.

[62] K.-H. Liu, X. Ling, X. Shen, and J. W. Mark, "Performance analysis of prioritized MAC in UWB WPAN with bursty multimedia traffic," *Vehicular Technology, IEEE Transactions on*, vol. 57, no. 4, pp. 2462–2473, 2008.

[63] D. Xu, E. Jung, and X. Liu, "Efficient and fair bandwidth allocation in multichannel cognitive radio networks," *Mobile Computing, IEEE Transactions on*, vol. 11, no. 8, pp. 1372–1385, 2012.

[64] Y. Yuan, P. Bahl, R. Chandra, P. Chou, J. Ferrell, T. Moscibroda, S. Narlanka, and Y. Wu, "KNOWS: Cognitive radio networks over white spaces," in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, 2007, pp. 416–427.

[65] D. Xu, E. Jung, and X. Liu, "Optimal bandwidth selection in multi-channel cognitive radio networks: How much is too much?" in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, 2008, pp. 1–11.

[66] N. Benvenuto and M. Zorzi, Eds., *Principles of Communications Networks and Systems*. John Wiley & Sons, Inc., 2011.

[67] M. Roger B., *Game Theory : Analysis of Conflict*. Harvard University Press, 1997.

[68] A. Likhodedov and T. Sandholm, "Methods for boosting revenue in combinatorial auctions," in *Proceedings of the 19th national conference on Artifical intelligence*, ser. AAAI'04, 2004, pp. 232–237.

[69] P. V. David Tse, *Fundamentals of Wireless Communication*. Cambridge University Press, 2005.

[70] S. Martello and P. Toth, *Knapsack problems: algorithms and computer implementations*. New York, NY, USA: John Wiley & Sons, Inc., 1990.

[71] H. Kellerer, U. Pferschy, and D. Pisinger, *Knapsack Problems*. Springer, 2004.

[72] D. Niyato and E. Hossain, "Market-equilibrium, competitive, and cooperative pricing for spectrum sharing in cognitive radio networks: Analysis and comparison," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 11, pp. 4273–4283, 2008.

[73] Y. Song, C. Zhang, and Y. Fang, "Multiple multidimensional knapsack problem and its applications in cognitive radio networks," in *Military Communications Conference, 2008. MILCOM 2008. IEEE*, 2008, pp. 1–7.

Publication List

[1] **C. Yi** and J. Cai, “Multi-item Spectrum Auction for Recall-based Cognitive Radio Networks with Multiple Heterogeneous Secondary Users,” *IEEE Transactions on Vehicular Technology*, accepted.

[2] **C. Yi** and J. Cai, ”Combinatorial Spectrum Auction with Multiple Heterogeneous Sellers in Cognitive Radio Networks,” *IEEE International Conference on Communications (ICC’2014)*, Sydney, Australia, June 10-14, 2014.