Dynamic Spectrum Sharing: A Game Theoretical Overview

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ABSTRACT

In order to fully utilize the scarce spectrum resources, with the development of cognitive radio technologies, dynamic spectrum sharing becomes a promising approach to increase the efficiency of spectrum usage. Game theoretical dynamic spectrum sharing has been extensively studied for more flexible, efficient, and fair spectrum usage through analyzing the intelligent behaviors of network users equipped with cognitive radio devices. This article provides a game theoretical overview of dynamic spectrum sharing from several aspects: analysis of network users' behaviors, efficient dynamic distributed design, and optimality analysis.

INTRODUCTION

The demand for wireless spectrum use has been growing rapidly with the dramatic development of the mobile telecommunication industry in the last decades. Recently, regulatory bodies like the Federal Communications Commission (FCC) in the United States are recognizing that traditional fixed spectrum allocation can be very inefficient, considering that bandwidth demands may vary highly along the time or space dimension. In order to fully utilize the scarce spectrum resources, with the development of cognitive radio technologies, dynamic spectrum access becomes a promising approach to increase the efficiency of spectrum usage, which allows unlicensed wireless users (secondary users) to dynamically access the licensed bands from legacy spectrum holders (primary users) on a negotiated or an opportunistic basis.

Cognitive radio technologies have the potential to provide wireless devices with various capabilities, such as frequency agility, adaptive modulation, transmit power control, and localization. The advances of cognitive radio technologies make more efficient and intensive spectrum access possible. The FCC began to consider more flexible and comprehensive use of available spectrum. The NeXt Generation program of the Defense Advanced Research Projects Agency (DARPA) also aims to dynamically redistribute allocated spectrum based on cognitive radio technologies.

The key component of dynamic spectrum access is dynamic spectrum sharing, which is responsible for providing efficient and fair spectrum allocation or scheduling solutions among primary and secondary users. Traditionally, dynamic spectrum sharing was generally regarded as similar to generic medium access control (MAC) problems in existing wireless systems and studied from the perspective of wireless resource allocation. However, one of the most important characteristics of network users equipped with cognitive radios is their cognitive intelligence, which enables network users to make intelligent decisions on spectrum usage and communication parameters based on the sensed spectrum dynamics and other users' decisions. Therefore, it is more natural to study the intelligent behaviors and interactions of network users (cooperative, selfish, or malicious) for dynamic spectrum sharing from the game theoretical perspective.

Generally speaking, game theory models strategic interactions among agents using formalized incentive structures. It not only provides game models for efficient self-enforcing distributed design, but also derives well defined equilibrium criteria to study the optimality of game outcomes for various game scenarios (static or dynamic, complete or incomplete information, non-cooperative or cooperative). These game models and equilibrium criteria have been extensively studied in the scenarios of dynamic spectrum sharing to achieve efficient and fair solutions for different network architectures (centralized/distributed), spectrum allocation behaviors (cooperative/non-cooperative) or spectrum access techniques (overlay/underlay). In this article we present a comprehensive overview of game theoretical dynamic spectrum sharing from several aspects: analysis of network users' behaviors, efficient dynamic distributed design, and optimality analysis.

SYSTEM MODEL

Dynamic spectrum access networks (DSANs), also known as NeXt Generation (xG) networks, will enable efficient spectrum usage to network users via dynamic spectrum access techniques and heterogeneous network architectures.

Specifically, secondary users are able to access spectrum resources from primary users through opportunistic or negotiation-based methods while not causing harmful interference or channel collision. The main features that define DSANs and those of interest for dynamic spectrum sharing are as follows:

- Consider a general scenario of DSANs with multiple primary users and multiple secondary users as shown in Fig. 1. Different from traditional static or centralized spectrum assignment among different base stations or systems in cellular networks, DSANs enable multiple systems to be deployed with overlapping spectrum or coverage. Moreover, ad hoc networking structures are also encouraged in DSANs. Therefore, flexible spectrum access is possible by allowing secondary users to gain access to multiple primary operators or having multiple secondary users compete for available spectrum.
- The network users are equipped with cognitive radio devices, which enable them to perform various dynamic spectrum access techniques including spectrum sensing, spectrum management, seamless handoff, and spectrum sharing.
- Spectrum pooling architecture is used to collect unused or underused licensed spectra and divide them into orthogonal frequency channels based on orthogonal frequency-division multiplexing (OFDM). In order to prevent interference to the communications of primary users, zeros can be fed into the channels primary users occupy through OFDM techniques.
- Considering different applications of DSANs, such as military, emergency, or civilian applications, different types of users coexist in wireless networks, including cooperative, selfish, and malicious users. Cooperative users unconditionally cooperate with each other to serve a common goal; selfish users aim to maximize their own interests; malicious users intend to cause as much damage as they can to the network.
- There may not be centralized authorities. A management point may exist to handle the billing information for spectrum leasing activities. Control channels are assumed for exchanging spectrum sharing information.
- The characteristics of spectrum resources may vary over frequency, time, and space due to user mobility, channel variations, or wireless traffic fluctuations.

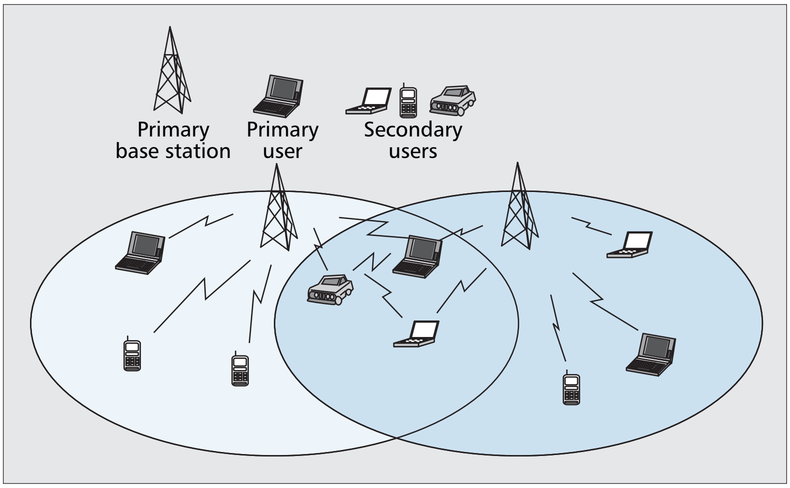

Figure 1. *Illustration of dynamic spectrum access networks.*

Game Theoretical Models for Dynamic Spectrum Sharing

In this section the motivation and importance of game theoretical approaches for dynamic spectrum sharing are illustrated first. Then the game models for dynamic spectrum sharing are discussed for various networking scenarios.

Motivation of Game Theoretical Dynamic Spectrum Sharing

The imbalance between the increasing demands of wireless spectra and limited radio resources poses an imminent challenge in efficient spectrum sharing. In order to have efficient dynamic spectrum sharing, several difficulties need to first be overcome: the unreliable and broadcast nature of wireless channels, user mobility and dynamic topology, various network infrastructures, and, most important, network users' behaviors. To be specific, network users can be cooperative, selfish, and even malicious. Traditional spectrum sharing approaches only assume cooperative, static, and centralized network settings. Before efficient dynamic spectrum sharing can be achieved, network users' intelligent behaviors and interactions have to be thoroughly studied and analyzed. Game theory studies conflict and cooperation among intelligent rational decision makers, which is an excellent match in nature to dynamic spectrum sharing problems.

The importance of studying dynamic spectrum sharing in a game theoretical framework is multifold. First, by modeling dynamic spectrum sharing among network users (primary and secondary users) as games, the network users' behaviors and actions can be analyzed in a formalized game structure, by which the theoretical achievements in game theory can be fully utilized. Second, game theory equips us with various optimality criteria for the spectrum sharing problem. Specifically, the optimization of spectrum usage in DSANs is generally a multi-objective optimization problem, which is very difficult to analyze and solve. Game theory provides us well defined equilibrium criteria to measure game optimality under various game settings (network scenarios in our context). Third, non-cooperative game theory, one of the most important game theories, enables us to derive efficient distributed approaches for dynamic spectrum sharing using only local information. Such approaches become highly desirable when centralized control is not available or flexible self-organized approaches are necessary.

Game Models

Generally speaking, a game in the strategic form has three elements: the set of players, the strategy space for each player, and the payoff function, which measures the outcome of each player. Similarly, the intelligent behaviors of cognitive

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network users in DSANs can be modeled as a dynamic spectrum sharing game (DSSG). The players in the DSSG are all the network users, including both primary and secondary users. The strategy space for each user consists of various actions related to spectrum sharing. Specifically, for secondary users, the strategy space includes which licensed channel they will use, what transmission parameters (e.g., transmission power or time duration) to apply, the price they agree to pay for leasing certain channels from the primary users, and so on. For primary users, the strategy space may include which unused channel they will lease to secondary users, how much they will charge secondary users for using their spectrum resources, and so on. Furthermore, the payoff functions in a DSSG may vary considering the nature of network users. To be specific, the payoff function of a group of cooperative users represents their common communication goal; the payoff functions of selfish users describe their self-interests; the payoff functions of malicious users illustrate their damage to DSANs.

Considering the availability of centralized authorities, we have non-cooperative DSSGs and cooperative DSSGs. In non-cooperative DSSGs, without centralized control, selfish network users do not cooperate, so any cooperation among them must be self-enforcing [1]. Thus, the study of dynamic spectrum sharing in non-cooperative DSSGs focuses on distributed game designs and cooperation stimulation. Note that the *Nash equilibrium* [1] is an important concept to measure the outcome of a non-cooperative game, which is a set of strategies, one for each player, such that no selfish player has incentive to unilaterally change his/her action. In order to further measure the efficiency of game outcomes, a Pareto optimality [1] is defined such that an outcome of a game is Pareto optimal if there is no other outcome that makes every player at least as well off and at least one player strictly better off.

In cooperative DSSGs, users are able to do enforceable spectrum sharing through centralized authorities. Thus, for cooperative DSSGs, the interests lie in how good the outcome of spectrum sharing can be; in other words, how to define and choose the optimality criteria in cooperative scenarios. It is worth mentioning that the Nash bargaining solution (NBS) [1] plays an important role in cooperative games, which is a unique Pareto optimal solution to the game modeling bargaining interactions based on six intuitive axioms. To be specific, the NBS divides the remaining spectrum resources among users in a ratio equal to the rate at which the payoff can be transferred after the users are assigned minimal resources [1]. The NBS can be represented as a product of extra resources assigned to each user, which is also referred to as a *linear-proportional fairness criterion* if no minimal resources are preassigned [2].

Considering that spectrum sharing in DSANs is a dynamic process, how the interactions among users evolve over time based on spectrum dynamics needs to be further studied. Therefore, in order to better model dynamic spectrum sharing, dynamic game models have been considered to study the static DSSG in a multistage manner or further represent DSSGs in extensive form if users take actions sequentially. In dynamic DSSGs, if complete information is available (i.e., the set of strategies and payoffs for each user are common knowledge), a subgame perfect equilibrium (SPE) can be used to study the game outcomes, which is an equilibrium such that users' strategies constitute a Nash equilibrium in every subgame [1] of the original game. If complete information is not available, *sequential equilibrium* [1] is a well defined counterpart of SPE under such circumstances, which guarantees that any deviations from the equilibrium will be unprofitable.

Considering the negotiated or leasing-based dynamic spectrum sharing, primary users attempt to sell unused spectrum resources to secondary users for monetary gain, while secondary users try to acquire spectrum usage permissions from primary users to achieve certain communication goals, which generally introduces reward payoffs for them. Noting that the users may be selfish and will not reveal their private information unless proper mechanisms have been applied to ensure that their interests will not be hurt, the interactions among users in such scenarios can be modeled as a multiplayer non-cooperative game with incomplete information, which is generally difficult to study as the players do not know the perfect strategy profile of others. However, based on the game setting of DSSGs, the well developed auction theory [3], one of the most important applications of game theory, can be applied to formulate and analyze the interactions.

In auction games [3], according to an explicit set of rules, the principles (auctioneers) determine resource allocation and prices on the basis of bids from the agents (bidders). In the DSSG the primary users can be viewed as the principles, who attempt to sell unused channels to the secondary users. The secondary users are the bidders who compete with each other to buy the permission of using primary users' channels. Furthermore, multiple sellers and buyers may coexist, which indicates the double auction scenario. This means that not only the secondary users but also the primary users need to compete with each other to make beneficial transactions possible by eliciting their willingness to pay in the form of bids or asks.

In the double auction scenarios of the DSSG, competitive equilibrium (CE) [3] is a well-known theoretical prediction of the outcomes. It is the price at which the number of buyers willing to buy is equal to the number of sellers willing to sell. Alternatively, CE can also be interpreted as where supply and demand match [3]. In DSSGs, the supply function can be defined as the relationship between the acquisition costs of primary users and the number of channels; the demand function can be defined as the relationship between the reward payoffs of secondary users and the number of channels. We describe the supply and demand functions in Fig. 2. Note that CE is also proved to be Pareto optimal in stationary double auction scenarios.

EFFICIENT DISTRIBUTED DYNAMIC SPECTRUM SHARING

The deregulation of wireless spectrum makes such a scarce resource a commodity that can be dynamically exchanged among network users. Considering the lack of centralized authorities and network users' selfishness, distributed dynamic spectrum sharing needs to be further exploited by studying users' intelligent behaviors from the game theoretical point of view. Recently, distributed dynamic spectrum sharing approaches [4–7] have been well studied to enable efficient and fair spectrum allocation distributively using local information available at each user.

LOCAL BARGAINING

In [4] the authors propose a local bargaining approach to achieve distributed conflict-free spectrum assignment adapted to network topology changes. The proposed local bargaining approach includes two bargaining strategies for different scenarios: one-to-one bargaining is proposed to efficiently exchange channels between two neighbor users; one-buyer-multiple-seller bargaining is proposed for a buyer user to purchase spectrum channels from several neighbors based on Feed Poverty strategies [4] for fairness considerations. Note that the product of user throughput is considered the optimization goal of local bargaining, which indicates the application of the NBS. By using the proposed local bargaining, the optimal spectrum assignment does not need to be completely recomputed after each topology change, which significantly decreases the computation and communication overhead.

REPEATED SPECTRUM SHARING GAME MODEL

In [5] the authors study the spectrum sharing problem among multiple secondary users for interference-constrained wireless systems in a non-cooperative game framework. Their study is focused on investigating self-enforcing spectrum sharing game rules and the corresponding game efficiency measured in total throughput obtained from available spectrum resources. Since the static game formulation leads to inefficient Nash equilibrium outcomes due to users' selfishness, a repeated game model is proposed to study the spectrum sharing interactions in a long-run scenario. Generally speaking, repeated games belong to the dynamic game family; they play a similar static game many times. The overall payoff in a repeated game is represented as a normalized discounted summation of the payoff at each stage game. Since the game is not played only once, the users in a repeated game are able to make decisions conditioned on past moves, thus allowing for reputation effects and retribution. One of the most important results in repeated game theory is *Folk Theorem* [1], which asserts that for infinite repeated games there exists a discount factor $\hat{\delta} < 1$ such that any feasible and individually rational payoff can be enforced by an equilibrium for any discount factor $\delta \in (\hat{\delta}, 1)$. Folk Theorem is further applied in [5] to show the efficiency of self-enforcing spectrum sharing in long-run scenarios.

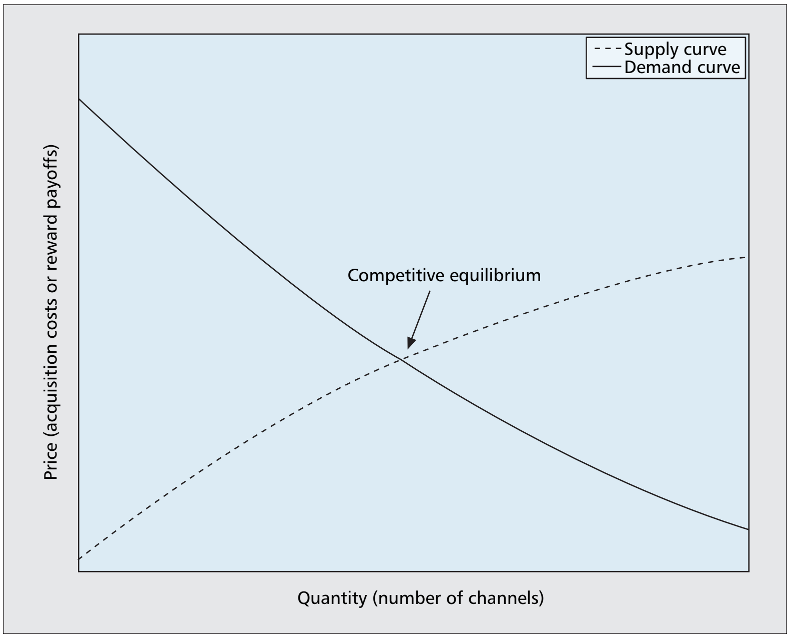

Figure 2. *Illustration of the relationship of the spectrum supply and demand.*

AUCTION-BASED SPECTRUM SHARING GAME

Considering the leasing relationship between primary and secondary users, the auction mechanism becomes a natural solution for efficient distributed spectrum sharing on a negotiated basis. An auction-based spectrum sharing approach was proposed in [6], in which many secondary users purchase channels from one primary user or spectrum broker through an auction process. For such scenarios, a Vickrey-Clarke-Groves (VCG) is usually used to achieve a socially optimal [3] solution, which may not be suitable for spectrum sharing due to the interference temperature constraints, information overhead, and computational burden. In [6] two auction mechanisms were proposed considering different payment metrics: one is to charge secondary users according to their received signal-to-interference-plus-noise ratio (SINR); the other is to charge secondary users according to their received power. Furthermore, an iterative and distributed bid updating algorithm was derived to have auction-based spectrum sharing converge to the social optimal equilibrium by VCG mechanisms.

BELIEF-ASSISTED PRICING

Considering the general scenarios of DSANs where multiple primary and secondary users coexist, dynamic spectrum sharing becomes much more complex, and the outcome of the DSSG is difficult to measure without proper theoretical criteria. Asmentioned in the previous section, such scenarios can be modeled using double auction mechanisms and measured using a competitive equilibrium. However, a double auction mechanism is usually implemented in powerful centralized authorities such as the New York Stock Exchange (NYSE). In DSANs that lack centralized control, having varying spectrum status and selfish users, it is difficult to imple-

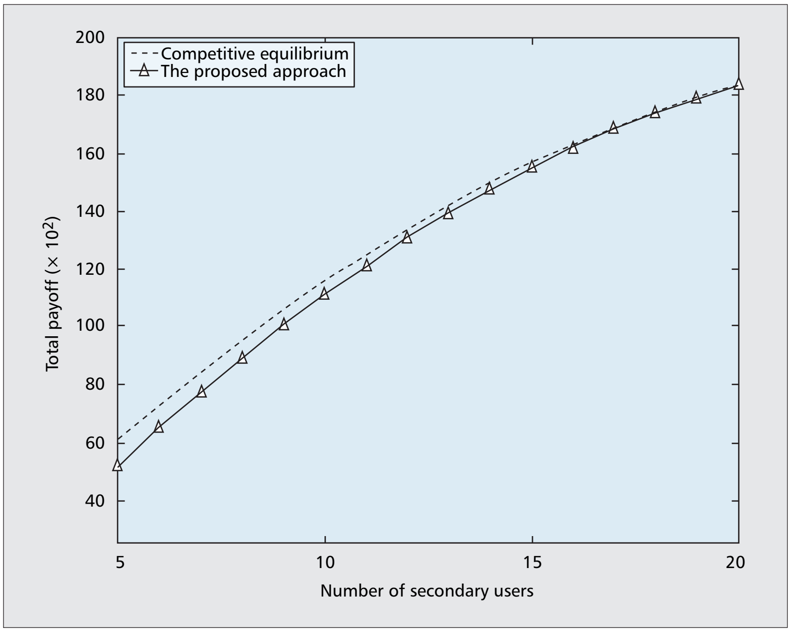

Figure 3. *Comparison of the total payoff for the belief-assisted scheme and theoretical competitive equilibrium.*

ment bilateral pricing through double auction mechanisms. In [7] the authors propose a belief-assisted pricing approach for multiple primary and secondary users to efficiently share spectrum resources.

In order to achieve efficient pricing distributively in DSSGs with incomplete information, the belief metrics are proposed in [7] to predict other users' future possible strategies according to the game histories and assist each user's decision making. Considering that there are multiple players with private information in the DSSG, and the bid/ask prices directly affect the outcome of the game, it is more efficient to define one belief function for each user based on the observable bid/ask prices instead of generating a specific belief of every other user's private information. Hence, primary/secondary users' beliefs are defined as the ratio of their bid/ask being accepted at different price levels. However, in DSSGs only a relatively small number of players are involved in spectrum sharing at a specific time. Beliefs cannot be practically obtained for any price level directly, so historical bid/ask information needs to be incorporated to build up empirical belief values.

In [7] the belief functions are obtained based on several intuitive observations: if an ask $\tilde{x} < x$ is rejected, the ask at x will also be rejected; if an ask $\tilde{x} > x$ is accepted, the ask at x will also be accepted; if a bid $\tilde{y} > x$ is made, the ask at x will also be accepted. By using the proposed belief functions, each user is able to make the optimal decision for the next bid/ask with only local information. Therefore, a distributed algorithm can be developed through the belief-based bidding process that can not only approach the optimal competitive equilibrium, but also substantially decrease the overhead of bid/ask information compared to traditional continuous double auction mechanisms.

Game Theoretical Optimality Analysis

One important aspect of dynamic spectrum sharing is how to analyze the optimality of the DSSG game outcomes. The original difficulty of optimality analysis comes from the fact that many users (primary or secondary) coexist in DSANs, which implies a complicated multi-objective optimization scenario. One common approach to such a problem is to generate an overall optimal criterion considering all users' objectives in certain ways, such as the max-min criterion or maximizing the total payoff. However, the desired spectrum sharing needs to be both efficient and fair instead of focusing on only one aspect. Moreover, in non-cooperative DSSGs, users will not follow the overall criteria, and aim to maximize their own payoffs. In this section a comprehensive optimality analysis overview is given for dynamic spectrum sharing from the game theoretical perspective.

Price of Anarchy

In non-cooperative DSSGs without centralized authorities, the interactions among selfish users may lead to inefficient Nash equilibriums. In order to study the optimality of the non-cooperative game outcomes, the *price of anarchy* is an important measure, which is the ratio between the worst possible Nash equilibrium and a social optimum that can be achieved only if a central authority is available. Thus, studying the bounds on the price of anarchy is of great importance in understanding the Nash equilibrium outcomes of non-cooperative DSSGs.

In [8] the price of anarchy is extensively studied for non-cooperative spectrum sharing games, in which channel assignment for access points (APs) is studied for WiFi networks. The price of anarchy in this scenario represents the ratio between the number of APs assigned spectrum channels in the worst Nash equilibrium and the optimal number of covered APs if a central authority assigns the channels. The analysis of Nash equilibrium in spectrum sharing games is performed by considering it as a maximal coloring problem. The theoretical bounds on the price of anarchy are derived for the scenarios of different numbers of spectrum buyers and sellers. One interesting finding is that the price of anarchy is unbounded in general DSSGs unless certain constraints are applied such as the distribution of users. Similarly, in [4] the price of anarchy is studied for spectrum assignment in local bargaining scenarios.

NBS in Spectrum Sharing Games

In order to achieve efficient and fair dynamic spectrum sharing, the NBS is important for optimality analysis in different spectrum sharing scenarios [4, 9]. In the scenarios of multiple secondary users sharing spectrum resources, a local bargaining process [4] is carried out to approach the NBS of spectrum sharing among many users proportional to their reward payoffs of using the acquired channels. In the scenarios of multiple primary and secondary users exchanging spectrum channels through pricing, the NBS can be applied to study efficient and fair spectrum sharing of the worst case considering user collusion among primary or secondary users [9], which can be described as follows.

An efficient spectrum sharing scheme can be achieved by balancing the supply and demand of spectrum resources as shown in Fig. 2. Thus, it is straightforward that the most inefficient spectrum allocation occurs when all the supply and demand information is concealed by the collusive behaviors of users, which happens only when two all-inclusive collusions are formed among the primary and secondary users, respectively. Under this situation, the spectrum allocation game becomes a bargaining game between two players: the primary user $p_{(1)}$ with the lowest acquisition cost and the secondary user $s_{(1)}$ with the highest reward payoff for the channels in the spectrum pool. Generally speaking, primary user $p_{(1)}$ and secondary user $s_{(1)}$ value a spectrum channel differently, so a surplus is created. The objective of the bargaining game is to determine in which way the primary and secondary users agree to divide the surplus. The NBS provides a unique and fair Pareto optimal solution under such a scenario, which also indicates the lower bound of spectrum efficiency in DSANs with user collusion [9].

Dynamic Programming for DSSGs

Considering the spectrum dynamics over time, frequency, or space, optimality analysis needs to be further performed in dynamic fashion such as in a dynamic programming framework. In [7], considering each secondary user has a total monetary budget for spectrum leasing, the optimal spectrum sharing needs to be solved using dynamic programming approaches. The optimal sequential strategies for each user can only be obtained by considering the spectrum sharing states, such as the number of channels to be allocated at each stage or the residual monetary budget at each spectrum sharing stage for secondary users. The Bellman equation [10] is applied in [7] to describe the expected payoff of each secondary user in the form of the summation of two terms: one represents its current payoff given current spectrum sharing states; the other represents its expected future payoff given the updated spectrum sharing states. Based on the principle of optimality in dynamic programming [10], the solution of the proposed Bellman equation is also the optimal solution for the general overall optimization problem. Moreover, the value iteration algorithm [10] can be directly applied to solve the spectrum sharing Bellman equation as long as the expected payoff function is bounded.

Numerical Results

In this section we consider a general scenario with multiple primary and secondary users in wireless networks, as in Fig. 1, and evaluate the performance of our proposed belief-assisted dynamic spectrum sharing approach [7]. Considering a wireless network covering a 100 m × 100 m area, we simulate J primary users by randomly placing them in the network. Here we assume that primary users' locations are fixed and their unused channels are available to secondary users within a distance of 50 m. Then we randomly deploy K secondary users in the network, which are assumed to be mobile devices. The mobility of the secondary users is modeled using a simplified random waypoint model as in [7]. The primary user's payoff is represented as the price paid by secondary users for his/her unused channels minus his/her acquisition cost for those channels. The secondary user's payoff is represented as the reward payoff of using the unused channels from primary users minus the corresponding price paid to primary users. Without loss of generality, let the cost of an available channel in the spectrum pool be uniformly distributed in [10, 30] and the reward payoff of leasing one channel be uniformly distributed in [20, 40]. If a channel is not available to some secondary users, let the corresponding reward payoffs of this channel be 0. Note that $J = 5$ and 10^3 spectrum sharing stages have been simulated. Assume that each primary user has four unused spectrum channels, and the discount factor of the repeated game is 0.99.

In Fig. 3 we compare the total payoffs of all users of the proposed belief-assisted scheme with those of the theoretical CE outcomes for different numbers of secondary users. The figure shows that the performance loss of the belief-assisted dynamic spectrum sharing is very limited compared to that of the theoretical optimal results. Moreover, when the number of secondary users increases, the proposed scheme approaches the optimal CE. Then we study the dynamic programming approach to spectrum allocation when each secondary user is constrained by his/her monetary budget. For comparison, we define a static scheme in which the secondary users make their spectrum sharing decisions without considering their overall budget limits. Assume that the budget constraints

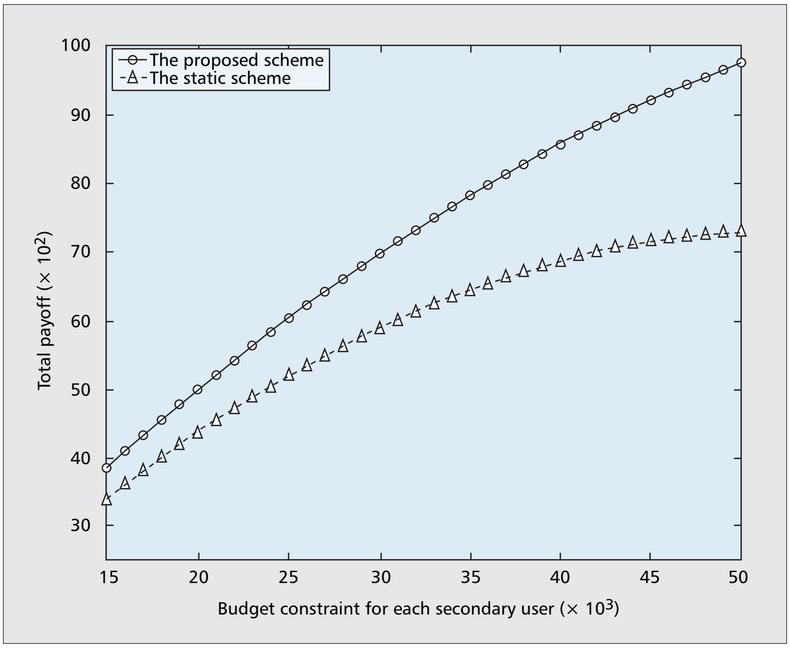

Figure 4. *Comparison of the total payoffs of the dynamic programming scheme with those of the static scheme.*

By studying the intelligent behaviors of cognitive users, game theoretical dynamic spectrum sharing is important for developing efficient distributed spectrum sharing schemes and ensuring the optimality of spectrum sharing in various scenarios.

for the secondary users are the same. In Fig. 4 we compare the total payoffs of the proposed dynamic programming scheme with those of the static scheme for different budget constraints. It can be seen from this figure that the proposed scheme achieves much higher spectrum efficiency than the static scheme by exploiting the time diversity of spectrum resources through dynamic programming.

Conclusions

Next-generation wireless networks are expected to use flexible spectrum sharing techniques for achieving more efficient and fair spectrum usage. By studying the intelligent behaviors of cognitive users, game theoretical dynamic spectrum sharing is important for developing efficient distributed spectrum sharing schemes and ensuring the optimality of spectrum sharing in various scenarios. However, to ensure efficient and fair spectrum sharing in next-generation networks, more research is needed along the lines of game theoretical study.

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