Resource Allocation in Traditional and Cooperative Cognitive Radio Networks

by

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfilment of the requirements of the degree of

MASTER OF SCIENCE

Department of Electrical and Computer Engineering

University of Manitoba

Winnipeg

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Abstract

Cognitive radio (CR) is a promising technique to improve spectrum efficiency for wireless communications. This thesis focuses on the resource allocation in two kinds of CR networks (CRNs), traditional CRNs (TCRNs) and cooperative CRNs (CCRNs). In TCRNs, CR sources and destinations communicate directly. By exploring the heterogeneity among CRs, a prioritized CSMA/CA is proposed for demand-matching spectrum allocation. A distributed game is formulated and no-regret learning is adopted to solve the game. Simulation results indicate increase on the number of satisfied CRs. In CCRNs, some nodes are selected as relays to assist the communication. A two-layer auction game is proposed with the first layer performing spectrum allocation and relay formation, and the second layer performing relay allocation. These two layers interact and jointly solve the resource allocation problem. Simulation results show that, compared to counterparts, both the network throughput and convergence time can be improved.

Acknowledgments

First, I would like to express my sincere gratitude to my adviser, Dr. Jun Cai, for all his patience and guidance during this tow year's program. His guidance helped me in all the time of research and writing of this thesis. Without his encouragement and advice, this thesis would not have been possible.

Besides my advisor, I would like to thank the rest of my advisory committee: Dr. Attahiru Alfa and Dr. Quan Wang, for their insightful comments and invaluable advice.

My sincere thanks also goes to all the academic professors in the Electrical and Computer Engineering department at the University of Manitoba, who have offered lectures and great help to me.

I thank my fellow labmates in the Robert Alan Kandy Communication Lab and Communication and Network Engineering Research (CNER) group, for the stimulating discussions in learning and research.

Finally, I would like to thank my family, for their boundless love which supports me spiritually throughout my life.

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1 Introduction

1.1 General Background

Limited spectrum results in the bottleneck for the development of wireless communications and for a long time it is a key issue in telecommunications research. However, in 2002 the common belief of spectrum scarcity was challenged by a report [1] from the Federal Communications Commission (FCC) that less than 10 percent of available spectrum is utilized at a given time and location. Even for licensed spectrum, the utilization portions are between 15 to 85 percent with a high variance in time [2]. The report also claimed that rather than spectrum scarcity, spectrum access is a more significant problem due to the legacy command-and-control regulation. The target to exploit these underutilized spectrum resources motivates the need for Cognitive Radio (CR), a technique that is capable of dynamically accessing spectrum through learning the environment and avoiding disruptions to Primary Users (PUs), i.e., the licensed users who own the spectrum. An example of the PUs is the analog TV broadcast stations.

The concept of CR was first presented by Mitola in 1998 in a seminar and later published in 1999 [3], as a novel approach in wireless communications to detect users' communication demands, to analyze the communication environment, and to adjust users' communication parameters in response to environment and user demands. It was proposed as an ideal goal for software-defined radio (SDR) platform to evolve. However, after FCC's report, CR is more preferred to be defined as a technique for radios which is capable to access spectrum opportunistically. It is expected to be a powerful technique to further improve the spectrum efficiency for the next generation wireless communication networks [2]. Today, it has been adopted by the IEEE 802.22 working group in developing standards for wireless regional area networks (WRANs) [4].

As secondary users to the spectrum, CRs are expected to be transparent to PUs. The key issue in CR networks is to provide suitable bandwidth to CR users without harming PUs through efficient resource allocation. In a CR network (CRN), a CR needs to sense a wide range of frequency band to find spectrum holes [5], the bands that have not been occupied by PUs, and selects an idle channel from these spectrum holes to transmit [6]. However, the channel selection problem is challenging as the channel availability dynamically changes over time and locations [7] [8]. Also, CRs competing on the same channels should be coordinated as to improve the network performance, e.g., the number of satisfied CRs in the network. In this thesis, we define it as the resource allocation problem in traditional CRNs (TCRNs). The TCRN denotes the scenarios that the CR transmitter communicates directly with the CR receiver or base station (BS).

Recently, there is a trend to introduce another important technology in wireless communications, called cooperative communication, which can offer significant benefits in capacity improvement [9], energy efficiency [10], outage probability deduction [11] and coverage range extension [12]. With the integration of cooperative communication, the cooperative cognitive radio networks (CCRNs) can further improve the network performance, while inducing new challenges to the resource allocation [13]. For example, in CCRNs, the resource allocation may not only address the traditional spectrum sharing problems in TCRNs, but also conduct relay formulation and relay allocation to communication pairs.

Our research motivation is to design efficient resource allocation algorithms for both TCRNs and CCRNs to improve the spectrum utilization and network performance in terms of satisfied traffic demands. Considering the properties of both kinds of CRNs, distinct objectives have been settled with the consideration of specific challenges, which in turn contribute to the algorithms design. Both algorithms should provide demand-matching resource allocation, network performance maximization and short convergence time.

1.2 Contribution of This Thesis

The contribution of this thesis consists of two aspects: 1) for TCRNs, a demand-matching spectrum sharing algorithm has been proposed. The heterogeneity among users, i.e., difference in user demands, spectrum availability, and spectrum quality, is explored. A distributed cooperative game is formulated with classified players. Prioritized CSMA/CA is adopted as the spectrum sharing technique, and CRs select channels and their priority to access channel based on their satisfaction history, a public signal for CRs to collaborate with others to achieve the Correlated Equilibrium (C.E.), a strategic solution of the game. A no-regret learning algorithm is adopted to learn the C.E. Simulation results show that the classified game can achieve up to 40% better performance compared to the unclassified game. This work has contributed to a conference paper which was accepted by the 6th International ICST Wireless Internet Conference (WICON); 2) A two-layer auction based resource allocation algorithm for CCRNs is proposed. Starting from a homogeneous network without predefined relays, CRs allocated with abundant resources become amateur relays to provide connectivity for those allocated with insufficient resources to the BS. Resource allocation to these relays is based on their channel connectivity to the BS, their own traffic demands, their channel connectivity to neighboring nodes, and the neighboring nodes' traffic demands. A modified time division multiple access (TDMA) scheme is adopted as the sharing technique. Prices charged by the BS for licensed channels and by the relays for assisting communications are used to leverage the resource allocation. A fast converging suboptimal algorithm is provided for the single level multi-buyer multi-seller multi-slot auction, and a modified two level auction algorithm is adopted to accelerate the convergence. Compared with the CRN without relay and the CRN with predefined relays, simulation results show that our algorithm can increase the network throughput significantly. This work is aimed to contribute to another conference paper, which will be submitted to IEEE ICC 2012.

1.3 Outline of This Thesis

The rest of the thesis is organized as follows. Chapter 2 introduces the background information and the related works. Motivated by the limits of existing spectrum sharing algorithms in TCRNs, a new demand matching spectrum sharing algorithm, called C.E. based classified game (CECG), has been proposed in Chapter 3. In Chapter 4, a two-layer auction game (TLAG) based resource allocation algorithm has been proposed by integrating demand matching, spectrum sharing and relay selection. Finally, Chapter 5 concludes the thesis with a discussion of possible extension and future research works in this area.

2 Background and Related Works

In this Chapter, background knowledge and related works on resource allocation in cognitive radio networks (CRNs) are introduced as the foundation for future reference. First, an overview of CRNs is presented with the introduction to the evolution and properties of CRNs and spectrum management in CRNs. After that, a description on resource allocation in traditional CRNs (TCRNs) is provided, where the objectives and the classification of resource allocation in TCRNs are briefly discussed. As the game theory has been widely applied in resource allocation modeling in CRNs, an overview of game theory is also presented. Finally, to illustrate the new arising concept of cooperative CRNs (CCRNs), we will briefly introduce the cooperative communication, and then the motivations and ideas of some recent research works on CCRNs are discussed.

2.1 Overview of Cognitive Radio Networks

2.1.1 The Evolution of Cognitive Radio Networks

Defined by Mitola [14], software defined radios (SDRs) is a radio frequency (RF) front end with a software-controlled tuner which is reconfigurable for the modulation scheme. In Mitola's dissertation [15], he extended the idea of SDR further to the concept of cognitive radio (CR). CR essentially strengthens SDR with artificial intelligence, so that it is capable of sensing the demands and the communication environment, and reacting accordingly. Mitola's definition of CR paid much attention on CRs' capacity in learning and adjusting to the environment.

Variant from Mitola's definition, the Federal Communications Commission (FCC) later proposed another more widely accepted definition of CR [1]. According to FCC, CRs are radios which could use licensed bands, provided they check the intense interfere with existing primary users (PUs). Rather than allowing CRs only to access channels not occupied by PUs (called CR overlay networks), FCC also proposed the interference temperature model [16], which allows CRs to access channels as long as the interference they introduced to PUs is less than a certain limit. This is called CR underlay networks.

In practice, started from 2004, the IEEE 802.22 standardization on Wireless Regional Area Networks (WRAN) is the first worldwide effort to define a standardized air interface based on CR techniques [17]. It aims at using CR techniques to allow broadband access to geographically unused spectrum allocated to the Television Broadcast Service on a non-interfering basis in rural areas. IEEE 802.22.1 Standard for the Enhanced Interference Protection of the Licensed Devices was published as an official IEEE standard on November 1, 2010 [18].

2.1.2 Properties of Cognitive Radio Networks

Although the CR networks (CRNs) share some similarities with traditional networks, certain properties make them unique [19]. For example, CRNs should be transparent to primary user, i.e., as in overlay CRNs, when primary users are using the spectrum, CRN should not access the same one, or as in underlay CRNs, the interference introduced by all CRs should be less than the interference temperature at the PUs. Thus, PUs' activity, i.e., switching between on/off and mobility, may severely impact the operation of CR networks in three aspects: 1) Spectrum availability of CRs may vary due to primary users' activity. This issue is called spectrum variability; 2) For a CRN under several different PUs, because each PU's activity may differ from each other, spectrum available to CR nodes in different locations may differ, which is called the spectrum heterogeneity. Such spectrum heterogeneity could become more severe if the CRN operates under several different PU networks. 3) PUs may also introduce interference to the CRNs in the underlay scenario.

2.1.3 Spectrum Management in Cognitive Radio Networks

The key issue in CRNs is to provide enough bandwidth to CR users without harming PUs via dynamic spectrum access. To achieve dynamic spectrum access, the CRN needs to realize following spectrum management functions [20] [21] [22]:

• sense spectrum holes, i.e., determine which portions of the spectrum are available. It provides the spectrum availability information to other spectrum management functions as well as upper layer, e.g., routing protocols. A detailed description of this function can be found in [23] [24] [25].

• make spectrum decision, i.e., select the best available spectrum holes. In the spectrum hole selection, it is important to characterize the spectrum band in terms of both radio environment and the statistical behaviors of the PUs. Because of the spectrum variability property, a prediction of PU activity should be conducted to incorporate dynamic spectrum characteristics in the decision making.

• divide the spectrum holes into channels and perform spectrum sharing, or to coordinate access to these channels with other users as well as to conduct resource allocation. As multiple CRs may compete to access the same spectrum, their transmissions should be coordinated to prevent collisions and at the same time to limit the interference to PUs. In the underlay CRNs, resource allocation may refer to the power allocation. The game theoretical approaches are commonly used to reach an equilibrium with low complexity, high output, and good fairness [26]. Furthermore, the spectrum sharing function necessitates a CR medium access control (MAC) protocol, which facilitates the sensing control to distribute the sensing task among the coordinating nodes as well as spectrum access to determine the scheduling for transmission.

• switch to another channel when a PU needs to use the current one. This procedure is named as spectrum mobility. If a PU is detected in the portion of the spectrum in use, CRs should vacate the spectrum immediately and try to find another vacant portion of the spectrum to continue their communications. For this, either a new spectrum must be chosen or the affected links may be circumvented entirely. Thus, spectrum mobility necessitates a spectrum handoff scheme to detect the link failure and to switch the current transmission to a new route or a new spectrum band with minimum quality degradation. This requires collaboration with spectrum sensing, neighbor discovery in a link layer, and routing protocols. Furthermore, this functionality needs a connection management scheme to sustain the performance of upper layer protocols by mitigating the influence of spectrum switching.

A summary of the interaction among the aforementioned functions can be found in Fig. 1 [21].

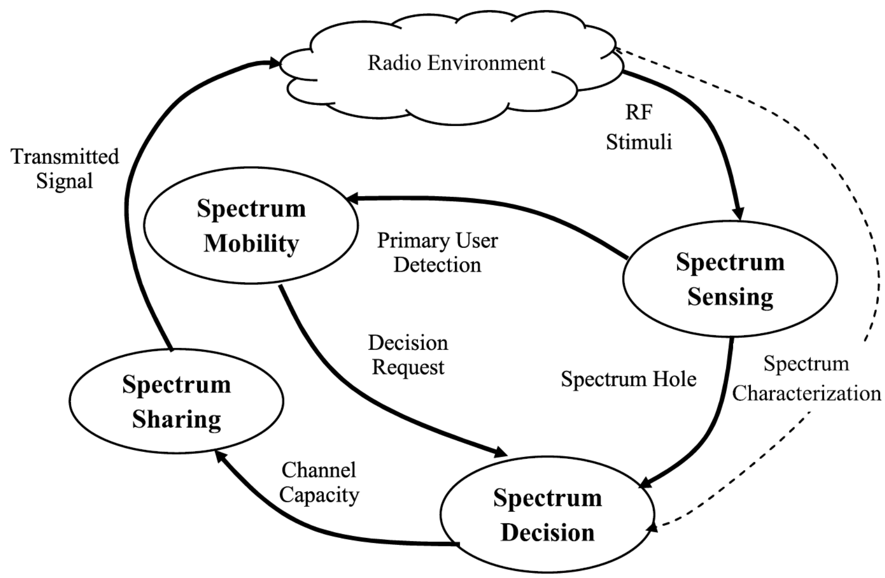

Figure 1: Cognitive Radio cycle

2.2 Resource allocation in Traditional Cognitive Radio Networks

Since TCRNs are the basic form of CRNs and the problems in TCRNs will also be encountered in other forms of CRNs, we adopt CRNs other than TCRNs in follows without ambiguities. In CRNs, the resource refers to the available spectrum and power. The resource allocation could be viewed as a combination of spectrum decision and spectrum sharing. In the resource allocation procedures, CRs must obey certain interference constraints so that their transmission will not interfere the communication of PUs. Moreover, communication in CRNs should be coordinated so as to improve the performance, e.g., network throughput. In this way, they are envisioned to be aware of the physical environment and capable to adjust their transmission to the environment, which are the basic requirements for spectrum sharing techniques.

2.2.1 Objectives

Resource allocation algorithms coordinate CRs to access available channels. Main objectives of resource allocation are [27]:

- interference protection. As CRs are secondary users to the spectrum, their interference to PUs should be limited.
- efficiency, i.e., to maximize the performance (e.g., throughput) of the CRNs.
- fairness. CRs should share equal rights to utilize the spectrum. Besides, the pay and return of each user should be balanced.

2.2.2 Challenges and Requirements

Because of the aforementioned properties of CRNs, there are many challenges and new requirements for the realization of efficient and seamless resource allocation. For example, how to encourage PUs to share their spectrum to CRs is an important issue for the implementation of CR. Many trading models have been built for this problem. In [28], CRs need to pay PUs for their access to licensed spectrum to stimulate PUs. Another challenge is on exchanging control information between CRs. In order to coordinate communications in the CRN, each CR's state information, e.g., channel availability and decision information (i.e., which channel it will select) should be exchanged with other CRs. It could be performed via a common control channel (CCC) which covers the whole network. However, a CCC may not be available to all CRs since non-neighboring CR users may have different views of spectrum availability as the result of spectrum heterogeneity. Even a CCC is available to all CRs, it could become a bottleneck as the control information exchanging is limited by the bandwidth of this CCC [29]. Since such CCC is very precious and the control information exchanging may introduce high overhead, distributed algorithms which based on local information only are preferred. Moreover, because of the spectrum variability, resource allocation algorithms are expected to be adaptive to the dynamic environment.

2.2.3 Algorithm Classifications

Numerous algorithms have been proposed to solve the resource allocation problem. In general, they can be classified based on three aspects: the architecture, the spectrum access technique and the spectrum allocation behavior.

Based on the architecture, algorithms can be classified to be centralized or distributed:

- Centralized algorithms: Spectrum allocation and access focus on infrastructure-based networks, in which a centralized coordinator or base station manages the spectrum allocation and sharing among the CR users [30]. The CRs, however, may participate in the spectrum sensing and provide channel information to the central controller.

- Distributed algorithms: Spectrum allocation and access are based on local information and local policies performed by each node distributively [31]. The introduction of distributed algorithms is mainly due to the ad hoc manner of the scenarios and the limitation of CCC.

According to the access technologies applied, the algorithms can be classified to be overlay and underlay :

- Overlay algorithms: CRs access the network by using a portion of the spectrum that is not used by PUs [32]. This minimizes interference to the primary network.

- Underlay algorithms: The spread spectrum techniques are commonly exploited so that the transmission of a CR is regarded as noise by PUs [33]. The power allocation among channels should be carefully performed so as to optimize the network performance as well as to guarantee that the interference to PUs is below the interference limits. Besides, the power limit of CR transceiver and the multi-user interference among CRs introduce constraints to this optimization problem. In [34], a modified water-filling algorithm in CDMA-OFDM underlay CRNs is proposed to maximize the network throughput. Although underlay techniques can utilize higher bandwidth, since it is not easy to acquire the interference limits (e.g. interference temperature) at every CR for every PU, the application of underlay algorithms is limited.

Based on the access behavior, the resource allocation algorithms can be classified to be cooperative or non-cooperative:

- Cooperative algorithms: Cooperative algorithms consider the effect of one CR's communication on other nodes and aim to maximize the performance of the whole network other than each individual CR. Note that here the "co-operative" refers to the type of algorithms, while in CCRNs, the "cooperative" refers to the cooperative communication. The interference measurements of each CR are shared with other CRs and are adopted by the spectrum allocation algorithms. In fact, all the centralized algorithms are belong to this category as the central controller maximizes the whole network performance [35]. There are also some distributed cooperative algorithms. For example, in [36], a distributed pricing algorithm was proposed to maximize the total profit of the CRNs, and cooperation exists among primary service providers.

- Non-cooperative algorithms: Contrary to the cooperative solutions, non-cooperative algorithms are selfish [37]. They are ordinarily performed distributively and aim to maximize local performance. Non-cooperative algorithms may result in low spectrum utilization. However, on the other hand, it reduces the communication requirements on exchanging control information. In practice, such trade-off should be balanced.

2.3 Game Theory

Game theory studies the behavior of interacting decision-makers, i.e., the players of the game, and suggests reasonable solutions for these games based on the players' preference and interactions. The application of game theory in resource allocation among multi-users, especially in CRNs where distributed, flexible and scalable control mechanisms are required, is appealing for its adaptivity to the environment, low complexity and distributed manner. As our proposed algorithms are based on game theory, basic information of game theory, classifications of games, and some applications in CRN are introduced in this section. More details can be found in [38].

2.3.1 Basic Elements of A Game

The basic elements of a game consist of the participants of the game (the decision-makers, or the players), the action (decision) space of these players, the outcomes corresponding to these actions, and the preference of these players on the outcomes, i.e., the utility function [39]. The details of each elements are shown as follows.

(1) Rational Players Each player is assumed to be "rational" as he has clear preferences on the outcomes of his actions, and chooses his action as a process to optimize the outcome. But it does not imply that the player is self-interested, as the outcomes could be defined as the global welfare other than individual profit, which results in a cooperative game. The concept and properties of cooperative and non-cooperative game will be discussed in details later.

(2) Action Space The action space is a set of actions from which the player makes his decision. Considering the interaction among players, the action space is also constrained by all other players.

(3) Utility Functions Each player may have different preferences for the outcome of a game. Utility is the numerical value that represents the preference of the players. Mathematically, a consequence function $g : A \to C$ associates the action space A with the corresponding outcome space C. The utility function $U : C \to \mathbb{R}$ defines a preference relation $\succeq$, i.e., $x \succeq y$ if and only if $U(x) \geqslant U(y)$. A rational player chooses an action $a* \in A$ which solves the problem $\arg\max_{a \in A} U(g(a))$.

(4) Information In the rational decision-making process, the players may need to learn certain information from the environment and other players, i.e., the utility corresponding to the action, actions of the other players, and the rationality of the other players.

2.3.2 Classifications of Games

Games can be classified based on different criterion as follows.

(1) Non-cooperative and Cooperative Games In a game, a player may interact with other players in making a decision. Two types of game model can be classified based on the players' behavior of decision-making: those in which the players choose action individually are referred as non-cooperative [40], while games where groups of players may enforce cooperative behavior, i.e., formulating coalitions by commitments, and competing among coalitions rather than among individual players, are referred as cooperative [41].

(2) Strategic Games, Extensive Games and Repeated Games In a strategic game, all players make decisions simultaneously and only for once, so that each player is not aware of other players' decisions when it is making decision. In contrast, in an extensive game, the sequencing of players' possible decisions are important. Players may have chance to make their decisions in different time, and when a player needs to make decision, it may take its previous players' decisions into consideration. The repeated game is a special type of extensive game. In a repeated game, although all players make decisions simultaneously, the same game is repeated for several times so that players can learn from previous games and adjust their decisions accordingly.

(3) Games with Complete and Incomplete, Perfect and Imperfect Information In a game, if each player is aware of all players' utility functions, such game is referred as a game with complete information; otherwise, it is a game with incomplete information. In an extensive game with complete information, when a player needs to make decision, it may be fully informed about others' previous decisions, this game is called a game with perfect information; otherwise, it is a game with imperfect information.

2.3.3 Nash Equilibrium

Nash Equilibrium (N.E.) is a list of actions where no player can further improve its utility by only changing his own strategy, given all other players not changing their actions. In other words, it is a list of the best response to other players' actions. The formal definition of N.E. in a strategic game is constructed as follows [38]:

For a strategic game $(N, (A_i), (\succeq_i))$, where N stands for the set of players, A_i stands for the action space of player $i \in N$, and $\succeq_i$ stands for the preference relation of player i. Let $a_i \in A_i$ be an action profile of player i and a_{-i} be an action profile of all players except for player i. A N.E. of this game is an action profile $a^* = \{a_i^* \in A_i, i = 1, 2, ..., N\}$ with the property that for every player $i \in N$,

$$(a_{-i}^*, a_i^*) \succeq (a_{-i}^*, a_i)$$

for all $a_i \in A_i$, where a_{-i}^* is the set of equilibrium actions for all players other than i.

2.3.4 Applications of Game Theory for Resource Allocation in CRNs

In CRNs, since players (based on different scenarios, CRs and /or PUs) arrive and departure stochastically [42] and these players may stay on the spectrum resource for different periods of time to complete their service [43], they need to compete for the resource for several times with different competitors. Thus, when game theory is applied for resource allocation in CRNs, the formulated games are inherently extensive games. Moreover, since in most CRNs, players are not aware of the utility function of other players at the beginning of games, the formulated games have only incomplete information.

However, in literature, in order to reduce the complexity, players are usually assumed to be unchanged and make decisions simultaneously, which results in strategic games [44] [45]. Furthermore, in order to exchange some necessary information in a distributed manner so as to overcome the CCC problem in Cognitive Ad hoc networks, repeated games were also proposed [46] [47], where each player learned other players' utility functions from their previous actions. Moreover, the selection between non-cooperative game and cooperative games in CRNs is based on the trade-off between complexity and network performance so that the non-cooperative game is adopted for its less complexity [48] [49], while the cooperative game is adopted for its better social welfare [47].

2.4 Cooperative Communication

Transmission bit rate and coverage range are two of the toughest demands in wireless communications. To satisfy these demands, multiple input multiple output (MIMO) has been proposed. In MIMO systems, multiple antennas are used at the transmitter or/and receiver so that the systems are capable to provide spatial multiplexing to increase the throughput, or to provide spatial diversity to increase the coverage range and reliability, without consuming extra radio frequency [50].

Meanwhile, the wireless ad hoc network is proposed to increase the flexibility of wireless networks [51]. However, highly interconnected ad hoc networks, i.e., the ad hoc sensor networks, make the multi-user interference more significant [52], and due to the limited size, volume number of users, and cost, equipping multiple antennas at the user terminal is infeasible. To address this challenge, the concept of cooperative communications was thus introduced [46].

In cooperative communications, two or more nodes share their information and transmit jointly as a virtual antenna array and formulate a virtual MIMO system. This enables them to obtain spatial diversity just as the traditional MIMO systems [53] [54]. The application of cooperative communication techniques in CRNs is expected to further improve the network performance. Since we propose a resource allocation algorithm based on this, basic ideas in cooperative communications are introduced here for future reference.

In cooperative communications, the direct connection between a source and its intended destination may not be always good due to the channel fading. However, some nodes within the transmission range of the source may have good link quality and could work as relays to cooperate with the source. These relays overhear the transmitted signal from the source and retransmit this signal to the destination. They are used as supportive antennas to form a virtual MIMO system. Due to the independent fading in each source-relay-destination link, the probability of having a good link from the source to the destination increases as the number of independent links to the destination increases, which provides significant performance gains for the wireless channel.

There are two types of relay protocols, i.e., amplify-and-forward (AF) and decode-and-forward (DF) [55]. In the AF relaying protocol, each relay node amplifies and retransmits the received signal directly to its destination, while in the DF relaying protocol, each relay first decodes the receiving signal with noise, then re-encodes this signal and sends to the destination. These two protocols differ in the achievable performance. For a same Source-Relay-Destination connection, DF can achieve higher signal-to-noise ratio (SNR) with increased complexity and longer delay. However, there is no difference in the structures of the network.

Several issues arise in the cooperative scenario. For example, it is important to find an appropriate set of the relays for cooperation. In addition, the algorithms to find these relays should be efficient, preferably distributed and scalable to the network size. It may also be useful to analyze the maximum achievable gain in different cooperation methods, and choose a better one for a specific framework.

2.5 Resource Allocation in Cooperative Cognitive Radio Networks

Two important issues stimulate the application of cooperative communications in CRNs, or cooperative cognitive radio networks (CCRNs). First, CRs may serve as relays for PUs to motivate PUs to share channels with CRs. Second, the introduction of relays to CRNs can assist the communications between pairs of CR transmitters and receivers. Resource allocation in CCRNs consists of not only the traditional spectrum sharing problems, but also the allocation of relays to these communication pairs.

In CCRNs, a node can communicate with its source/destination nodes directly, or select other nodes as its relays and transmit and/or receive data under these relays' cooperation. The introduction of relays can improve performance of CRNs in two scenarios: 1) When cooperation between PUs and CRs exists, since PUs can satisfy their own requirements more easily via the help of CRs, the idle probability of the licensed channels can be increased and so is CRs' probability to access channels. In this way, performance of both PUs and CRs can be improved [56] [57]; 2) When the heterogeneity of the CRN increases due to the location and impact of PUs, different CRs may have different channel availability and channel conditions. Thus, it is possible that pairs of CR transmitters and CR receivers can not satisfy their communication requirements through direct links. If CRs with abundant channels can serve as relays for them, more communication pairs can be satisfied because of the decreased outage probability [58] or improved throughput [59].

Since 2005, research on CCRNs has attracted great interests. In [60], an orthogonal frequency-division multiple access (OFDMA) based CCRN was studied with both channel and power allocation, where the interference power constraints of the primary system was considered. Zhao et al [61] [62] also worked on joint power and channel allocation and relay selection in CCRNs with main consideration on the spectrum heterogeneity with DF protocol. Channels were classified into three different categories based on their availability may, and both optimal and sub-optimal allocation algorithms were proposed for each category to improve the overall convergence time. In [63], relays can exploit the retransmission slot for its own traffic during its cooperation with the source. An auction mechanism was adopted to decide the relays for the source, and the portion of a slot a relay could utilize for its own transmission. Other works include, for example, Zou et al, worked on relay selection and outage probability, and jointly considered spectrum sensing and relay transmission [64] [65]. In [66], cooperative communication was applied in spectrum sensing, called cooperative spectrum sensing, where all CRs' sensing results are forwarded to a common receiver, and fused to infer the presence of the PU.

In most existing publications in literature on CCRNs, relay nodes are predefined and differentiated from the source nodes. The research commonly jointly considered relay selection and resource allocation, and several games were formulated to solve this joint optimization problem [67] [68] [69]. However, if predefined relays are not available, two-layer resource allocation should be designed, where in layer 1, suitable nodes should be selected as relays and allocated with adequate resource, and in layer 2, these selected relays should be further allocated to the required source nodes. Therefore new resource allocation algorithms should be proposed.

3 Demand-matching Spectrum Sharing with a Classified Game

In cognitive radio networks (CRNs), due to the complexity and cost to setup a common control channel (CCC) for control information exchange, and due to the popular application of CRNs to Ad hoc networks which are lack of centralized controllers, distributed approaches become necessary. The key issue in designing distributed spectrum sharing is to determine the way to coordinate communications suitably, where decisions are made independently by each radio based only on the local information. In [32], a biologically-inspired algorithm is proposed, which enabled the cognitive radio (CR) to eventually learn the appropriate spectrum band and adapt the probability to select a channel. In [70], a non-cooperative game model was used to obtain the spectrum allocation among a primary user and multiple secondary users. The problem was formulated as a market competition, and the Nash Equilibrium (N.E.) is considered as the solution of this game. The Correlated Equilibrium (C.E.), which is more general than the N.E., was considered for dynamic spectrum access in [71] and [72] to achieve better performance.

Although all of these papers provide indepth insights in spectrum sharing in CRNs with consideration of optimization, adaptivity and fairness, the heterogeneity among CRs, in terms of quality of service (QoS) requirements, channel availability, and channel conditions, was missed and should be explored to further improve the network performance. Moreover, traditional CSMA/CA technique adopted in [71] and [72] which allocates channels to CRs equally. Inspired by prioritized CSMA in IEEE802.11e [73] [74], we introduce a priority to classify

CRs to improve the network performance, in terms of the number of satisfied CRs by allocating different portion of the channel to CRs based on their demands. A new algorithm to estimate the number of CRs in different priority levels is also proposed. In the channel allocation process, each CR jointly determine its channel selection and priority based on its possible satisfaction and the loss it may introduce to other CRs. Such trade-off between satisfaction and cost results in a distributed cooperative game which can maximize the satisfaction of the whole network. No-regret learning algorithm is adopted to reach the C.E. of the proposed game. Simulation results show that the C.E. based classified game (CECG) can achieve up to 40% better performance compared to the unclassified game in highly heterogeneous networks.

3.1 System Model

Consider an overlay CRN. The primary users have a strict priority on the spectrum access while CRs can only access spectrum not being utilized by PUs. As we focus on the competition and collaboration among CRs in spectrum sharing, we ignore the cost and faults from spectrum sensing. Namely, each CR is equipped with a perfect spectrum sensing technique, which can always detect the presence of PUs instantly. We consider a simple CR transceiver which can be tuned in a wide range of spectrum, but can operate only on one channel at any time. All CRs are in the interference range of each other, and thus have to compete for the idle channels. CSMA/CA is used as the sharing technique. To improve the efficiency by considering network heterogeneity, we introduce priority mechanism to differentiate users with respect to their specific transmission requirements and channel qualities. Since applying multiple (> 2) priorities may introduce high complexity with marginal improvement on performance, as shown in simulation results, we consider two priority levels in our algorithm.

3.1.1 Network Structure

Assume that there are N channels in the system, represented as a channel set $\{C_N\}$. Each channel is licensed to a PU and total I CRs seek for channel access opportunistically. CRs belong to two different classes, denoted as class 1 and class 2, with low and high priority to access channels, respectively. Time is divided into slots and we label them as $t = 1, 2, ...$. In a slot, both PUs' activities and CRs' strategies keep unchanged. Each CR's action consists of tow parts: channel selection and priority selection. At the beginning of any slot t, each CR i, $i = 1, 2, ..., I$, knows the following:

1) $r_i^{req} \in R^+$: the demand of CR i (in bits per time slot) to satisfy its QoS requirements, where R^+ denotes the set of positive real numbers.

2) $C_{i,n}^t \in R^+$: the channel quality in terms of transmission rate in bits per time slot for CR i on channel n at time t.

3) $A_{i,n}^t \in \{0, 1\}$: the availability of channel n for CR i at time t, which is determined by PUs' activities and the locations of both PUs and CR i. $A_{i,n}^t = 1$ if channel n is available for CR i at time t; otherwise, $A_{i,n}^t = 0$. $A_i^t = (A_{i,1}^t, ..., A_{i,N}^t)^T$ is the channel availability vector for CR i.

An example of the channel availability to the CRs is illustrated in Fig.2. All CRs are in the interference range of each other. There are 4 channels (CH 1, 2, 3

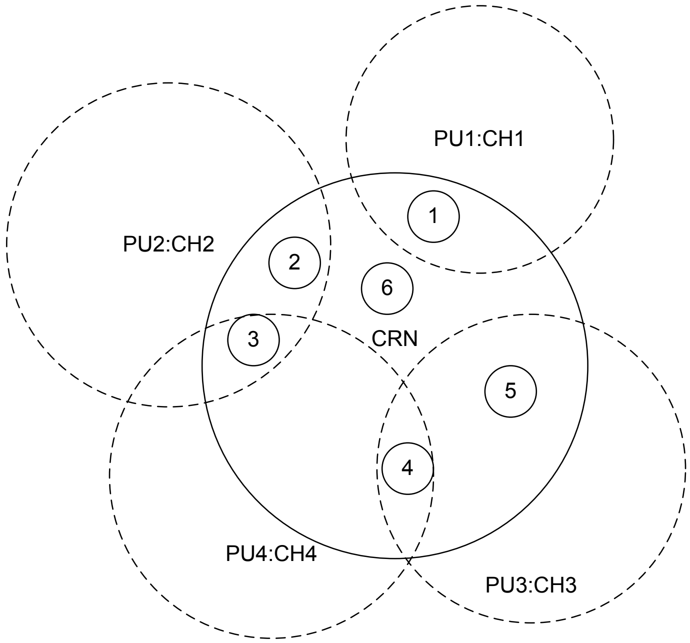

Figure 2: Network Structure in Spectrum Sharing

and 4), 4 PUs, and 6 CRs. All CRs in the solid circle form the CRN. Let PU 1, 2, 3 and 4 occupy channel 1, 2, 3 and 4, respectively. Then, the secondary users 1 to 6 have channel availability vectors as $(0, 1, 1, 1)^T$, $(1, 0, 1, 1)^T$, $(1, 0, 1, 0)^T$, $(1, 1, 0, 0)^T$, $(1, 1, 0, 1)^T$ and $(1, 1, 1, 1)^T$, respectively.

4) Ac_i^{t-1}: the action of CR i in the last slot $t-1$. $Ac_i^{t-1} = (X_i^{t-1}, P_i^{t-1})$ is chosen from the action space

$$\Omega_i^{t-1} = S_i^{t-1} \times Sp_i^{t-1} \tag{1}$$

In (1), S_i^{t-1} is the channel allocation decision space and can be represented as

$$S_i^{t-1} = \{X_i^{t-1} \in (0,1)^c : X_i^{t-1^T}(1 - A_i^{t-1}) = 0, \sum_{n \in C_N} X_{i,n}^{t-1} \leq 1\} \tag{2}$$

where $X_i^{t-1} = (X_{i,1}^{t-1}, ..., X_{i,N}^{t-1})^T$ is the channel allocation decision of CR i. As indicated in (2), CR i can only select one available channel n with $X_{i,n}^{t-1} = 1$. Sp_i^{t-1} is the priority space of CR i, i.e.,

$$Sp_i^{t-1} = \{1, 2\} \tag{3}$$

We have $P_i^{t-1} \in Sp_i^{t-1}$. $P_i^{t-1} = 1$ stands for low priority, while $P_i^{t-1} = 2$ stands for high priority.

5) $r_i^{t-1} \in R^+$: the achieved average channel rate for CR i in the last slot $t-1$, which is determined by the number of CRs in the allocated channel and their priorities in the last slot, i.e., by CR i's action Ac_i^{t-1} and all other users' actions, denoted as Ac_{-i}^{t-1}. This data can be acquired from the amount of data transmitted in the last time slot.

6) $N1_n^{t-1*}$ and $N2_n^{t-1*}$: the estimated number of users of class 1 and class 2 in the last slot $t-1$ on the selected channel n, respectively. An estimation method will be discussed later.

Based on the aforementioned information, each CR i makes its decision Ac_i^t for slot t. Note that CRs make their decisions based on local information only, which allows decentralized algorithms.

3.1.2 Prioritized CSMA/CA

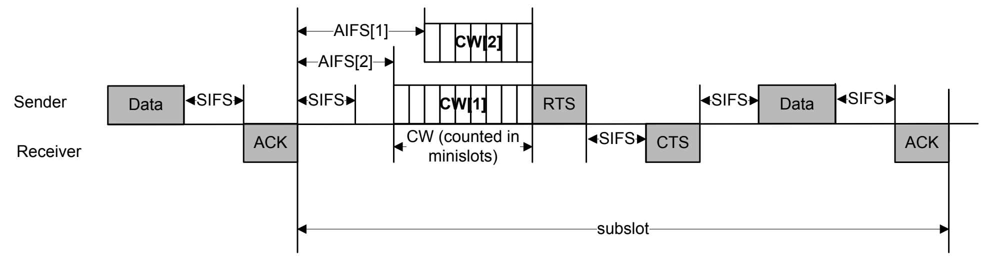

Figure 3: Multiple Backoff in Prioritized CSMA/CA

CRs share channels using a prioritized CSMA/CA scheme. By allocating less waiting time on average to CRs with higher priority, these CRs have a higher chance to capture the channel than others.

We introduce following definitions for protocol description:

1) subslot: the time needed for a CSMA attempt. We assume K subslots constitute a slot which are denoted as $t_1, t_2, ..., t_K$. Note that the length of subslots are not equal and so is the length of slots.

2) minislot: the time needed by CR to determine whether another station has accessed the medium.

3) SIFS (Short Interframe Space): the smallest period between packets. It has a duration at least enough for CR to sense the channel clear and switch between receiving and transmitting modes.

4) AIFS (Arbitration Interframe Space): the smallest waiting time before sending a packet. It depends on the corresponding priority class and is larger than SIFS.

5) RTS/CTS: Request to Send frame/ Clear to Send frame.

6) DATA/ACK: Data frame/ Acknowledgment frame.

7) CW: Contention Window which depends on the corresponding priority class.

Fig. 3 shows the protocol of prioritized CSMA/CA. As illustrated in the figure, in any subslot t_k, for CR i wishing to send data, it generates its backoff time $\tau_i(t_k)$ according to a uniform distribution within the interval $(0, CW[P_i^t])$. The backoff counter starts decreasing after detecting that the channel is idle for an $AIFS[P_i^t]$. Upon expiry of the backoff counter, the CR sends an RTS to initiate its data transmission if the channel is still sensed clear. Only one radio with the smallest waiting time $WT_i = \tau_i(t_k) + AIFS[P_i^t]$ will transmit successfully on channel n in subslot t_k. For simplicity, we set $AIFS[1] + CW[1] = AIFS[2] + CW[2]$, and assume $AIFS[1] > AIFS[2]$. The values of $AIFS$ and CW are set to guarantee that CRs in class 2 can have a smaller expectation of WT than those in class 1, so that they are more likely to take a smaller waiting time. Thus, CRs in class 2 have a higher priority to access the channel. The probability for CR i to catch channel n is

if $P_i^t = 2$

$$\begin{aligned} Prob_{i,n} = \tfrac{1}{CW[2]} \textstyle\int_0^\delta (1 - \tfrac{\tau}{CW[2]})^{N2_n - 1} d\tau + \\ \tfrac{1}{CW[2]} \textstyle\int_\delta^{CW[2]} (1 - \tfrac{\tau}{CW[2]})^{N2_n - 1} (1 - \tfrac{\tau-\delta}{CW[1]})^{N1_n} d\tau \end{aligned} \tag{4}$$

if $P_i^t = 1$

$$Prob_{i,n} = (1 - \frac{\delta}{CW[2]})^{N2_n} \frac{1}{CW[1]} \int_0^{CW[1]} (1 - \frac{\tau}{CW[1]})^{N1_n + N2_n - 1} d\tau \tag{5}$$

where $\delta = AIFS[1] - AIFS[2]$, and

$$N1_n^t = \sum_{i=1}^{I} \{X_{i,n}^t = 1\}\{P_i^t = 1\} \tag{6}$$

$$N2_n^t = \sum_{i=1}^{I} \{X_{i,n}^t = 1\}\{P_i^t = 2\} \tag{7}$$

Each CR will determine its own priority based on its utility, a function of its demand and satisfaction. The utility function will be discussed later.

3.1.3 Decision-Feedback-Reaction Model

At the beginning of the t-th slot, each CR makes its decision based on the information about the network and its satisfaction, and holds this decision for the whole period of the slot. Note that channel catching probability and contention probability for CR i at slot $t-1$ are determined by all CRs on channel n, and they are known to CR i before slot t from channel catching results in the last slot. Hence, such probability can be seen as the feedback of CR i's action in the $(t-1)$-th slot. In realistic application, the number of subslots in a slot should be large enough to provide an accurate feedback. Based on this feedback, CR can make estimation of $N1_n^{t-1*}$ and $N2_n^{t-1*}$, predict its future utility, and update its action in the next slot.

We introduce a simple estimation method for $N1_n^{t-1*}$ and $N2_n^{t-1*}$as follows.

For CR i, if $P_i^t = 2$, the probability for CR i to successfully catch the channel after waiting a period in the range of $(AIFS[1], AIFS[2])$ is

$$Pcat21_{i,n} = \frac{1}{CW[2]} \int_{0}^{\delta} (1 - \frac{\tau}{CW[2]})^{N2_n - 1} d\tau \tag{8}$$

Obviously, $Pcat21_{i,n}$ is only determined by $N2_n$, and could be acquired from CR i's competition results. Hence, $N2_n^*$ can be estimated from $Pcat21_{i,n}$ by, for example, maximum-likelihood estimation [75]. Then, substituting $N2_n$ in (4) , we can have the estimated value of $N1_n$.

Similarly, if $P_i^t = 1$, the probability for CR i to contend on the channel after waiting a period in the range of $(AIFS[1], AIFS[2])$ is

$$Pcon11_{i,n} = 1 - (1 - \frac{\delta}{CW[2]})^{N2_n} \tag{9}$$

which is also only determined by $N2_n$. Thus, we can similarly estimate $N2_n^*$ from $Pcon11_{i,n}$ and then estimate $N1_n$ by substituting $N2_n$ in equation (5).

In this chapter, accurate estimates of $N1_n$ and $N2_n$ are considered, i.e., $N1_n^* = N1_n$ and $N2_n^* = N2_n$. However, as shown in the simulation, even up to 30% estimation error will not affect the performance of the proposed algorithm significantly.

3.2 Optimization Problem and Game Formulation

For applications with strict QoS requirements, for instance, voice transmission, a meaningful global system objective should aim to guarantee as many CRs' satisfaction as possible. Here, the satisfaction means that the achieved average rate should be no less than the required one. Hence, we adopted a utility function different from the best effort utility functions in [72] to better match the scenarios with strict QoS requirements. As a decentralized scheme is required, a local utility function is defined to guide the allocation decision of each CR. In follows, we will first introduce the global optimization problem, and then discuss the distributed game and utility function in details.

3.2.1 Global Optimization Problem

The global objective is to maximize the number of satisfied users. As the optimization problem is held for any time t, we ignore the index t for simplicity. Let $Ac = (Ac_1, ..., Ac_I)$ be the joint action of all CRs. The optimization problem can be formulated as:

$$\max_{Ac} \sum_{i=1}^{I} (G(r_i, r_i^{req})) \tag{10}$$

s.t.

$$Ac \in \Omega = \Omega_1 \times ... \times \Omega_I \text{ (joint action set of all radios)} \tag{11}$$

where

$$r_i = \sum_{n \in C_N} X_{i,n} r_{i,n} \leq 1 \tag{12}$$

$$r_{i,n} = Prob_{i,n} A_{i,n} C_{i,n} \tag{13}$$

$r_{i,n}$ is the achievable rate for CR i on channel n. $Prob_{i,n}$ is the probability for CR i to catch the channel n, as defined in (4) and (5). $G(a, b)$ is a logic function to check whether CR i is satisfied, i.e.,

$$G(a,b) = \begin{cases} 1 & , \quad a \geq b \\ 0 & , \quad a < b \end{cases} \tag{14}$$

Note that once CR's QoS is satisfied, it has no intention to further increase its achievable rate.

However, this global optimization problem requires global information of the network. For example, the actions of all CRs and the corresponding rates they can achieve should be learned by all CRs, which is difficult to achieve. In this way, we will propose a distributed game, which relies only on local information, other than solve this global optimization problem.

3.2.2 Distributed Game and Local Utility

Each CR tries to access channel to satisfy its QoS requirements, while at the same time such access may cause loss to other CRs on the same channel, as it decreases other users' probability to catch the channel. Intuitively, if each CR tries to satisfy itself, and at the same time limits the loss it causes to other CRs, more CRs in the system could be satisfied. That is to say, CRs should select channels with better channel condition and less users on it. Thus, for a cooperative distributed game which aims to improve the global performance, the local utility for each CR should be a trade-off between its satisfaction and other CRs' loss. From the game theory point of view, the satisfaction acts as the income while other CRs' loss as the price.

Note that the local utility function is only an estimation from the last slot.

For instance, since the reward of each CR's action is determined by other CRs' actions, the estimated achievable average rate calculated at the beginning of a slot may differ from the exactly achieved one. However, our simulation indicates that the proposed algorithm converges after a number of rounds.

We define a distributed game as follows:

CRs are players in the game. Ac_i^t, the action of CR i in slot t, is selected from action space Ω_i^t which is defined in (1). Since any CR's utility is determined not only by itself but by other CRs' actions, the local utility for CR i is defined as:

$$U_i(Ac_i^t, Ac_{-i}^t) = U_i^1(Ac_i^t) + \alpha U_i^2(Ac_i^t) \tag{15}$$

where Ac_{-i}^t represents all other CRs' actions.

In (15)

$$U_i^1(Ac_i^t, Ac_{-i}^t) = G(r_i^t, r_i^{req}) \tag{16}$$

stands for the satisfaction, where r_i^t is defined in (12), and

$$U_i^2(Ac_i^t, Ac_{-i}^t) = -P_i^t(\alpha_1 N1_n^{t-1*} + \alpha_2 N2_n^{t-1*}) \tag{17}$$

stands for the cost of CR i, i.e., the loss of all other users in the channel n with $X_{i,n} = 1$. Since it is hard to learn the real decrement on the channel rates for other users, a rough estimation is adopted. Note that if CR i chooses to act with higher priority, it may induce more loss to all other CRs in the same channel, and thus it should pay more. Therefore, if a CR can be satisfied with low priority, there is no motivation for it to select the high priority in the same channel.

In (15) and (17), $\alpha, \alpha_1, \alpha_2$ are user-defined trade-off factors. Since the actual effect of CR i's action on the global utility is unknown, these weights are adjustable.

3.3 Correlated Equilibrium and No-Regret Learning

In this section, we adopt the concept of C.E. and introduce a no-regret learning algorithm as a distributed adaptive learning algorithm to solve the optimization problem defined in the previous section.

3.3.1 Correlated Equilibrium

A C.E. is a solution concept that is more general than the well known N.E. [76]. Given a public signal (the satisfaction history of CRs), a strategy consists of recommendatory actions to every possible observation of the public signal a player can make. Players reach the C.E. if no player would want to deviate from a recommended strategy. Note that N.E. corresponds to the special case of a C.E. The C.E. considers the interaction among players to make decision and thus could achieve better performance than N.E..

In the proposed distributed game, the C.E. is defined as: if and only if, for all player i, $Ac_i \in \Omega_i$ is i's action, a probability distribution $Pr(Ac_i, Ac_{-i})$ satisfies

$$\sum_{Ac_{-i} \in \Omega_{-i}} Pr(Ac_i, Ac_{-i})[U_i(Ac'_i, Ac_{-i}) - U_i(Ac_i, Ac_{-i})] \leq 0, \quad \forall Ac'_i, Ac_i \in \Omega_i \tag{18}$$

where $Pr(Ac_i, Ac_{-i})$ is called the correlated strategy.

3.3.2 No-Regret Learning

No-regret learning (also called regret tracking or regret matching) is a kind of adaptive learning algorithms with fast convergence [77]. In no-regret learning, the probability to conduct an action is proportional to the "regret" for not having played other actions, and the stationary solution of the learning algorithm exhibits no regret. This algorithm will almost surely converge to C.E., as proved in [78].

For the action of CR i in slot t, $Ac_i^t \in \Omega_i^t$, we denote actions in the state space as $j \in \{0, 1, 2, ..., 2N\}$ for simplicity, i.e.: if $\exists X_{i,n}^t = 1$, $j = 2n + P_i^t - 2$; otherwise, $j = 0$.

Each CR i executes the following steps:

1) Initialize arbitrarily probability of taking action for CR i. Set $\theta^{i,0} = 0$.

2) Generate regret matrix H^i with elements

$$H_{jk}^i = I\{Ac_i^t = j\} \times (U_{i,n}(k, Ac_{-i}^t) - U_{i,n}(j, , Ac_{-i}^t)) \tag{19}$$

which stands for the regret of not using action k other than the real action j in slot t.

3) Set a regret value

$$\theta_{jk}^{i,t+1} = \theta_{jk}^{i,t} + \epsilon(H_{jk}^i - \theta_{jk}^{i,t}), 0 < \epsilon << 1 \tag{20}$$

which stands for the average gain that i would have received had he chosen action

k in the past (from time 0 to t) instead of j. Here, ϵ is the learning rate.

4) Update action

CR i updates action $Ac_i^{t+1} = k$ with probability

$$P(Ac_i^{t+1} = k | Ac_i^t = j) = \begin{cases} \max(\theta_{jk}^{i,t+1}, 0)/\mu_i & , \quad k \neq j \\ 1 - \sum_{i \neq j} \max(\theta_{jk}^{i,t+1}, 0)/\mu_i & , \quad k = j \end{cases} \tag{21}$$

In (21), μ_i is an arbitrary updating rate that is sufficiently large, i.e.,

$$\mu_i > (N_{Ac_i} - 1)(u_i^{\max} - u_i^{\min}) \tag{22}$$

where N_{Ac_i} is the number of actions for CR i, $u_i^{\max}$ is the maximum achievable utility, and $u_i^{\min}$ is the minimum utility for CR i. In our work, we set $\mu_i = (N_{Ac_i} + 1)(u_i^{\max} - u_i^{\min})$.

Note that the algorithm requires that CR i knows what utility it would have received for each action, even if that action was not taken. This puts a request to know the number of users of each class on each channel. In fact, a modified regret tracking algorithm can be used without such information [72] [78]. However, the convergence is far too slow.

3.4 Simulation Results

We focus on slightly congested systems, with total capacity of channels slightly less than the total user demand to highlight the effect of spectrum sharing algorithms on the resource utilization efficiency. For each CR, some randomly selected channels are set to be unavailable to reflect the occupation of PUs. For CRs' channel condition and required rate, we adopt randomly generated data following Gaussian distribution for simplicity to introduce heterogeneity among CRs.

In simulations, AIFS[1]=150, CW[1]=100, AIFS[2]=100, and CW[2]=150, all in a unit of minislots. In the case that there is only one user in each class on the same channel, the probability to catch channel for user in class 1 is 0.32, and for class 2 is 0.65. Learning rate $\epsilon = 0.1$, trade-off factor $\alpha = 0.015$, $\alpha_1 = 1.1$ and $\alpha_2 = 2$ are obtained from simulation results.

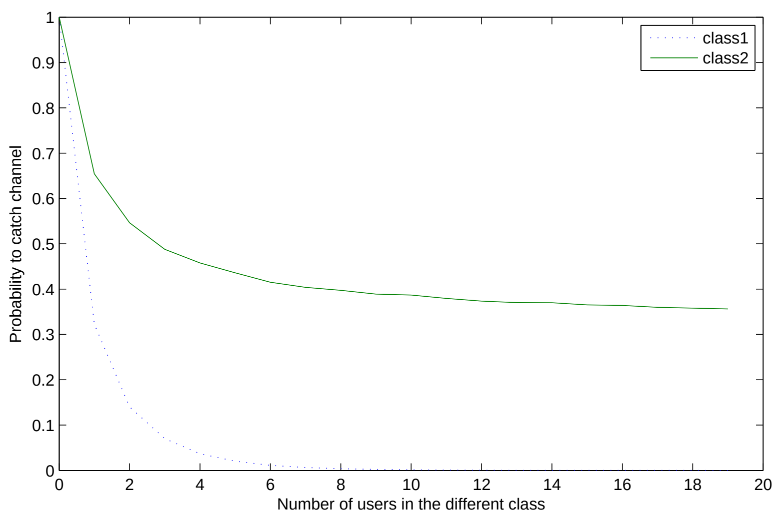

Figure 4: The Comparison of Catching Probability with Number of Users of Different Class

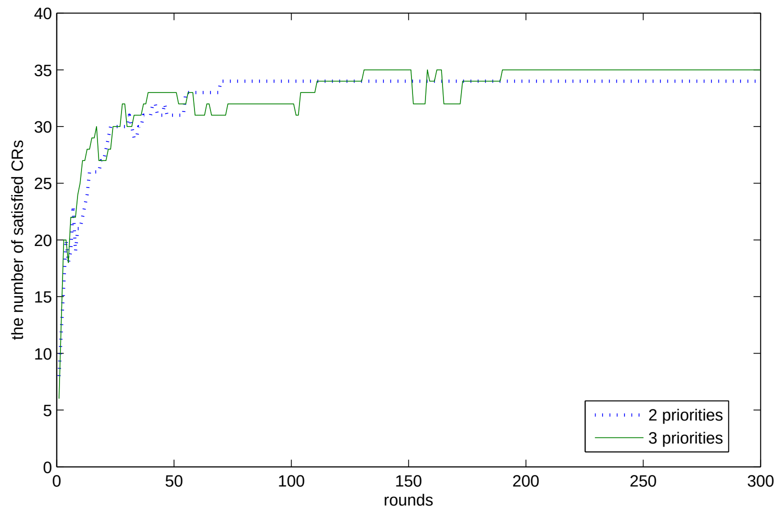

Figure 5: $N = 3$, $I = 50$. Channel condition follow a Gaussian distribution with mean 30, variance 7. Required rate follow a Gaussian distribution with mean 3, variance 3.

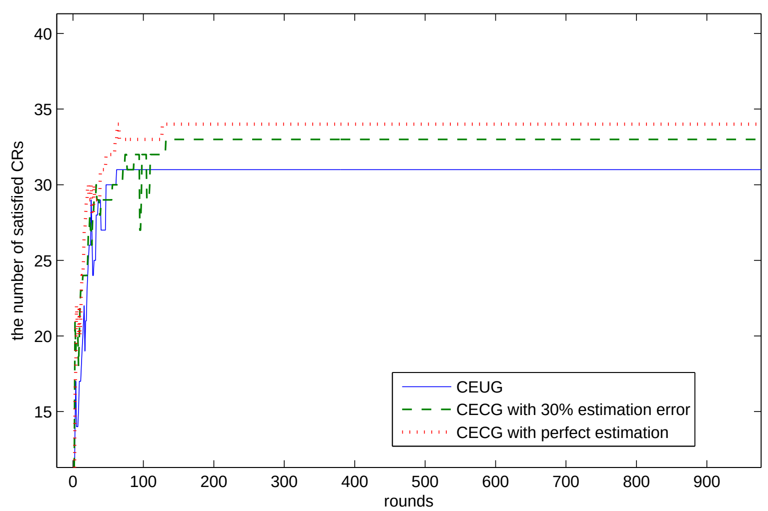

Figure 6: $N = 3$, $I = 50$. Channel condition follow a Gaussian distribution with mean 30, variance 7. Required rate follow a Gaussian distribution with mean 3, variance 3.

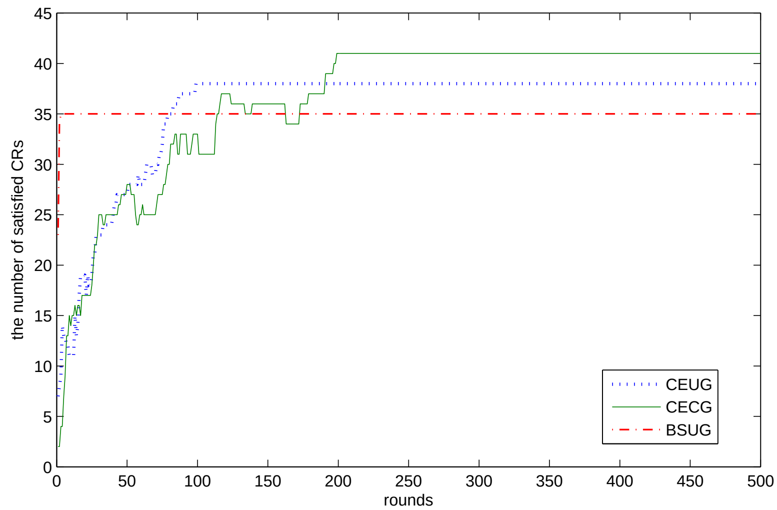

Figure 7: The Comparison of Satisfied Number of $N = 50$, $I = 100$. Channel condition follow a Gaussian distribution with mean 15, variance 7. Required rate follow a Gaussian distribution with mean 7, variance 3.

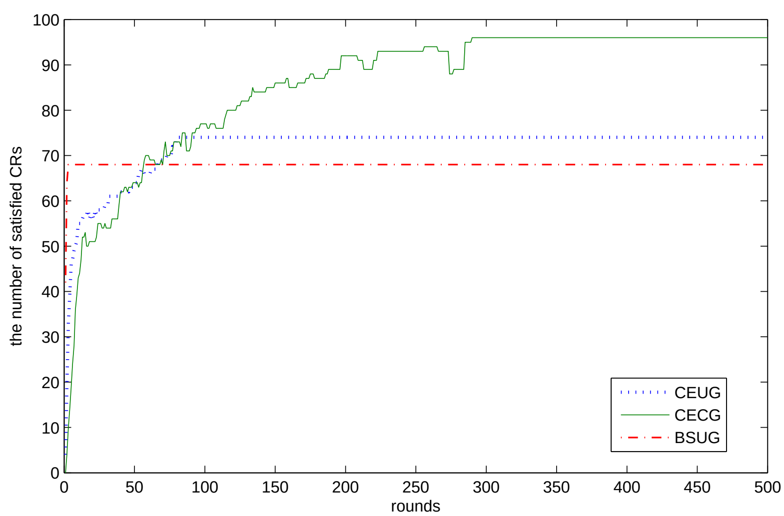

Figure 8: $N = 25$, $I = 100$. Channel condition follow a Gaussian distribution with mean 15, variance 7. For 50 Users $r^{req} = 7$, and other 50 Users $r^{req} = 1$. Totally the variance among required rate is 9.09.

Fig. 4 compares the catching probability and sensitivity of users in different classes. From this figure, we can see that for a user in class 1, if we increase the number of users in class 2, the catching probability decreases rapidly; while for the user in class 2, if we increase the number of users in class 1, the probability decreases much slower and converges to a non-zero limitation. That is because, for the catching probability of class 2, the first part in equation (4) is not affected by $N1_n$, and the second part in (4) converges to 0 with large $N1_n$; while for catching probability of class 1, with $N2_n$ in the exponent, it decreases rapidly with increasing $N2_n$.

Fig. 5 compares the performance if 3 other than 2 priority levels are applied. For the 3-priority level case, we set AIFS[1]=150, CW[1]=100, AIFS[2]=125, CW[2]=125, AIFS[3]=100 and CW[3]=150. From this figure, we can see that with 3-level priority, the algorithm can only provide marginal performance improvement, but much slower convergence rate. That is because more priority levels will introduce a larger action space, which increases the complexity. Moreover, as in the proposed sharing algorithm, an unsatisfied CR can switch to the channel with better channel condition and lighter competition to increase its throughput other than continuously increasing its priority in the same channel, the effects by introducing more priorities becomes marginal. This justifies our selection of 2 priority levels.

Fig. 6 shows the influence of estimation error. The performance of the C.E. based unclassified game (CEUG) in [72] is adopted as a comparison benchmark. From this figure we can see that for up to 30% estimation error, the performance of our algorithm is just affected slightly. The reason is that users are dispersed in all actions so that the number of users with the same action is not large. Thus, the estimation error can only change the number of users with the same action slightly.

Fig. 7 compares the performance of the proposed CECG algorithm with CEUG in [72]. The best response algorithm with unclassified game (BSUG) in [79] is also adopted for comparison. In the BSUG algorithm, in every round each CR selects the channel with largest utility, and it has been proved in [79] that the N.E. of this unclassified game can be achieved. From the figure, performance improvement can be obviously observed in terms of the number of satisfied users. The introduction of C.E. brings in about 10% improvement comparing to the BSUG algorithm, as it considers the cooperation among CRs, at the cost of convergence rate. Note that if all CRs chose to be in the same class, our algorithm will degrade to that in [72]. Comparing to [72], since the proposed algorithm has a larger action space including those in CEUG, at least we can acquire a same performance as the CEUG algorithm.

Fig. 8 demonstrates the influence of heterogeneity of users on the performance where two groups of CRs with difference in demands are applied. Comparing the results in Fig. 7 and Fig. 8, we can find that the improvement of CECG over CEUG (about 40%) is larger in the latter case than that in the former (about 10%). The simulation results further justify the necessity to apply the proposed algorithm for performance improvement in CRNs, especially when significant heterogeneity exists among CRs.

4 Two Layer Auction Game in Cooperative Cognitive Radio Networks

In cooperative cognitive radio networks (CCRNs), it is reasonable to select some CRs with good throughput on licensed bands to the base station (BS) to communicate with other CRs' via free band, i.e., the ISM band, and then relay this communication to the BS. One example of such networks could be a vehicle network where an access point (AP) in the vehicle communicates with these personal terminals via Wi-Fi as the free band, and then works as the relay to communicate with the BS via cellular network in the licensed band. It is possible that personal terminals are also equipped with a CDMA transceiver, and then people may need to determine which network they should use for their gadgets.

In this chapter, we address resource allocation problem in CCRNs by formulating a Two-Layer Auction Game (TLAG). Simulation results show that comparing the TLAG with the Direct Sharing (DS) algorithm and the Auction with Predefined Best Relays (APBR) algorithm, this two-layer auction game algorithm can greatly improve the network throughput.

4.1 System Model and Problem Formulation

4.1.1 System Model

We consider an overlay CCRN as shown in Fig 9, which consists of one BS, M PUs, N licensed channels, and I CRs. $\mathbb{M}$, $\mathbb{N}$, $\mathbb{I}$ are the set of PUs, licensed channels, and CRs, respectively. Each CR can communicate with the BS via

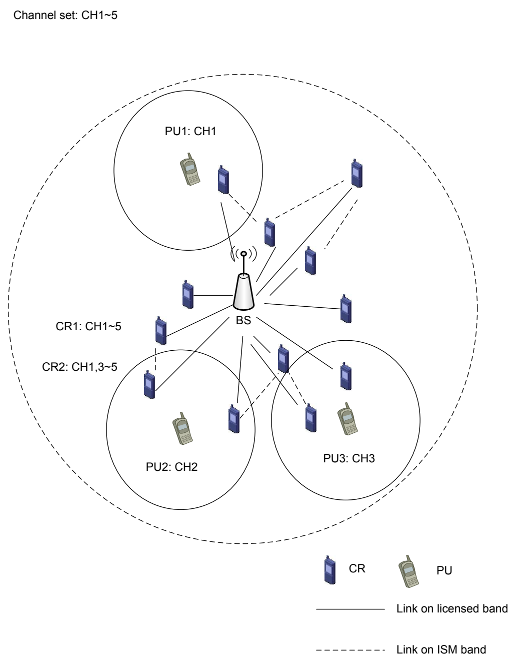

Figure 9: System model of the CCRN

licensed channels. Each PU is allocated a specific licensed channel and has a strict priority to access. A variation of TDMA-based sharing technique is adopted here, i.e., in each channel, time is divided into frames of equal size of T slots. Based on the channel availability, channel conditions and traffic demands of CRs, the BS allocates time slots to CRs without interference to PUs. The demands of CRs are modeled as the average rate in a frame. Let $P_{i,n}(t) \in \{0, 1\}$ be the channel-slot allocation status, i.e., $P_{i,n}(t) = 1$ stands for the fact that the t-th slot of channel n is allocated to CR i . Otherwise $P_{i,n}(t) = 0$, $t = \{1, ..., T\}$.

Each CR is equipped with two radios which can operate simultaneously. One of them, called CR transceiver (CRT), works on the licensed band for the communication between the CR and the BS, while the other, called ISM transceiver (IT), works on the free ISM band for the short range communication between CRs. CRs allocated with abundant resource on the licensed band become relays, while those unsatisfied CRs are called pure source nodes without performing relay. Relays can set up links with these pure source nodes on the ISM band, and help their communication with the BS so as to improves the satisfaction of the whole CRN.

As the communication between relays and pure source nodes on the ISM band is short-ranged, we assume a local ISM channel available to each pair of CRs without interfering other CRs, while each CR is in the interference range of all others to share the licensed band. We further set the channel switching cost to be zero. For simplicity, only up-link communication is considered here, i.e., CRs send packets directly to the BS or via the help of CR relays. However, a similar way can be applied to the downlink as well. Also, we consider a slowly variant CRN, i.e., PUs' locations and activities, CRs' demands, and the channel conditions keep unchanged in a frame.

4.1.2 Problem Formulation

We define that the satisfaction of a CR follows a best effort manner, i.e., the gross utility gain for CR i is the meaningful throughput

$$u_i = min(R_i, Rreq_i) \tag{23}$$

where $Rreq_i \in \mathbb{R}^+$ is the predefined demand of CR i , which is the required average rate in a frame in the term of bits per time slot, to fully satisfy its QoS requirements, e.g., throughput, and R_i is the achievable average rate for CR i in a frame.

The objective is to maximize the overall meaningful throughput in the network, which can be formulated as

$$\max_{\mathbf{P},\mathbf{P}^r} \sum_{i \in \mathbb{I}} u_i \tag{24}$$

where $\mathbf{P} = \{P_{i,n}(t), i = 1, 2, ...I, n = 1, 2, ..., N\}$, $\mathbf{P}^r = \{P^r_{i,j}(t), i = 1, 2, ...I, n = 1, 2, ..., N\}$, $P^r_{i,j}(t)$ is the relay allocation status. $P^r_{i,j}(t) = 1$ means that relay i is allocated to j in time slot t; otherwise $P^r_{i,j}(t) = 0$. Apparently, the allocation of each slot from each link should be solved.

Let $\mathbb{R}_l$ be the set of relays and $\mathbb{S}$ be the set of pure source nodes. Apparently, $\mathbb{R}_l \cup \mathbb{S} = \mathbb{N}$, and$\mathbb{R}_l \cap \mathbb{S} = \varnothing$. Then, we have

$$R_i = \begin{cases} \sum_{n \in \mathbb{N}} \sum_{t=1}^{T} P_{i,n}(t) C_{i,n} & i \in \mathbb{R}_l \\ \sum_{n \in \mathbb{N}} \sum_{t=1}^{T} P_{i,n}(t) C_{i,n} + \sum_{k \in \mathbb{R}_l} \sum_{t=1}^{T} P^r_{i,k}(t) C^r_{i,k} & i \in \mathbb{S} \end{cases} \tag{25}$$

The constraints to the objective function are listed as follows.

$$P_{i,n}(t) \le A_{i,n} \tag{26}$$

$$\text{if } R_i \ge Rreq_i, i \in \mathbb{R}_l \text{ ; otherwise } i \in \mathbb{S} \tag{27}$$

$$\text{if } i \in \mathbb{R}_l, R_i \geq Rreq_i + \sum_{j \in \mathbb{S}} \sum_{t=1}^{T} P^r_{j,i}(t) C^r_{j,i} \tag{28}$$

$$\sum_{n \in \mathbb{N}} P_{i,n}(t) \leq 1 \tag{29}$$

$$\sum_{i \in \mathbb{I}} P_{i,n}(t) \leq 1 \tag{30}$$

$$\sum_{k \in \mathbb{R}_l} P^r_{i,k}(t) \leq 1 \tag{31}$$

$$\sum_{j \in \mathbb{S}} P^r_{j,i}(t) \leq 1 \tag{32}$$

where $C_{i,n} > 0$ is the channel quality in terms of transmission rate in bits per time slot for CR i on channel n; $C^r_{j,i} > 0$ is the channel quality in terms of transmission rate in bits per time slot from CR i to CR j; and $A_{i,n} \in \{0, 1\}$ is the availability of channel n for CR i, which is determined by PUs' activities and the locations of both PUs and CR i. $A_{i,n} = 1$ if channel n is available for CR i; otherwise, $A_{i,n} = 0$. Condition (26) is the constraint on licensed channel availability. Condition (27) guarantees that a relay node has to satisfy its own demands first. Condition (28) means that the overall traffic demands for a relay should be smaller than its capacity. Conditions (29)~(32) mean that in a slot, each CRT can only work on at most one specific channel, each time slot of a licensed channel can be allocated to at most one CR, each relay can only serve at most one pure source node, and each pure source node can only be served by one relay, respectively.

The problem of channel allocation in CRNs belongs to the class of Mixed Integer Nonlinear Programming (MINLP) problems which is known to be NP-Hard [80]. Besides channel allocation, the optimization problem defined in (24)~(32) needs relay allocation which makes the defined problem at least NP-hard. Since for a given link, all slots in a frame have the same quality, R_i is determined by the number of slots from different links allocated to CR i, rather than by specific slots of a same link. Here, a link refers to a channel between a CR and the BS, or a connection between a pure source node and a relay. However, as conditions (29)~(32) require each slot to be used exclusively, the allocation of each slot should be solved, i.e., a certain order should be determined for CRs to access the resource. Thus, heuristically, the optimization problem can be decoupled into two subproblems, i.e., slot allocation which figures out the number of slots from different links allocated to CRs, and scheduling which determines the order for CRs to utilize these slots. In follows, these two subproblems will be solved separately.

(1) Slot Allocation Let $Pur_{i,n} = \sum_{t=1}^{T} P_{i,n}(t)$ stand for the number of slots allocated to CR i on channel n, and $Pur_{i,j}^{rin} = \sum_{t=1}^{T} P_{i,j}^{r}(t)$ the number of slots allocated to pure source node i from relay j. Then, we can rewrite the optimization problem in (24) as

$$\max_{\mathbf{Pur}, \mathbf{Pur}^{rin}} \sum_{i \in \mathbb{I}} u_i \tag{33}$$

s.t.

$$Pur_{i,n}(1 - A_{i,n}) = 0 \tag{34}$$

$$\text{if } R_i \geq Rreq_i, i \in \mathbb{R}_l \text{ ; otherwise } i \in \mathbb{S} \tag{35}$$

$$\text{if } j \in \mathbb{R}_l, \sum_{i \in \mathbb{S}} Pur_{i,j}^{rout} + Rreq_j \leq R_j, \text{ where } Pur_{i,j}^{rout} = Pur_{i,j}^{rin} C_{i,j}^r \tag{36}$$

$$\sum_{i \in \mathbb{I}} Pur_{i,n} \leq T \tag{37}$$

$$\sum_{n \in \mathbb{N}} Pur_{i,n} \leq T \tag{38}$$

$$\sum_{j \in \mathbb{R}_l} Pur_{i,j}^{rin} \leq T \tag{39}$$

$$\sum_{i \in \mathbb{S}} Pur_{i,j}^{rin} \leq T, j \in \mathbb{R}_l \tag{40}$$

where $\mathbf{Pur} = \{Pur_{i,n}, i = 1, 2, ...I, n = 1, 2, ..., N\}$, $\mathbf{Pur}^{rin} = \{Pur_{i,j}^{rin}, i = 1, 2, ...I, n = 1, 2, ..., N\}$, $u_i = \min(R_i, Req_i)$, and $R_i = \sum_{n \in \mathbb{N}} Pur_{i,n} C_{i,n} + \sum_{j \in \mathbb{R}_l} Pur_{i,j}^r C_{i,j}^r$. Conditions (37)~(40) are constraints for the number of available slots in a link.

Obviously, in the redefined optimization problem, only the number of slots in different links are considered. Comparing with the original optimization problem which needs to consider each specific slot, the complexity has been significantly reduced. By solving this problem, we acquire $Pur_{i,n}$ and $Pur^r_{i,j}$.

(2) Scheduling After obtaining $Pur_{i,n}$ and $Pur^r_{i,j}$, the scheduling problem is to solve $P_{i,n}(t)$ and $P^r_{i,j}(t)$ based on the following equations

$$\begin{aligned} Pur_{i,n} &= \sum_{t=1}^{T} P_{i,n}(t) \\ Pur^{rin}_{i,j} &= \sum_{t=1}^{T} P^r_{i,j}(t) \end{aligned} \tag{41}$$

subject to the exclusive utilization conditions (29)~(32).

4.2 Game Formulation for Slot Allocation

In our case, the BS first allocates licensed channels to CRs, and then CRs with abundant resources become relays and assign their relay capacity to pure source nodes. Thus, the slot allocation problem could be formulated as a two-level auction game, with BS serving as the first level resource owner and relays serving as second level resource owners. In auction games, the price paid for the owners should not be larger than the gross utility of buyers, and owners with limited resources will accept users based on their prices.

In the first level, all CRs compete to share all licensed channels. Although only one BS works as the coordinator, since each CR may have different channel availability and channel conditions, the prices each CR is willing to pay for different channels are thus different. Therefore, each channel can be seen as a virtual seller with each CR as a buyer, which result in a multi-sell multi-buyer multi-slots allocation problem.

In the first level, the gross utility for a CR i (or buyer i) is only associated with the meaningful throughput on the licensed channel, i.e.,

$$u_i = \min(R_i^1, Rreq_i') \tag{42}$$

where $R_i^1 = \sum_{n \in \mathbb{N}} Pur_{i,n} C_{i,n}$, $Rreq_i' = Rreq_i + R_i^{pr}$, and R_i^{pr} is the prediction of traffic required for i to relay. If $i \in \mathbb{S}$, $R_i^{pr} = 0$; otherwise $R_i^{pr} = \sum_{j \in \mathbb{S}} Pur_{i,j}^{rin} C_{i,j}^{r}$. Note that $Pur_{i,j}^{rin}$ is acquired from the second level auction game. At the beginning of the auction, since all CRs are pure source nodes directly contacting the BS, we have $R_i^{pr} = 0, \forall i$.

Define $Pr_{i,n}$ as the price charged by channel n to CR i, we define channel cost function as

$$U_i^c = -\sum_{n \in \mathbb{N}} Pur_{i,n} Pr_{i,n} \tag{43}$$

Then, the local utility function of buyer i becomes

$$U_i = u_i - U_i^c \tag{44}$$

and the local utility function of virtual seller n becomes

$$U_n^{BS} = \sum_{i \in \mathbb{I}} Pur_{i,n} Pr_{i,n} \tag{45}$$

Once the first level auction is solved, licensed band resources are allocated to CRs. Then CRs can be separated into relays and pure source nodes. In the second level auction, all pure source nodes which serve as buyers are competing to use resources in relays which serve as sellers. For the relays, the relay process consists of two steps: receiving and relay. The resources consumed by a relay process thus consist of the receiving slots for relays' ITs, and the transmitting slots for relay's CRTs, where two different kinds of prices should be charged for these two steps. Let $Pr_{i,j}^{rin}$ denote the price between pure source node i and relay j for a slot of receiving, and $Pr_{i,j}^{rout}$ denote the price between pure source node i and relay j for one bit of relay traffic. We have gross utility for buyer $i \in \mathbb{S}$ as

$$u_i^s = \min(R_i^1 + \sum_{j \in \mathbb{R}_l} Pur_{i,j}^{rin} C_{i,j}^r, Rreq_i) - \min(R_i^1, Rreq_i) \tag{46}$$

which stands for the meaningful rate via relays. The overall relay cost function is

$$U_i^{rc} = -(\sum_{j \in \mathbb{R}_l} Pur_{i,j}^{rin} Pr_{i,j}^{rin} + \sum_{j \in \mathbb{R}_l} Pur_{i,j}^{rout} Pr_{i,j}^{rout}) \tag{47}$$

and the local utility is

$$U_i^s = u_i^s + U_i^{rc} \tag{48}$$

Note that R_i^{pr} and relay resources are updated after solving the second level auction. The overall algorithm structure is an interaction of these two levels of

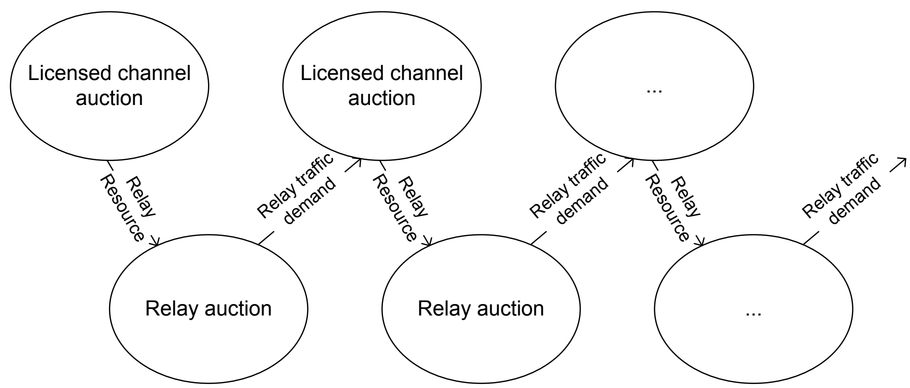

Figure 10: Interaction of these two levels of games

games, as shown in Fig. 10.

For both levels of auction games, local utility is maximized subject to all constraints for the slot allocation problem defined in (34)~(36), as well as constraints

$$0 \leq Pr_{i,n} \leq C_{i,n} \tag{49}$$

$$0 \leq Pr_{i,j}^{rin} + C_{i,j}^{r} Pr_{i,j}^{rout} \leq C_{i,j}^{r}, \forall i \in \mathbb{S},\ j \in \mathbb{R}_l \tag{50}$$

$$Pr_{i,j}^{rin} \geq 0, Pr_{i,j}^{out} \geq 0 \tag{51}$$

which guarantee the prices are positive and no larger than utilities available to each layer.

4.3 Algorithm Analysis

4.3.1 Game Analysis

(1) Single Level Auction Analysis In [81], an auction game is proposed as the optimal converging solution to the multi-seller multi-buyer allocation problem. However, in [81], each buyer can only purchase 1 slot from the seller, while in our case, CRs may purchase several slots from each seller. To our best knowledge, there is no optimal solution to such multi-seller multi-buyer multi-slot allocation problem. Although the problem can be converted to the original multi-seller multi-buyer problem if we treat each slot of every channel as an independent resource for allocation, to allocate slots of the same channel independently is quite inefficient in terms of complexity and memory cost. In order to solve the problem with low computational complexity, we propose a new method, called Dynamic Multi-seller Multi-buyer Slot Allocation (DMMSA) algorithm.

We start with the DMS algorithm proposed in [81], which is to find the best buyer-seller combination to match the buyers' utilities with sellers' intrinsic values on the auction items so as to maximize the total network utility. For each auction item, the auction procedure is started with an initial bidding price. However, if all the competing buyers in all the auctions with similar items, i.e., slots from a same link, remain unchanged, a same auction will repeat on each slot and each buyer's bidding price and the allocation results on these slots will be same. As in the considered scenario, since buyers have demands for multiple slots, the overall auction procedure may be composed of several different repeated games. Thus, rather than dealing different slots of a same link differently, we require that each buyer has the same bidding price on all slots of the same link, and in each auction round, we only update each buyer's action by at most one slot on each link, so that transitions between different games are smoothed. Following this idea, we proposed a suboptimal algorithm, where the computational complexity is reduced since the auction procedure in the repeated games is simplified.

The procedure of the proposed algorithm consists of 2 phases: buyer phase and seller phase. In the buyer phase, buyers update their bidding prices based on the last rejection status, and then update the number of slots they request on each link. In the seller phase, unless the demands are less than the capacity, buyers with the smallest bidding price on each link are rejected. The pseudo code of the proposed algorithm is shown as follows.

1. Initialization: $l = 1$, $Pr_{i,n}(l-1) = 0$, $Pur_{i,n}(l-1) = 0$

2. Buyer phase:

For each CR i

a) If CR i's request is rejected by channel n in step l–1, i.e., $Rej_{i,n} = 1$, update its bidding price $Pr_{i,n}(l) = Pr_{i,n}(l\text{–}1) + e$; otherwise $Pr_{i,n}(l) = Pr_{i,n}(l\text{–}1)$. Reset $Rej_{i,n} = 0$. e is the price updating step determines the convergence time of the algorithm, i.e., the smaller the e, the more convergence time is required. On the other hand, e should be small enough to differentiate CRs' utility on different channels.

b) If $Pr_{i,n}(l) > C_{i,n}$, $Pr_{i,n}(l) = C_{i,n}$, and update $Pur_{i,n}(l) = Pur_{i,n}(l) - 1$. If $Pur_{i,n}(l) < 0$, $Pur_{i,n}(l) = 0$.

c) Update R_i and channel profit $u_{i,n} = C_{i,n} - Pr_{i,n}(l)$.

d) If $R_i < Req_i$ and $\sum_{n \in \mathbb{N}} Pur_{i,n}(l) < T$, increase the purchase on the channel with maximum positive profit $u_{i,n}$ by one

e) Send out a request to each channel n with $Pr_{i,n}(l)$ and $Pur_{i,n}(l)$.

3. Seller phase: For each channel n that has received purchasing requests from CRs

a) if $\sum_{i \in \mathbb{I}} Pur_{i,n}(l) \leq T$, it will accept all requests. Otherwise, it rejects the CR with the smallest bidding prices, i.e., $Rej_{i^*,n} = 1$ for $i^* = \arg\min_i Pr_{i,n}(l)$.

b) if no rejection is issued and no request is different from that in the last step, algorithm stops; otherwise $l = l + 1$, go back to buyer phase.

The convergence of the proposed algorithm is guaranteed since each CR will end either with its largest bidding prices or with its largest purchasing on these channels. Compared to the DMS algorithm in [81], it only needs as much as$1/T$ memory cost. Moreover, with smaller number of sellers, it also converges faster than the DMS algorithm.

(2) Modified Two Level Auction The interaction of two levels of games as in Fig.10 may take very long time to converge. Here, we propose a modified two-level auction, where the relay request is updated before the first level auction is solved. The basic idea is to partition the whole auction into three phases, i.e., the BS phase, the Relay phase, and the pure source node phase. In the BS phase, the BS decides whether to reject a CR i's request in channel n based on its bidding price $Pr_{i,n}$ and the total demands in channel n; in the Relay phase, the relay node j first updates its bidding price $Pr_{j,n}$ and purchase $Pur_{j,n}$ according to the rejection result $Rej_{j,n}$ and utility, and then decides whether to reject a pure source node i's request based on i's bidding price and the demands for receiving and for retransmission; and in the Pure source node phase, a pure source node i updates its price and purchase on channels and relays according to the rejection results and utilities. The pseudo-code of CR's actions in each phase is shown as follows.

Algorithm:

1.Initialization:

Treat all CRs as pure source nodes. Set all corresponding prices, purchase and rejections as 0 at the initial step $l = 0$. Let $l = 1$.

2. BS phase:

For each channel n receiving purchasing requests from CRs, if $\sum_{i \in N} Pur_{i,n}(l-1) \leq T$, it will accept all requests. Otherwise, it rejects the SU with the lowest bidding price.

3. Relay phase:

If the CR is a relay node:

a) Relay-BS price updating sub-phase

(1) If Relay j's request is rejected by channel n in step l, update $Pr_{j,n}(l) = Pr_{j,n}(l{-}1) + e_1$. Otherwise, $Pr_{j,n}(l) = Pr_{j,n}(l{-}1)$. e_1 is the price updating step for the prices of channels.

(2) If $Pr_{j,n}(l) > C_{j,n}$, $Pr_{j,n}(l) = C_{j,n}$ and $Pur_{j,n}(l) = Pur_{j,n}(l) - 1$. If $Pur_{j,n}(l) < 0$, $Pur_{j,n}(l) = 0$.

(3) Update R_j and $u_{j,n} = C_{j,n} - Pr_{j,n}(l)$.

(4) Compute relay capacity $R^j_{cap} = R_j - Req_j$. If $R^j_{cap} < 0$, change j's status to pure source node and jump to pure source node phase.

(5) Compute the retransmission base price for pure source node i, $Pr_{RB}(i, j) =$

$\dfrac{\sum\limits_{n\in\mathbb{N}} Pr_{j,n}Pur_{j,n}}{\sum\limits_{n\in\mathbb{N}} C_{j,n}Pur_{j,n}} C^r_{i,j}$, which is the amount of money that relay j need to pay the BS for relaying a slot of traffic from the pure source node i.

b) Relay-CR rejection sub-phase

For relay receiving purchasing requests from CRs:

(1) Receiving requests checking:

If $\sum\limits_{i\in\mathbb{S}} Pur^{rin}_{i,j}(l) < T$, it will accept all requests. Otherwise, it rejects the CR with the lowest bidding price.

(2) Transmitting requests checking:

If $\sum\limits_{i\in\mathbb{S}} Pur^{rout}_{i,j}(l) \leq R^j_{cap}$, it will accept all requests. Otherwise, it rejects the CR with the lowest bidding price.

c) Relay-BS purchase

If $\sum\limits_{i\in\mathbb{S}} Pur^{rout}_{i,j}(l) \geq R^j_{cap}$ and $\sum\limits_{n\in\mathbb{N}} Pur_{j,n}(l) < T$, increase the purchase on the channel with the maximum positive utility by one.

4. Pure source node phase

a) Pure source-BS sub-phase

(1) If source node i's request is rejected by Channel n in step l–1, $p_{i,n}(l) = p_{i,n}(l–1) + e_1$. Otherwise, $p_{i,n}(l) = p_{i,n}(l–1)$

(2) If $Pr_{i,n}(l) > C_{i,n}$, $Pr_{i,n}(l) = C_{i,n}$, and $Pur_{i,n}(l) = Pur_{i,n}(l) - 1$. If $Pur_{i,n}(l) < 0$, $Pur_{i,n}(l) = 0$.

(3) Update R_i and $u_{i,n}$

(4) If $R_i \geq Req_i$ and $\sum\limits_{n\in\mathbb{N}} Pur_{i,n}(l) \leq T$, change CR i's status to relay node, go to phase 3.

b) Pure source-Relay sub phase

(1) If source node i's request is rejected by Relay j in step $t{-}1$ for receiving checking, $Pr^{rin}_{i,j}(l) = p^{rin}_{i,j}(l-1) + e_2$. Otherwise, $Pr^{rin}_{i,j}(l) = p^{rin}_{i,j}(l-1)$. e_2 is the price updating step for the prices of relays.

(2) If $Pr^{rin}_{i,j}(l) > C^r_{i,j} - Pr^{rout}_{i,j}(l-1)$, $Pr^{rin}_{i,j}(t) = C^r_{i,j} - Pr^{rout}_{i,j}(l)$, and $Pur^{rin}_{i,j}(l) = Pur^{rin}_{i,j}(l) - 1$. If $Pur^{rin}_{i,j}(l) < 0$, $Pur^{rin}_{i,j}(l) = 0$.

(3) If source node i's request is rejected by Relay j in step $t{-}1$ for transmitting checking, update the retransmission offset $Pr^{RP}_{i,j}(l) = Pr^{RP}_{i,j}(l-1) + e_2$. Otherwise, $Pr^{RP}_{i,j}(l) = Pr^{RP}_{i,j}(l-1)$. The retransmission offset is the price charged for competition of relay j.

(4) Compute the out relay price as $Pr^{rout}_{i,j}(l) = Pr_{RB}(i,j) + Pr^{RP}_{i,j}(l)$

(5) If $Pr^{rout}_{i,j}(l) > C^r_{i,j} - p^{rin}_{i,j}(l)$, $Pr^{rout}_{i,j}(l) = C^r_{i,j} - Pr^{rin}_{i,j}(l)$, $Pur^{rin}_{i,j} = Pur^{rin}_{i,j}(l) - 1$. If $Pur^{rin}_{i,j} < 0$, $Pur^{rin}_{i,j} = 0$.

c) Pure source purchase sub-phase

(1) Update R_i, $u^r_{i,j}$

(2) If $R_i < Req_i \sum\limits_{n\in\mathbb{N}} Pur_{i,n} \leq T$, and $\sum\limits_{j\in\mathbb{R}_l} Pur^r_{i,j} \leq T$, list all channels and relays in decreasing order, and increase the purchase on the seller (channel or relay) with maximum positive utility by one.

If there is no rejection and no request changing, algorithm ends; otherwise $l = l + 1$, go to phase 2.

4.3.2 Scheduling Algorithm

Since each CR's two transceivers can work simultaneously on different bands without interference, the scheduling problems for licensed band allocation and relay resource allocation are thus decoupled. Since the scheduling problems for both allocation are similar, we only consider the licensed band allocations as an example.

In the licensed band allocation, each channel could be seen as a server, and the slot allocation on each channel is the traffic demand for this server. The objective for the scheduling algorithm is to complete all traffic demands within the smallest time. Note that because of the exclusive utilization of slots, the overall consumed time is determined by the channel with the heaviest traffic demand. Thus, at any time, CRs should select channels with heaviest traffic demand for service. On the other hand, on each channel, CR with the largest demand should be served first. The detailed procedure is described as follows.

1. Denote $Pur_{i,n}$ as $Pur^0_{i,n}$. Let the traffic demand on channel n be $D_n = \sum_{i \in \mathbb{I}} Pur^0_{i,n}$ and $\overrightarrow{D} = \{D_1, ..., D_N\}^T$. Set step $l = 1$ and time slot $t = 0$

2. Sort $\overrightarrow{D}$ in descending order. For each channel, select the CR with the largest no-zero purchase on this channel if it has not been selected before in this step, i.e., $j_n = arg\max_j Pur^{l-1}_{j,n}$, where $Pur^{l-1}_{j_n,n} > 0$, $j_n \notin \{j_1, ..., j_{n-1}\}$. If there is no unselected CR with non-zero purchase on a channel, this channel is ignored in this step l.

3. Let $time_l = min_n Pur^{l-1}_{j_n,n}$.

4. For each channel n, let $P_{j_n,n}(\tau) = 1$, for $\tau = t,\ t+1,\ ...,\ t + time_l$. Let

$t = t + time_l$, and $Pur^l_{j_n,n} = max(0, Pur^{l-1}_{j_n,n} - time_l)$;

5. If all $Pur^l_{i,n} = 0$, stop; otherwise let $l = l + 1$, go to phase 2.

The combination of the modified two level auction and the scheduling algorithm compose of the proposed TLAG algorithm.

4.4 Simulate Results

In simulation, we focus on slightly congested systems, i.e., the total capacity of channels is slightly less than the total user demands, to highlight the effect of spectrum sharing algorithms on the resource utilization efficiency. CRs and PUs are randomly generated in a $100m \times 100m$ area with the BS at the center. There are N channels and $I = 10N$ CRs. Each channel is assigned a PU as the licensed user and CRs can not access this channel within 10m of this PU. Channel between CRs and BS experience shadowing with log-normal distribution. Demands of CRs follows Gaussian distribution with mean 5, variance 3.

For comparison purpose, two other algorithms are also simulated. One is the DS algorithm where only direct communication between CRs and the BS is allowed without any relays. An one-layer auction algorithm is adopted among CRs and a sub-optimal result is reached. The other is the APBR algorithm. In the APBR algorithm, we first perform a one-layer auction among CRs, but set CRs' demands as infinite so that all channel resources are allocated only to CRs with best channel conditions without considering their demands. These CRs are then selected as relays, and the second layer auction is performed to further allocate these relay resources.

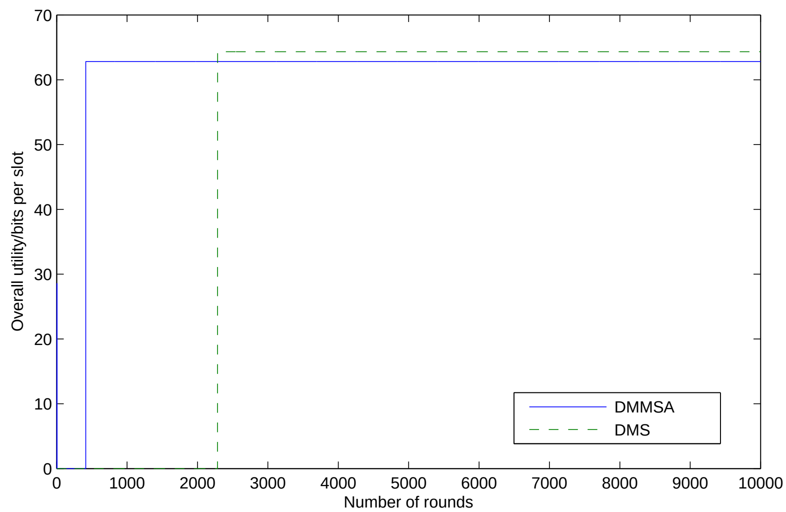

Figure 11: Fast convergence of the proposed suboptimal algorithm

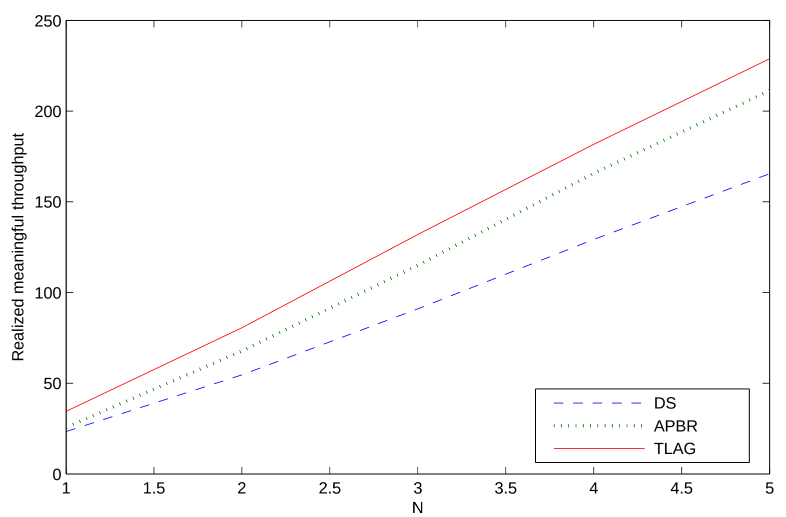

Figure 12: Comparison of the realized meaningful throughput

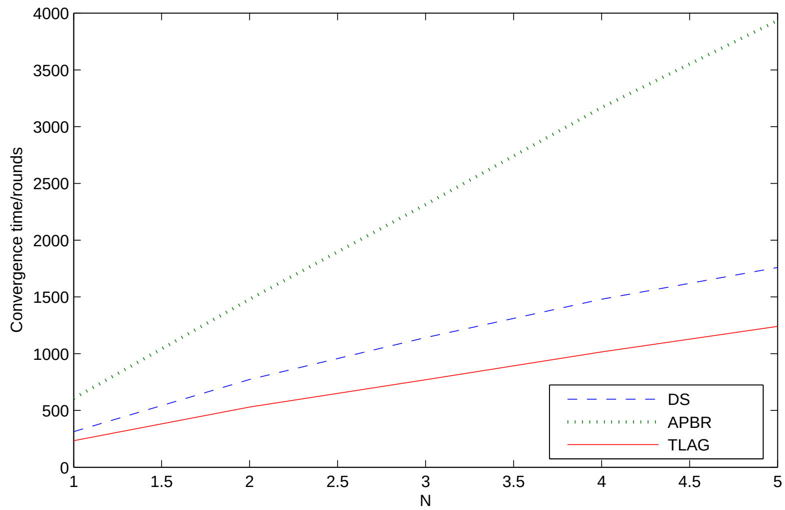

Figure 13: Comparison of the convergence time

Fig. 11 compares the performance of the optimal DMS algorithm and the proposed suboptimal DMMSA algorithm for the single level auction. Performance metrics acquired before convergence are considered as 0 since they are not realizable. From this figure, we can find that the proposed algorithm can converge 70% more faster than the optimal algorithm with only less than 5% degradation in performance. It is because the seller set becomes smaller in the proposed scheme, which is critical in determining the convergence time.

Fig. 12 compares the performance of the three algorithms, i.e., TLAG, DS, and APBR, in term of overall meaningful throughput in the network. From this figure we can see that the APBR algorithm outperforms the DS algorithm by $10\% \sim 20\%$, as the introduction of relays helps the communication of those pure source nodes which do not have good connections with the BS. The proposed TLAG algorithm can further result in improvement over the APBR algorithm by about

10%. It is because in the TLAG algorithm, resources are allocated to relays with the considerations of both the relays' own traffic, channel condition, and relay demands.

Fig. 13 compares the performance of the three algorithms in term of convergence time. From this figure, it can be observed that the APBR algorithm takes about 100% more rounds to converge than the DS algorithm. It is because two auction games need to converge in serial. However, in the proposed TLAG algorithm, since CRs are classified into two groups, i.e., relays and pure source nodes, which makes less buyers participate in the auction, it can converge about 30% faster than the DS algorithm without relay.

In summary, the proposed TLAG algorithm demonstrates performance improvement in both network throughput and convergence time.

5 Conclusion and Future Work

5.1 Conclusion and Comments

In this thesis, the history and the recent development of CRNs have been introduced first. Then the properties of CRNs were described in details. As the CRNs are distinct from traditional networks by their spectrum heterogeneity and spectrum variability, novel resource allocation algorithms are needed to address these new challenges and to improve the network performance.

A novel demand matching spectrum sharing algorithm, which takes into consideration users' heterogeneity in demands, channel availability and channel conditions, was proposed. A distributed cooperative game with classified players is formulated in this thesis, where CRs select channel and their priority based on their satisfaction history. This satisfaction history is used as a public signal for CRs to collaborate with each other. A prioritized game is formulated and no regret learning algorithm is adopted to reach the Correlated Equilibrium (C.E.). The proposed sharing algorithm solves the equal allocation problem in traditional CSMA algorithms, so that it is more suitable for CRNs. The simulation results demonstrate that the proposed algorithm is able to greatly improve the number of satisfied users for CRNs.

In order to further improve the performance of the CRNs, CCRNs have been introduced with a two-layer auction game to conduct channel slots allocation, relay formation, and relay selection. Starting from a homogeneous network without predefined relays, CRs allocated with abundant resources become amateur relays to provide connectivity for those allocated with insufficient resources. Prices charged on slots of relays and channels are used to leverage resource allocation. A suboptimal algorithm is provided for the single level auction. Modified two level auction is adopted to accelerate the convergence. Compared with the traditional DS algorithm and APBR algorithm, the proposed algorithm can improve both the network throughput and the convergence time.

5.2 Future Work

Providing efficient and dynamic resource allocation algorithms in CRNs is still an open topic. Plenty of future works are possible to further improve network performance. For the spectrum sharing in TCRNs, one potential extension is to consider the spectrum variability, i.e., PUs' on/off. By conducting PU activity prediction and learning the statistical behaviors of the PUs, dynamic and adaptive allocation algorithms can be proposed for more efficient resource utilization. Moreover, the duration of idle channels may also be taken into account to match CRs' specific communication requirements. Besides, in practice the interference among users in the CRN is complex. The allocation of channels is also influenced by CRs' interfering neighbors, which introduces new challenges to resource allocation algorithm design. The cross-layer design, i.e., joint resource allocation and routing design, is another promising direction for future research.

In the CCRNs, we considered a simple overlay CRN with a BS as the central controller in the proposed algorithm. Such network structure is plausible as it is similar to the one in IEEE 802.22 standard. However, with the increased applications of ad hoc networks and their integration with CRNs, designing resource allocation algorithm for such highly distributed networks becomes necessary. Since there is no central controllers in ad hoc networks, the resource allocation algorithm is expected to be fully distributed based on local information only, and has more strict constraints on the overhead related to the control information exchange. Besides, similar to the spectrum sharing in direct CRNs, spectrum variability and more practical interference environment should be taken into account in future works.

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