ABSTRACT

Title of Dissertation: GAME THEORETICAL FRAMEWORK FOR COOPERATION IN AUTONOMOUS WIRELESS NETWORKS

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With the explosive growth of wireless networking techniques in the last decade, connecting to the world from any place, at any time and for any body is no longer just a dream. New concepts of network infrastructures such as mobile ad hoc networks or dynamic spectrum access networks emerged in recent years to provide more flexible wireless networking, efficient spectrum usage and robust network connections. With the development of intelligent wireless devices such as cognitive radios, the network users' capability has been largely increased. It becomes important to analyze and understand the network users' intelligent behaviors, especially selfish behaviors. Therefore, we focus our study on these new types of wireless networks with selfish users, which need to be self-organizing and decentralized. They are also referred to as *autonomous wireless networks*.

In order to analyze the selfish behaviors of network users for efficient autonomous wireless networking, we analyze the cooperation in autonomous wireless networks under a comprehensive game theoretical framework. 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 measure the optimality of game outcomes for various scenarios.

In this dissertation, we first study the cooperation enforcement in autonomous wireless networks under noise and imperfect information. We model the interactions among users as multi-stage games and propose a set of belief-assisted approaches to ensure cooperation by allowing reputation effects or retribution. For instance, a user in an ad hoc network will forward packets for the others if they have built up high belief values through their past cooperative behaviors, i.e., forwarding packets. Further, we investigate the impacts of network dynamics on game theoretical cooperation stimulation/enforcement in autonomous wireless networks. We model the dynamic interaction among users as multi-stage dynamic games and develop various dynamic pricing approaches to stimulate cooperation among users by using payments as incentives based on auction rules and dynamic programming. Finally, we exploit the collusive selfish behaviors in autonomous wireless networks in a non-cooperative game theoretical framework and devise countermeasures to combat or alleviate collusive behaviors.

GAME THEORETICAL FRAMEWORK FOR COOPERATION IN AUTONOMOUS WIRELESS NETWORKS

by

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DEDICATION

To my parents.

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Chapter 1

Introduction

1.1 Motivation

With the explosive growth of wireless networking techniques in the last decade, connecting to the world from any place, at any time and for any body is no longer just a dream. The traditional centralized, fixed networks can no longer satisfy the dramatically increasing demand for wireless services and connections, which poses imminent challenges on network management and control. New concepts of network infrastructures emerged in recent years to provide more flexible wireless networking, efficient spectrum usage and robust network connections. For instance, mobile ad hoc networks (MANETs) [1,2] aim to provide wireless services through multi-hop networking by a set of mobile nodes without requiring centralized administration or fixed network infrastructures. In order to fully utilize the wireless spectrum resources, dynamic spectrum access networks (DSAN) [3–7] 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. Moreover, different from the traditional emergency or military situations, these emerging networks are mostly envisioned in civilian applications, where network users typically do not belong to a single authority and may not pursue a common goal. Fully cooperative behaviors such as unconditionally forwarding packets for other users cannot be pre-assumed and the users may tend to be "selfish". Therefore, these new types of networks need to be self-organizing and decentralized, in which the network functions can be run solely by end users. We refer to such networks as *autonomous wireless networks*.

Considering the selfishness of network users, before autonomous wireless networks can be successfully deployed in practice, the critical issue of cooperation must be resolved first. Generally speaking, the selfish network users' objectives are to maximize their own interests. The users' cooperative behaviors in wireless networks, such as forwarding packets for others or mitigating the interference/collision to others by keeping silent or lowering their own transmitting power, will usually harm their own interests. As a result, without sophisticated mechanisms to stimulate or enforce cooperation among selfish users, the system performance (throughput, power consumption or connectivity) of autonomous wireless networks may be largely deteriorated by the selfish users' behaviors. Moreover, considering the node mobility, dynamic topology and unreliable wireless channels, not only the performance of autonomous networks will be further affected but also it becomes more difficult to detect the selfish users' cheating behaviors. Therefore, we need to analyze the cooperation in autonomous wireless networks based on the selfish users' behaviors and further develop efficient and robust cooperation enforcement approaches to enhance the system performance in various network scenarios.

One of the most important characteristics of autonomous networks is the intelligence of selfish network users, which capability becomes even stronger with the development of smart wireless devices such as cognitive radios. For instance, cognitive radios have the potential to provide the users with frequency agility, adaptive modulation, transmit power control and spectrum sensing ability. It enables them to make intelligent decision on networking behaviors such as packet forwarding, trust/belief evaluation, or communication parameters such as transmitting power, rate, or operating frequency. Based on the above, different from traditional centralized networking approaches, it is more natural to study the intelligent behaviors and interactions of selfish users in autonomous wireless networks from the game theoretical perspective. Generally speaking, game theory [8–10] 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 information or incomplete information, non-cooperative or cooperative). To be specific, considering the network dynamics and selfish users, non-cooperative dynamic game theory is an excellent match to the cooperation study in autonomous wireless networks.

Recently, several schemes have been proposed to enforce or stimulate cooperation in autonomous wireless networks such as MANETs and DSANs [11–29]. These schemes can be roughly categorized into two types: pricing-based and reputation-based. In pricing-based methods, such as in [11–16], a selfish node in MANETs will forward packets for other nodes only if it can get some payment from those requesters as compensation. As for DSANs, the unused spectrum resources from legacy spectrum holders can be shared with unlicensed users through auction-based pricing mechanisms [17–19]. In reputation-based methods, such as in [20–29], a node determines whether it should interact with others based on their past behaviors, such as forwarding packets for other nodes or request other nodes to forward packets for it in MANETs, adjusting the transmitting power or time duration in unused licensed spectrum bands in DSANs. Besides, some efforts have been made towards mathematical analysis of cooperation in autonomous ad hoc networks using game theory, such as in [30–38].

Although the cooperation in autonomous wireless networks has been studied in many existing works and also been analyzed from the game theoretical perspective, there are still some fundamental issues needed to be exploited in a comprehensive game theoretical framework. First, most of existing approaches for cooperation enforcement have assumed perfect observation by network users, and not considered the effect of noise on the strategy design. However, in autonomous wireless networks, since central monitoring is in general not available, perfect public observation is either impossible or too expensive; due to the mobility and wireless channel variations, the network users' actions may be disturbed and not correctly observed even if we assume accurate monitoring of other users. For instance, when a node has decided to forward a packet for another node, this packet may still be dropped due to link breakage or transmission errors. Therefore, how to enforce cooperation in autonomous wireless networks under noise and imperfect observation still remains unanswered. Second, cooperation in autonomous wireless networks has been mostly modeled and analyzed in a static way in existing works. Considering the network dynamics including node mobility, dynamic topology and wireless traffic variations, the dynamic game theory needs to be further applied to analyze the cooperation evolvement in long-run scenarios for autonomous wireless networks. Third, the users' selfish behaviors have been mostly studied from an individual point of view. It is worth mentioning that the collusive selfish behaviors are able to largely affect the system performance and will be more difficult to be detected and combatted. How to formally analyze the cooperation under collusive situations in a game theoretical framework is another highly important issue.

1.2 Contributions and Thesis Organization

This dissertation focuses on developing a comprehensive game theoretical framework for cooperation in autonomous wireless networks under various network scenarios. The contributions lie in the following three aspects.

First, distributive cooperation enforcement have been extensively studied in a comprehensive game theoretical framework for autonomous wireless networks under noise and imperfect observation [39–44]. In the autonomous MANETs, we focus on the most basic networking functionality, namely packet forwarding. Considering the nodes need to infer the future actions of other nodes based on their own imperfect observations, in order to optimally quantify the inference process with noise and imperfect observation, a belief evaluation framework is proposed to stimulate the cooperation, i.e., packet forwarding between nodes and maximize the expected payoff of each selfish node by using repeated game theoretical analysis [39–41]. Further, we not only show that the packet forwarding strategy obtained from the proposed belief evaluation framework achieves a sequential equilibrium [10] that no user has incentive to deviate from, but also derive its performance bounds. In the autonomous DSANs, we model the spectrum sharing as a dynamic pricing game and develop a belief system to assist selfish users to update their sharing strategies adaptive to the spectrum dynamics only based on their local incomplete information [42–44]. The proposed belief-assisted pricing approach not only can achieve the theoretical optimal outcomes using local information, but also will introduce much less overhead than traditional approaches.

Second, we enhance the cooperation in dynamic networking scenarios through dynamic game theoretical studies [42, 45, 46]. Considering the interactions of network users happen numerous times in autonomous wireless networks, we are able to stimulate or enforce the cooperation among users based on their past behaviors in long-run scenarios, which achieves better cooperation than traditional static game theoretical schemes. We analyze the routing process in autonomous MANETs using multi-stage dynamic games and propose an optimal pricing-based approach to dynamically maximize the sender/receiver's payoff over multiple routing stages considering the dynamic nature of MANETs, meanwhile, keeping the forwarding incentives of the relay nodes by optimally pricing their packet-forwarding actions based on the auction rules [45, 46]. Also, by modeling the spectrum sharing in DSANs as a dynamic pricing game, we are able to coordinate the spectrum allocation among primary and secondary users through a trading process to maximize the payoffs of both primary and secondary users adapting to the spectrum dynamics [42].

Third, we study the collusive selfish behaviors in autonomous wireless networks in a non-cooperative game theoretical framework [47, 48]. In order to have efficient and robust dynamic spectrum sharing, we propose a collusion-resistant dynamic pricing approach with optimal reserve prices designed to combat and alleviate the impact of user collusion. Moreover, the belief system that is proposed for cooperation under noise and imperfect observation can also be extended to combat collusive behaviors. Note that by using appropriate equilibrium concepts from game theory, the performance bounds of the networks with collusive users is also derived in this dissertation.

The remainder of this dissertation is organized as follows. Chapter 2 introduces the related works and game theoretical models for autonomous wireless networks. The cooperation enforcement in autonomous MANETs under noise and imperfect observation is presented in Chapter 3. In Chapter 4, an optimal dynamic pricing framework is discussed for self-organized routing in MANETs. In Chapter 5, the belief-assisted dynamic game theoretical approach is described for dynamic spectrum allocation in DSANs. Further, the collusion-resistant multi-stage pricing game is studied for robust dynamic spectrum allocation in Chapter 6. Finally, Chapter 7 concludes this dissertation and discusses the future work.

Chapter 2

Background

2.1 Related Works

2.1.1 Cooperation in Autonomous Ad Hoc Networks

In the literature, many schemes have been proposed to address the issue of cooperation stimulation in ad hoc networks [11, 13, 20–22, 26]. One way to enforce cooperation among selfish nodes is to use pricing-based schemes such as [11–13], in which a selfish node will forward packets for other nodes only if it can get some payment from those requesters as compensation. For example, a cooperation enforcement approach was proposed in [11, 12] by using a virtual currency called nuglets as payments for packet forwarding, which requires tamper-proof hardware in each node. Another payment-based system, SPRITE [13], releases the requirement of tamper-proof hardware, but requires some online central banking service trusted by all nodes. Another way to enforce cooperation among selfish nodes is to use reputation-based schemes with necessary traffic monitoring mechanisms such as [20–22, 26], in which a node determines whether it should forward packets for other nodes or request other nodes to forward packets for it based on their past behaviors. In [20], a reputation-based system was proposed for ad hoc networks to mitigate nodes' misbehaviors, where each node launches a "watchdog" to monitor its neighbors' packet forwarding activities. Following [20], CORE and CONFIDANT systems [21,22] were proposed to enforce cooperation among selfish nodes which aim at detecting and isolating misbehaving node and thus making it unattractive to deny cooperation. Moreover, ARCS was proposed in [26] to further defend against various attacks while providing the incentives for cooperation.

Recently, some efforts have been made towards mathematical analysis of cooperation in autonomous ad hoc networks using game theory, such as [23, 24, 30–33, 36, 37]. In [30], Srinivasan et al. provided a mathematical framework for cooperation in ad hoc networks, which focuses on the energy-efficient aspects of cooperation. In [31], Michiardi et al. studied the cooperation among selfish nodes in a cooperative game theoretic framework. In [32], Felegyhazi et al. defined a game model and identified the conditions under which cooperation strategies can form an equilibrium. In [33], Altman et al. studied the packet forwarding problem using a non-cooperative game theoretic framework. Further, Trust modeling and evaluation framework [23, 24] have been extensively studied to enhance cooperation in autonomous distributed networks, which utilized trust (or belief) metrics to assist decision-making in autonomous networks through trust recommendation and propagation. The study of selfish behavior in ad hoc networks using game theory has also been addressed in [36, 37].

Considering the above approaches mostly focus on the basic functionality of ad hoc networks, namely, packet-forwarding, the cooperation during the routing process needs to be built upon successful packet forwarding among the nodes and is much more complicated than packet forwarding for several reasons. First, the routing in ad hoc networks involves many selfish nodes at the same time for multi-hop packet forwarding and the behaviors of the selfish nodes may be correlated. Moreover, in MANETs, there usually exist multiple possible routes from the source to the destination. Furthermore, due to mobility, the available routes between the sources and the destinations may change frequently. In this dissertation, we refer to *path diversity* as the fact that in general there exist multiple routes between a pair of nodes, each with different characteristics, such as the number of hops, cost (or requested price), and valid time of this route. We refer to *time diversity* as the fact that due to the mobility, dynamic topology, and traffic variations, the routes between two nodes will keep changing over time. In order to achieve efficient routing in autonomous MANETs, a comprehensive study needs to be carried out considering the above aspects.

Several approaches have been proposed to exploit the path diversity during the routing process in autonomous MANETs such as [14–16]. Based on the ideas of the auction-like pricing and routing protocols for the Internet [49, 50], the authors in [14–16] have introduced some auction-like methods for the cost-efficient and truthful routing in MANETs, where the sender-centric Vickrey auction has been adopted to discover the most cost-efficient routes, which has the advantage that its incentive compatible property ensures the truthful routing among the nodes. Router-based auction approaches [51], [52] have also been proposed to encourage the packet-forwarding in MANETs, where each router constitutes an auction market instead of submitting bids to the sender. Besides, a strategy-proof pricing algorithm for the truthful multi-cast routing has been proposed in [53].

2.1.2 Cooperation in Autonomous Dynamic Spectrum Access Networks

The imbalance between the increasing demands of wireless spectrums and limited radio resources poses an imminent challenge on efficient spectrum sharing. In order to have efficient dynamic spectrum sharing in autonomous wireless networks, several difficulties need to be first overcome: unreliable and broadcast nature of wireless channels, user mobility and dynamic topology, various network infrastructures, and, most importantly, the network users' behaviors. Traditional spectrum sharing approaches only assume cooperative, static and centralized network settings. Before efficient dynamic spectrum sharing can be achieved, the 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 advances of cognitive radio technologies make more efficient and intensive spectrum access possible on a negotiated or an opportunistic basis. The FCC has began to consider more flexible and comprehensive use of available spectrum [6,7]. The NeXt Generation program of DARPA also aims to dynamically redistribute allocated spectrum based on cognitive radio technologies [4,5]. Therefore, great attentions have been drawn to explore the dynamic spectrum access systems [54,55]. Traditionally, network-wide spectrum assignment is carried out by a central server, namely, spectrum broker [56, 57]. Recently, distributed spectrum allocation approaches [19,27] have been studied to enable efficient spectrum sharing only based on local observations. In [19], local bargaining mechanism was introduced to distributively optimize the efficiency of spectrum allocation and maintain bargaining fairness among secondary users. In [27], the authors proposed a repeated game approach to increase the achievable rate region of spectrum sharing, in which the spectrum sharing strategy can be enforced by the Nash Equilibrium of dynamic games. Moreover, efficient spectrum sharing has also been studied from a practical point of view, such as in [58] and [29], which analyzed spectrum sharing games for WiFi networks and cellular networks, respectively.

From economical point of view, the deregulation of spectrum use further encourages market mechanisms for implementing efficient spectrum allocation in autonomous wireless networks, which requires sophisticated game theoretical study on the behaviors and interactions of network users. Researchers have already started to study dynamic spectrum access via pricing and auction mechanisms [17, 18, 58, 59]. In [17], the authors proposed an auction-based mechanism to efficiently share spectrum among the users in interference-limited systems. In [58], the price of anarchy was analyzed for spectrum sharing in WiFi networks. A demand responsive pricing framework was proposed in [59] to maximize the profits of legacy spectrum operators while considering the users' response model to the operators' pricing strategy. In [18], the authors considered multi-unit sealed-bid auction for efficient spectrum allocation.

2.2 Game Theoretical Models

Game theory models the interactions among rational, mutually aware players, where the decisions of some players impacts the payoffs of others. A game consists of a set of players, a set of moves (or strategies) available to those players, and a specification of payoffs for each combination of strategies.

The intelligent behaviors of selfish users in autonomous wireless networks can

Prisoner A \ Prisoner B	**Prisoner B Stays Silent**	**Prisoner B Betrays**
Prisoner A Stays Silent	Both serve six months	Prisoner A serves ten years Prisoner B goes free
Prisoner A Betrays	Prisoner A goes free Prisoner B serves ten years	Both serve two years

Figure 2.1: Prisoner's dilemma in strategic form.

be studied using game theoretical models [39, 40, 42, 43, 45–47, 60]. For instance, in autonomous MANETs, the players are all the network nodes, which may act as service providers: packets are scheduled to be generated and delivered to certain destinations; or act as relays: forward packets for other nodes. The strategy space may include packet forwarding decision, route participation, route selection, or belief/trust build-up and update. The payoff can be defined considering various system measurements such as throughput, lifetime or power consumption. In autonomous DSANs, the players are all the network users including both primary and secondary users. The strategy space for each user consists of various actions related to dynamic spectrum sharing. Specifically, for secondary users, the strategy space includes which licensed channel they will use, what transmission parameters (such as transmission power or time duration) to be applied, what is the price they agree to pay for leasing certain channels from the primary users, etc. For primary users, the strategy space may include which unused channel they will lease to secondary users and how much they will charge secondary users for using their spectrum resources, etc. The payoff functions are modeled to measure each selfish user's throughput or spectrum efficiency.

There are two ways of representing games: *normal form* and *extensive form*

[8–10]. The normal form (or strategic form) game is usually represented by a matrix which shows the players, strategies, and payoffs. An example of prisoner's dilemma in strategic form can be shown in Figure 2.1. The extensive form can be used to formalize games with some important order. Games in extensive form are often presented as trees. Each vertex (or node) represents a point of choice for a player. The player is specified by a number listed by the vertex. The lines out of the vertex represent a possible action for that player. The payoffs are usually specified at the bottom of the tree.

2.2.1 Non-cooperative and Cooperative Games

Considering the availability of centralized authorities, game theoretical study can be categorized into two types: non-cooperative game and cooperative game. In non-cooperative games, without centralized control, the selfish network users do not cooperate so that any cooperation among them must be self-enforcing [9]. Thus, the study on cooperation in autonomous wireless networks matches the scenarios of non-cooperative games very well. The non-cooperative game theory provides us efficient distributed game designs and cooperation stimulation mechanism. In order to have an efficient autonomous wireless network considering the users' selfishness, the corresponding algorithm may generally result in a multi-objective optimization problem. Non-cooperative game theory also equips us well-defined optimization criteria to measure the optimality in the above scenarios with multiple agents. To be specific, **Nash Equilibrium** [9] 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, **Pareto Op-**

timality [9] 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 games, the users are able to make enforceable outcomes through centralized authorities. Thus, for cooperative games, the interests lie in that how good the game outcome can be. In other words, how to define and choose the optimality criteria in cooperative scenarios. Although cooperative game theory may not directly help us solve the cooperation issue in autonomous wireless networks, it is useful to measure the efficiency of the solution that we obtain from non-cooperative game study on autonomous wireless networks. Further, it is worth mentioning that **Nash Bargaining Solution** (NBS) [9] 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, 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 with the minimal resources [9]. NBS can be represented as a product of extra resources assigned to each user, which is also referred to as linear-proportional fairness criterion if no minimal resources are pre-assigned [61, 62].

2.2.2 Repeated Games

In the above example of prisoner's dilemma, although a better outcome can be achieved if both prisoners stay silent, the selfishness of each prisoner will lead to the non-cooperative Nash Equilibrium outcome that both prisoners betray. Thus, the question rises that how to achieve better game outcomes in non-cooperative games. Considering that a strategic game may not be played only once, if a similar strategic game is played numerous times, the game is called a repeated game. Unlike a game played once, a repeated game allows for a strategy to be contingent on past moves, thus allowing for reputation effects and retribution. The player's payoff in a repeated game is a discounted summation of her/his payoff at each stage. One of the most important results in repeated game theory is **Folk Theorem** [9], which asserts that for infinite repeated games there exists a discount factor $\widehat{\delta} < 1$ such that any feasible and individually rational payoff can be enforced by an equilibrium for any discount factor $\delta \in (\widehat{\delta}, 1)$. Thus, by playing a strategic game many times, more efficient Nash Equilibria can be achieved in a repeated game framework. Note that in a repeated game, the strategic space needs to be the same for each player in every stage of the repeated game; otherwise, the game becomes a general multi-stage game.

In autonomous MANETs, the packet forwarding interactions between the network users can be similarly modeled as repeated games. For instance, it is obvious that if the packet forwarding interaction between two users happens only once, both users will have no incentive to forward packets for the other; if the packet forwarding interaction may happen many times between two users, one user may tend to help the other to forward packets by considering that the other user may return the favor in the future for mutual benefits. Based on the above, studying the user behaviors in autonomous MANETs in a repeated game framework will enable efficient cooperation among selfish users by reputation effects or retribution.

2.2.3 Dynamic Games

Considering that the cooperation in autonomous wireless networks is a dynamic process, how the interactions among network users evolve over time based on the network dynamics needs to be further studied. Therefore, general dynamic game models need to be considered to study the strategic game in multi-stage manner or further represent it in extensive form if the users take actions sequentially. In dynamic games, if complete information is available, i.e., the set of strategies and payoffs for each user are common knowledge, **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 [9] of the original game. If complete information is not available, **Sequential Equilibrium** [9] is a well-defined counterpart of SPE under such circumstance, which guarantees that any deviations from the equilibrium will be unprofitable. Moreover, in non-cooperative games with incomplete information, the players need to build up certain beliefs of other players' future possible strategies to assist their decision making. The concept of **Perfect Bayesian Equilibrium** (PBE) [8,10] is built upon the belief system to measure the game outcomes in the above scenarios. To be specific, a PBE is a set of strategies and beliefs such that, at any stage of the game, strategies are optimal given the beliefs, and the beliefs are obtained from equilibrium strategies and observed actions using Bayes' rule.

2.2.4 Auction Games

Considering the negotiated or leasing-based dynamic spectrum sharing in autonomous DSANs, primary users attempt to sell unused spectrum resources to secondary users for monetary gains, 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 won't 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 multi-player 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 above game settings, the well-developed auction theory [63], one of the most important applications of game theory, can be applied to formulate and analyze the interactions.

In auction games [63], 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 dynamic spectrum sharing games, the primary users can be viewed as the principles, who attempts to sell the 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. Further, multiple sellers and buyers may coexist, which indicates the double auction scenario. It means that not only the secondary users but also the primary users need to compete with each other to make the beneficial transactions possible by eliciting their willingness of the payments in the forms of bids or asks. In the double auction scenarios of the DSSG, **Competitive Equilibrium** (CE) [63] 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. As for autonomous MANETs, considering there may exist multiple possible routes between a source-destination pair, auction-like pricing-based mechanisms [14–16] can also be introduced for the cost-efficient and truthful self-organized routing.

Chapter 3

Cooperation Enforcement in Autonomous Ad Hoc Networks

Mobile ad hoc networks (MANET) have drawn extensive attention in recent years due to the increasing demands of its potential applications [1, 2]. In traditional crisis or military situations, the nodes in a MANET usually belong to the same authority and work in a fully cooperative way of unconditionally forwarding packets for each other to achieve their common goals. Recently, the MANETs are also envisioned to be deployed for civilian applications [11, 13, 20–22, 26, 30, 45], where nodes typically do not belong to a single authority and may not pursue a common goal. Consequently, fully cooperative behaviors cannot be directly assumed as the nodes are selfish to maximize their own interests. The cooperation enforcement becomes important for the above autonomous MANETs.

Although several schemes have been proposed to perform game theoretical analysis on cooperation in autonomous ad hoc networks as we discuss in Chapter 2, most of them have assumed perfect observation, and not considered the effect of noise on the strategy design. In this chapter we study the cooperation enforcement for autonomous mobile ad hoc networks under noise and imperfect observation, and focus on the most basic networking functionality, namely packet forwarding. Considering the nodes need to infer the future actions of other nodes based on their own imperfect observations, in order to optimally quantify the inference process with noise and imperfect observation, a belief evaluation framework is proposed to stimulate the packet forwarding between nodes and maximize the expected payoff of each selfish node by using repeated game theoretical analysis. Specifically, a formal belief system using Bayes' rule is developed to assign and update beliefs of other nodes' continuation strategies for each node based on its private imperfect information. Further, we not only show that the packet forwarding strategy obtained from the proposed belief evaluation framework achieves a sequential equilibrium [10] that no user has incentive to deviate from, but also derive its performance bounds. The simulation results illustrate that the proposed packet forwarding approach can enforce the cooperation in autonomous ad hoc networks under noise and imperfect observation with only a small performance degradation compared to the unconditionally cooperative outcomes.

The remainder of this chapter is organized as follows. In Section 3.1, we illustrate the system model of autonomous ad hoc networks under noise and imperfect observation. In Section 3.2, static and repeated packet-forwarding game models are provided. Vulnerability analysis for autonomous MANETs under noise and imperfect observation is carried out in Section 3.3. In Section 3.4, we propose the belief evaluation framework and carry out the equilibrium and efficiency analysis for one-hop and multi-node multi-hop packet forwarding. The simulation studies are provided in Section 3.5. Finally, Section 3.6 summarizes this chapter.

3.1 System Model

We consider autonomous ad hoc networks where nodes belong to different authorities and have different goals. Assume all nodes are selfish and rational, that is, their objectives are to maximize their own payoff, not to cause damage to other nodes. Each node may act as a service provider: packets are scheduled to be generated and delivered to certain destinations; or act as a relay: forward packets for other nodes. The sender will get some payoffs if the packets are successfully delivered to the destination and the forwarding effort of relay nodes will also introduce certain costs.

In this chapter we assume that some necessary traffic monitoring mechanisms, such as those described in [13,20,26], will be launched by each node to keep tracking of its neighbors' actions. However, it is worth mentioning that we do not assume any public or perfect observation, where a public observation means that when an action happens, a group of nodes in the network will have the same observation, and perfect observation means all actions can be perfectly observed without any mistake. In ad hoc networks, due to its multi-hop nature and the lack of central monitoring mechanism, public observation is usually not possible. Meanwhile, to our best knowledge, there exist no such monitoring mechanisms in ad hoc networks which can achieve perfect observation. Instead, in this chapter, we study the cooperation-enforcement strategies based on imperfect private observation. Here, private means that the observation of each node is only known to itself and won't or cannot be revealed to others.

We focus on two scenarios causing imperfect observation in ad hoc networks. One scenario is that the outcome of a forwarding action may be a packet-drop due to link breakage or transmission errors. The other scenario is that a node

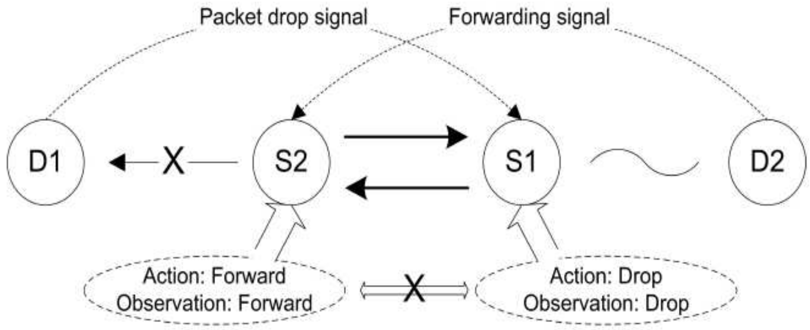

Figure 3.1: Packet forwarding in autonomous ad hoc networks under noise and imperfect observation.

has dropped a packet but is observed as forwarding the packet, which may happen when the watchdog mechanism [20] is used and the node wants to cheat its previous node on the route. Figure 3.1 illustrates our system model by showing a network snapshot of one-hop packet forwarding between two users at a certain time stage under noise and imperfect observation. In this figure, there are two source-destination pairs (S_1, D_1) and (S_2, D_2). S_1 and S_2 need to help each other to forward packets to the destination nodes. At this stage, node S_1 drops the packet and observes the packet-drop signal of node S_2's action, while node S_2 forwards the packet and observes the forwarding signal of node S_1's action. The action and observation of each node are only known to itself and cannot or will not be revealed to other nodes. Due to transmission errors or link breakage between S_2 and D_1, S_2's forwarding action is observed as a packet-drop signal; due to possible cheating behavior between S_1 and D_2, a forfeit forwarding signal may be observed by S_2. Therefore, it is important to design strategies for each node to make the optimal decision solely based on these imperfect private information.

3.2 Packet-Forwarding Game Models

We model the process of routing and packet-forwarding between two nodes forwarding packets for each other as a game. The players of the game are two network nodes, denoted by $i \in I = \{1, 2\}$. Each player is able to serve as the relay for the other player and needs the other player to forward packets for him based on current routing selection and topology. Each player chooses his action, i.e., strategy, a_i from the action set $A = \{F, D\}$, where F and D are packet forwarding and dropping actions, respectively. Also, each player observes a private signal ω of the opponent's action from the set $\Omega = \{f, d\}$, where f and d are the observations of packet forwarding and dropping signals, respectively. Since the player's observation cannot be perfect, the forwarding action F of one player may be observed as d by the other player due to link breakage or transmission errors. We let such probability be p_f. Also, the noncooperation action D may be observed as the cooperation signal f under certain circumstances. Without loss of generality, let the observation error probability be p_e in our system, which is usually caused by malicious cheating behaviors and indicates that the group of packets is actually dropped though forwarding signal f is observed. For each node, the cost of forwarding a group of packets for the other node during one stage of play is ℓ, and the gain it can get for the packets that the other node has forwarded for it is $\widetilde{g}$. Usually, the gain of successful transmission is for both the source and destination nodes. Noting that the source and destination pair in ad hoc networks usually serves for a common communication goal, we consider the gain goes to the source for the game modeling without loss of generality.

We first consider the packet forwarding as a static game [8], which is only played once. Given any action profile $a = (a_1, a_2)$, we refer to $u(a) = (u_1(a), u_2(a))$ as the

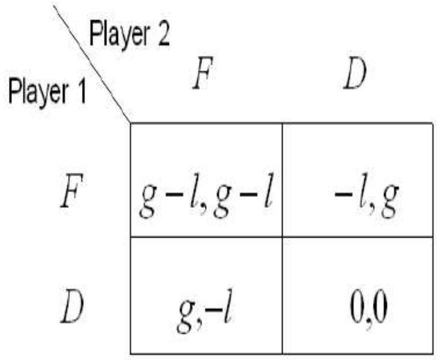

Figure 3.2: Two-player packet forwarding game in strategic form.

expected payoff profile. Let a_{-i} and $\mathrm{Prob}(\omega_i|a_{-i})$ be the action of the ith player's opponent and the probability of observation ω_i given a_{-i}, respectively. Then, $u_i(a)$ can be obtained as follows.

$$u_i(a) = \sum_{\omega_i \in \Omega} \widetilde{u}_i(a_i, \omega_i, a_{-i}) \cdot \mathrm{Prob}(\omega_i|a_{-i}), \tag{3.1}$$

where $\widetilde{u}_i$ is the ith player's payoff determined by the action profile and his own observation. Then, calculating $u(a)$ for different strategy pairs, we have the strategic form of the static packet forwarding game as a matrix in Figure 3.2. Note that $g = (1 - p_f) \cdot \widetilde{g}$, which can be obtained from (3.1) considering the possibility of the packet-drop.

To analyze the outcome of a static game, the Nash Equilibrium [8, 10] is a well-known concept, which is a set of strategies, one for each player, such that no selfish player has incentive to unilaterally change his/her action. Noting that our two-player packet-forwarding game is similar to the setting of the prisoner's dilemma game, the only Nash equilibrium is the action profile $a^* = (D, D)$, and the better cooperation payoff outcome $(g - \ell, g - \ell)$ of the cooperation action profile $\{F, F\}$ cannot be practically realized in the static packet-forwarding game due to the greediness of the players. However, generally speaking, the above packet forwarding game will be played many times in real ad hoc networks. It is natural to extend the above static game model to a multistage game model [8]. Considering that the past packet-forwarding behaviors do not influence the feasible actions or payoff function at current stage, the multistage packet forwarding game can be further analyzed using the repeated game model [8, 10]. Basically, in the repeated games, the players face the same static game at every period, and the player's overall payoff is a weighted average of the payoffs at each stage over time. Let ω_i^t be the privately observed signal of the ith player in period t. Suppose that the game begins in period 0 with the null history h^0. In this game, a private history for player i at period t, denoted by h_i^t, is a sequence of player i's past actions and signals, i.e., $h_i^t = \{a_i^\tau, \omega_i^\tau\}_{\tau=1}^{t-1}$. Let $H_i^t = (A \times \Omega)^t$ be the set of all possible period-t histories for the ith player. Denote the infinite packet-forwarding repeated game with imperfect private histories by $G(p, \delta)$, where $\delta \in (0, 1)$ is the discount factor and $p = (p_f, p_e)$. Assume that $p_f < 1/2$ and $p_e < 1/2$. Then, the overall discounted payoff for player $i \in I$ is defined as follows [8].

$$U_i(\delta) = (1 - \delta) \sum_{t=0}^{\infty} \delta^t u_i^t(a_1^t(h_1^t), a_2^t(h_2^t)). \tag{3.2}$$

Folk Theorems for infinite repeated games [8] assert that there exists $\widehat{\delta} < 1$ such that any feasible and individually rational payoff can be enforced by an equilibrium for all $\delta \in (\widehat{\delta}, 1)$ based on the public information shared by players. However, one crucial assumption for the Folk Theorems is that players share common information about each other's actions. In contrast, the nature of our repeated packet forwarding game for autonomous ad hoc networks determines that the nodes' behaviorial strategies can only rely on the private information histories including their own past actions and imperfectly observed signals. Such a minor game-setting change from the public observation to the private observation due to noise and imperfect observation will make a substantial difference in analyzing the efficiency of the packet-forwarding game. In the situation of imperfect private observation, no recursive structure [64] exists for the forwarding strategies since the player decides their actions according to various private histories. Each node must conduct statistical inference to detect potential deviations and estimate what others are going to do next, which can become extremely complex due to the imperfect observation [65, 66].

3.3 Vulnerability Analysis

In this section, we analyze the vulnerability caused by noise and imperfect observation in autonomous MANETs. First, we study the system vulnerability in the scenario of one-hop packet forwarding. Then, we further exploit the effect of noise and imperfect observation in the scenario of multi-hop packet forwarding.

In the scenario of one-hop packet forwarding, the interactions between a pair of nodes forwarding packets for each other can be modeled as the two-player game in the previous section. Although it is seemly a minor game-setting change from the public observation to the private observation due to noise and imperfect observation, such change on game-setting introduces substantial challenges on the interactions, outcomes and efficiency of our packet-forwarding game, which can be illustrated as follows. First, the noise and observation errors indicate that simple TIT-for-TAT [33,67] strategies is not able to enforce efficient cooperation paradigm among users since such equivalent retaliation strategy leads to inefficient noncooperative outcomes. Second, considering the selfishness of the users along with the effects of noise and imperfect observations, the users won't share their action information or observations of others' actions, which indicates that no public information available for the users. Therefore, the users are not able to coordinate their strategies for efficient outcomes relying only on private histories, i.e., no recursive structure [64] exists for the forwarding strategies since the players decide their actions according to various private histories. Third, although the dynamic game theory has studied and defined the equilibrium concepts on the outcomes of the game with imperfect information, such as Sequential Equilibrium (SE) [8, 10] or Perfect Bayesian Equilibrium (PBE) [8, 10], it doesn't provide generalized efficient mechanisms to achieve SE or PBE in the scenarios of private information. Note that generous tit-for-tat (GTFT) [67] is able to partly alleviate the impact of noise and imperfect observation on the efficiency of the packet forwarding game outcomes by assuming that the nodes may be generous to contribute more to the network than to benefit from it. However, if the constraint of the private information is taken into consideration, GTFT cannot work properly. Because, due to the game-setting of private observation, one user doesn't know the other user's observation of her/his actions and only has the imperfect observation of the other user's actions, which leads to the result that efficient TFT cannot be carried out.

Based on the above discussions, the noise and imperfect observation cause several vulnerability issues even for simple one-hop packet forwarding in autonomous MANETs, which can be illustrated as follows.

- Since the nodes make decisions based on private information, Each node must conduct statistical inference to detect potential deviations and estimate what others are going to do next. Existence of noise and the constraint of imperfect observation will result in false alarms or detection errors. Selfish nodes may be able to utilize such fact to contribute fewer efforts while getting more benefits from others.

- Considering that the nodes are not willing to or not able to share their information, the nodes cannot rely on others' past experiences or recommendations on the nodes' behaviors, which gives the selfish nodes more flexibility on their cheating behaviors.

- With the presence of noise or observation errors, the cooperative nodes may falsely accuse other cooperative nodes of seemly non-cooperative behaviors, which is actually caused by link breakage or transmission errors. How to maintain the cooperative paradigm in such scenarios remains a challenging problem.

In the scenario of multi-node and multi-hop packet forwarding, more sophisticated vulnerability issues will be raised considering the challenges of the self-organizing routing and the correlation of the nodes' actions. In general, due to the multi-hop nature, when a node wants to send a packet to a certain destination, a sequence of nodes need to be requested to help forwarding this packet. We refer to the sequence of (ordered) nodes as a route, the intermediate nodes on a route as relay nodes, and the procedure to discover a route as route discovery. The routing process includes route discovery and packet forwarding. The route discovery carries out three steps consecutively. First, the requester notifies the other nodes in the network that it wants to find a route to a certain destination. Second, other nodes in the network will make their decisions on whether agreeing to be on the discovered route or not. Third, the requester will determine which route should be used. Based on the discussion of the routing process, we can see that the action and observation of one node on a route will largely affect the behaviors of other nodes on this route or alternative routes between the source and destination nodes, which in reverse affects the the behavior of the original node. The above properties of multi-node and multi-hop packet forwarding may lead to more vulnerability issues than one-hop packet forwarding illustrated as follows.

- In the scenarios of multiple nodes on one route, in order to detect or punish the users with cheating behaviors, the coordination needs to be built up among multiple nodes to have effective detection or punishment, which becomes very complicated and requires sophisticated strategy designs considering only private information available to each node.

- Since the routing process involves different steps, the seemingly cooperative behaviors at each stage may jointly have cheating effects across multiple steps. From the game theoretical point of view, each stage game in our dynamic packet forwarding game consists of several subgames, such as route participation subgame or route selection subgame. The vulnerability issues need to be considered not only for each subgame but also for the overall game.

- The multi-hop routing makes the observation of nodes more difficult as the packet-drop action at one node will affect the outcome of the multi-hop routing. Such propagation effects can be taken advantage of by selfish nodes to cheat for more payoffs.

In order to combat the above vulnerability issues on autonomous MANETs under noise and imperfect observation, it is important to study novel strategy framework comprehensively considering these issues.

3.4 Belief-Based Cooperation Enforcement

In this section, we first develop a belief evaluation framework for two-player packet forwarding game in attempt to shed light on the solutions to the more complicated multi-player case. Efficiency study is then carried out to analyze the equilibrium properties and performance bounds. Further, a belief evaluation framework is proposed for general networking scenarios with multiple nodes and multi-hop routing.

3.4.1 Two-Player Belief-Based Packet Forwarding

In order to have an efficient and robust forwarding strategy based on each node's own imperfect observation and actions, enlightened by [66], we propose a belief evaluation framework to enforce cooperation.

First, we define two strategies, i.e., σ_F and σ_D. Let σ_F be the trigger cooperation strategy, which means that the player forwards packets at current stage, and at the next stage the player will continue to forward packets only if it observes the other player's forwarding signal f. Let σ_D be the defection strategy, which means that the player always drops packets regardless of its observation history. Such strategies are also called continuation strategies [66]. Since both of the two strategies also determine the player's following actions at every private history, the strategy path and expected future payoffs caused by any pair of the two strategies are fully specified. Let $V_{\alpha,\beta}(p,\delta), \alpha, \beta \in \{F, D\}$ denote the repeated game payoff of σ_α against σ_β, which can be illustrated by the following Bellman equations [68] for different pairs of continuation strategies.

$$V_{FF} = (1-\delta)(g-\ell) + \delta((1-p_f)^2 V_{FF} + p_f(1-p_f)V_{FD} + p_f(1-p_f)V_{DF} + p_f^2 \cdot V_{DD}), \tag{3.3}$$

$$V_{FD} = -(1-\delta)\ell+\delta((1-p_f)(1-p_e)V_{DD}+p_f(1-p_e)V_{DD}+p_e(1-p_f)V_{FD}+p_f p_e V_{FD}), \tag{3.4}$$

$$V_{DF} = (1-\delta)g+\delta((1-p_f)(1-p_e)V_{DD}+p_e(1-p_f)V_{DF}+p_f(1-p_e)V_{DD}+p_e p_f V_{DF}), \tag{3.5}$$

$$V_{DD} = (1-\delta)\cdot 0+\delta((1-p_e)^2 V_{DD}+p_e(1-p_e)V_{DD}+p_e(1-p_e)V_{DD}+p_e^2\cdot V_{DD}). \tag{3.6}$$

Note that the first terms on the right hand side (RHS) of the above equations represent the normalized payoffs of current period, while the second terms illustrate the expected continuation payoffs considering four possible outcomes due to the noise and imperfect observation. By solving the above equations, $V_{\alpha,\beta}(p,\delta)$ can be obtained as follows.

$$V_{FF} = (1-\delta)(g-\ell)+\delta((1-p_f)^2 V_{FF}+ \\ p_f(1-p_f)V_{FD}+p_f(1-p_f)V_{DF}+p_f^2\cdot V_{DD}), \tag{3.7}$$

$$V_{FD} = -(1-\delta)\ell+\delta((1-p_f)(1-p_e)V_{DD}+ \\ p_f(1-p_e)V_{DD}+p_e(1-p_f)V_{FD}+p_f p_e V_{FD}), \tag{3.8}$$

$$V_{DF} = (1-\delta)g+\delta((1-p_f)(1-p_e)V_{DD}+ \\ p_e(1-p_f)V_{DF}+p_f(1-p_e)V_{DD}+p_e p_f V_{DF}), \tag{3.9}$$

$$V_{DD} = (1-\delta)\cdot 0+\delta((1-p_e)^2 V_{DD}+ \\ p_e(1-p_e)V_{DD}+p_e(1-p_e)V_{DD}+p_e^2\cdot V_{DD}). \tag{3.10}$$

Then, we have $V_{DD} > V_{FD}$, for any δ, p. Furthermore, if $\delta > \delta_0$, then $V_{FF} > V_{DF}$, where δ_0 can be obtained as

$$\delta_0 = \frac{\ell}{(1-p_f-p_e)g-[p_f(1-p_f)-p_e]\ell}. \tag{3.11}$$

Suppose that player i believes that his opponent is playing either σ_F or σ_D, and is playing σ_F with probability μ. Then the difference between his payoff of playing

σ_F and the payoff of playing σ_D is given by

$$\triangle V(\mu;\delta,p)=\mu\cdot(V_{FF}-V_{DF})-(1-\mu)\cdot(V_{DD}-V_{FD}). \tag{3.12}$$

Hence $\triangle V(\mu)$ is increasing and linear in μ and there is a unique value $\pi(p,\delta)$ to make it zero, which can be obtained as follows.

$$\pi(\delta,p)=\frac{-V_{FD}(\delta,p)}{V_{FF}(\delta,p)-V_{DF}(\delta,p)-V_{FD}(\delta,p)}, \tag{3.13}$$

where $\pi(p,\delta)$ is defined so that there is no difference for player i to play σ_F or σ_D when player j plays σ_F with probability $\pi(\delta,p)$ and σ_D with probability $1-\pi(\delta,p)$. For simplicity, $\pi(\delta,p)$ may be denoted as π under the circumstances with no confusion. In general, if node i holds the belief that the other node will help him to forward the packets with a probability smaller than 1/2, node i is inclined not to forward packets for the other node. Considering such situation, we let δ be such that $\pi(\delta,p)>1/2$.

It is worth mentioning that equation (3.12) is applicable to any period. Thus, if a node's belief of an opponent's continuation strategy being σ_F is μ, in order to maximize its expected continuation payoff, the node prefers σ_F to σ_D if $\mu>\pi$ and prefers σ_D to σ_F if $\mu<\pi$. Starting with any initial belief μ, the ith player's new belief when he takes action a_i and receives signal ω_i can be defined using Bayes' rule [8] as follows.

$$\mu(h_i^{t-1},(F,f))=\frac{\mu(h_i^{t-1})(1-p_f)^2}{\mu(h_i^{t-1})(1-p_f)+p_e\cdot(1-\mu(h_i^{t-1}))}, \tag{3.14}$$

$$\mu(h_i^{t-1},(F,d))=\frac{\mu(h_i^{t-1})(1-p_f)\cdot p_f}{\mu(h_i^{t-1})\cdot p_f+(1-p_e)\cdot(1-\mu(h_i^{t-1}))}, \tag{3.15}$$

$$\mu(h_i^{t-1},(D,f))=\frac{\mu(h_i^{t-1})(1-p_f)\cdot p_e}{\mu(h_i^{t-1})\cdot(1-p_f)+p_e\cdot(1-\mu(h_i^{t-1}))}, \tag{3.16}$$

$$\mu(h_i^{t-1},(D,d))=\frac{\mu(h_i^{t-1})p_f\cdot p_e}{\mu(h_i^{t-1})\cdot p_f+(1-p_e)\cdot(1-\mu(h_i^{t-1}))}. \tag{3.17}$$

Table 3.1: Two-Player Packet Forwarding Algorithm

1. Initialize using system parameter configuration (δ, p_e, p_f)**:** Node i initializes his belief μ_i^1 of the other node as $\pi(\delta, p)$ and chooses the forwarding action in period 1.
2. Belief update based on the private history: Update each node's belief μ_i^{t-1} into μ_i^t using (3.14-3.17) according to different realizations of private history.
3. Optimal Decision of the player's next move: If the continuation belief $\mu_i^t > \pi$, node i plays σ_F; If the continuation belief $\mu_i^t < \pi$, node i plays σ_D; If the continuation belief $\mu_i^t = \pi$, node i plays either σ_F or σ_D.
4. Iteration: Let $t = t + 1$, then go back to Step 2.

From on the above discussion, we propose a two-player packet forwarding algorithm based on the developed belief evaluation framework in Table 3.1. Note that by using the proposed belief system, each node only needs to maintain its belief value, its most recent observation and action instead of the long-run history information of interactions with other users.

3.4.2 Efficiency Analysis

In this part, we show that the behaviorial strategy obtained from the proposed algorithm with well-defined belief system is a sequential equilibrium [10] and further analyze its performance bounds.

First, we briefly introduce the equilibrium concepts of the repeated games with imperfect information. As for the infinitely repeated game with perfect information, the Nash Equilibrium concept is a useful concept for analyzing the game outcomes. Further, in the same scenario with perfect information, **Subgame Perfect Equilibrium** (SPE) [10] can be used to study the game outcomes, which is an equilibrium such that users' strategies constitute a Nash equilibrium in every subgame [8] of the original game, which eliminate those Nash Equilibria in which the players' threats are incredible. However, the above equilibrium criteria for the infinitely repeated game require that perfect information can be obtained for each player. In our packet forwarding game, each node is only able to have its own strategy history and form the beliefs of other nodes' future actions through imperfect observation. **Sequential Equilibrium** [10] is a well-defined counterpart of subgame perfect equilibrium for multi-stage games with imperfect information, which has not only sequential rationality that guarantees that any deviations will be unprofitable but also consistency on zero-probability histories.

In our packet-forwarding game with private history and observation, the proposed strategy with belief-system can be denoted as (σ^*, μ), where $\mu = \{\mu_i\}_{i \in I}$ and $\sigma^* = \{\sigma_i^*\}_{i \in I}$. By studying (3.14), we find that there exists a point ϕ such that $\mu(h_i^{t-1}, (F, f)) < \mu(h_i^{t-1})$ as $\mu(h_i^{t-1}) > \phi$ while $\mu(h_i^{t-1}, (F, f)) > \mu(h_i^{t-1})$ as $\mu(h_i^{t-1}) < \phi$. Here, ϕ can be calculated as $\phi = [(1 - p_f)^2 - p_e]/(1 - p_f - p_e)$. It is easy to show that $\mu(h_i^{t-1}, (a_i, \omega_i)) < \mu(h_i^{t-1})$ when $(F, d), (D, f)$ and (D, d) are reached. Since we initialize the belief with π we have $\mu_i^t \leq \phi$ after any belief-updating operation if $\pi < \phi$. Considering the belief updating in the scenario that $\pi \geq \phi$ becomes trivial, we assume $\pi < \phi$ thus $\mu_i^t \in [0, \phi]$ and $\phi \geq 1/2$. Then, let the proposed packet-forwarding strategy profile σ^* be defined as: $\sigma_i^*(\mu_i) = \sigma_F$ if $\mu_i > \pi$ and $\sigma_i^*(\mu_i) = \sigma_D$ if $\mu_i < \pi$; if $\mu_i = \pi$, the node forwards packets with probability π and drops them with probability $1 - \pi$. Noting that $\pi(\delta, p) \leq \phi$, we obtain another constraint on δ, which can be written as follows.

$$\delta \geq \underline{\delta} = \frac{\ell}{[(1 - p_f)^2 - p_e] \cdot g + \ell \cdot p_e}. \tag{3.18}$$

Using the above equilibrium criteria for the repeated games with imperfect information, we then analyze the properties of the proposed strategy illustrated in Table 3.1 through the following theorems.

Theorem 3.4.1 *The proposed strategy profile σ^* with belief-system μ from Table 3.1 is a sequential equilibrium for $\pi \in (1/2, \phi)$.*

Proof See the appendix at the end of this chapter. ■

Theorem 3.4.2 shows that the strategy profile σ^* and the belief system μ obtained from the proposed algorithm is a sequential equilibrium, which not only responds optimally at every history but also has consistency on zero-probability histories. Thus, the cooperation can be enforced using our proposed algorithm since the deviation will not increase the players' payoffs. Then, similar to [66], it is straightforward to prove the following theorem, which addresses the efficiency of the equilibrium and shows that when the p_e and p_f are small enough, our proposed strategy approaches the cooperative payoff $g - \ell$.

Theorem 3.4.2 *Given g and ℓ, there exist $\widetilde{\delta} \in (0, 1)$ and $\widetilde{p}$ for any small positive τ such that the average payoff of the proposed strategy σ^* in the packet-forwarding repeated game $G(p, \delta)$ is greater than $g - \ell - \tau$ if $\delta > \widetilde{\delta}$ and $p_e, p_f < \widetilde{p}$.*

However, in real ad hoc networks, considering the mobility of the node, channel fading and the cheating behaviors of the nodes, it may be not practical to assume very small p_e and p_f values. A more useful and important measurement is the performance bounds of the proposed strategy given some fixed p_e and p_f values. We further develop the following theorem studying the lower bound and upper bound of our strategy to provide a performance guideline. In order to model the prevalent data application in current ad hoc networks, we assume the game discount factor is very close to 1.

Theorem 3.4.3 *Given the fixed* (p_e, p_f) *and discount factor of the repeated game* δ_G *close to 1, the payoff of the proposed algorithm in Table 3.1 is upper bounded by*

$$\bar{U} = (1-\kappa)\cdot(g-\ell), \tag{3.19}$$

where

$$\kappa = \frac{p_f \cdot [g(1-p_f)+\ell]}{(1-p_f-p_e)(g-\ell)}. \tag{3.20}$$

The lower bound of the performance will approach the upper bound when the discount factor of the repeated game δ_G *approaches 1 and the packet forwarding game is divided into* N *sub-games as follows: the first sub-game is played in period* $1, N+1, 2N+1, ...$ *and the second sub-game is played in period* $2, N+2, 2N+2, ...$*, and so on. The optimal* N *is*

$$N = \lfloor \log \underline{\delta} / \log \delta_G \rfloor, \tag{3.21}$$

The proposed strategy is played in each sub-game with equivalent discount factor δ_G^N*.*

Proof By substituting $V_{\alpha,\beta}$ obtained from (3.7)-(3.10) into (3.13), we have

$$\pi(\delta, p) = \frac{\ell}{g-\ell} \cdot \frac{1-\delta(1-p_f)^2}{\delta(1-p_f-p_e)}. \tag{3.22}$$

Then, since the node i is indifferent of forwarding or dropping packets if its belief of the other node is equal to π, the expected payoff of the node i at the sequential equilibrium (σ^*, μ) can be written as

$$V(\pi, \delta, p) = \pi(\delta, p)\cdot V_{DF}(\delta, p) + (1-\pi(\delta, p))\cdot V_{DD}(\delta, p). \tag{3.23}$$

It is easy to show that $V(\pi(\delta, p), \delta, p)$ is a decreasing function in δ when $\delta \in (0, 1)$. Then, the upper bound of the expected payoff can be obtained by letting δ be the smallest feasible value. From (3.11) and (3.18), we have $\delta > \underline{\delta}$ and $\delta > \delta_0$. Since $\underline{\delta} > \delta_0$, we can derive the upper bound of the payoff of the proposed algorithm as (3.19) by substituting $\underline{\delta}$ into (3.23).

However, the discount factor of our game is usually close to 1. Generally, $\underline{\delta}$ is a relatively smaller value in the range of $(0, 1)$. In order to emulate the optimal discount factor $\underline{\delta}$, we introduce the following game partition method. We partition the original repeated game $G(p, \delta_G)$ into N distinct sub-games as the theorem illustrates. Each sub-game can be regarded as a repeated game with the discount factor δ_G^N. The optimal sub-game number N, which minimizes the gap between δ_G^N and $\underline{\delta}$, can be calculated as $N = \lfloor \log \underline{\delta} / \log \delta_G \rfloor$.

As there is always difference between δ_G^N and $\underline{\delta}$, it is more important to study the maximal gap, which results in the lower bound of the payoff using our game partition method. Similar to [69], we can show that by using the optimal N, $\delta_G^N \in [\underline{\delta}, \bar{\delta}]$, where $\bar{\delta} = \underline{\delta}/\delta_G$. Substituting $\bar{\delta}$ into (3.23), we have the lower bound of the payoff of our proposed algorithm with the proposed game partition method. When δ_G approaches 1, and $\bar{\delta}$ approaches $\underline{\delta}$, the payoff of our algorithm achieves the payoff upper-bound. ■

In the above theorem, the idea of dividing the original game into some sub-games is useful to maintain the efficiency when δ approaches one for our game setting. A larger δ indicates that future payoffs are more important for the total payoff, which results in more number of sub-games. Since there are multiple sub-games using the belief-based forwarding strategy, even if the outcomes of some sub-games become the non-cooperation case due to the observation errors and noise, cooperation plays can still continue in other sub-games to increase the total payoff.

3.4.3 Multi-Node Multi-Hop Packet Forwarding

In the previous parts, we mainly focus on the two-player case, while in an ad hoc network there usually exist many nodes and multi-hop routing is generally enabled. In this section, we model the interactions among selfish nodes in an autonomous ad hoc network as a multi-player packet forwarding game, and develop the optimal belief evaluation framework based on the two-player belief system.

Multi-Node Multi-Hop Game Model

In this section, we consider autonomous ad hoc networks where nodes can move freely inside a certain area. For each node, packets are scheduled to be generated and sent to certain destinations. Different from the two-player packet forwarding game, the multi-player packet forwarding game studies multi-hop packet forwarding which involves the interactions and beliefs of all the nodes on the route. Before studying the belief-based packet forwarding in this scenario, we first model the multi-player packet forwarding game as follows:

- There are M players in the game, which represent M nodes in the network. Denote the player set as $I_M = \{1, 2, ..., M\}$.
- For each player $i \in I_M$, he has groups of packets to be delivered to certain destinations. The payoff of successfully having a group of packets delivered during one stage is denoted by $\widetilde{g}$.
- For each player $i \in I_M$, forwarding a group of packets for another player will incur the cost ℓ.
- Due to the multi-hop nature of ad hoc networks, the destination player may be not in the sender i's direct transmission range. Player i needs to not only

find the possible routes leading to the destination (i.e., route discovery), but also choose an optimal route from multiple routing candidates to help forwarding the packets (i.e., route selection).

- Each player only knows his own past actions and imperfect observation of other players' actions. Note that the information history consisting of the above two parts is private to each player.

Similar to [30], we assume the network operates in discrete time. In each time slot, one node is randomly selected from the M nodes as the sender. The probability that the sender finds r possible routes is given by $q_r(r)$ and the probability that each route needs $\hbar$ hops is given by $q_{\hbar}(\hbar)$ (assume at lease one hop is required in each time slot). Note that the $\hbar$ relays on each route are selected from the rest of nodes with equal probability and $\hbar \leq \lfloor \widetilde{g}/\ell \rfloor$. Assume each routing session lasts for one slot and the routes remain unchanged within each time slot. In our study, we consider that delicate traffic monitoring mechanisms such as receipt-submission approaches [13] are in place, hence the sender is able to have the observation of each node on the forwarding route.

Belief Evaluation System Design

In this part, we develop an efficient belief evaluation framework for multi-hop packet forwarding games based on the proposed two-player approach. Since a successful packet transmission through a multi-hop route depends on the actions of all the nodes on the route, the belief evaluation system needs to consider the observation error caused by each node, which makes a direct design of the belief system for the multi-player case very difficult. However, the proposed two-player algorithm can be applied to solve the multi-player packet forwarding problem by considering the multi-node multi-hop game as many two-player games between the source and each relay node. Let R_i^t denote the set of players on the forwarding route of player i in tth period. Let $\mu_{i,j}$ denote the sender i's belief value of the node j on the route. The proposed forwarding strategy for the multi-player case is illustrated as follows.

Belief-based Multi-hop Packet Forwarding (BMPF) Strategy: In the multi-node multi-hop packet forwarding game, given the discount factor δ_G and $p = (p_e, p_f)$, the sender and relay nodes act as follows during different phases of routing process.

- Game partition and belief initialization: Partition the original game into N sub-games according to (3.21). Then, each node initializes its belief of other nodes as $\pi(\delta_G^N, p)$ and forwards packets with probability $\pi(\delta_G^N, p)$.
- Route participation: The selected relay node on each route participates in the routing if and only if its beliefs of the sender and other forwarding nodes are greater than π.
- Route selection: The sender selects the route with the largest $\mu_i = \Pi_{j \in R_i} \mu_{ij}$ with $\mu_{ij} > \pi$ from the route candidates.
- Packet forwarding: The sender updates its belief of each relay node's continuation strategy using (3.14)-(3.17) and decides the following actions based on its belief.

In the above strategy, the belief value of each node plays an important role. The nodes who intentionally drop packets will be gradually isolated by other nodes since the nodes who have low belief value of the misbehaved nodes will not cooperate with them or participate in the possible routes involving these nodes. With the help of route participation and selection stage, our strategy successfully simplifies the complicated multi-node multi-hop packet forwarding game into multiple two-player games between the sender and relay nodes. But, the equivalent two-player gain g here is different from that in Table 3.1, which needs to further cope with the error propagation and routing diversity depending on the routing statistics such as $q_r(r)$ and $q_{\hbar}(\hbar)$. Note that the roles of sender or relay nodes may change over time depending on which source-destination pair has packets to transmit. As each node is selfish and trying to maximize its own payoff, all nodes are inclined to follow the above strategy for achieving the optimal payoff. In order to formally show the cooperation enforcement, we have the following theorem.

Theorem 3.4.4 *The packet forwarding strategy and belief evaluation system specified by the BMPF Strategy lead to a sequential equilibrium for the multi-player packet forwarding game.*

Proof A sequential equilibrium for the game with imperfect information is not only sequential rational but also consistent [10]. First, we prove the sequential rationality of the proposed strategy using the one-step deviation property [10], which indicates that (σ, μ) is sequentially rational if and only if no player i has a history h_i at which a change in $\sigma_i(h_i)$ increases his expected payoff.

In route participation stage, we assume each forwarding node $j \in R_i$ has built up a belief value of the sender i as μ_{ji} and the belief values of any other relay node $k \in R_i$. One-step deviation property is considered for the following three subcases for any forwarding node j: First, if $\mu_{ji} > \pi$ and $\mu_{jk} > \pi, k \neq j$, a one-step deviation is not to participate in the routing. In this case, the forwarding node will miss the opportunity of cooperating with the sender, which has been shown to be profitable for the forwarding node in (3.12). Second, if $\mu_{ji} < \pi$ and

$\mu_{jk} > \pi, k \neq j$, a one-step deviation is to participate in the routing. Since the relay node j will drop the packet from the sender i, the equivalent cooperation gain g in Table 3.1 will decrease due to packet-drop of the participated nodes, which also decreases the future gain of node j. Although node j does not afford the cost to forward packets for node i, its future gain will be damaged due to a smaller g. Thus, one-step deviation is not profitable in this subcase. Third, if $\mu_{ji} < \pi$ and there exists node k such that $\mu_{jk} < \pi$, the noncooperation forwarding behavior may happen since node j's belief of node k is lower than the threshold π. Such possible noncooperation outcome may decrease the expected equivalent gain g, which results in future payoff loss as (3.19) shows. Therefore, in all of the above three subcases of the route participation stage, one-step deviation from the BMPF Strategy cannot increase the payoffs of the nodes.

In route selection stage, two subcases need to be considered for one-step deviation test. First, if the largest μ_i with $\mu_{ij} < \pi, \exists j$ is selected as the forwarding route, there are noncooperation interactions between the sender i and relay j, which decreases the expected equivalent gain g and then lower the future payoffs. Second, if not the route with largest μ_i is selected, the expected gain g can still be increased by another route with larger successful forwarding probability. Thus, one-step deviation is not profitable in the route selection stage.

Further, Theorem 3.4.2 can be directly applied here to prove the sequential rationality for every packet-forwarding stage. To sum up, the BMPF Strategy is sequential rational for the multi-node multi-hop packet-forwarding game. Besides, following the definition of the consistency for sequential equilibria [10], it is straightforward to prove it for our BMPF Strategy. Therefore, the proposed multi-player packet-forwarding strategy is a sequential equilibrium. ■

Since the above theorem has proved that the BMPF Strategy is a sequential equilibrium, the cooperation among the nodes can be enforced and no selfish node will deviate from the equilibrium. As all nodes will follow the proposed strategy to have optimal payoffs, the expected gain g in Table 3.1 can be written as follows.

$$g = \widetilde{g} \cdot E_{r,\hbar}[1 - [1 - (\pi(1 - p_f))^{\hbar}]^r] - E(\hbar) \cdot \pi\ell, \tag{3.24}$$

where $E(\hbar)$ is the expected number of hops and $E_{r,\hbar}$ represents the expectation with respect to the random variables r and $\hbar$. The first term on the RHS of (3.24) is the expected gain of the sender considering multiple hops and possible routes; the second term on the RHS is the expected forwarding cost of sender i for returning the forwarding favor of the other relay nodes on its route. Note that π in (3.24) is also affected by g as shown in (3.22), which makes the computation of g more complicated. However, as we show in Theorem 3.4.2, the optimal π approaches ϕ when δ approaches $\underline{\delta}$. Considering the situations when δ_G approaches 1, π can be very close to ϕ as $\underline{\delta}$ is approached. Then, we can approximate g by substituting π with ϕ in (3.24), which is only determined by p_f and p_e.

3.5 Simulation Studies

In this section, we investigate the cooperation enforcement results of our proposed belief-based approach by simulation.

We first focus our simulation studies on one-hop packet forwarding scenarios in ad hoc networks, where the two-player belief-based packet forwarding approach can be directly applied to. Let $M = 100$, $g = 1$ and $\ell = 0.2$ in our simulation. In each time slot, any one of the nodes is picked with equal probability as the relay node for the sender. For comparison, we define the cooperative strategy, in

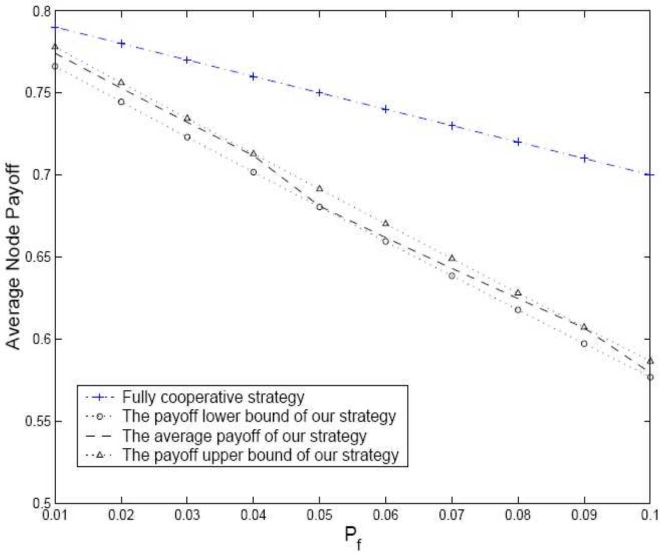

Figure 3.3: The average payoffs of the cooperative strategy and proposed strategy.

which we assume every node will unconditionally forward packets with no regard to other nodes' past behaviors. Such cooperative strategy is not implementable in autonomous ad hoc networks. But it can serve as a loose performance upper bound of the proposed strategy to measure the performance loss due to noise and imperfect observation.

Figure 3.3 shows the average payoff and performance bounds of the proposed strategy based on our belief evaluation framework for different p_f by comparing them with the cooperative payoff. Note that $p_e = 0.01$ and $\delta_G = 0.99$. It can be seen from Figure 3.3 that our proposed approach can enforce cooperation with only small performance loss compared to the unconditionally cooperative payoff. Further, this figure shows that the average payoff of our proposed strategy satisfies the theoretical payoff bounds developed in Theorem 3.4.2. The fluctuation of the payoff curve of our strategy is because only integer number of sub-games can be

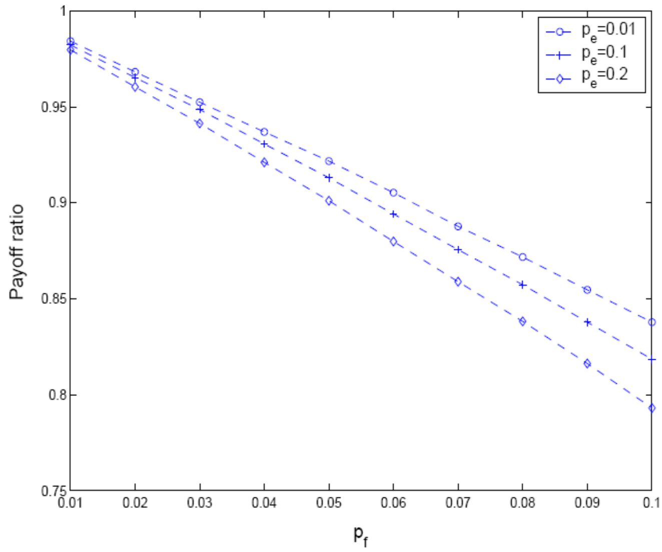

Figure 3.4: Payoff ratios of the proposed strategy to the cooperative strategy.

partitioned into from the original game. Figure 3.4 shows the ratio of the payoffs of our strategy to those of the cooperative strategy for different p_e and p_f . Here we let $\delta_G = 0.999$ to approach the payoff upper bound. It can be seen from Figure 3.4 that even if p_f is as large as 0.1 due to link breakage or transmission errors, our cooperation enforcement strategy can still achieve as high as 80% of the cooperative payoff.

In order to show that the proposed strategy is cheat-proof among selfish users, we define the deviation strategies for comparison. The deviation strategies differ from the proposed strategy only when the continuation strategy σ_F and observation F are reached. The deviation strategies will play σ_D with some deviating probability p_d instead of playing σ_F as the proposed belief evaluation framework. Figure 3.5 compares the nodes' average payoffs of the proposed strategy, cooperative strategy and deviation strategies with different deviating probabilities. Note that $\delta_G = 0.999$ and $pe = 0.1$. This figure shows that the proposed strategy has much better payoffs than the deviating strategies.

Then, we study the performance of the proposed multi-hop multi-node packet forwarding approach. Before evaluating the performance of our proposed strategy, we first need to obtain the routing statistics such as $q_r(r)$ and $q_\hbar(\hbar)$. An autonomous ad hoc network is simulated with $\mathcal{M}$ nodes randomly deployed inside a rectangular region of $10\gamma \times 10\gamma$ according to the 2-dimension uniform distribution. The maximal transmission range is $\gamma = 100$m for each node, and each node moves according to the random waypoint model [70]. Let the "thinking time" of the model be the time duration of each routing stage. Dynamic Source Routing (DSR) [70] is used as the underlying routing to discover possible routes. Let $\lambda = \mathcal{M}\pi/100$ denote the normalized node density, i.e., the average number of neighbors for each node in the network. Note that each source-destination pair is formed by randomly picking two nodes in the network. Moreover, multiple routes with different number of hops may exist for each source-destination pair. Since the routes with the minimum number of hops achieve the lowest costs, without loss of generality, we only consider the minimum-hop routes as the routing candidates.

In order to study the routing statistics, we first conduct simulations to study the hop number on the minimum-hop route for source-destination pairs. Let $h_{\min}(n_i, n_j) = \lceil \mathrm{dist}(n_i, n_j)/\gamma \rceil$ denote the ideal minimum number of hops needed to traverse from node i to node j, where $\mathrm{dist}(n_i, n_j)$ denotes the physical distance between node i and j, and let $\widetilde{\hbar}(n_i, n_j)$ denote the number of hops on the actual minimum-hop route between the two nodes. Note that we simulate 10^6 samples of topologies to study the dynamics of the routing in ad hoc networks. Firstly, Figure 3.6 shows the approximated cumulative probability mass function (CMF) of the difference between the $\widetilde{\hbar}(n_i, n_j)$ and $h_{\min}(n_i, n_j)$ for different node densities. Based

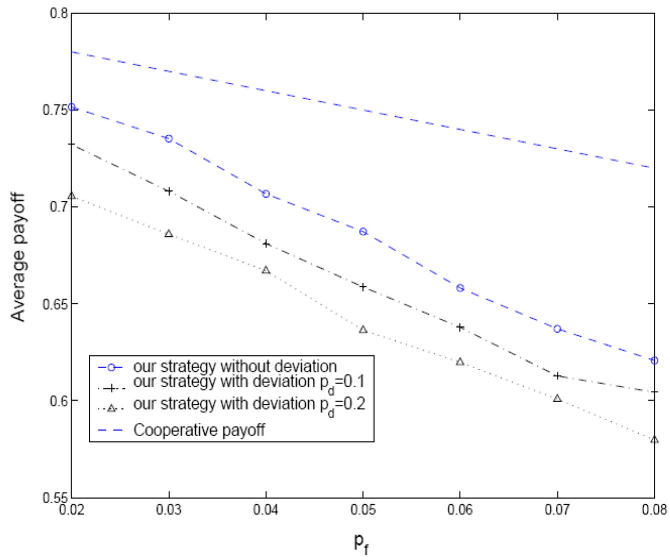

Figure 3.5: Payoff comparison of the proposed strategy and deviating strategies.

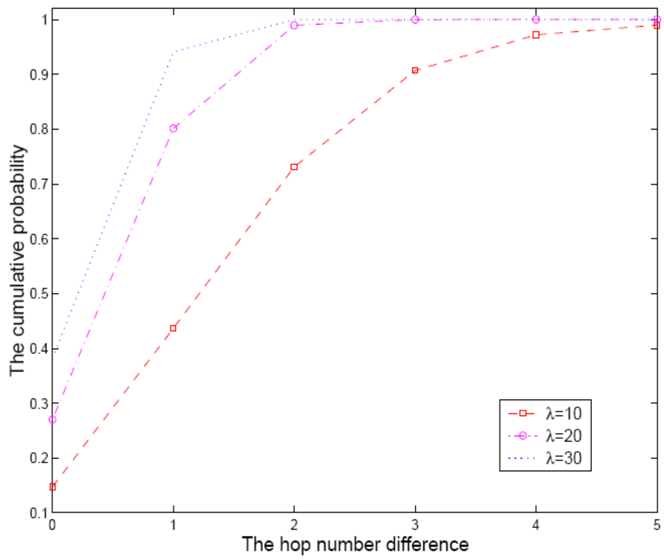

Figure 3.6: The cumulative probability mass function of the hop-number difference between the $\widetilde{\hbar}(n_i, n_j)$ and $h_{\min}(n_i, n_j)$.

on these results, the average number of hops associated to the minimum-hop route from node i to j can be approximated using the $\text{dist}(n_i, n_j)$, γ, and the corresponding CMF of hop difference, which also gives the statistics of $q_{\hbar}(\hbar)$. Besides, it can be seen from Figure 3.6 that lower node density results in having a larger number of hops for the minimum-hop routes, since the neighbor nodes are limited for packet forwarding in such scenarios. Secondly, we study the path diversity of the ad hoc networks by finding the maximum number of minimum-hop routes for the source-destination pair. Note that there may exist the scenarios where the node may be on multiple minimum-hop forwarding routes for the same source-destination pair. For simplicity, we assume during the route discovery phase, the destination randomly picks one of such routes as the routing candidate and feedbacks the routing information of all node-disjoint minimum-hop routes to the source. Figure 3.7 shows the CMF of the number of the minimum-hop routes for different hop number when the node density is 30. This figure actually shows the $q_r(r)$ statistics when the ideal minimum hop number is given. Based on the routing statistics given in Figure 3.6 and Figure 3.7, we are able to obtain the expected equivalent two-player payoff table for multi-node and multi-hop packet forwarding scenarios using (3.24).

We compare the payoff of our approach with that of the cooperative one in Figure 3.8. Note that multi-hop forwarding will incur more costs to the nodes since one successful packet delivery involves the packet forwarding efforts of many relay nodes. Also, the noise and imperfect observation will have more impact on the performance as each node's incorrect observation will affect the payoffs of all other nodes on the selected route. We can see from Figure 3.8 that our proposed strategy maintains high payoffs even when the environment is noisy and the observation

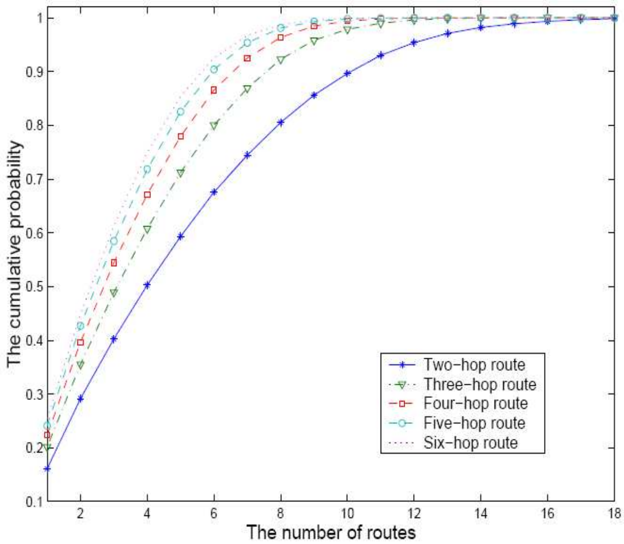

Figure 3.7: The cumulative probability mass function of the number the minimum-hop route when the node density is 30.

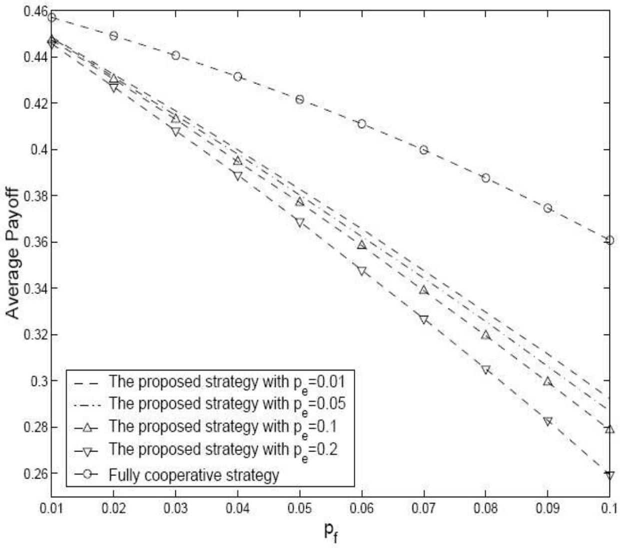

Figure 3.8: Average payoffs of the proposed strategy in multi-node multi-hop scenarios.

error is large. For instance, when $p_e = 0.2$ and $p_f = 0.1$, our proposed strategy still achieves over 70% payoffs of the unconditionally cooperative payoff.

3.6 Summary

In this chapter, we study the cooperation enforcement in autonomous ad hoc networks under noise and imperfect observation. By modeling the packet forwarding as a repeated game with imperfect information, we develop the belief evaluation framework for packet forwarding to enforce cooperation in the scenarios with noise and imperfect observation. We show that the behaviorial strategy with well-defined belief system in our proposed approach not only achieves the sequential equilibrium, but also maintains high payoffs for both two-player and multi-player cases. Notice that only each node's action history and imperfect private observation are required for the proposed strategy. The simulation results illustrate that the proposed belief-based cooperation enforcement approach achieves stable and near-optimal equilibria in ad hoc networks under noise and imperfect observation.

3.7 Appendix: Proof of Theorem 3.4.2

First, we prove the sequential rationality of the solution obtained by our algorithm. It is already shown in [10] that (σ, μ) is sequentially rational if and only if no player i has a history at which a change in $\sigma_i(h_i)$ increases his expected payoff. This is also called the one-step deviation property for sequential equilibrium, which we use in our proof to show the sequential rational property of the proposed solution.

There are three possible outcomes considering the relation between μ and π.

1) If $\mu_i(h_i^{t-1}) > \pi$, a one-step deviation from σ^* is to drop packets in current

period and continue with σ^* in the next period. Since the action player i chooses is D, the operators (3.16) and (3.17) need to be considered for updating beliefs. Noting that $\mu_i(h_i^{t-1}, (D, f))$ is an increasing function with respect to $\mu(h_i^{t-1})$ and $\mu(h_i^{t-1}) \leq 1$, we can obtain that $\mu_i(h_i^{t-1}, (D, f)) < p_e$. Since $\pi > 1/2$ and $p_e < 1/2$, we have the continuation belief satisfying $\mu_i(h_i^{t-1}, (D, f)) < \pi$. Then only the following two sub-cases need to be considered.

(i) Suppose $\mu_i(h_i^{t-1}, (D, d)) \leq \pi$. In this case, since $\mu_i(h_i^{t-1}, (D, d)) \leq \pi$ and $\mu_i(h_i^{t-1}, (D, f)) \leq \pi$, the one-step deviation results in the continuation strategy σ_D. Considering the node's current action D, the deviated node will play σ_D in this sub-case. But, (3.12) shows that the rational node prefers σ_F than σ_D when $\mu_i(h_i^{t-1}) > \pi$. Then, a one-step deviation here cannot increase the payoff of the node.

(ii) Suppose $\mu_i(h_i^{t-1}, (D, d)) > \pi$. The one-step deviation is to drop packets in current period and continue with σ_D if the history information set (D, f) is reached or continue with σ_F if (D, d) is reached. Compared with the first sub-case, we find that the one-step deviation differs from σ_D only when the information set (D, d) is reached. Let $\triangle\widehat{V}(\mu)$ be the payoff difference between the proposed solution and the one-step deviation, which can be written as

$$\triangle\widehat{V}_i(\mu_i^{t-1}) = \triangle V_i(\mu_i^{t-1}) - \delta[\mu_i^{t-1} \cdot p_f + (1 - p_e) \cdot (1 - \mu_i^{t-1})] \cdot \triangle V_i(\mu(h_i^{t-1}, (D, d))), \tag{3.25}$$

where the first term on the RHS is the payoff difference between σ_F and σ_D, and the second term on the RHS is the conditional payoff difference when (D, d) is reached. Noting that (3.17) indicates $\mu_i(h_i^{t-1}, (D, d)) < \mu_i(h_i^{t-1})$ and $\triangle V(\mu)$ is an increasing function in μ. we have $\triangle V_i(\mu_i(h_i^{t-1})) > \triangle V_i(\mu_i(h_i^{t-1}, (D, d)))$. Moreover, as the coefficient of the second term in (3.25) is less than one, $\triangle\widehat{V}_i(\mu_i(h_i^{t-1}))$ is strictly greater than zero. Thus, the one-step deviation is not profitable in this sub-case.

Since there is no sub-cases other than the above ones, we show that if $\mu_i(h_i^{t-1}) > \pi$, the one-step deviation cannot increase the payoff for the node.

2) If $\mu_i(h_i^{t-1}) < \pi$, a one-step deviation from σ^* is to forward packets in current period and continue with σ^* in the next period. Considering $\pi < \phi$ and $\mu_i(h_i^{t-1}, (F,d))$ is an increasing function in $\mu_i(h_i^{t-1})$, we can show that $\mu_i(h_i^{t-1}, (F,d)) < 1/2$ if $\mu_i(h_i^{t-1}) < \pi$, thus $\mu_i(h_i^{t-1}, (F,d)) < \pi$. Then, there are two sub-cases:

(i) If $\mu_i(h_i^{t-1}, (F,f)) \geq \pi$, the one-step deviation from σ^* becomes playing the cooperation strategy σ_F. As we have shown in (3.12), σ_D is preferable to σ_F if $\mu_i(h_i^{t-1}) < \pi$.

(ii) If $\mu_i(h_i^{t-1}, (F,f)) < \pi$, the deviated strategy differs from σ_F only when the private history (F,f) is reached. Let $\triangle\widetilde{V}(\mu_i(h_i^{t-1}))$ be the payoff difference between the equilibrium strategy σ_D and the one-step deviation strategy, which can be obtained as

$$\triangle\widetilde{V}(\mu_i(h_i^{t-1})) = \triangle V(\mu_i(h_i^{t-1})) - \delta[\mu_i(h_i^{t-1})(1-p_f) + p_e \cdot (1-\mu_i(h_i^{t-1}))] \cdot \triangle V(\mu_i(h_i^{t-1}), (F,f)). \tag{3.26}$$

Note that $\triangle V(\mu_i(h_i^{t-1})) < \triangle V(\mu_i(h_i^{t-1}), (F,f))$. considering $\mu_i(h_i^{t-1}, (F,f)) > \mu_i(h_i^{t-1})$. As the coefficient of the second term on the RHS in (3.26) is less than one, we have a positive $\triangle\widetilde{V}(\mu_i(h_i^{t-1}))$, which shows that the one-step deviation in this subcase cannot increase payoff.

3) If $\mu_i(h_i^{t-1}) = \pi$ the node is indifferent between forwarding packets and dropping packets from (3.12). Obviously, a one-step deviation will not change the expected payoff.

By studying the above three cases, we prove that the proposed strategy (σ^*, π) of the packet forwarding game is sequential rational when $\pi \in (1/2, \phi)$.

Then, we prove the consistency of the proposed strategy. Since the proposed strategy is a pure strategy when $\mu_i \neq \pi$ we construct a completely mixed strategy $(\sigma_i^\epsilon, \mu_i^\epsilon)$, which is constructed by allowing a tremble with a small probability ϵ from purely forwarding strategy or dropping strategy. By applying (3.14)-(3.17) to calculate the belief-update system with tremble, it is easy to show that μ_i^ϵ converges to μ_i when ϵ approaches zero. Therefore, given a sequence $\bar{\epsilon} = (\epsilon_n)_{n=1}^{\infty}$ satisfying $\lim_{n\to\infty} \epsilon_n = 0$, we can show that the sequence $(\sigma_i^{\epsilon_n}, \mu_i^{\epsilon_n})_{n=1}^{\infty}$ of strategies with completely mixed strategies converges to the proposed strategy (σ^*, μ) while the belief system being updated by Bayes' rule.

Therefore, since the proposed strategy satisfies the sequential rationality and consistency properties when $\pi \in (1/2, \phi)$, it is a sequential equilibrium for the packet-forwarding game with imperfect private observation.

Chapter 4

Optimal Dynamic Pricing for Autonomous Ad Hoc Networks

In this chapter, we study the cooperation among selfish users during the routing process in autonomous ad hoc networks, which is built upon the cooperation of the packet forwarding among users and requires more sophisticated mechanisms to stimulate cooperation while more network users are involved for efficient self-organized routing.

Although the existing pricing-based approaches [14–16] have achieved some success in cost-efficient and incentive-compatible routing for MANETs with selfish users, most of them assume that the network topology is fixed or the routes between the sources and the destinations are known and pre-determined. Further, none of the existing approaches have addressed how to exploit the time diversity for efficient routing. In order to encourage cooperation among selfish users and achieve optimal pricing-based routing, both path diversity and time diversity of MANETs should be exploited. Specifically, the source (here we assume the source pays to the forwarding nodes) is responsible for exploiting the path diversity, such as introducing competition among the multiple available routes through auction, to minimize the payment needed at the current stage. Each node also needs to exploit the time diversity to maximize its overall payoff over time. In each stage the source adaptively decides the number of packets being transmitted according to the price it needs to pay, which is determined by the current routing conditions. For instance, when the routing conditions are good (i.e., the cost to transmit a packet is low), more packets should be transmitted in the current stage; otherwise, less or no packets should be transmitted in the current stage.

In this chapter, we consider the routing process as multi-stage dynamic games and propose an optimal pricing-based approach to dynamically maximize the sender/receiver's payoff over multiple routing stages considering the dynamic nature of MANETs, meanwhile, keeping the forwarding incentives of the relay nodes by optimally pricing their packet-forwarding actions based on the auction rules. The main contribution of this chapter are multi-fold: First, by modeling the pricing-based routing as a dynamic game, the senders are able to exploit the time diversity in MANETs to increase their payoffs by adaptively allocating the packets to be transmitted into different stages. Considering the mobility of the nodes, the possible routes for each source-destination pair are changing dynamically over time. According to the path diversity, the sender will pay a lower price for transmitting packets when there are more potential routes. Thus, the criterion for allocation can be developed based on the fact that the sender prefers to send more packets in the stage with lower costs. Second, an optimal dynamic programming approach is proposed to implement efficient multi-stage pricing for autonomous MANETs. Specifically, the Bellman equation is used to formulate and analyze the above dynamic programming problem by considering the optimization goal in terms of two parts: current payoffs and future opportunity payoffs. A simple allocation algorithm is developed and its optimality is proved based on the auction structure and routing dynamics. Third, the path diversity of MANETs is exploited using the optimal auction mechanism in each stage. The application of the optimal auction [71] makes it possible to separately study the optimal allocation problem and the mechanism design of the auction protocol based on the well-known Revenue Equivalence Theorem [71], which simplifies the dynamic algorithm while keeping the optimality.

The remainder of this chapter is organized as follows: The system model of autonomous MANETs are illustrated in Section 4.1. In Section 4.2, we formulate the pricing process as dynamic games based on the system model. In Section 4.3, the optimal dynamic auction framework is proposed for the optimal pricing and allocation of the multi-stage packet transmission. In Section 4.4, extensive simulations are conducted to study the performance of the proposed approach. Finally, summary is given in Section 4.5.

4.1 System Description

We consider autonomous mobile ad hoc networks where nodes belong to different authorities and have different goals. We assume that each node is equipped with a battery with limited power supply, can freely move inside a certain area, and communicates with other nodes through wireless connections. For each node, packets are scheduled to be generated and delivered to certain destinations with each packet having a specific delay constraint, that is, if a packet cannot reach the destination within its delay constraint, it will become useless.

In our system model, we assume all nodes are selfish and rational, that is, their objectives are to maximize their own payoff, not to cause damage to other nodes. However, node are allowed to cheat whenever they believe cheating behaviors can help them increasing their payoff. Since nodes are selfish and forwarding packets on behalf of others will incur some cost, without necessary compensation, nodes have no incentive to forward packets for others. In our system model, we assume that if a packet can be successfully delivered to its destination, then the source and/or the destination of the packet can get some benefits, and when a node forwards packets for others, it will ask for some compensation, such as virtual money or credits [12, 13], from the requesters to at least cover its cost. In our system model, to simplify our illustration, we assume that the source of a packet pays to the intermediate nodes who have forwarded the packet for it. However, the proposed schemes can also be easily extended to handle the situation that the destinations pay. Like in [13], we assume that there exist some bank-like centralized management points, whose only function is to handle the billing information, such as performing credit transfer among nodes based on the submitted information by these nodes. Each node only needs to contact these central banking points periodically or aperiodically.

In general, due to the multi-hop nature of ad hoc networks, when a node wants to send a packet to a certain destination, a sequence of nodes need to be requested to help forwarding this packet. We refer to the sequence of (ordered) nodes as a route, the intermediate nodes on a route as relay nodes, and the procedure to discover a route as route discovery. The routing protocols are important for MANETs to establish communication sessions between each source-destination pair. Here, we consider the on-demand (or reactive) routing protocols for ad hoc networks, in which a node attempts to establish a route to some destination only when it needs to send packets to that destination. Since on-demand routing protocols are able to handle many changes of node connectivity due to the node's mobility, they perform better than periodic (or proactive) routing protocols in many situations [72–74] by having much lower overheads. In MANETs, due to the mobility, nodes need to frequently perform route discovery. In this chapter, we refer to the interval between two consecutive route discovery procedures as a routing stage, and assume that for each source-destination pair, the selected route between them will keep unchanged in the same routing stage. Furthermore, to simplify our analysis, we assume that for each source-destination pair, the discovered routes in different routing stages are independent.

After performing route discovery in each stage, multiple forwarding routes can be exploited between the source and the destination. Assume there are ℓ possible routes and let $v_{i,j}$ be the forwarding cost of the jth node on the ith route, which is also referred to as the node type in this chapter. Considering possible node mobility in MANET, ℓ and $v_{i,j}$ are no longer fixed values, which can be modelled as random variables. Let the probability mass function (PMF) of ℓ be $\widetilde{f}(\ell)$ and the corresponding cumulative density function (CMF) be $\widetilde{F}(\ell)$. And, $v_{i,j}$ is characterized by its probability density function (PDF) $\widehat{f}_{i,j}$ and the cumulative density function (CDF) $\widehat{F}_{i,j}$. Define the cost vector of the ith route as $\mathbf{v}_i = \{v_{i,1}, v_{i,2}, ..., v_{i,h_i}\}$, where h_i is the number of forwarding nodes on the ith route. Thus, we have the total cost on the ith route $r_i = \sum_{j=1}^{h_i} v_{i,j}$, which is also a random variable. Let the PDF and CDF of r_i be f_i and F_i, respectively.

Figure 4.1 illustrates our system model by showing a network snapshot of pricing-based multi-hop routing between a source-destination pair. It can be seen from this figure that there are three routing candidates with different number of hops and routing costs (such as energy-related forwarding costs) between the source-destination pair. Each route will bid as one entity for providing the packet forwarding service for the source-destination pair at this routing stage. Then, the source will choose the route with the lowest bid to transmit the packets. The price that the source pays to the selected route may be equivalent to the asked price or include a premium than the true forwarding cost. Note that the asking prices from each route and the payment from the source may vary according to the applied pricing mechanisms. Further, the payment that the source provides to the selected route needs to be shared among the nodes on the selected route in a way that no node on the selected route has incentive to deviate from the equilibrium strategy. Considering the network dynamics due to the node mobility, dynamic topology or channel fading, the number of available routes, the number of required hops and the forwarding costs will change over time. In Figure 4.2, we consider a dynamic scenario and illustrate the relationship of the number of packets to be transmitted and the lowest cost of the available routes at each stage. In order to maximize its payoff by utilizing the time diversity, the source tends to transmit more packets when the cost is lower and transmit less packets when the cost is higher. The optimal relationship between them will be derived in later sections.

4.2 Pricing Game Models

In this chapter, we model the process of establishing a route between a source and a destination node as a game. The players of the game are the network nodes. With respect to a given communication session, any node can play only one of the following roles: sender, relay node, or destination. In autonomous MANET, each node's objective is to maximize its own benefits. Specifically, from the sender's

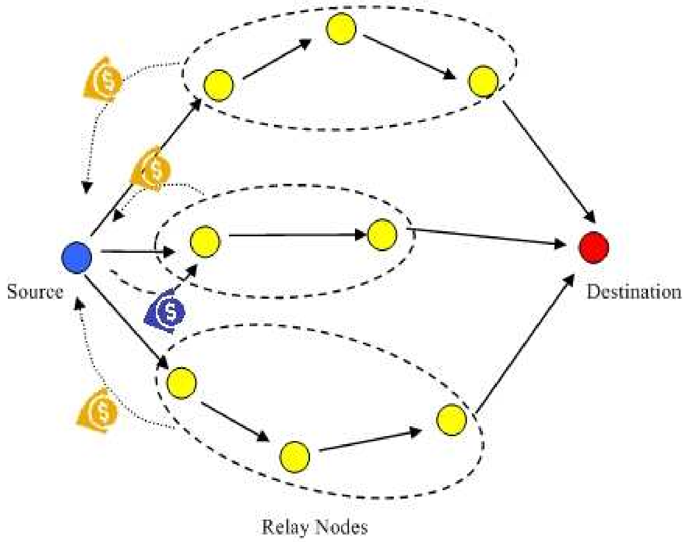

Figure 4.1: Pricing-based routing in autonomous MANETs.

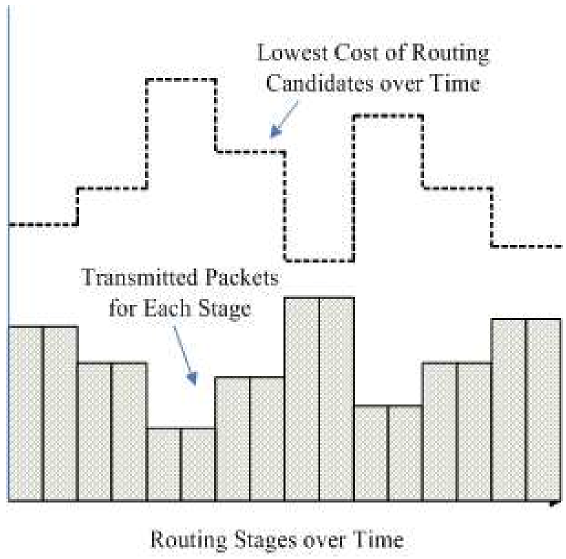

Figure 4.2: Dynamic pricing-based routing considering time diversity.

point of view, he/she aims to transmit its packets with the least possible payments; from the relaying nodes' points of view, they want to earn the payment which not only covers their forwarding cost but also gain as much extra payment as possible; while from the network designers' point of view, they prefer that the network throughput and/or lifetime can be maximized. Therefore, the source-destination pair and the nodes on the possible forwarding routes construct a non-cooperative pricing game [8]. Since the selfish nodes belong to different authorities, the nodes only have the information about themselves and will not reveal their own types to others unless efficient mechanisms have been applied to guarantee that truth-telling does not harm their interests. Generally, such non-cooperation game with imperfect information is complex and difficult to study as the players do not know the perfect strategy profile of others. But based on our game setting, the well-developed auction theory can be applied to analyze and formulate the pricing game.

The auction games belong to a special class of game with incomplete information known as games of mechanism design, in which there is a "principal" who would like to condition his actions on some information that is privately known by the other players, called "agents". In auction, according to an explicit set of rules, the principle (auctioneer) determines resource allocation and prices on the basis of bids from the agents (bidders). In the pricing game, the source can be viewed as the principle, who attempts to buy the forwarding services from the candidates of the forwarding routes. The possible forwarding routes are the bidders who compete with each other for serving the source node, by which they may gain extra payments for future use. In order to maximize their own interests, the selfish forwarding nodes will not reveal their private information, i.e., the actual forwarding costs, to others. They compete for the forwarding request by eliciting their willingness of the payments in the forms of bids. Thus, because of the path diversity of MANET, the sender is able to lower its forwarding payment by the competition among the routing candidates based on the auction rules. It is important to note that instead of considering each node as a bidder [14, 15], we consider each route as a bidder in this chapter, which has the following advantages: First, by considering the nodes on the same forwarding route as one entity, the sender can fully exploit the path diversity to maximize its own payoffs. Second, since it has been proved in [14] that there does not exist a forwarding-dominant protocol for ad hoc pricing games, the route-based bidding approach makes it possible to study the payoff-maximization allocation and cheat-proof mechanism design sequentially. Moreover, less bidding information is required for route-based approach.

In this section, we first consider the static pricing game (SPG), which is only played once for the fixed topology. Then, the dynamic pricing game (DPG) is studied and formulated considering playing the pricing game for multiple stages.

4.2.1 The Static Pricing Game

In this subsection, we study the static pricing game model. By taking advantage of the auction approach, our goal is to maximize the profits of the source-destination communication pair for transmitting packets while keeping the forwarding incentives of the forwarding routes. Specifically, considering an auction mechanism $(\mathbf{Q}, \mathbf{M})$ consists of a pair of functions $\mathbf{Q} : \mathcal{D} \to \mathcal{P}$ and $\mathbf{M} : \mathcal{D} \to R^N$, where $\mathcal{D}$ is the set of announced bids, $\mathcal{P}$ is the set of probability distributions over the set of routes $\mathcal{L}$. Note that $Q_i(\mathbf{d})$ is the probability that the ith route candidate will be selected for forwarding and $M_i(\mathbf{d})$ is the expected payment for the ith route, where

$\mathbf{d}$ is the vector of bidding strategies for all routes, i.e., $\mathbf{d} = \{d_1, d_2, .., d_\ell\} \in \mathcal{D}$. Then, the payoff function of the ith forwarding route can be represented as follows

$$U_i(d_i, d_{-i}) = M_i(d_i, d_{-i}) - Q_i(d_i, d_{-i}) \cdot r_i. \tag{4.1}$$

Before studying the equilibria of the auction game, we first define the *direct revelation mechanism* as the mechanism in which each route bids its true cost, $d_i = r_i$. The *Revelation Principle* [71] states that given any feasible auction mechanism, there exists an equivalent feasible direct revelation mechanism which gives to the auctioneer and all bidders the same expected payoffs as in the given mechanism. Thus, we can replace the bids $\mathbf{d}$ by the cost vector of the routes, i.e., $\mathbf{r} = \{r_1, r_2, ..., r_L\}$ without changing the outcome and the allocation rule of the auction game. Therefore, the equilibrium of the SPG can be obtained by solving the following optimization problem to maximize the sender's payoff while providing incentives for the forwarding routes

$$E_{\ell,\mathbf{r}}\left[\max_{\mathbf{Q},\mathbf{M}}\left\{g \cdot \sum_{i=1}^{\ell} Q_i(\mathbf{r}) - \sum_{i=1}^{\ell} M_i(\mathbf{r})\right\}\right] \tag{4.2}$$

$$s.t. \qquad U_i(r_i, d_{-i}) \geq U_i(d_i, d_{-i}), \forall d_i \in \mathcal{D} \tag{4.3}$$

$$Q_i(\mathbf{r}) \in \{0, 1\}, \sum_{i=1}^{\ell} Q_i(\mathbf{r}) \leq 1.$$

where the constraint (4.3) is also referred as the incentive compatibility (IC) constraint, which ensures the users to report their true types, and g is the marginal profit of transmitting one packet.

4.2.2 The Dynamic Pricing Game

Considering the dynamic nature of MANET, the network topology may change over time due to the mobility of the nodes. Thus, the route discovery needs to be performed frequently. Moreover, for different routing stages, there may exist different number of available routes with different number of hops. It is important for each source-destination pair to decide the transmission and payment behaviors for each stage according to the route conditions. Therefore, the pricing game under such dynamic situation can no longer be modelled as static games. Game theorists use the concept of dynamic games to model such multi-stage games and analyze the long-run behaviors of players. In dynamic games, the strategies of the players not only depend on the opponents' current strategies but also the past outcomes of the game and the future possible actions of other players. Our pricing game for MANET falls exactly into the category of dynamic games. In this chapter, we will focus on studying the dynamic pricing game.

Intuitively, the sender prefers to transmit more packets when more routing candidates are available and the number of hops is small. Because, considering the application of auction protocols in each stage, the sender has a higher probability to get the service with a lower price when there are more bidders (routes) with lower type values. Moreover, the practical constraints in MANET need to be considered in DPG, such as the delay constraint of packet transmission or the bandwidth constraint of the maximal number of packets being able to be transmitted within an unit time duration. Therefore, in order to maximize their profits, the source-destination pair needs not only to optimally allocate the packets to the routes within one time period but also to schedule the packets for all periods. In our DPG, it is important to note that the optimal packet transmission strategy for each source-destination pair is affected by both the past plays and the future possible outcomes. Generally speaking, the packet transmission decision is made by comparing the current transmission profit and future opportunity profits. Also, due to the delay and bandwidth constraints, the past transmission plays affect current decision-making. Capturing the dynamics becomes the key to the optimal solution of our DPG. Let ℓ_t denote any realization of the route number at the tth stage and $\mathbf{r}$ be a realization of the types of all routing candidates. Consider a T-period dynamic game, the overall payoff maximization problem for the source-destination pair can be formulated as follows.

$$\sum_{t=1}^{T} \beta^t \cdot E_{\ell_t,\mathbf{r}_t}\left[\max_{\mathbf{Q},k_t}\left\{\left[G(\mathcal{K}_t)\cdot\sum_{i=1}^{\ell_t} Q_i - k_t\cdot\sum_{i=1}^{\ell_t} M_i(\mathbf{r}_t)\right]\right\}\right]$$

$$\begin{aligned} s.t. \quad & U_{i,t}(r_{i,t}, d_{-i,t}) \geq U_{i,t}(d_{i,t}, d_{-i,t}), \forall d_{i,t} \in \mathcal{D} \\ & Q_i \in \{0,1\}, \sum_{i=1}^{L} Q_i \leq 1. \\ & k_t \leq \mathcal{B}, \sum_{t=1}^{T} k_t = M. \end{aligned} \tag{4.4}$$

where k_t is the number of packets transmitted in the tth stage and $\mathcal{K}_t$ is the vector of the numbers of the transmitted packets in the first $T-t+1$ stages, which can be represented as $\mathcal{K}_t = \{k_T, k_{T-1}, ..., k_t\}$. Note that a smaller t in this chapter stands for a later time stage. Here, $G(\mathcal{K}_t)$ is the profit that the sender gains in the tth stage, which may not only depend on how many packets are transmitted in current stage, i.e., k_t, but also be affected by how many packets have been transmitted in previous stages, $\mathcal{K}_{t+1}$. Considering the rate-distortion theory [75], we assume the profit function is concave in k_t. For example, the marginal profit of transmitting one more packet when a lot of packets have already been transmitted should be limited. Also, β is the discount factor for multistage games, and the subscript t indicates the tth routing stage. Note that T and $\mathcal{B}$ are the delay constraint and the bandwidth constraint, respectively. M is the total number of packets to be transmitted within T stages.

The above DPG formulation (4.4) extends the optimal pricing problem to the time dimension, which can exploit the potential of time diversity in the autonomous ad hoc network considering its dynamic nature. However, directly solving the nonlinear integer programming problem is very difficult. Because, not only does the current routing realization affect the allocation decision, but also the past play and allocation decision influence the feasible actions and payoff functions in the current period.

4.3 Optimal Dynamic Pricing-Based Routing

In order to achieve efficient self-organized routing in the DPG considering the dynamic nature of MANETs, we propose the optimal pricing-based routing approach in this section. First, the optimal auction mechanism is considered for maximizing the payoffs for the source-destination pair while keeping the forwarding incentives of the relaying nodes. Then, the dynamic multi-stage game is further formulated using the optimal auction and dynamic programming approach. Finally, the mechanism design and the profit-sharing among the nodes on the selected route are considered for the proposed approach.

4.3.1 Optimal Auction for Static Pricing-Based Routing

In Section 4.2, we have formulated the static pricing game based on the auction principles as the optimization problem (4.2). Here, we further utilize the results of the optimal auction [76] to simplify the optimization problem. From [76], we know that by considering the optimal auction, the sender's expected total payoff can be expressed only in terms of the allocation $\mathbf{Q}$, which is independent of the payment to each route candidate. Specifically, the optimization problem (4.2) can be rewritten as follows.

$$E_{\ell,\mathbf{r}}\left[\max_{\mathbf{Q}}\left\{g\cdot\sum_{i=1}^{\ell}Q_i(\mathbf{r})-\sum_{i=1}^{\ell}J_i(r_i)Q_i(\mathbf{r})\right\}\right], \tag{4.5}$$

$$\text{s. t.}\quad Q_i(\mathbf{r})\in\{0,1\},\quad \sum_{i=1}^{\ell}Q_i(\mathbf{r})\leq 1.$$

where $J(r_i)=r_i+1/\rho(r_i)$, and $\rho(r_i)=f_i(r_i)/F_i(r_i)$ is the hazard rate [76] function associated with the distribution of the routing cost. Note that $J(r_i)$ is also called the virtual type of the ith player. It's proved in [76] that the solution of the above optimization also satisfies the incentive compatible constraint. The assumptions for the above formulation are rather general: (1) F is continuous and strictly increasing, (2) the allocations $Q_i(r_i, r_{-i})$ are increasing in r_i. From (4.5) and the *Revenue Equivalence Theorem*, it follows that all mechanisms that result in the same allocations $\mathbf{Q}$ for each realization of $\mathbf{r}$ yield the same expected payoff. Thus, in order to obtain the optimal pricing strategies, the mechanism design process proceeds in two steps: First, find the optimal allocation $\mathbf{Q}(\mathbf{r})$; second, find an implementable mechanism that produces $\mathbf{Q}$ for each realization $\mathbf{r}$. By using the optimal auction approach for pricing, the payoff-maximized allocation for the sender is to choose the route with the minimal virtual type $J(r_i)$ when $g-J(r_i)\geq 0$, otherwise the sender will not transmit the packet as it will cause negative payoff and violate his individual rationality. Therefore, if we assume $J(v)$ is strictly increasing in v, we can define $v* = \max_v\{(g-J(v))=0\}$ as the reserved price for the sender, which is the largest payment he/she can offer for transmitting a packet. Note that the distributions that have increasing $J(v)$ include the uniform, normal, logistic, exponential distributions, etc.

Based on the above discussion, we find that the static pricing game is not efficient if the current routing realization shows a high cost. Considering the dynamic properties of MANET, a more efficient pricing mechanism can be achieved by studying it as a multistage game and optimally allocating the packet transmissions over multiple time periods.

4.3.2 Optimal Dynamic Auction for Dynamic Pricing-Based Routing

Considering the optimal auction results in the DPG model formulated in Section 4.2, we further propose the optimal dynamic auction framework for pricing in autonomous MANET. As it is difficult to directly solve (4.4), we study the dynamic programming approach in our proposed framework to simplify the multistage optimization problem.

Define the value function $V_t(x)$ as the maximum expected profit obtainable from periods $t, t-1, ..., 1$ given that there are x packets to be transmitted within the constraint of time periods. Simplifying (4.4) using the Bellman equation, we have the maximal expected profit $V_t(x)$ written as follows

$$V_t(x) = E_{\ell_t,\mathbf{r}}\left[\max_{\mathbf{Q},k_t}\left\{\left[G(\mathcal{K}_t)\cdot\sum_{i=1}^{\ell_t} Q_i - k_t\cdot\sum_{i=1}^{\ell_t} J(v_i)Q_i\right] + \beta\cdot V_{t-1}(x-k_t)\right\}\right], \quad (4.6)$$

$$\text{s.t.} \qquad Q_i(\mathbf{r}) \in \{0,1\}, \quad \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}) = 1, \quad k_t \leq \mathcal{B}.$$

Moreover, the boundary conditions for the above dynamic programming problem are

$$V_0(x) = 0, x = 1, ..., M, \quad (4.7)$$

Recall that we have the delay constraint T of the maximal allowed time stages and the bandwidth constraint $\mathcal{B}$ of the maximal number of packets able to be transmitted for each stage. Based on the principle of optimality in [68], an allocation $\mathbf{Q}$ that achieves the maximum in (4.6) given x, t and $\mathbf{r}$ is also the optimal solution for the overall optimization problem (4.4). Note that the above formulation is similar to that of the multi-unit sequential auction [77] studied by the economists.

First, note that from (4.6) and the monotonicity of $J(\cdot)$, it is clear that if the sender transmits k packets within one time period, these packets should be all awarded to the forwarding route with the lowest cost r_i. Therefore, define

$$R_t(k) = \max_{\mathbf{Q}} \left\{ G(\mathcal{K}_t) \cdot \sum_{i=1}^{\ell_t} Q_i(\mathbf{r}) - k \cdot \sum_{i=1}^{\ell_t} J(r_i) Q_i(\mathbf{r}) : Q_i(\mathbf{r}) \in \{0,1\}, \sum_i Q_i(\mathbf{r}) = 1 \right\}, \tag{4.8}$$

which can also be solved and written as

$$R_t(k) = \begin{cases} 0 & if\ k = 0, \\ G(k, \mathcal{K}_{t+1}) - k \cdot J(r_{(1)}) & if\ k > 0, \end{cases} \tag{4.9}$$

where $r_{(1)}$ means the lowest cost of the forwarding routes. Thus, the dynamic optimization objective (4.6) can therefore be rewritten in terms of $R_t(k)$ as follows:

$$V_t(x) = E_{\ell_t, \mathbf{r}} \left[\max_{0 \le k_t \le \min\{\mathcal{B}, x\}} \{ R_t(k_t) + \beta \cdot V_{t-1}(x - k_t) \} \right], \tag{4.10}$$

which is also subject to (4.7). Let $k_t^*(x)$ denote the optimal solution above, which is the optimal number of packets to be transmitted on the winning route at the tth stage given remaining capacity x. Letting $\triangle R_t(i) \equiv R_t(i) - R_t(i-1)$ and $\triangle V_t(i) \equiv V_t(i) - V_t(i-1)$, we can rewrite the maximal expected profit $V_t(x)$ as

$$V_t(x) = E_{\ell_t, \mathbf{r}} \left[\max_{0 \le k_t \le \min\{\mathcal{B}, x\}} \left\{ \sum_{i=1}^{k_t} [\triangle R_t(i) - \beta \cdot \triangle V_{t-1}(x - i + 1)] \right\} \right] + \beta \cdot V_{t-1}(x). \tag{4.11}$$

The above formulation will help us to simplify the optimal dynamic pricing problem.

Then, in order to solve the dynamic pricing problem (4.6)-(4.7), we need to first introduce the following lemmas based on (4.11).

Lemma 4.3.1 *If* $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$, *then* $k_t^*(x) \leq k_t^*(x+1) \leq k_t^*(x) + 1, \forall x \geq 0$.

Proof We study the left hand side (LHS) inequality first. If $k_t^*(x) = 0$, the inequality holds true. If $k_t^*(x) > 0$ and considering the assumption $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$, the optimal allocation $k_t^*(x+1)$ may be higher due to the additional packet in queue. Hence, $k_t^*(x+1) \geq k_t^*(x)$.

As for the right hand side (RHS) inequality, we prove it by contradiction. Assume $k_t^*(x+1) \geq k_t^*(x) + 2$. From (4.9), we know that $R(k)$ is decreasing in its argument. Further, from (4.11) and the assumption of this lemma $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$, we obtain that achieving the optimal k for the tth stage in (4.11) is equivalent to finding the maximal k satisfying the following inequality

$$\triangle R_t(k) > \beta \cdot \triangle V_{t-1}(x - k + 1). \tag{4.12}$$

Therefore, given the optimal $k_t^*(x+1)$, we have

$$\triangle R_t(m) > \beta \cdot \triangle V_{t-1}(x + 1 - m + 1), \text{for } m = 1, 2, ..., k_t^*(x+1). \tag{4.13}$$

As we assume $k_t^*(x+1) \geq k_t^*(x)+2$ and letting $m = k_t^*(x)+2$ in (4.13), we obtain

$$\begin{aligned} \triangle R_t(k_t^*(x) + 2) &> \beta \cdot \triangle V_{t-1}(x + 1 - (k_t^*(x) + 2) + 1) \\ &= \beta \cdot \triangle V_{t-1}(x - (k_t^*(x) + 1) + 1). \end{aligned} \tag{4.14}$$

Since $R(k)$ is decreasing in k, (4.14) can be further written as

$$\begin{aligned} \triangle R_t(k_t^*(x)+1) &\geq \triangle R_t(k_t^*(x)+2) \\ &> \beta \cdot \triangle V_{t-1}(x-(k_t^*(x)+1)+1). \end{aligned} \tag{4.15}$$

Considering the optimality criterion of $k_t^*(x)$ in (4.12), $k_t^*(x)$ should be the largest number of packets satisfying (4.12). Therefore, (4.15) contradicts the optimality of $k_t^*(x)$. The RHS inequality is proved. ■

It can be seen from the proof of Lemma 4.3.2 that the optimal allocation of packet transmission over multiple stages can also be determined under the condition $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$. Then, we will prove the above condition holds for all t in the following lemma.

Lemma 4.3.2 $\triangle V_t(x)$ *is decreasing in* x *for any fixed* t *and is increasing in* t *for any fixed* x.

Proof See the Appendix at the end of this chapter. ■ The idea of this lemma can also be illustrated in an intuitive way as follows. At any fixed time period, the marginal benefit $\triangle V_t(x)$ of each additional packet declines because the future possible routes are limited; therefore, the chance of transmitting the additional packet at low prices also decreases. Similarly, for any given remaining packet number x, the marginal benefit of an additional packet increases with t, because more number of possible future routes are available when more remaining time periods; therefore, the chance of getting a higher marginal benefit goes up. Also, Lemma 4.3.2 relaxes the assumption of Lemma 4.3.2 and we always have $k_t^*(x) \leq k_t^*(x+1) \leq k_t^*(x)+1, \forall x \geq 0$.

Considering Lemma 4.3.2 and Lemma 4.3.2, the optimal allocation of packet transmission for the proposed dynamic auction framework can be characterized by the following theorem.

Theorem 4.3.3 *For any realization $(\ell_t, \mathbf{r})$ at the tth stage, the optimal number of packets to transmit in state (x, t) is given by*

$$k_t^*(x) = \begin{cases} \max\{1 \le k \le min\{x, \mathcal{B}\} : \triangle R_t(k) > \beta \cdot \triangle V_{t-1}(x-k+1)\} \\ \qquad\qquad if \;\; R_t(1) > \beta \cdot \triangle V_{t-1}(x); \\ 0 \qquad\qquad otherwise. \end{cases} \tag{4.16}$$

Moreover, it is optimal to allocate these $k_t^*(x)$ packets to the route with the lowest cost r_i.

Proof $V_t(x)$ is the summation of two terms in (4.11). As the second term is fixed given x, the optimal k_t^* maximizing the first term needs to be studied. Based on the definition (4.9), $\triangle R(\cdot)$ is decreasing in its argument. Also, $\triangle V_{t-1}(\cdot)$ is decreasing in its argument from Lemma 4.3.2. Thus, $\triangle R(k) - \beta \cdot \triangle V_{t-1}(x-k+1)$ is also monotonically decreasing in k. Therefore, the optimal allocation at tth time period with x packets in queue, $k_t^*(x)$, is the largest k for which this difference is positive. ■

Theorem 4.3.2 shows how the source node should allocate packets into different time periods. The basic idea is to progressively allocate the packets to the route with the smallest realization of $J(r_{(1)})$ until the marginal benefit $\triangle R_t(i)$ drops below the marginal opportunity cost $\triangle V_{t-1}(x-i+1)$.

In order to have the optimal allocation strategies using Theorem 4.3.2, we first need to know the expected profit function $\triangle V_t(x), \forall t, x$. For finite number of time periods, T, in problem (4.6), the optimal dynamic programming proceeds backward using the Bellman equation [68] to obtain $\triangle V_t(x)$. Due to the randomness of the route number and its type, it is difficult to obtain the close-form expression of $\triangle V_t(x)$. Thus, we use simulation to approximate the values of $\triangle V_t(x)$ for different

t and x, which proceeds as follows: Start from the routing stage 0. For each stage t, generate N samples of the number of available routes and their types, which follow the PDF $f_\ell(\ell)$ and $f_i(r_i)$, respectively. For each realization and for each pair of values (x, t), calculate $k_t^*(x)$ using Theorem 4.3.2. By using the conclusion of Lemma 4.3.2, we simplify the computation of $k_t^*(x)$ and only need $O(NM)$ operations to calculate $V_t(x)$ for all x at fixed t time period. Therefore, $O(NMT)$ operations are required for the whole algorithm. Note that the computation of $V_t(x)$ can be done off-line, which will not increase the complexity of finding the optimal allocation for each realization.

We then study the expected profit function for infinite number of routing stages. Such scenario gives the upper-bound of the expected profit, because the source node can wait until low-cost routes being available for transmission. For infinite horizon, the maximal profit $V_t(x)$ in (4.6) can be rewritten as

$$V^*(x) = E_{\ell,\mathbf{r}}\left[\min_{\mathbf{Q},k}\left\{\sum_{i=1}^{\ell_t}(G(\mathcal{K}) - k \cdot J(r_i))Q_i(\mathbf{r}) + \beta \cdot V^*(x-k)\right\}\right] \qquad (4.17)$$

or, equivalently, $V^* = \mathcal{T}V^*$, where $\mathcal{T}$ is the operator updating V^* using (4.17). Assuming S is the feasible set of states, The convergence proposition of the dynamic programming algorithm [68] states that: for any bounded function $V : S \to \mathcal{R}$, the optimal profit function satisfies $V^*(x) = \lim_{p\to\infty}(\mathcal{T}^pV)(x), \forall x \in S$. As $V(x)$ is bounded in our algorithm, we are able to apply the value iteration method to approximate the optimal $V(x)$, which proceeds as follows: Start from some initial function for $V(x)$ as $V^0(x) = g(x)$, where the superscript stands for the iteration number. Then, iteratively update $V(x)$ by letting $V^{p+1}(x) = (\mathcal{T}V^p)(x)$. The iteration process ends until $|V^{p+1}(x) - V^p(x)| \le \epsilon$, for all x, where ϵ is the error bound for $V^*(x)$.

4.3.3 Mechanism Design

In the previous part, we have developed the optimal dynamic pricing-based routing approach. Next, our task is to find auction mechanisms that achieve the derived optimal strategy. Many auction forms can be applied to achieve the optimal strategy. Considering the truth-telling property of the second-price auction, we focus on this mechanism in our chapter.

In a traditional second-price auction, the bidder with the highest bid wins the item and pays the second highest bid for it. In our framework, the source node is trying to find the route with the lowest cost, which implies the application of reverse second-price auction. The source node allocates the packet transmission to the route with the lowest payment bid and actually pay the second-lowest bid to the selected route. Moreover, the auction mechanism can be performed in many forms, such as open auctions and sealed-bid auctions. Open auctions allows the bidders to submit bids many times until finally only one bidder stays in the game. In sealed-bid auctions, the bidders only submit their bids once. Considering the sealed-bid auctions require less side-information and hence save the wireless resources, we analyze the sealed-bid second-price auction for our optimal allocation policy.

It is important to note that the straightforward application of the reverse second-price auction can not guarantee the truth-telling property of the bidders. Let $\widetilde{J}_t(r) = G(1, \mathcal{K}_{t+1}) - J(r)$ and $\widetilde{r}_t = \widetilde{J}_t^{-1}(\triangle V_{t-1}(x_t))$, where x_t is the packets to be transmitted from the tth stage. Considering the scenario where the lowest cost of the routes $r_{(1)}^t > \widetilde{r}_t$, it can be seen from Theorem 4.3.2 that no packet will be assigned for forwarding within current time period. Hence, the route with the lowest cost may have incentive to bid below their true cost and satisfy the threshold constraint. In this way, this route will win the packet and get positive payoff as the sender awards it the second lowest bid. But the expected profit of the sender will decrease according to (4.11). Therefore, we need to modify the second-price mechanism by using $\widetilde{r}_t$ as the reserved price for every stage, which is the highest price that the sender agrees to pay for transmitting one packet within current time period. Specifically, given the submitted bid vector, $\mathbf{d}_t = \{d_{1,t}, d_{2,t}, ..., d_{\ell,t}\}$, the sender allocates the packet to the route with lowest bid below the reserved price and the selected route gets the payment $\max\{d_{(2)}, \widetilde{r}\}$, where $d_{(2)}$ is the second lowest type of the forwarding routes.

Note that the mechanism we developed above can prevent the single route from not reporting the true cost. But in the presence of collusion of the routes, it may be not able to maintain the truth-telling property. This problem can be fixed from two aspects: First, the greediness of the selfish routes can help to prevent the collusion. Assume two routes collude to increase their profits. The collusion requires the two routes to act and share the extra gain cooperatively. But, the greediness of the routes decide that the cooperative game can not be carried out between them. The noncooperative behaviors will eventually lead to an inefficient outcome and break the collusion of the players. Second, in our scheme, the sender can discourage the collusion among the routes by setting a higher reserve price. The collusion behaviors of bidders is also referred as the bidding ring in the context of the auction theory. The optimal reserve price is analyzed in [71] to combat the collusion of bidders, which can be directly applied to our scheme for handling the route collusion.

4.3.4 Profit Sharing among the Nodes on a Selected Route

In the above sections, we have developed the optimal dynamic routing approach through multi-stage pricing in MANETs and designed the mechanism of the second-price auction with reserved prices to assure the truth-telling property of each route. But, we consider each route as an entity. Thus, the residual problem is that how to share the forwarding profits of the route defined as in (4.1) among the forwarding nodes on the route. Although the proposed mechanism can ensure the truth-telling of each route as one bidder, the cooperation among the nodes on one route can not be pre-assumed and truth-telling mechanisms need to be further designed for the profit-sharing problem. In this part, we will first prove that no dominant truth-telling strategy exists for each node on the selected multi-hop forwarding route in static profit-sharing scenarios. Then, the truth-telling profit-sharing mechanisms are designed to enforce the cooperation among the nodes on the selected route in dynamic scenarios.

As the nodes on the same forwarding route belong to their own authorities, they will act greedily to get more profits from the total profits that the route gains, which forms a static profit-sharing game (SPSG). The players in the profit-sharing game are all the nodes on the same forwarding route. The payoff of each node is defined as the profits it obtained through packet forwarding efforts, which is represented as $P_{i,j}$ for the jth node on the ith route. The action strategy of the jth node on the ith discovered route can be represented as $\{\alpha_{i,j}, \widehat{v}_{i,j}\}$, where $\alpha_{i,j}$ is the the percentage of profits that this node will get for its packet forwarding efforts and $\widehat{v}_{i,j}$ is the forwarding cost that it reported while performing the route-based pricing. Note that $\widehat{v}_{i,j}$ may not be the true forwarding cost and our aim is to design mechanisms to enforce the truth-telling behaviors. Assume the number of hops on the ith route is h_i. Let the profit-sharing vector for the ith route be $\alpha_i = \{\alpha_{i,1}, \alpha_{i,2}, ..., \alpha_{i,h_i}\}$, where $\sum_{j=1}^{h_i} \alpha_{i,j} = 1$. Denote the reported cost vector of the nodes on the ith route as $\widehat{\mathbf{v}}_i = \{\widehat{v}_{i,1}, \widehat{v}_{i,2}, ..., \widehat{v}_{i,h_i}\}$. Recall that the type vector of the nodes on the ith route is defined as $\mathbf{v}_i = \{v_{i,1}, v_{i,2}, ..., v_{i,h_i}\}$ and the PDF of v_i is $\widehat{f}_i$, which we assume to be identical for all nodes without loss of generality. Then, we study the existence of the dominant truth-telling strategies in the following theorem.

Theorem 4.3.4 *There exists no dominant truth-telling strategy* $\{\alpha_i, \widehat{\mathbf{v}}_\mathbf{i}\}$ *in the static profit-sharing game.*

Proof We prove this theorem by contradiction. Assume α_i^* is a dominant truth-telling profit-sharing strategy in the static profit-sharing game, which means by using α_i^*, every forwarding node's dominant strategy on the ith route is to report its true type (or cost). Equivalently, if the jth node reports a higher cost, $\widehat{v}_{i,j} = v_{i,j}+\epsilon$, than its true type $v_{i,j}$ while other nodes report the true value, the jth node will get a lower profit. In order to show the dominant strategy α_i^*, we need to calculate and compare the node's profit when it is cheating or not. First, the total profits of the ith route are obtained and then we study the profit of each node. Based on our second-price mechanism and considering (4.1), the total profits of the ith route can be represented as follows.

$$U_i(\widehat{r}_i) = Prob(\widehat{r}_i < r_{(1)}(\mathbf{r}_{-i})) \cdot (E_{\mathbf{r}_{-i}}[r_{(1)}(\mathbf{r}_{-i}) | \widehat{r}_i < r_{(1)}(\mathbf{r}_{-i})] - \widehat{r}_i), \tag{4.18}$$

where $\widehat{r}_i$ is the bidding cost of the ith route, which the ith route believes to be the true cost, but may be not if some node on the ith route is cheating by reporting a higher type value, and $r_{(1)}(\mathbf{r}_{-i})$ represents the lowest cost of all routes except the ith route. Without loss of generality, we assume the PDF of r_i to be identical for all routes as f. By using the results of order statistics [78], we have the condition expectation of the payment as follows.

$$E_{\mathbf{r}_{-i}}[r_{(1)}(\mathbf{r}_{-i})|\widehat{r}_i < r_{(1)}(\mathbf{r}_{-i})] = \frac{1}{[1-F(\widehat{r}_i)]^{\ell-1}} \int_{\widehat{r}_i}^{\infty} [1-F(x)]^{\ell-1} dx. \tag{4.19}$$

Noting that the probability of winning the auction for the ith route is

$$Prob(\widehat{r}_i < r_{(1)}(\mathbf{r}_{-i})) = [1-F(\widehat{r}_i)]^{\ell-1}. \tag{4.20}$$

Substituting (4.19) and (4.20) into (4.18), the total profits can be written as

$$U_i(\widehat{r}_i) = \int_{\widehat{r}_i}^{\infty} [1-F(x)]^{\ell-1} dx. \tag{4.21}$$

Then, using the profit-sharing strategy α_i^*, the profit of the jth node on the ith route can be calculated. We consider two cases: (a) the node reports the true type $v_{i,j}$; (b) the node cheats and reports a higher value $\widehat{v} = v_{i,j} + \epsilon$. For case (a), the profit of the jth node on the ith route is represented as follows.

$$\begin{aligned} U_{i,j}(v_{i,j}) &= \alpha_{i,j}^* \cdot U_i(r_i) \\ &= \alpha_{i,j}^* \cdot \int_{r_i}^{\infty} [1-F(x)]^{\ell-1} dx. \end{aligned} \tag{4.22}$$

For case (b), the profit includes the cheating profit of reporting an extra cost ϵ and the allocated profit from the ith route, which can be written as

$$\begin{aligned} U_{i,j}(\widehat{v}_{i,j}) &= \epsilon \cdot Prob(\widehat{r}_i < r_{(1)}(\mathbf{r}_{-i})) + \alpha_{i,j}^* \cdot U_i(\widehat{r}_i) \\ &= \epsilon \cdot [1-F(r_i+\epsilon)]^{\ell-1} + \alpha_{i,j}^* \cdot \int_{r_i+\epsilon}^{\infty} [1-F(x)]^{\ell-1} dx. \end{aligned} \tag{4.23}$$

Subtracting (4.22) from (4.23), we have

$$U_{i,j}(\widehat{v}_{i,j}) - U_{i,j}(v_{i,j}) = [1-F(r_i+\epsilon)]^{\ell-1} \times \left\{ \epsilon - \alpha_{i,j} \int_{r_i}^{r_i+\epsilon} \frac{[1-F(x)]^{\ell-1}}{[1-F(r_i+\epsilon)]^{\ell-1}} dx \right\}. \tag{4.24}$$

From the Mean Value Theorem, we know that there exists some $\lambda \in [0,1]$ satisfying

$$\int_{r_i}^{r_i+\epsilon} \frac{[1-F(x)]^{\ell-1}}{[1-F(r_i+\epsilon)]^{\ell-1}} dx = \epsilon \cdot \left(\frac{[1-F(r_i+\lambda\epsilon)]}{[1-F(r_i+\epsilon)]} \right)^{\ell-1}. \tag{4.25}$$

And, for simplicity, let

$$\Psi(\epsilon) = \left(\frac{[1-F(r_i+\lambda\epsilon)]}{[1-F(r_i+\epsilon)]} \right)^{\ell-1}, \tag{4.26}$$

which is a decreasing function in ϵ, and has the limit

$$\lim_{\epsilon \to 0} \Psi(\epsilon) = 1. \tag{4.27}$$

Thus, there always exists a positive value δ. When $\epsilon < \delta$, $\Psi(\epsilon) < 1/\alpha_{i,j}^*$. Further, by putting (4.25) into (4.24), we have

$$U_{i,j}(\widehat{v}_{i,j}) - U_{i,j}(v_{i,j}) = \epsilon \cdot [1-F(r_i+\epsilon)]^{\ell-1}[1-\alpha_{i,j}^* \cdot \Psi(\epsilon)]. \tag{4.28}$$

Therefore, $\exists \delta$, for $\epsilon < \delta$, $U_{i,j}(\widehat{v}_{i,j}) - U_{i,j}(v_{i,j}) > 0$, which contradicts the assumption that $\alpha_{i,j}^*$ is a dominant truth-telling strategy. Considering such contradiction holds for any $\alpha_{i,j}^*$, we finally prove that there does not exist a cheat-proof strategy for the profit-sharing game. ■

Since there is no dominant truth-telling strategy in static profit-sharing games as Theorem 4.3.4 shows, it is necessary to design certain mechanisms to enforce the cooperation among the forwarding nodes on the same forwarding route. There are many ways to design such mechanisms. For instance, an intuitive idea is to provide over-payment to the nodes on the winning route as the compensation for their cooperative behaviors. The over-payment should be more than the cheating gain the nodes can obtain. But who is responsible for the over-payment? It is not reasonable to ask the sender for the payment-compensation. Because, in this way, the sender may have incentives to switch his/her transmission to the route with higher true cost, which asks for less over-payment. It is also a rational behavior for such route to require a less over-payment, which may make them have a positive payoff instead of losing the auction with zero payoffs. Therefore, a more practical way is to let the central-bank periodically compensate the forwarding nodes with some payments. The over-payment amount can be decided based on the Vickrey-Clarke-Groves (VCG) mechanism [15, 71], which pays each node the difference between the routing cost without this node and the other nodes' routing cost with the presence of this node. It is important to note that the application of the VCG mechanism here does not conflict with our dynamic pricing mechanism. They are carried out separately by the central bank and the sender for ensuring the cooperation of forwarding nodes on one route and maximizing the total profits of the sender, respectively.

However, the over-payment method still requires some information of the overall topology and forward costs, which may not be available in dynamic scenarios. In order to have enforceable truth-telling mechanisms, it is reasonable to model the profit-sharing interactions as a **repeated game** for each route. Generally speaking, repeated games belong to the dynamic game family, which 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. A strategy in the repeated game is a complete plan of action, that defines the players' actions in every stage game. At the end of each stage, all the players can observe the outcome of the stage game and decide the future actions using the history of plays. The repeated profit-sharing game (RPSG) can be defined as follows.

Definition 4.3.5 *Let Γ be a static profit-sharing game and β be a discount factor. The T-period profit-sharing repeated game, denoted as $\Gamma(T, \beta)$, consists of game Γ*

repeated T times. The repeated game payoff is given by

$$\mathcal{P}_{i,j} = \sum_{t=0}^{T-1} \beta^t P_{i,j}^t, \tag{4.29}$$

where $P_{i,j}^t$ denotes the payoff of the jth node on the i the route in period t. If T goes infinity, then $\Gamma(\infty, \beta)$ is referred to as the infinite repeated game.

Note that **Nash Equilibrium** [8] is an important concept to measure the outcome of the SPSG, which is a set of strategies, one for each player, such that no selfish player has incentive to unilaterally change his/her action. However, the selfishness of players will result in inefficient non-cooperative Nash Equilibriums in static games. As for dynamic games, **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 [8] of the original game. In the RPSG, since the game is not played only once, the players is able to make decisions conditioning on past moves for better outcomes, thus allowing for reputation effects and retribution. Therefore, in order to measure the outcome of the RPSG, we apply the **Folk Theorems** [8,64] of the infinite repeated games to have the following theorem.

Theorem 4.3.6 *In RPSG, there exists a discount factor $\widehat{\beta} < 1$ such that any feasible and individually rational payoff can be enforced by an equilibrium for any discount factor $\beta \in (\widehat{\beta}, 1)$.*

The above theorem illustrates that feasible profit-sharing outcomes can be enforced in the RPSG when no dominant strategy is available. However, it didn't answer the question that how the feasible profit-sharing outcomes can be enforced, that is, how to design the enforcing mechanisms in the RPSG. First, we define two strategies: the cooperative strategy and non-cooperative strategy. In cooperative strategy, the node will report the true forwarding cost; in non-cooperative strategy, the node will report a very high forwarding cost so that the route with this node will not be selected for packet forwarding. Similar to [64, 79, 80], we propose the following mechanism to enforce truth-telling strategies for the RPSG.

CArtel Maintenance Profit-sharing (CAMP) mechanism:

(1) Each node on the selected route plays the cooperative strategy at the first stage;

(2) If the cooperation strategy is played in stage t and $U_i = \sum_{j=1}^{h_i} P_{i,j} \geq \widetilde{U}$, each node plays the cooperative strategy in stage $t+1$;

(3) If the cooperation strategy is played in stage t and $U_i < \widetilde{U}$, each node switches to a punishment phase for $\mathcal{T} - 1$ stages, in which the non-cooperative strategy is played regardless of the realized outcomes. At the $\mathcal{T}$th period, each node switches back to the cooperative strategy.

Note that $\widetilde{U}$ is the cartel maintenance threshold. Similar to [64, 79, 80], the optimal $\widetilde{U}$ and $\mathcal{T}$ can be obtained using the routing statistics. The proposed CAMP mechanism uses the non-cooperative punishment launched by all nodes to prevent any deviating strategies from the cooperative strategy. Specifically, although the deviating behaviors may benefit a node at current stage, its payoff will be decreased more in future stages. By using the CAMP mechanism, the truth-telling profit sharing is enforceable among the nodes on the selected route. Based on Theorem 4.3.4, we can enforce any feasible profit sharing strategy such as equal sharing or proportional sharing according to the effort of each node.

4.4 Simulation Studies

In this section, we evaluate the performance of the proposed dynamic pricing approach in multi-hop ad hoc networks. Note that the simulation setup is similarly to that in Chapter 3. We consider an ad hoc network where $\mathcal{N}$ nodes are randomly deployed inside a rectangular region of $10\gamma\ m \times 10\gamma\ m$ according to the 2-dimension uniform distribution with the maximal transmission range $\gamma = 100m$ for each node. Let $\lambda = \mathcal{N}\pi/100$ denote the normalized node density, that is, the average number of neighbors for each node in the network. Each node moves according to the *random waypoint* model [70]: a node starts at a random position, waits for a duration called the *pause time*, then randomly chooses a new location and moves toward the new location with a velocity uniformly chosen between v_{min} and v_{max}. When it arrives at the new location, it waits for another random pause time and repeats the process. The physical layer assumes that two nodes can directly communicate with each other successfully only if they are in each other's transmission range. The MAC layer protocol simulates the IEEE 802.11 Distributed Coordination Function (DCF) with a four-way handshaking mechanism [81]. Table 4.1 shows all simulation parameters. Note that each source-destination pair is formed by randomly picking two nodes in the network. And, multiple routes with different hop number may exist for each source-destination pair. Since the routes with the minimum number of hops have much higher probabilities to achieve lower costs, without loss of generality, we only consider the minimum-hop routes as the bidding routes for simplicity in the proposed optimal dynamic auction framework. Considering the mobility of each node, its forwarding cost is no longer a fixed value and we assume that its PDF $\widehat{f}(v)$ follows the uniform distribution $\mathcal{U}[\bar{u}, \underline{u}]$, which has the mean μ and the variance σ^2. Thus, using the Central Limit Theorem [78], the cost of a

Table 4.1: Simulation Parameters

Node Density	10, 20, 30
Minimum Velocity (v_{min})	10 m/s
Maximum Velocity (v_{max})	30 m/s
Average Pause time	100 seconds
Dimensions of Space	1000m $\times$ 1000m
Maximum Transmission Range	100 m
Average Packet Inter-Arrival Time	1 seconds
Data Packet Size	1024 bytes
Link Bandwidth	8 Mbps

h-hop route can be approximated by the normal distribution with the mean $h \cdot \mu$ and variance $h \cdot \sigma^2$. In our simulation, we first study the dynamics of MANET and then illustrate the performance of our proposed framework for different network settings.

In order to study the dynamics of MANET, we first conduct simulations to study the number of hops on the minimum-hop route for source-destination pairs, which can be found in Chapter 3 and shown in Figure 3.6. Secondly, we study the time and path diversity of MANET by finding the maximum number of minimum-hop routes for the source-destination pair. Note that there may exist the scenarios where the node may be on multiple minimum-hop forwarding routes for the same source-destination pair. For simplicity, we assume during the route discovery phase, the destination randomly picks one of such routes as the routing candidates and feedbacks the routing information of node-disjoint minimum-hop routes to the source. Figure 4.3 shows the CMF of the number of the minimum-hop routes for different hop number when the node density is 10. The results for the node den-

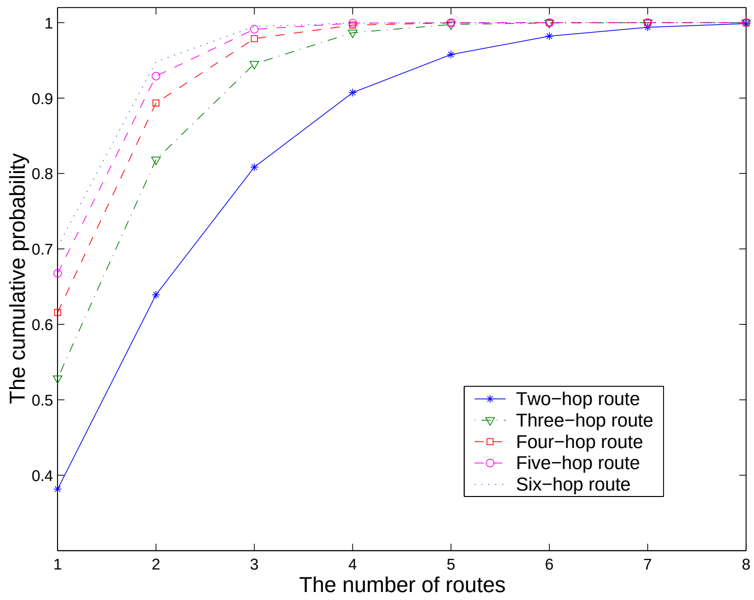

Figure 4.3: The cumulative probability mass function of the number of the minimum-hop route when the node density is 10.

sity 20 and 30 are shown in Figure 4.4 and Figure 3.7, respectively. It can be seen from the above figures that when the node density is increasing, the probability of having more routes between each source-destination pair is becoming much higher. Such facts also indicate a higher order of path diversity can be exploited when each node has more neighbors. Moreover, the possibility of getting more routes for the route with more hops is much lower since the path diversity for multi-hop routing is limited by the forwarding node with the worst neighboring situation. Therefore, the number of routing candidates and their types can be approximated using the above results.

In the following parts, we consider the performance for three different schemes: our scheme with finite time horizon, our scheme with infinite time horizon and the fixed allocation scheme. Note that the infinite time horizon can not be achieved in real application. But it can serve as a upper bound for measuring the performance

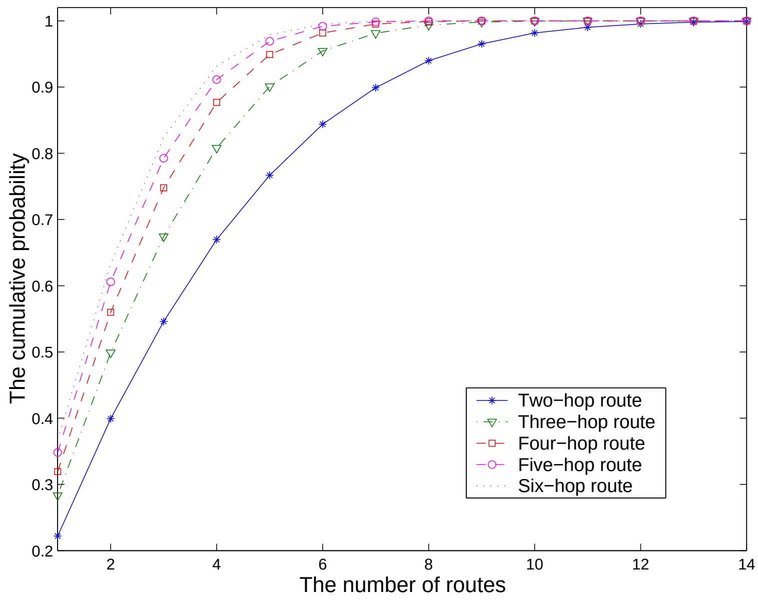

Figure 4.4: The cumulative probability mass function of the number of the minimum-hop route when the node density is 20.

of our scheme. The fixed scheme allocates a fixed number of packets into each stage while also using the optimal auction at each stage. Assume the cheat-proof profit sharing mechanisms are in place to ensure the cooperation of the forwarding nodes on the same route. Let the benefit function be $G(\mathcal{K}) = g \cdot k$, where g is the benefit of successfully transmitting one packet. Note that the simulation parameters are set as $T = 20$, $M = 100$ and $\mathcal{B} = 10$. Let $g = 60$, $\bar{u} = 10$, and $\underline{u} = 15$. In Figure 4.5, we compare the overall profits of the three schemes for different node densities. The concavity of the simulated value functions of our scheme matches the theoretical statement in Lemma 4.3.2. It can be seen from the figure that our scheme achieves significant performance gains over the fixed scheme, which mainly comes from the time diversity exploited by the dynamic approach. We observe that the performance gap of the two schemes becomes larger when the node density decreases. Thus, in order to increase the profits under the situations of low node

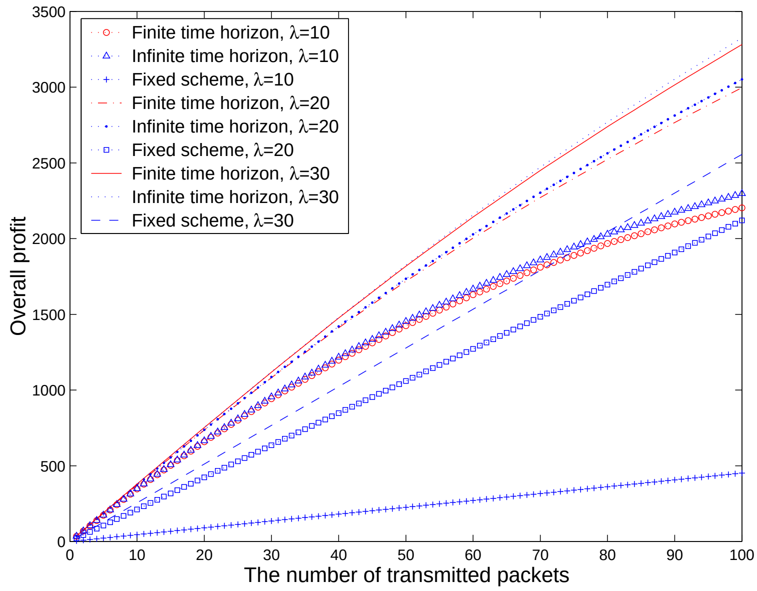

Figure 4.5: The overall profits of our scheme with finite time horizon, our scheme with infinite time horizon and the fixed scheme.

densities, it becomes much more important to exploit the time diversity. Also, the total profits of our scheme increases with the increment of the node density due to the higher order of path diversity. Besides, since the performance gap between the schemes with finite and infinite time horizon is small, only a few routing stages are required to exploit the time diversity.

In Figure 4.6, the average profits of the three schemes are shown for different node densities. This figure shows that the average profit of transmitting one packet decreases as there are more packets to be transmitted. It is because the packets need to share the limited routing resources from both the time diversity and path diversity. When the node density is 30, the average profit degrades much slower than other cases since the potential of utilizing both the time diversity and path diversity is high. The overall profits of our scheme with finite time horizon are compared for different total packets in Figure 4.7 for node density being 10. This

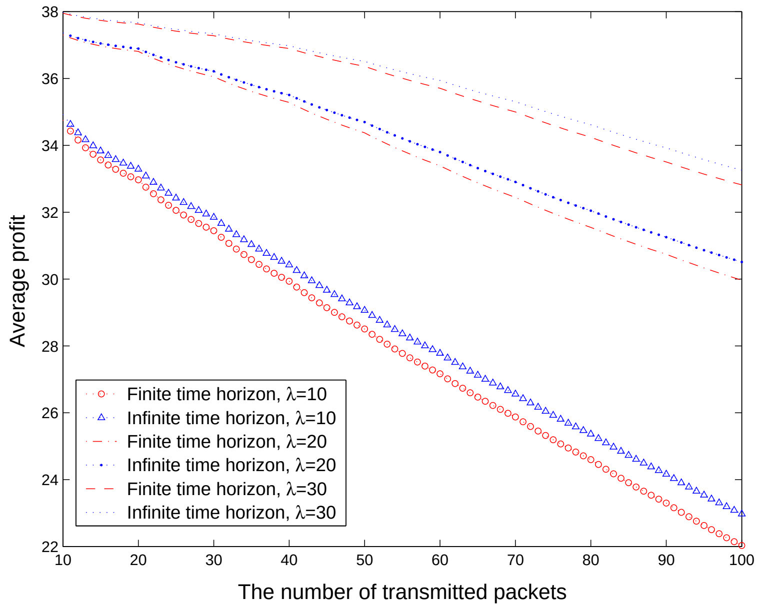

Figure 4.6: The average profits of our scheme with finite time horizon, our scheme with infinite time horizon and the fixed scheme.

figure shows that the overall profits increases with more routing stages due to the time diversity. Also, the saturation behavior can be observed when using more stages. In Figure 4.8, the overall profits are compared for different time stages. Considering the limited routing resource, the overall profits saturate when the packet number is high.

4.5 Summary

In this chapter, we study how to conduct efficient pricing-based routing in autonomous MANETs by assuming that the packet-forwarding will incur a cost to the relay node and the successful transmission brings benefits to the source-destination pairs. Considering the dynamic nature of MANET, we model the routing procedure in autonomous MANETs as a multi-stage pricing game and propose an optimal

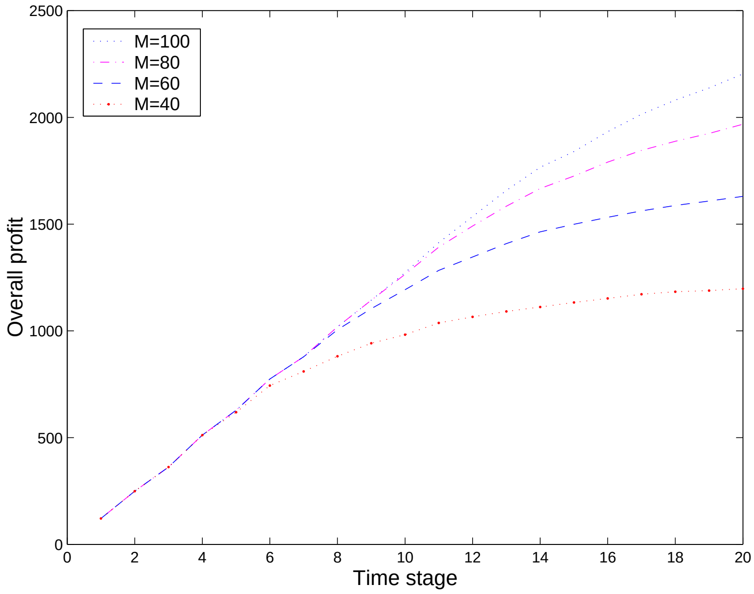

Figure 4.7: The overall profits of our scheme with different packets to be transmitted when the node density is 10.

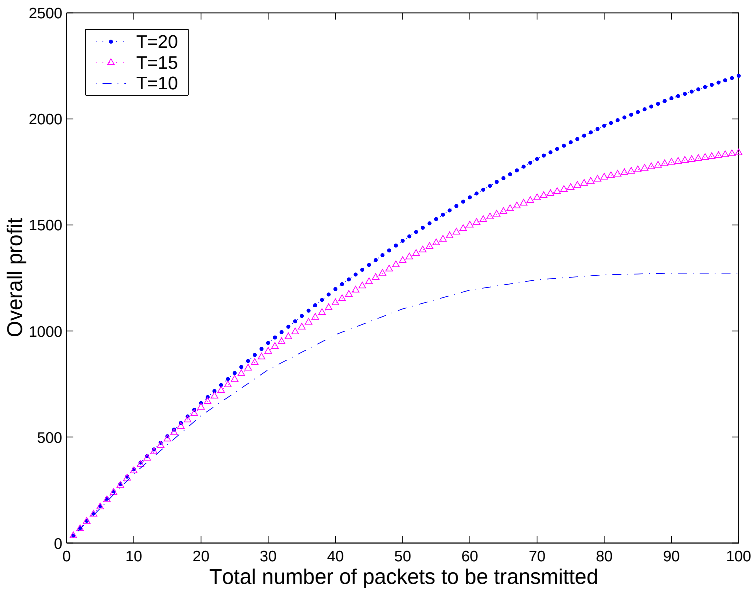

Figure 4.8: The overall profits of our scheme with different time stages when the node density is 10.

dynamic pricing-based routing approach to maximize the payoffs of the source-destination pair while keeping the forwarding incentives of the relay nodes on the selected routes by optimally pricing their packet-forwarding services through the auction protocol. It is important to notice that not only the path diversity but also the time diversity in MANETs can be exploited by our dynamic pricing-based approach. Also, the optimal dynamic auction algorithm is developed to achieve the optimal allocation of packets to be transmitted, which provides the corresponding pricing rules while taking into consideration of the node's mobility and the routing dynamics. Extensive simulations have been conducted to study the performances of the proposed approach. The results illustrate that the proposed approach achieves significant performance gains over the existing static routing approaches.

4.6 Appendix: Proof of Lemma 4.3.2

Proof First, we prove that $\triangle V_t(x)$ is decreasing in x at any fixed time period t. Note that the induction method is used to prove this part of Lemma 4.3.2. For $t = 0$, the lemma obviously holds since $V_0(x) = 0$ for all x. Assume the inductive hypothesis for period $t-1$ as $\triangle V_{t-1}(x) \geq \triangle V_{t-1}(x+1)$. Then, we will show that if the inductive hypothesis holds, $\triangle V_t(x)$ also decreases.

Consider a realization of ℓ_t routes and their cost vector $\mathbf{r} = (r_1, r_2, ..., r_{\ell_t})$. Define the inner maximized term in (4.10) as follows

$$U_t(x, \ell_t, \mathbf{r}) = \max_{0 \leq k \leq \min\{\mathcal{B}, x\}} \{R_t(k) + \beta \cdot V_{t-1}(x-k)\}, \tag{4.30}$$

and define the difference function as

$$\triangle U_t(x, \ell_t, \mathbf{r}) = U_t(x, \ell_t, \mathbf{r}) - U_t(x-1, \ell_t, \mathbf{r}). \tag{4.31}$$

Thus $\triangle V_t(x)$ can be obtained as

$$\triangle V_t(x) = E_{\ell_t,\mathbf{r}}[\triangle U_t(x, \ell_t, \mathbf{r})]. \tag{4.32}$$

For simplicity and without loss of generality, we omit the arguments $\ell_t, \mathbf{r}$ in $\triangle U_t(x, \ell_t, \mathbf{r})$ and simply use $\triangle U_t(x)$. Moreover, it can be seen from (4.32) that it is sufficient to prove that $\triangle U_t(x)$ is decreasing in x for the proof that $\triangle V_t(x)$ is decreasing in x.

Using the inductive hypothesis and Lemma 4.3.2, we have the constraint on $k_t^*(x+1)$ as

$$k_t^*(x) \leq k_t^*(x+1) \leq k_t^*(x) + 1. \tag{4.33}$$

Based on the constraint, we then study the value of $\triangle U_t(x+1)$ for the two possible outcomes, $k_t^*(x+1) = k_t^*(x)$ and $k_t^*(x+1) = k_t^*(x) + 1$:

1). If $k_t^*(x+1) = k_t^*(x)$, then $\triangle U_t(x+1) = \beta \cdot \triangle V_{t-1}(x - k_t^*(x) + 1)$ from (4.30) and (4.31). Also, from the optimal condition of k in (4.12), we know

$$\triangle R_t(k_t^*(x+1) + 1) \leq \beta \cdot \triangle V_{t-1}(x + 1 - (k_t^*(x+1) + 1) + 1). \tag{4.34}$$

Considering $k_t^*(x+1) = k_t^*(x)$, (4.34) can be rewritten as

$$\triangle R_t(k_t^*(x) + 1) \leq \beta \cdot \triangle V_{t-1}(x - k_t^*(x) + 1). \tag{4.35}$$

2). Similarly, If $k_t^*(x+1) = k_t^*(x) + 1$, then $\triangle U_t(x+1) = \triangle R_t(k_t^*(x) + 1)$ from (4.30) and (4.31), and

$$\triangle R_t(k_t^*(x) + 1) > \beta \cdot \triangle V_{t-1}(x - k_t^*(x) + 1). \tag{4.36}$$

Thus, it can be concluded from the above two cases that $\triangle U_t(x+1)$ satisfies

$$\triangle U_t(x+1) = \max\{\triangle R_t(k_t^*(x) + 1), \beta \cdot \triangle V_{t-1}(x - k_t^*(x) + 1)\}. \tag{4.37}$$

Consider now $\triangle U_t(x+1)$ and $\triangle U_t(x)$ and compare their values. Given the constraint on $k_t^*(x)$ by Lemma 4.3.2, the value of $\triangle U_t(x+1)$ in (4.37), and considering that $\triangle R_t(m)$ and $\triangle V_{t-1}(m)$ decrease in their arguments, we have the following expressions.

$$\begin{aligned}
& \triangle U_t(x) \\
= \;& \max\{\triangle R_t(k_t^*(x-1)+1), \beta \cdot \triangle V_{t-1}(x-1-k_t^*(x-1)+1)\} \\
\geq \;& \max\{\triangle R_t(k_t^*(x)+1), \beta \cdot \triangle V_{t-1}(x-(k_t^*(x)-1))\} \\
= \;& \triangle U_t(x+1). \qquad (4.38)
\end{aligned}$$

Therefore, the first part of Lemma 4.3.2 is proved by the above discussion.

Next, we show that $\triangle V_t(x)$ is increasing in t for any fixed x. Similarly, it suffices to prove the statement for a particular realization $\ell_t, \mathbf{r}$.

Following the results in (4.37), we get that

$$\triangle U_t(x) \geq \beta \cdot \triangle V_{t-1}(x - k_t^*(x)), \qquad (4.39)$$

and from the fact that $\triangle V_{t-1}(\cdot)$ is decreasing, we have

$$\triangle U_t(x) \geq \beta \cdot \triangle V_{t-1}(x). \qquad (4.40)$$

As taking the expectation with respect to $\ell_t, \mathbf{r}$ on both sides of (4.40) does affect the inequality, we prove

$$\triangle V_t(x) \geq \triangle V_{t-1}(x). \qquad (4.41)$$

■

Chapter 5

Belief-Assisted Pricing for Dynamic Spectrum Allocation

5.1 Introduction

Recently, regulatory bodies like the Federal Communications Commission (FCC) in the United States are recognizing that current static spectrum allocation can be very inefficient considering the bandwidth demands may vary highly along the time dimension or the 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 to dynamically access the licensed bands from legacy spectrum holders based on leasing agreements.

Cognitive radio technologies have the potential to provide the 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 on a negotiated or an opportunistic basis. Although the existing dynamic spectrum access schemes described in Chapter 2 have achieved some success on enhancing the spectrum efficiency and distributive design for autonomous DSANs, most of them focus on efficient spectrum allocation given fixed topologies and cannot quickly adapt to the dynamics of wireless networks due to node mobility, channel variations or varying wireless traffic. Furthermore, existing cognitive spectrum sharing approaches generally assume that the network users will act cooperatively to maximize the overall system performance, which is a reasonable assumption for traditional emergency or military situations. However, with the emerging applications of mobile ad hoc networks envisioned in civilian usage, the users may not serve a common goal or belong to a single authority, which requires that the network functions can be carried out in a self-organized way to combat the selfish behaviors. In dynamic spectrum allocation scenarios, the users' selfishness causes more challenges for efficient mechanism design, such as incentive-stimulation and price of anarchy [8, 58]. Therefore, novel spectrum allocation approaches need to be developed considering the dynamic nature of wireless networks and users' selfish behaviors.

Considering a general network scenario in which multiple primary users (legacy spectrum holders) and secondary users (unlicensed users) coexist, primary users attempt to sell unused spectrum resources to secondary users for monetary gains while secondary users try to acquire spectrum usage permissions from primary users to achieve certain communication goals, which generally introduces reward payoffs for them. In order to solve the above issues, we consider the spectrum sharing in autonomous DSANs as multistage dynamic games and propose a dynamic pricing approach to optimize the overall spectrum efficiency, meanwhile, keeping the participating incentives of the users based on double-auction rules and coping with the budget constraints by dynamic programming. The main contributions of this chapter are multi-fold. First, by modeling the spectrum sharing as a dynamic pricing game, we are able to quickly and accurately coordinate the spectrum allocation among primary and secondary users through a trading process to maximize the payoffs of both primary and secondary users. Further, we develop a belief system to assist greedy users update their strategies adaptive to the spectrum demand and supply changes, which not only approaches the theoretical optimal outcomes of the spectrum allocation problem but also substantially decreases the pricing overhead due to frequent bid/ask updates and message exchange. Third, by considering the budget constraints of the secondary users, the proposed dynamic pricing approach is able to further exploit the time diversity of spectrum resources.

The remainder of this chapter is organized as follows: The system model of dynamic spectrum allocation is described in Section 5.2. In Section 5.3, we formulate the spectrum allocation as pricing games based on the system model. In Section 5.4, the belief-based dynamic pricing approach is proposed for the optimal spectrum allocation. The simulation studies are provided in Section 5.5. Finally, Section 5.6 summarizes this chapter.

5.2 System Description

We consider the wireless networks where multiple primary users and secondary users operate simultaneously in a wireless network, which may represent various network scenarios. For instance, the primary users can be the spectrum broker connected to the core network and the secondary users are the base stations equipped with cognitive radio technologies; or the primary users are the access points of a mesh network and the secondary users are the mobile devices. On one hand, every primary user has the license of using a certain spectrum range, which can be divided into non-overlapping orthogonal channels. Considering that the authorized spectrum of primary users may not be fully utilized over time, they prefer to lease the unused channels to the secondary users for monetary gains. On the other hand, since the unlicensed spectrums become more and more crowded, the secondary users may try to lease some unused channels from primary users for more communication gains by providing leasing payments.

In our system model, we assume all users are selfish and rational, that is, their objectives are to maximize their own payoffs, not to cause damage to other users. However, users are allowed to cheat whenever they believe cheating behaviors can help them to increase their payoffs. Generally speaking, in order to acquire the spectrum licenses from regulatory bodies such as FCC, the primary users have certain operating costs. With regard to secondary users, in order to have the rewards of achieving certain communication goals, they want to utilize more spectrum resources. The selfishness of both primary and secondary users will prevent them from revealing their private information such as acquisition costs or reward payoffs, which makes traditional spectrum allocation approaches not applicable under this scenario. Therefore, novel spectrum allocation approaches need to be developed which not only optimize the spectrum efficiency but also extract the private information from the selfish parties through certain mechanisms to assist the optimization of spectrum allocation.

Specifically, we consider the collection of the available spectrums from all primary users as a spectrum pool, which totally consists of N non-overlapping channels. Assume there are J primary users and K secondary users, indicated by the set $\mathbf{P} = \{p_1, p_2, ..., p_J\}$ and $\mathbf{S} = \{s_1, s_2, ..., s_K\}$, respectively. We represent the channels authorized to primary user p_i using a vector $\mathbf{A}_i = \{a_i^j\}_{j \in \{1,2,...,n_i\}}$, where a_i^j represents the channel index in the spectrum pool and n_i is the total number of channels which belong to user p_i. Define $\mathbf{A}$ as the set of all the channels in the spectrum pool. Moreover, denote the acquisition costs of user p_i's channels as the vector $\mathbf{C}_i = \{c_i^{a_i^j}\}_{j \in \{1,2,...,n_i\}}$, where the jth element represents the acquisition cost of the jth channel in $\mathbf{A}_i$. For simplicity, we write $c_i^{a_i^j}$ as c_i^j. As for secondary user s_i, we define her/his payoff vector as $\mathbf{V}_i = \{v_i^j\}_{j \in \{1,2,...,N\}}$, where the jth element is the reward payoff if this user successfully leases the jth channel in the spectrum pool.

5.3 Pricing Game Model

In this chapter, we model the dynamic spectrum allocation problem as a pricing game to study the interactions among the players, i.e., the primary and secondary users. Based on the discussion in the previous section, we are able to have the payoff functions of the players in our dynamic game. Specifically, if primary user p_i reaches agreements of leasing all or part of her/his channels to secondary users, the payoff function of this primary user can be written as follows.

$$U_{p_i}(\phi_{\mathbf{A}_i}, \alpha_i^{\mathbf{A}_i}) = \sum_{j=1}^{n_i} (\phi_{a_i^j} - c_i^j) \alpha_i^{a_i^j}, \tag{5.1}$$

where $\phi_{\mathbf{A}_i} = \{\phi_{a_i^j}\}_{j \in \{1,2,...,n_i\}}$ and $\phi_{a_i^j}$ is the payment that user p_i obtains from the secondary user by leasing the channel a_i^j in the spectrum pool. Note that $\alpha_i^{\mathbf{A}_i} = \{\alpha_i^{a_i^j}\}_{j \in \{1,2,...,n_i\}}$ and $\alpha_i^{a_i^j} \in \{0, 1\}$ which indicates if the jth channel of user p_i has been allocated to a secondary user or not. For simplicity, we denote $\alpha_i^{a_i^j}$ as

α_i^j. Similarly, the payoff function of secondary user s_i can be modeled as follows.

$$U_{s_i}(\phi_{\mathbf{A}}, \beta_i^{\mathbf{A}}) = \sum_{j=1}^{N} (v_i^j - \phi_j)\beta_i^j, \tag{5.2}$$

where $\phi_{\mathbf{A}} = \{\phi_j\}_{j\in\{1,2,\ldots,N\}}$, $\beta_i^{\mathbf{A}} = \{\beta_i^j\}_{j\in\{1,2,\ldots,N\}}$. Note that $\beta_i^j \in \{0,1\}$ illustrates if secondary user s_i successfully leases the jth channel in the spectrum pool or not. Hence, the strategies of the primary users and secondary users are actually defined by $\alpha_i^{\mathbf{A}_i}$ and $\beta_i^{\mathbf{A}}$, respectively.

Since the players may have conflict interests with each other, our dynamic spectrum sharing game can be modeled as a multi-stage non-cooperation game. To be specific, from the primary users' point of view, they want to earn the payments by leasing the unused channels which not only cover their spectrum acquisition costs but also gain as much extra payments as possible; from the secondary users' point of view, they aim to accomplish their communication goals by providing the least possible payments to lease the channels; while from the network designers' point of view, they attempt to maximize the network performance, which in our case is the spectrum efficiency. Therefore, the spectrum users involved in the spectrum sharing process construct a non-cooperative pricing game [8, 10]. Since the selfish users are their own authorities, they will not reveal their private information to others unless some mechanisms have been applied to guarantee that it is not harmful to disclose the private information. Generally, such non-cooperative game with incomplete information is complex and difficult to study as the players do not know the perfect strategy profile of others. But based on our game setting, the well-developed auction theory [63] can be applied to formulate and analyze the pricing game.

In auction games [63], 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 our spectrum allocation pricing game, the primary users can be viewed as the principles, who attempts to sell the 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, by which they may gain extra payoffs for future use. In our pricing game, multiple sellers and buyers coexist, which indicates the double auction scenario. It means that not only the secondary users but also the primary users need to compete with each other to make the beneficial transactions possible by eliciting their willingness of the payments in the forms of bids or asks. Specifically, the double auction is one of the most common exchange mechanisms, used extensively in stock markets such as the New York Stock Exchange (NYSE) or commodity markets such as Chicago Merchandize Exchange (CME). The most important property of double auction mechanism is its high efficiency, which is still not fully understood in economic theory. Moreover, it can respond quickly to changing conditions of auction participants. However, in order to achieve the full efficiency of the double auction mechanism, a lot of messages need to be exchanged among the auction participants, which can be easily implemented by powerful central authorities in stock or commodity markets. It is worth noticing that in autonomous wireless networks either central authorities can be pre-assumed or the bandwidth of control channels is very limited. Therefore, we aims to develop an efficient pricing approach for spectrum allocation, which not only has the prevalence of the double auction mechanism but also uses simple message exchanges to quickly and accurately coordinate the spectrum sharing.

5.4 Belief-Assisted Dynamic Pricing

5.4.1 Static Pricing Game and Competitive Equilibrium

Assume that the available channels from the primary users are leased for usage of certain time period T. Also, we assume that the cost of the primary users and reward payoffs of the secondary users remain unchanged over this period. Before this spectrum sharing period, we define a trading period τ, within which the users exchange their information of bids and asks to achieve agreements of spectrum usage. The time period $T + \tau$ is considered as one stage in our pricing game. We first study the interactions of the players in static pricing games. Note that the users' goals are to maximize their own payoff functions. As for the primary users, the optimization problem can be written as follows.

$$O(p_i) = \max_{\phi_{\mathbf{A}_i}, \alpha_i^{\mathbf{A}_i}} U_{p_i}(\phi_{\mathbf{A}_i}, \alpha_i^{\mathbf{A}_i}), \quad \forall i \in \{1, 2, ..., J\} \tag{5.3}$$

$$\text{s.t.} \quad U_{\widehat{s}_{a_i^j}}(\{\phi_{-a_i^j}, \phi_{a_i^j}\}, \beta_i^{\mathbf{A}}) \geq U_{\widehat{s}_{a_i^j}}(\{\phi_{-a_i^j}, \widetilde{\phi}_{a_i^j}\}, \beta_i^{\mathbf{A}}),$$
$$\widehat{s}_{a_i^j} \neq 0, a_i^j \in \mathbf{A}_i. \tag{5.4}$$

where $\widetilde{\phi}_{a_i^j}$ is any feasible payment and $\phi_{-a_i^j}$ is the payment vector excluding the element of the payment for the channel a_i^j . Note that $\widehat{s}_{a_i^j}$ is defined as follows.

$$\widehat{s}_{a_i^j} = \begin{cases} s_k & \text{if } \beta_k^{a_i^j} = 1, \\ 0 & \text{if } \beta_k^{a_i^j} = 0, \forall k \in \{1, 2, ..., K\}. \end{cases} \tag{5.5}$$

Thus, (5.4) is the incentive compatible constraint [63]. It means that the secondary users have incentives to provide the optimal payment because they cannot have extra gains by cheating on the primary users. Similarly, the optimization problem can be written for the secondary users as follows.

$$O(s_i) = \max_{\phi_{\mathbf{A}}, \beta_i^{\mathbf{A}}} U_{s_i}(\phi_{\mathbf{A}}, \beta_i^{\mathbf{A}}), \quad \forall i \in \{1, 2, ..., K\} \tag{5.6}$$

$$\text{s.t.} \quad U_{\widehat{p}_j}(\{\phi_{-j}, \phi_j\}, \beta_i^{\mathbf{A}}) \geq U_{\widehat{p}_j}(\{\phi_{-j}, \widetilde{\phi}_j\}, \beta_i^{\mathbf{A}}),$$
$$\widehat{p}_j \neq 0, \beta_i^j = 1. \tag{5.7}$$

where $\widehat{p}_j$ is defined as

$$\widehat{p}_j = \begin{cases} p_k & \text{if } \beta_i^j = 1, j \in \mathbf{A}_k, \alpha_k^j = 1 \\ 0 & \text{otherwise}, \forall k \in \{1, 2, ..., J\}. \end{cases} \tag{5.8}$$

Similarly, (5.7) is the incentive compatible constraint for the primary users, which guarantees that the primary user will give the usage permission of their channels to the secondary users so that they can receive the optimal payments.

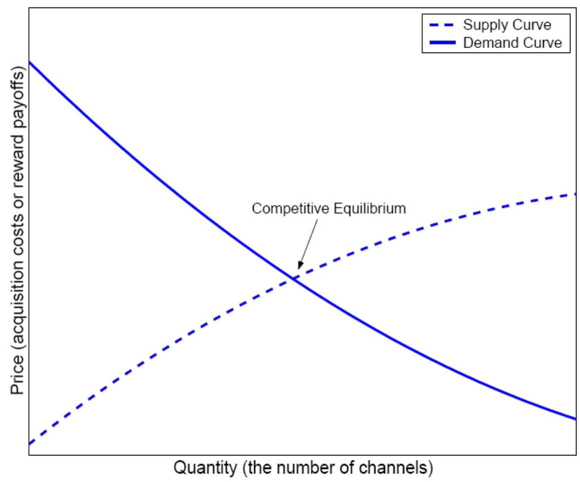

Figure 5.1: Illustration of supply and demand functions.

From (5.3) and (5.6), we can see that in order to obtain the optimal allocation and payments, a multi-objective optimization problem needs to be solved, which becomes extremely complicated due to our game setting that only involves incomplete information. Thus, in order to make this problem tangible, we analyze it from the game theory point of view. Generally speaking, game theory provides well-developed equilibrium concepts or optimality criteria to study the outcomes of games. For instance, **Nash Equilibrium** [10] is an important concept to measure the outcome of a non-cooperation 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, **Pareto Optimality** [8] is defined such that a Pareto optimal outcome cannot be improved upon without hurting at least one player. Often, a Nash equilibrium is not Pareto optimal while Pareto optimal outcomes may not be sustained considering the selfishness of the players. Further, considering the double auction scenarios of our pricing game, **Competitive Equilibrium** (CE) [82] 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 the supply and demand match [63]. The supply function can be defined as the relationship between the acquisition costs of primary users and the number of corresponding channels; the demand function can be defined as the relationship between the reward payoffs of secondary users and the number of corresponding channels. We describe the supply and demand functions in Figure 5.1. Note that CE is also proved to be Pareto optimal in stationary double auction scenarios [83]. It is worth noting that in order to achieve the CE the traditional continuous bid/ask interactions among players will involve a great amount of message exchanges and require powerful centralized control, which may not be applicable to wireless networking scenarios due to the limited bandwidth of control channels.

5.4.2 Belief-Assisted Dynamic Pricing Scheme

Considering network dynamics due to mobility, channel variations or wireless traffic variations, the secondary users may have different reward payoffs of acquiring certain channels from primary users at different time stages. Specifically, since the secondary users can be mobile devices, they may move out the access range of certain channels and hence the corresponding reward payoffs v_i^j are regarded as 0. Or, the secondary users may face various channel fading conditions within different spectrum ranges or during different time periods, which changes their payoff values v_i^j at different time stages. Moreover, the costs of primary users will also change over time due to network dynamics. For instance, if the legacy users themselves have larger spectrum demands, some legacy channels may not be available for leasing anymore, which actually indicates an infinite leasing cost of those channels in our pricing model. In brief, c_i^j and v_i^j need to be considered as random variables in dynamic scenarios, which we assume to satisfy the probability density functions (PDF) $f_c(c)$ and $f_v(v)$, respectively. Therefore, considering dynamic network conditions, we further model the spectrum sharing as a multi-stage dynamic pricing game. Let γ be the discount factor of the multi-stage game. Based on (5.3) and (5.6), the objective functions for the primary users and secondary users can be rewritten as follows.

$$\widetilde{O}(p_i) = \max_{\phi_{\mathbf{A}_i,t},\alpha_{i,t}^{\mathbf{A}_i}} E_{c_i^j,v_i^j}[\sum_{t=1}^{\infty} \gamma^t \cdot U_{p_i,t}(\phi_{\mathbf{A}_i,t}, \alpha_{i,t}^{\mathbf{A}_i})], \tag{5.9}$$

$$\widetilde{O}(s_i) = \max_{\phi_{\mathbf{A},t},\beta_{i,t}^{\mathbf{A}}} E_{c_i^j,v_i^j}[\sum_{t=1}^{\infty} \gamma^t \cdot U_{s_i,t}(\phi_{\mathbf{A},t}, \beta_{i,t}^{\mathbf{A}})], \tag{5.10}$$

where the subscript t indicates the tth stage of the multi-stage game. Generally speaking, there may exist some overall constraints of spectrum sharing such as each secondary user's total budget for leasing spectrum resources or each primary user's total available spectrum supply. Under these constraints, the above problem need to be further modeled as a dynamic programming process [45,68] to obtain optimal sequential strategies by considering some state parameters such as the number of channels to be allocated at every stage or the residual monetary budget. However, the major difficulty of dynamic spectrum sharing lies in that how to efficiently and quickly update the spectrum sharing strategies adapt to the changing network conditions only based on local information. Therefore, in the following parts, we first focus on developing a belief-assisted dynamic pricing approach, which can not only approach CE outcomes but also responds quickly to networking dynamics while only introducing limited overhead. Then, the total budget constraint is taken into consideration and a dynamic programming approach is further proposed to obtain the optimal sequential strategies.

Belief-Assisted Dynamic Pricing for Efficient Spectrum Allocation

Since our pricing game belongs to the non-cooperation games with incomplete information [10], the players need to build up certain beliefs of other players' future possible strategies to assist their decision making. Considering that there are multiple players with private information in the pricing game and what directly affect the outcome of the game are the bid/ask prices, it is more efficient to define one common belief function based on the publicly observed bid/ask prices than generating specific belief of every other player's private information. Hence, enlightened by [82], we consider the primary/secondary users' beliefs as the ratio their bid/ask being accepted at different price levels. At each time during the dynamic spectrum sharing, the ratio of asks from primary users at x that have been accepted can be written as follows.

$$\widetilde{r}_p(x) = \frac{\mu_A(x)}{\mu(x)}, \tag{5.11}$$

where $\mu(x)$ and $\mu_A(x)$ are the number of asks at x and the number of accepted asks at x, respectively. Similarly, at each time during the dynamic spectrum sharing, the ratio of bids from secondary users at y that have been accepted is

$$\widetilde{r}_s(y) = \frac{\eta_A(y)}{\eta(y)}, \tag{5.12}$$

where $\eta(y)$ and $\eta_A(y)$ are the number of bids at y and the number of accepted bids at y, respectively. Usually, $\widetilde{r}_p(x)$ and $\widetilde{r}_s(y)$ can be accurately estimated if a great number of buyers and sellers are participating in the pricing at the same time. However, in our pricing game, only a relatively small number of players are involved in the spectrum sharing at the specific time. The beliefs, namely, $\widetilde{r}_p(x)$ and $\widetilde{r}_s(y)$ cannot be practically obtained so that we need to further consider using the historical bid/ask information to build up empirical belief values. Considering the characteristics of double auction, we have the following observations:

- If an ask $\widetilde{x} < x$ is rejected, the ask at x will also be rejected;
- If an ask $\widetilde{x} > x$ is accepted, the ask at x will also be accepted;
- If a bid $\widetilde{y} > x$ is made, the ask at x will also be accepted.

Based on the above observations, the players' beliefs can be further defined as follows using the past bid/ask information.

Definition 5.4.1 *Primary users' beliefs: for each potential ask at x, define*

$$\widehat{r}_p(x) = \begin{cases} 1 & x = 0 \\ \frac{\sum_{w \geq x} \mu_A(w) + \sum_{w \geq x} \eta(w)}{\sum_{w \geq x} \mu_A(w) + \sum_{w \geq x} \eta(w) + \sum_{w \leq x} \mu_R(w)} & x \in (0, M) \\ 0 & x \geq M \end{cases} \tag{5.13}$$

where $\mu_R(w)$ is the number of asks at w that has been rejected, M is a large enough value so that the asks greater than M won't be accepted. Also, it is intuitive that the ask at 0 will be definitely accepted as no cost is introduced.

Definition 5.4.2 *Secondary users' beliefs: for each potential bid at y, define*

$$\widehat{r}_s(x) = \begin{cases} 0 & y = 0 \\ \frac{\sum_{w \le y} \eta_A(w) + \sum_{w \le y} \mu(w)}{\sum_{w \le y} \eta_A(w) + \sum_{w \le y} \mu(w) + \sum_{w \ge y} \eta_R(w)} & y \in (0, M) \\ 1 & y \ge M \end{cases} \tag{5.14}$$

where $\eta_R(w)$ is the number of bids at w that has been rejected. And, it is intuitive that the bid at 0 will not be accepted by any primary users.

Noting that it is too costly to build up beliefs on every possible bid or ask price, we can update the beliefs only at some fixed prices and use interpolation to obtain the belief function over the price space. Then, it is worth discussing the effect of the available public information on the efficiency of the above belief system. First, in the scenario that only local information is available to each user, the user updates the belief based on her/his own observed past bid/ask information, which results in more message exchanges to achieve the equilibrium price. Second, considering the broadcast nature of wireless channels, the neighbors' bid/ask information may be observed by the users, which can also be utilized to update the beliefs. In this scenario, the users may have part of the public information besides of their private information, which may accelerate their belief-updating pace and result in more efficient pricing process. Moreover, if the users have the access to all the public information such as ask/bid interactions through some centralized point, the above belief function is able to quickly reflect current supply and demand relationships.

Before using our defined belief functions to assist the strategy decisions, we first look at the Spread Reduction Rule (SRR) of double auction mechanisms.

Generally, before the double auction pricing game converges to CE, there may exist a gap between the highest bid and lowest ask, which is called the spread of double auction. The SRR states that any ask that is permissible must be lower than current lowest ask, i.e., outstanding ask [82], and then either each new ask results in an agreed transaction or it becomes the new outstanding ask. A similar argument can be applied to bids. By defining current outstanding ask and bid as ox and oy, respectively, we let $\bar{r}_p(x) = \widehat{r}_p(x) \cdot I_{[0,ox)}(x)$ for each x and $\bar{r}_s(y) = \widehat{r}_s(x) \cdot I_{(oy,M](y)}$ for each y, which are modified belief function considering the SRR. Note that $I_{(a,b)}(x)$ is defined as

$$I_{(a,b)}(x) = \begin{cases} 1 & \text{if } x \in (a,b); \\ 0 & \text{otherwise.} \end{cases} \tag{5.15}$$

By using the belief function $\bar{r}_p(x)$, the payoff maximization of selling the ith primary user's jth channel can be written as

$$\max_{x \in (oy,ox)} E[U_{p_i}(x,j)], \tag{5.16}$$

where $U_{p_i}(x,j)$ represents the payoff introduced by allocating the jth channel when the ask is x, and then $E[U_{p_i}(x,j)] = (x - c_i^j) \cdot \bar{r}_p(x)$. Similarly, as for the secondary user s_i, the payoff maximization of leasing the jth channel in the spectrum pool can be written as

$$\max_{y \in (oy,ox)} E[U_{s_i}(y,j)], \tag{5.17}$$

where $U_{s_i}(y,j)$ represents the payoff introduced by leasing the jth channel in the spectrum pool when the bid is y, and then $E[U_{s_i}(y,j)] = (v_i^j - y) \cdot \bar{r}_s(y)$. Therefore, by solving the optimization problem for each primary and secondary user using (5.16) and (5.17), respectively, primary and secondary users can make the optimal decision of spectrum allocation at every stage conditional on dynamic spectrum

Table 5.1: Belief-assisted dynamic spectrum allocation

1. Initialize the users' beliefs and bids/asks ⋄ The primary users initialize their asks as large values close to M and their beliefs as small positive values less than 1; ⋄ The secondary users initialize their bids as small values close to 0 and their beliefs as small positive values less than 1.
2. Belief update based on local information: Update primary and secondary users' beliefs using (5.13) and (5.14), respectively
3. Optimal bid/ask update: ⋄ Obtain the optimal ask for each primary user by solving (5.16); ⋄ Obtain the optimal bid for each secondary user by solving (5.17).
4. Update leasing agreement and spectrum pool: ⋄ If the outstanding bid is greater than or equal to the outstanding ask, the leasing agreement will be signed between the corresponding users; ⋄ Update the spectrum pool by removing the assigned channel.
5. Iteration: If the spectrum pool is not empty, go back to Step 2.

demand and supply. Based on the above discussions, we illustrate our belief-assisted dynamic pricing algorithm for spectrum allocation in Table 5.1.

Dynamic Pricing with Budget Constraints

Based on the belief-assisted dynamic pricing algorithm developed above, in this part we further consider the optimal spectrum allocation when each secondary user is constrained by a total monetary budget for leasing spectrum usage. Note that the spectrum allocation problem can be similarly solved when the overall constraints exist for primary users.

Considering the budget constraints of secondary users, we rewrite their optimization objectives as follows.

$$\widehat{O}(s_i) = \max_{\phi_{A,t},\beta_{i,t}^{A},\psi_i} E_{c_i^j,v_i^j}[\sum_{t=1}^{\infty}\gamma^t \cdot U_{s_i,t}(\phi_{A,t},\beta_{i,t}^{A},\widetilde{\psi}_{i,t})], \tag{5.18}$$

$$\text{s.t.} \quad U_{\widehat{p}_j,t}(\{\phi_{-j,t},\phi_{j,t}\}) \geq U_{\widehat{p}_j,t}(\{\phi_{-j,t},\widetilde{\phi}_{j,t}\}), \tag{5.19}$$

$$\sum_{t=1}^{\infty}\psi_t \leq B_i. \tag{5.20}$$

where $\psi_i = \{\psi_{i,t}\}_{t\in\{1,2,\ldots,\infty\}}$ and $\psi_{i,t}$ is the total monetary payment used during the tth stage for the ith secondary user leasing the channels. Moreover, B_i is the ith secondary user' total budget. Note that $\widetilde{\psi}_{i,t} = B_i - \sum_{\tau=1}^{\tau=t-1}\psi_{i,\tau}$, which is the residual budget at the tth stage and can be considered as a state parameter. Hence, (5.19) and (5.20) are the incentive compatible constraint and total budget constraint, respectively. As it is difficult to directly solve (5.18), we study the dynamic programming approach to simplify the multistage optimization problem.

Define the value function $Q_{s_i,t}(\widetilde{\psi}_i)$ as the ith secondary user's maximum expected payoff obtainable from periods $t, t+1, ..., \infty$ given that the monetary budget left is $\widetilde{\psi}_i$. Simplifying (5.18) using the Bellman equation [68], we have the maximal expected payoff $Q_{s_i,t}(\widetilde{\psi}_i)$ written as follows.

$$Q_{s_i,t}(\widetilde{\psi}_i) = \max_{\phi_{\mathbf{A},t},\beta_{i,t}^{\mathbf{A}},\psi_i}\{E_{c_i^j,v_i^j}[U_{s_i,t}(\phi_{\mathbf{A},t},\beta_{i,t}^{\mathbf{A}},\widetilde{\psi}_i) + \gamma\cdot Q_{s_i,t+1}(\widetilde{\psi}_i - \psi_{i,t})]\}, \tag{5.21}$$

$$\text{s.t.} \quad U_{\widehat{p}_j,t}(\{\phi_{-j,t},\phi_{j,t}\}) \geq U_{\widehat{p}_j,t}(\{\phi_{-j,t},\widetilde{\phi}_{j,t}\}). \tag{5.22}$$

The boundary conditions for the above dynamic programming problem are

$$Q_{s_i,\infty}(\widetilde{\psi}_i) = 0, \quad \widetilde{\psi}_i \in (0, B_i]. \tag{5.23}$$

Note that the first term on the right hand side (RHS) of (5.21) represents the payoff at current stage and the second term on the RHS of (5.21) represents the future payoff obtained after the tth stage give the budget state $\widetilde{\psi}_i - \psi_{i,t}$. Further, applying the principle of optimality in [68], the spectrum sharing configuration $\{\phi_{\mathbf{A},t}, \beta_{i,t}^{\mathbf{A}}, \psi_i\}$ that achieves the maximum in (5.21) given $\widetilde{\psi}_i$, t and the statistics of c_i^j, v_i^j is also the optimal solution for the overall optimization problem (5.18).

In order to obtain $Q_{s_i,t}(\widetilde{\psi}_i)$, the maximal payoff of one stage needs to be first derived for different residual budget values $\widetilde{\psi}_i$. The difference of the current payoff function in (5.18) and the one-stage payoff function in (5.6) lies in that the applied budget constraint affects the outcomes of the pricing game. For instance, even though both the primary users and secondary users can achieve higher payoffs by assigning a channel to user s_i, the user s_i may not have enough budgets to lease this channel. Thus, the algorithm in Table 5.1 cannot be directly applied here for optimal spectrum sharing. We need to modify the bid update step as follows: user s_i updates his/her bid by $\min\{\widetilde{\psi}_i, y\}$, where y is obtained from (5.17). Note that it is highly complicated to derive the close-form solution for the one-stage payoff function in (5.18) [63, 83].Thus, we use simulation to approximate it for different residual budget values, which proceeds as follows: Generate a large number of samples of the secondary and primary users with reward payoffs and costs satisfying $f_v(v)$ and $f_c(c)$, respectively. Using the above modified version of the algorithm in Table 5.1, calculate the average one-stage payoffs given different $\widetilde{\psi}$ based on the outcomes of the spectrum allocation samples.

By using the numerical results of the one-stage payoff function, we then derive $Q_{s_i,t}(\widetilde{\psi}_i)$ using dynamic programming methods. Considering infinite spectrum allocation stages, the maximum payoff $Q_{s_i,t}(\widetilde{\psi}_i)$ in (5.21) can be written as follows.

$$Q_{s_i}^*(\widetilde{\psi}_i) = \max_{\phi_{\mathbf{A},t}, \beta_{i,t}^{\mathbf{A}}, \psi_i} \{E_{c_i^j, v_i^j}[U_{s_i,t}(\phi_{\mathbf{A},t}, \beta_{i,t}^{\mathbf{A}}, \widetilde{\psi}_i) + \gamma \cdot Q_{s_i}^*(\widetilde{\psi}_i - \psi_{i,t})]\}, \tag{5.24}$$

or, equivalently, $Q_{s_i}^* = \mathcal{T} Q_{s_i}^*$, where $\mathcal{T}$ is the operator updating $Q_{s_i}^*$ using (5.24).

Let $\mathcal{S}$ be the feasible set of the state parameter. The convergence proposition of the dynamic programming algorithm [68] can be applied here, which states that: for any bounded function $Q : \mathcal{S} \to \mathcal{R}$, the optimal payoff function satisfies $Q^*(x) = \lim_{p\to\infty}(\mathcal{T}^p Q)(x), \forall x \in \mathcal{S}$. As $Q_{s_i}(\widetilde{\psi}_i)$ is bounded in our algorithm, we are able to apply the value iteration method to approximate the optimal $Q_{s_i}(\widetilde{\psi}_i)$, which proceeds as follows: Start from some initial function for $Q_{s_i}(\widetilde{\psi}_i)$ as $Q^0_{s_i}(\widetilde{\psi}_i) = g(x)$, where the superscript stands for the iteration number. Then, iteratively update $Q_{s_i}(\widetilde{\psi}_i)$ by letting $Q^{p+1}_{s_i}(\widetilde{\psi}_i) = (\mathcal{T} Q^p_{s_i})(\widetilde{\psi}_i)$. The iteration process ends until $|Q^{p+1}_{s_i}(\widetilde{\psi}_i) - Q^p_{s_i}(\widetilde{\psi}_i)| \leq \epsilon$, for all $\widetilde{\psi}_i \in \mathcal{S}$, where ϵ is the error bound for $Q^*_{s_i}(\widetilde{\psi}_i)$.

Intuitively, the basic idea behind our dynamic pricing approach for spectrum allocation with budget constraints can be explained as follows: Considering the overall budget constraints, the users make their spectrum sharing decisions not only based on their current payoffs but also based on expected future payoffs. Specifically, if the competition for spectrum resources is high at current stage, the users prefer to save their monetary budgets for future usage, which will yield higher overall payoffs for the users. Therefore, by using our proposed dynamic pricing approach, the spectrum allocation can be optimized not only in the space and frequency domains but also in the the time domain.

5.5 Simulation Studies

In this section, we evaluate the performance of the proposed belief-assisted dynamic spectrum sharing approach in wireless networks. Considering a wireless network covering 100×100 area, we simulate J primary users by randomly placing them in the network. These primary users can be the base stations serving for different wireless network operators or different access points in a mesh network. Here

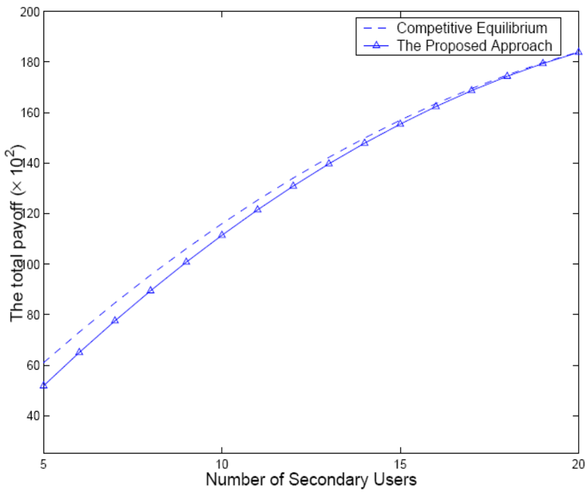

Figure 5.2: Comparison of the total payoff for the proposed scheme and theoretical Competitive Equilibrium.

we assume the primary users' locations are fixed and their unused channels are available to the secondary users within the distance of 50. 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 [70], where we assume the "thinking time" at each waypoint is close to the effective duration of one channel-leasing agreement, the waypoints are uniformly distributed within the distance of 10, and the traveling time is much smaller than the "thinking time". Let the cost of an available channel in the spectrum pool be uniformly distributed in $[10, 30]$, 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 pricing stages have been simulated. Let $n_i = 4$, $\forall i \in \{1, 2, ..., J\}$ and $\gamma = 0.99$.

We first focus our simulation studies on dynamic spectrum sharing without

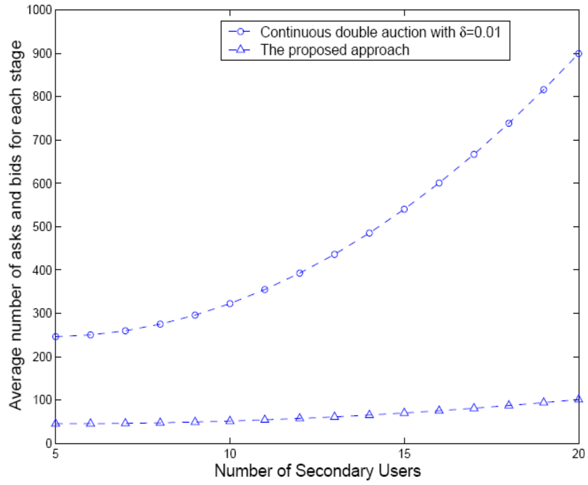

Figure 5.3: Comparison of the overhead between the proposed scheme and continuous double auction scheme.

budget constraints, which can be used to illustrate the efficiency of the proposed belief-assisted pricing algorithm for spectrum allocation. In our simulation, the local bid/ask information within the transmission range of each node is used for belief construction and update. In Figure 5.2, we compare the total payoff of all users of our proposed approach with that of the theoretical CE outcomes for different number of secondary users. It can be seen from this figure that the performance loss of our approach is very limited compared to that of the theoretical optimal solutions. Moreover, when the number of secondary users increases, our approach is able to approach the optimal CE. It is because that the belief function reflects the spectrum demand and supply more accurately when more users are involved in spectrum sharing.

Now we study the overhead of our pricing approach. Here we measure the pricing overhead by showing the average number of bids and asks for each stage. In Figure 5.3, the overhead of our pricing approach is compared to that of the traditional continuous double auction when the same total payoff is achieved. As-

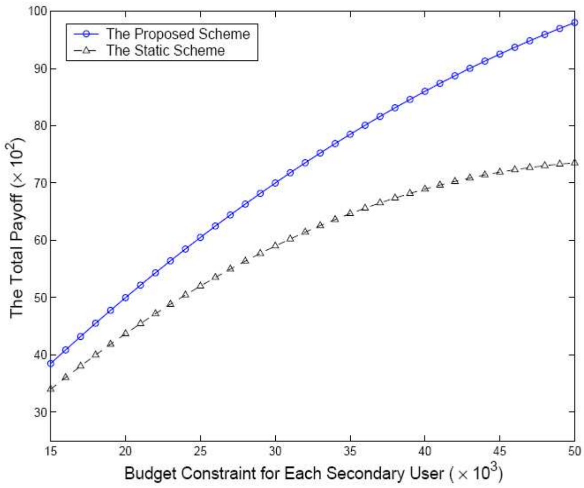

Figure 5.4: Comparison of the total payoffs of the proposed scheme with those of the static scheme.

sume the minimal bid/ask step δ of the continuous double auction to be 0.01. It can be seen from the figure that our approach substantially decreases the pricing communication overhead. Note that when decreasing the overhead, our proposed approach may introduce extra complexity to update the beliefs.

Then, we study the dynamic 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-leasing decisions without considering their budget limits. Without loss of generality, we assume that the budget constraints for the secondary users are the same. In Figure 5.4, we compare the total payoffs of our proposed dynamic programming scheme with those of the static scheme for different budget constraints. It can be seen from the figure that our proposed scheme achieves significant performance gains over the static scheme when the budget constraints are taken into consideration. Also, when the budget limits increase, the proposed scheme achieves higher gain by further exploiting the time diversity.

5.6 Summary

In this chapter, we have studied dynamic pricing for efficient spectrum allocation in wireless networks with selfish users. We model the dynamic spectrum allocation as a multi-stage game and propose a belief-assisted dynamic pricing approach to maximize the users' payoffs while providing them the participating incentives via double auction rules. Further, the dynamic pricing under the budget constraints of secondary users is analyzed using dynamic programming. Simulation results show that the proposed scheme can approach the optimal performances by only using limited overhead. Moreover, the time diversity of spectrum resources can be fully exploited when budget constraints exist.

Chapter 6

Multi-Stage Pricing Game for Collusion-Resistant Dynamic Spectrum Allocation

In this chapter, we focus on studying the collusive behavior of selfish users in autonomous DSANs. We first discuss the impact of user collusion on auction-based dynamic spectrum allocation approaches in Section 6.1. In Section 6.2, we study collusion-resistant dynamic spectrum allocation for two simplified scenarios: (1) multiple secondary users and one primary user (MSOP); (2) one secondary user and multiple primary users (OSMP). Further, we extend our study to a more generalized spectrum allocation scenario with multiple primary users and multiple secondary users (MSMP) in Section 6.3. The simulation studies and summary are provided in Section 6.4 and Section 6.5, respectively.

6.1 User Collusion in Auction-Based Spectrum Allocation

In order to have a robust dynamic spectrum allocation mechanism in wireless networks with selfish users, the cheating behaviors of selfish users need to be well studied and counteracted. Otherwise, the spectrum allocation mechanism may become unsustainable and leads to unpredictable outcomes. On one hand, spectrum allocation can be generally regarded to be similar to generic medium access control (MAC) problems in existing systems and studied from the perspective of wireless resource allocation [19, 27, 57]. On the other hand, efficient spectrum allocation can be achieved by studying it from the perspective of the driving economic force and mechanisms [18, 42, 59]. Therefore, the unique property of dynamic spectrum allocation imposes new challenges on its mechanism design against cheating behaviors. Basically, all the cheating behaviors related to MAC problems in wireless system still threaten the functionalities of spectrum sharing mechanisms. More importantly, wireless spectrum becomes a scarce resource and has huge economical potential, which can only be exploited through efficient pricing-based market designs. Thus, the cheating threats on these market designs make the robust dynamic spectrum access a even more complicated problem. Since the cheating behaviors on MAC protocols can still be solved using traditional countermeasures and the auction mechanisms has the incentive-compatible property for each single user, we will focus our study on efficient collusion-resistant dynamic spectrum allocation mechanism.

Although incentive-compatibility can be assured in most auction-based dynamic spectrum allocation approaches such as the optimal auction [45,63] or Vick-

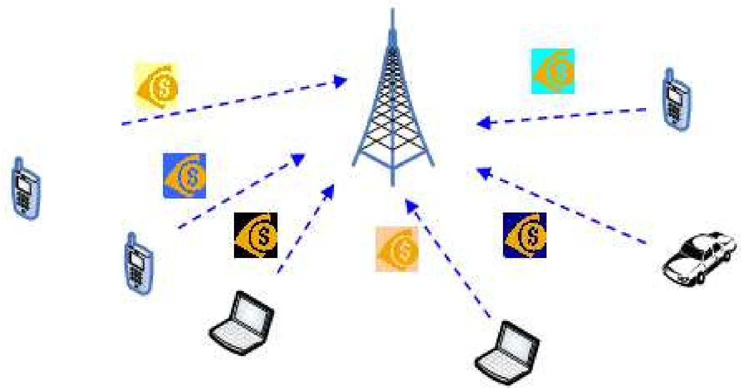

Figure 6.1: No collusion in pricing-based dynamic spectrum allocation.

rey auction [63], which indicates that no selfish user will cheat on the auction mechanism unilaterally, one prevalent cheating behavior, the bidding collusion among users, has been generally overlooked. To be specific, the bidders (or sellers) act collusively and engage in bid rigging with a view to obtaining lower prices (or higher prices). The resulting arrangement is called the bidding ring. In the scenarios of auction-based spectrum allocation, the bidding ring among the primary users (or secondary users) will result in increasing their utilities by collusively leasing the spectrum channels at a higher price (or at a lower price). Considering the spectrum dynamics caused by wireless channel variations, user mobility or varying wireless traffic, it becomes difficult to tell if the price variation comes from possible bidding collusion or the varying demand and supply of spectrum resources. Hence, traditional auction-based spectrum allocation mechanisms become vulnerable and unstable with the presence of collusive behaviors.

In Figure 6.1 and Figure 6.2, we illustrate a snapshot of pricing-based dynamic spectrum access networks where there is no user collusion and exists user collusion, respectively. In the above figures, we consider the primary base station as the

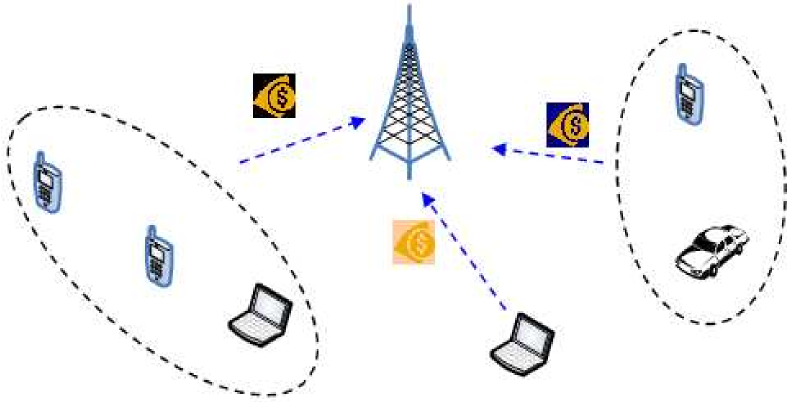

Figure 6.2: User collusion in pricing-based dynamic spectrum allocation.

primary user and the unlicensed mobile users as the secondary users. When there is no user collusion as in Figure 6.1, the pricing interactions between the primary user and secondary users leads to efficient spectrum allocation. When there exist several bidding rings as in Figure 6.2, each bidding ring will elicit only one effective bid for spectrum resources, which distorts the supply and demand of spectrum resources and yields inefficient spectrum allocation. Further, in the extreme case that all secondary users collude with each other, arbitrary low bid price will become eligible. Thus, collusion-resistant dynamic spectrum allocation is important for efficient next generation wireless networking.

In the scenarios of traditional open ascending price, i.e., English auction (or reverse English auction) [63], there is one seller and multiple buyers (or one buyer and multiple sellers). In order to combat the bidding ring, the seller (or buyer) can enhance their utilities by setting proper reserve prices as in [63] based on the size of the bidding ring, i.e, the number of collusive users, and the statistics of each user's true value. However, in our scenarios of dynamic spectrum allocation with multiple primary and secondary users having only local information, either the number of collusive users are not available or the determination of reserve price becomes very complicated given limited imperfect information. Therefore, how to design efficient collusion-resistant dynamic spectrum allocation mechanisms becomes an imminent and crucial task.

6.2 MSOP and OSMP Scenarios

In this part, we develop the robust dynamic spectrum allocation mechanisms against user collusion in the scenarios of MSOP and OSMP. Note that the MSOP scenarios may indicate the situations that several mobile users are competing for the spectrum resources from the base station in cellular wireless systems; while the OSMP scenarios may illustrate the situations that several network operators or service providers are competing for offering spectrum services to the users. Now, we study the MSOP scenarios first and similar analysis can be applied to OSMP scenarios.

Consider there are one primary user and multiple secondary users in a snap shot of wireless networks, which indicates that only one primary user p_i is available for providing spectrum leasing services. The standard ascending price open auction is chosen for the secondary users to compete for the spectrum resources, which is theoretically equivalent to sealed-bid second-price auction [63]. Here, the presence of user collusion among secondary users may generate extra utilities for the collusive users by suppressing competition for spectrum resources. Due to the network dynamics and imperfect available information, neither the primary user can make a credible assumption about the presence of user collusion or the number of collusive users, nor there exist trust-worthy anti-cartel authorities in the network. Therefore, the only instrument giving the primary user possible leverage against collusion is to set an optimal reserve price. In the rest of this part, we first derive the theoretical optimal reserve price for our spectrum allocation game similar to [63]. Then, by considering the properties of our spectrum allocation game such as unknown number of collusive users and imperfect/local bidding information, a collusion-resistant dynamic spectrum allocation mechanism is developed to efficiently allocate spectrum resources while combating collusive cheating behaviors.

Specifically, we assume that K secondary users are divided into K_r bidding rings and the size of the kth bidding ring is m_k. Note that $\sum_{k=1}^{K_r} m_k = K, m_k \geq 1$. Basically, the collusion among the secondary users within each bidding ring does not affect the strategies of users out of the bidding ring. Further, the bidding ring can be represented by the collusive secondary user with the highest reward payoff [63]. The other collusive users only submit non-serious bids at or below reserve price, which substantially limits the competition among secondary users. Thus, instead of K effective competing secondary users, only K_r effective users should be considered for bidding spectrum resources. Assume the equivalent reward payoff of the kth bidding ring is $\nu_{m_k}^{a_i^j}$, the highest reward payoff among m_k collusive users for the a_i^jth channel in the spectrum pool. Thus, the payoff vector for effective users can be represented as $\{\nu_1^{a_i^j}, \nu_2^{a_i^j}, ..., \nu_{K_r}^{a_i^j}\}$. Note that we omit the superscript a_i^j in the following parts for simplicity if the spectrum assignment is only considered for one specific channel. Further, let the highest and second highest reward payoff among all effective secondary users to be $v_{(1)}$ and $v_{(2)}$, respectively.

In order to combat the collusive behaviors of secondary users, the primary user needs to set a reserve price, which means its spectrum resources won't be sold lower than the reserve price. Considering the theoretical equivalence of open ascending price auction and second-price auction, we then study the optimal reserve price for second-price auction setting in our spectrum allocation game. Let the optimal reserve price to be ϕ_{r,p_i}. Then, the spectrum channel can be leased by p_i if and only if $v_{(1)} > \phi_{r,p_i}$. Moreover, if $v_{(2)} > \phi_{r,p_i}$, the spectrum channel is leased for $v_{(2)}$; otherwise, it is leased at the reserve price ϕ_{r,p_i}. Let $F_{v_{(1)}}(x)$ and $F_{v_{(2)}}(x)$ denote the cumulative density functions (CDF) of $v_{(1)}$ and $v_{(2)}$, respectively. Let $f_{v_{(1)}}(x)$ and $f_{v_{(2)}}(x)$ denote the probability density functions (PDF) of $v_{(1)}$ and $v_{(2)}$, respectively. Now, the expected utility gain of the primary user with reserve price ϕ_{r,p_i} by leasing her/his jth channel can be written as

$$\begin{aligned} E_{\mathbf{V}_i, c_i^{a_i^j}}[U_{p_i}(a_i^j, \phi_{r,pi})] = (\phi_{r,p_i} - E[c_i^{a_i^j}])(F_{v_{(2)}}(\phi_{r,p_i}) - F_{v_{(1)}}(\phi_{r,p_i})) \\ + \int_{\phi_{r,p_i}}^{M} (z - E[c_i^{a_i^j}]) f_{v_{(2)}}(z) dz, \end{aligned} \tag{6.1}$$

Where M represents the largest possible v_i^j. Note that the first term on the right hand side (RHS) of (6.1) represents the utility when the spectrum channel is leased at the reserve price. This happens if $v_{(1)} > \phi_{r,p_i}$ but $v_{(2)} < \phi_{r,p_i}$. The second term on the RHS of (6.1) represents the utility when $v_{(2)} \geq \phi_{r,p_i}$.

Assuming that an interior maximum exists for (6.1), the optimal reserve price ϕ^*_{r,p_i} satisfies the following first-order condition of (6.1).

$$F_{v_{(2)}}(\phi^*_{r,p_i}) - F_{v_{(1)}}(\phi^*_{r,p_i}) - (\phi^*_{r,p_i} - E[c_i^{a_i^j}]) f_{v_{(1)}}(\phi^*_{r,p_i}) = 0. \tag{6.2}$$

Thus the optimal reserve price can be determined by the above (6.2) if the statistical descriptions for $v_{(1)}$ and $v_{(2)}$ are available.

Similarly, in the scenarios of OSMP, if we let the lowest and second lowest acquisition costs among all effective primary users be $c_{(1)}$ and $c_{(2)}$, respectively, the expected utility gain of the secondary user s_i with reserve price ϕ_{r,s_i} by leasing a channel from the primary users can be written as

$$E_{\mathbf{V_i},\mathbf{C}}[U_{s_i}(\phi_{r,s_i})] = (E[v_i^j]-\phi_{r,s_i})(F_{c_{(1)}}(\phi_{r,s_i})-F_{c_{(2)}}(\phi_{r,s_i}))+\int_0^{\phi_{r,s_i}}(E[v_i^j]-z)f_{c_{(2)}}(z)dz. \tag{6.3}$$

Correspondingly, the first-order condition of (6.3) can be obtained as follows if an interior maximum exists for (6.3).

$$F_{c_{(2)}}(\phi^*_{r,s_i}) - F_{c_{(1)}}(\phi^*_{r,s_i}) + (E[v_i^j] - \phi^*_{r,s_i})f_{c_{(1)}}(\phi^*_{r,s_i}) = 0. \tag{6.4}$$

However, in general scenarios of spectrum allocation, each user operates only based on her/his local information and there may be no anti-cartel authorities. Thus, the number of collusive users and the number of bidding rings are unknown to each user. Consequently, even though the statistics of each user's reward payoff is available or can be estimated under homogeneous settings, the order statistics [78] of $v_{(2)}$ and $c_{(2)}$ cannot be derived without the information of the number of collusive users. Then, how to further obtain the optimal reserve prices considering the constraints in our spectrum allocation game remains unanswered.

Since our pricing game belongs to the non-cooperation games with incomplete information [10], the players need to build up certain beliefs of other players' future possible strategies to assist their decision making. In order to obtain the optimal reserve prices from (6.2) and (6.4) for robust spectrum allocation, we first derive the belief functions for primary and secondary users in the scenarios of MSOP and OSMP, respectively. Similar to Chapter 5, we consider the primary/secondary users' beliefs as the ratio their bid/ask being accepted at different price levels as in (5.11) and (5.12). The primary and secondary users' beliefs, namely, $\widetilde{r}_p(x)$ and $\widetilde{r}_s(y)$ cannot be practically obtained so that we need to further consider using the historical bid/ask information to build up empirical belief values. In the scenarios of MSOP, we have the following observations: if a bid $\widetilde{y} > y$ is rejected, the bid at

y will also be rejected; if a bid $\widetilde{y} < y$ is accepted, the bid at y will also be accepted. Based on the these observations, the secondary users' beliefs can be further defined as follows using the past bidding information.

Definition 6.2.1 *Secondary users' beliefs: for each potential bid at y, define*

$$\breve{r}_s(y) = \begin{cases} 0 & y = 0 \\ \frac{\sum_{w \le y} \eta_A(w)}{\sum_{w \le y} \eta_A(w) + \sum_{w \ge y} \eta_R(w)} & y \in (0, M) \\ 1 & y \ge M \end{cases} \tag{6.5}$$

where $\eta_R(w)$ is the number of bids at w that has been rejected, M is a large enough value so that the bids greater than M will definitely be accepted. And, it is intuitive that the bid at 0 will not be accepted by any primary users.

In the scenarios of OSMP, the primary users' beliefs can be similarly derived as follows using past ask information.

Definition 6.2.2 *Primary users' beliefs: for each potential ask at x, define*

$$\breve{r}_p(x) = \begin{cases} 1 & x = 0 \\ \frac{\sum_{w \ge x} \mu_A(w)}{\sum_{w \ge x} \mu_A(w) + \sum_{w \le x} \mu_R(w)} & x \in (0, M) \\ 0 & x \ge M \end{cases} \tag{6.6}$$

where $\mu_R(w)$ is the number of asks at w that has been rejected. Also, it is intuitive that the ask at 0 will be definitely accepted as no cost is introduced.

Noting that it is too costly to build up beliefs on every possible bid or ask price, we can update the beliefs only at some fixed prices and use interpolation to obtain the belief function over the price space. Considering the characteristics of open ascending auction in the scenarios of MSOP, the secondary user with the highest reward payoff doesn't need to bid her/his true value to win the auction.

In stead, she/he only needs to bid at the second highest possible payoff to have all other secondary users drop out of the auction. Therefore, the secondary users' belief function (6.5) actually represents the CDF of $v_{(2)}$. Similarly, the primary users' belief function (6.6) represents the CDF of $c_{(2)}$.

Further, since the total number of active secondary user and the statistics of the reward payoff for each user are generally available, the PDF of $v_{(1)}$ in the scenarios of MSOP can be easily obtained using the order statistics in [78] as follows.

$$F_{v_{(1)}}(x) = \prod_{i \in \{1,2,\ldots,K\}} F_{v_i}(x). \tag{6.7}$$

Also, the PDF of $c_{(1)}$ in the scenarios of OSMP can be similarly obtained as follows [78].

$$F_{c_{(1)}}(y) = 1 - \prod_{i \in \{1,2,\ldots,J\}} (1 - F_{c_i}(y)). \tag{6.8}$$

Therefore, the optimal reserve price for the primary user to combat user collusion in the scenarios of MSOP can be obtained from (6.2) using (6.5) and (6.7). Moreover, as for the scenarios of OSMP, the optimal reserve price for the secondary user can be obtained from (6.4) using (6.6) and (6.8).

6.3 MSMP Scenarios

In the general scenarios of MSMP, efficient collusion-resistant spectrum allocation needs to be carried out among multiple primary users and secondary users while considering various user collusion patterns happening on both sides of spectrum markets, which becomes highly complicated and difficult to be analyzed. In this part, we will first derive a collusion-resistant dynamic spectrum allocation mechanism for MSMP scenarios based on the results for the OSMP/MSOP scenarios. Then, a lower bound is developed to measure the performance of the proposed mechanism by considering the extreme case of all-inclusive collusion within primary users and secondary users.

Before we derive the collusion-resistant dynamic spectrum allocation mechanism, let's discuss several upcoming challenges due to MSMP scenarios. First, the user collusion may happen not only within the primary users but also within the secondary users. The outcomes of the spectrum allocation game are determined by the collusive behaviors on both sides of the spectrum market. Second, the user collusion highly distorts the true supply and demand of spectrum resources so that the spectrum allocation efficiency will be deteriorated. It is because that except the primary user with the lowest acquisition cost and the secondary user with the highest reward payoff, the supply or demand of the spectrum resources from other users in the bidding rings will no longer be elicited through bidding process. Also, the dynamic nature of spectrum resources requires that the countermeasures to the user collusion are able to easily adapt to the spectrum dynamics by using only limited resources such as bandwidth of control channels or implementation complexity.

Consider an important property of the bidding ring in our game settings that the collusive behaviors within a bidding ring won't affect the strategies of the users who are not in the bidding ring. It means that, for instance, a primary user's optimal reserve price is only determined by the spectrum demand statistics and won't be affected by the collusive behaviors of other primary users. Similar arguments can be applied to the secondary users. Therefore, an efficient collusion-resistant dynamic spectrum allocation approach in MSMP scenarios can be similarly derived based on the results of the above discussion on the scenarios of OSMP and MSOP.

First, the definition of the beliefs of primary users and secondary users need to be redefined according to the characteristics of double auction. We have the following new observations in the scenarios of MSMP:

- If a bid $\widetilde{y} > x$ is made, the ask at x will also be accepted;
- If an ask $\widetilde{x} < y$ is made, the bid at y will also be accepted.

Based on the above observations, the users' beliefs in the scenarios of MSMP can be further refined as follows using the past bid/ask information. Note that Definition 5.4.1 for the primary users and Definition 5.4.2 for the secondary users $\widehat{r}_p(x)$ and $\widehat{r}_s(x)$, respectively, in Chapter 5 can also be applied here. By using these belief functions and the order statistics of $v_{(1)}$ and $c_{(1)}$ given the number of active primary and secondary users, the optimal reserve price for the primary user p_i and secondary user s_i can be obtained for MSMP scenarios as ϕ^*_{r,p_i} and ϕ^*_{r,s_i}, respectively.

Similarly, after applying the Spread Reduction Rule of double auction, we use the belief function $\bar{r}_p(x)$ from Chapter 5. Considering the optimal reserve price ϕ^*_{r,p_i}, the payoff maximization of selling the ith primary user's jth channel can be written as

$$\max_{x \in (oy,ox), x > \phi^*_{r,p_i}} E[U_{p_i}(x,j)], \tag{6.9}$$

where $U_{p_i}(x,j)$ represents the payoff introduced by allocating the jth channel when the ask is x, and then $E[U_{p_i}(x,j)] = (x - c_i^j) \cdot \bar{r}_p(x), x > \phi^*_{r,p_i}$. Similarly, considering the optimal reserve price ϕ^*_{r,s_i} for the secondary user s_i, the payoff maximization of leasing the jth channel in the spectrum pool can be written as

$$\max_{y \in (oy,ox), y < \phi^*_{r,s_i}} E[U_{s_i}(y,j)], \tag{6.10}$$

where $U_{s_i}(y,j)$ represents the payoff introduced by leasing the jth channel in the spectrum pool when the bid is y, and then $E[U_{s_i}(y,j)] = (v_i^j - y) \cdot \bar{r}_s(y), y <$

Table 6.1: Collusion-resistant dynamic spectrum allocation

1. Initialize the users' beliefs and bids/asks
⋄ The primary users initialize their asks as large values close to M
and their beliefs as small positive values less than 1;
⋄ The secondary users initialize their bids as small values close to 0
and their beliefs as small positive values less than 1.
2. Belief update based on local information:
Update primary and secondary users' beliefs
using (5.13) and (5.14), respectively
3. Optimal reserve price for primary and secondary users:
Update primary users' optimal reserve prices ϕ^*_{r,p_i} using (6.2), (6.7) and (5.13);
Update secondary users' optimal reserve prices ϕ^*_{r,s_i} using (6.4), (6.8) and (5.14).
4. Optimal bid/ask update:
⋄ Obtain the optimal ask for each primary user by solving (6.9) given ϕ^*_{r,p_i};
⋄ Obtain the optimal bid for each secondary user by solving (6.10) given ϕ^*_{r,s_i}.
5. Update leasing agreement and spectrum pool:
⋄ If the outstanding bid is greater than or equal to the outstanding ask,
the leasing agreement will be signed between the corresponding users;
⋄ Update the spectrum pool by removing the assigned channel.
6. Iteration:
If the spectrum pool is not empty, go back to Step 2.

ϕ^*_{r,s_i}. Therefore, by solving the optimization problem for each effective primary and secondary users using (6.9) and (6.10), respectively, the optimal decisions of spectrum allocation at every stage can be made conditional on dynamic spectrum demand and supply. Note that when a leasing agreement for one specific spectrum channel is achieved for a pair of primary and secondary users, the order statistics of $v_{(1)}$ and $c_{(1)}$ need to be updated as well as the optimal reserve prices for achieving the next leasing agreement. Based on the above discussions, we illustrate our collusion-resistant dynamic pricing algorithm for spectrum allocation in Table 6.1.

In order to measure the performance of the proposed collusion-resistant dynamic spectrum allocation mechanism, we derive its performance lower bound with the presence of user collusion in the following parts.

An efficient spectrum allocation scheme can be achieved by balancing the supply and demand of spectrum resources as shown in Chapter 5. Thus, it is straightforward that the most inefficient spectrum allocation occurs when all the supply and demand information are concealed by the collusive behaviors of selfish users, which happens when two all-inclusive collusion are formed among the primary users and secondary users, respectively. Under this situation, the spectrum allocation game becomes a bargaining game between two players, i.e, the primary user $p_{(1)}$ with lowest acquisition cost $c_{(1)}$ and the secondary user $s_{(1)}$ with highest reward payoff $v_{(1)}$. By studying this extreme case, the lower bound of the proposed collusion-resistant scheme can be obtained.

Generally speaking, the primary user $p_{(1)}$ and secondary user $s_{(1)}$ value a spectrum channel differently so that 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. Considering our bargaining game only involves two players, assume the minimal utilities that the users may obtain during the bargaining process to be $\underline{U}_{p_{(1)}}$ and $\underline{U}_{s_{(1)}}$ for user $p_{(1)}$ and $s_{(1)}$, respectively. Let $\underline{\mathbf{U}} = \{\underline{U}_{p_{(1)}}, \underline{U}_{s_{(1)}}\}$. Assume $\mathbf{S}$ to be a closed and convex subset of R^2, which represents the set of feasible utilities that the users can achieve if they cooperate with each other. Thus, our bargaining game between primary user $p_{(1)}$ and secondary user $s_{(1)}$ can be represented by $(\mathbf{s}, \underline{\mathbf{U}})$. Moreover, assume a bargaining solution to $(\mathbf{s}, \underline{\mathbf{U}})$ to be represented as $\varphi(\mathbf{s}, \underline{\mathbf{U}}) = (U^b_{p_{(1)}}, U^b_{s_{(1)}})$. Among all possible bargaining outcomes, the **Nash Bargaining Solution** [9] provides a unique and fair Pareto optimal outcome considering that the bargaining solution satisfies the following six axioms.

- **Individual Rationality**: $(U^b_{p_{(1)}}, U^b_{s_{(1)}}) \geq (\underline{U}_{p_{(1)}}, \underline{U}_{s_{(1)}})$;

- **Feasibility**: $(U^b_{p_{(1)}}, U^b_{s_{(1)}}) \in \mathbf{S}$;

- **Pareto Optimality**: If $(U_p, U_s) \in \mathbf{S}$, and $(U_p, U_s) \geq (U^b_{p_{(1)}}, U^b_{s_{(1)}})$, then $(U_p, U_s) = (U^b_{p_{(1)}}, U^b_{s_{(1)}})$;

- **Independence of Irrelevant Alternatives**: If $(U^b_{p_{(1)}}, U^b_{s_{(1)}}) \in \widetilde{\mathbf{S}} \subset \mathbf{S}$, and $(U^b_{p_{(1)}}, U^b_{s_{(1)}}) = \varphi(\mathbf{S}, \underline{\mathbf{U}})$, then $(U^b_{p_{(1)}}, U^b_{s_{(1)}}) = \varphi(\widetilde{\mathbf{S}}, \underline{\mathbf{U}})$;

- **Independence of Linear Transformations**: For any linear transformation ψ, $\varphi(\psi(\mathbf{S}), \psi(\underline{\mathbf{U}})) = (\psi(U^b_{p_{(1)}}), \psi(U^b_{s_{(1)}}))$;

- **Symmetry**: If $\mathbf{S}$ is invariant under all exchanges of agents and $\underline{U}_{p_{(1)}} = \underline{U}_{s_{(1)}}$, then $U^b_{p_{(1)}} = U^b_{s_{(1)}}$.

Noting that the above axioms are generally true for our bargaining game $(\mathbf{s}, \underline{\mathbf{U}})$, the corresponding Nash Bargaining Solution can be represented as follows.

$$\max_{\phi_b} \quad E_{c_{(1)},v_{(1)}}[U_{p_{(1)}}(\phi_b, c_{(1)}) \cdot U_{s_{(1)}}(\phi_b, v_{(1)})] \tag{6.11}$$

$$\text{s.t.} \quad G(U_{p_{(1)}}, U_{s_{(1)}}) \leq \widetilde{U}, \tag{6.12}$$

$$U_{p_{(1)}}, U_{s_{(1)}} \geq 0, \tag{6.13}$$

where $U_{p_{(1)}}(\phi_b, c_{(1)}) = \phi_b - c_{(1)}$ and $U_{s_{(1)}}(\phi_b, v_{(1)}) = v_{(1)-\phi_b}$. The two constraints give the feasible sets of $U_{p_{(1)}}$ and $U_{s_{(1)}}$. Note that based on the definition of linear utility functions for the users, the constraint (6.12) can be simplified as $U_{p_{(1)}} + U_{s_{(1)}} \leq v_{(1)} - c_{(1)}$. Therefore, the lower bound of the spectrum efficiency in the presence of user collusion can be obtained by solving (6.11). Moreover, after a leasing agreement is achieved between a primary user and a secondary user, the spectrum allocation continues by solving (6.11) with updated statistics of $v_{(1)}$ and $c_{(1)}$.

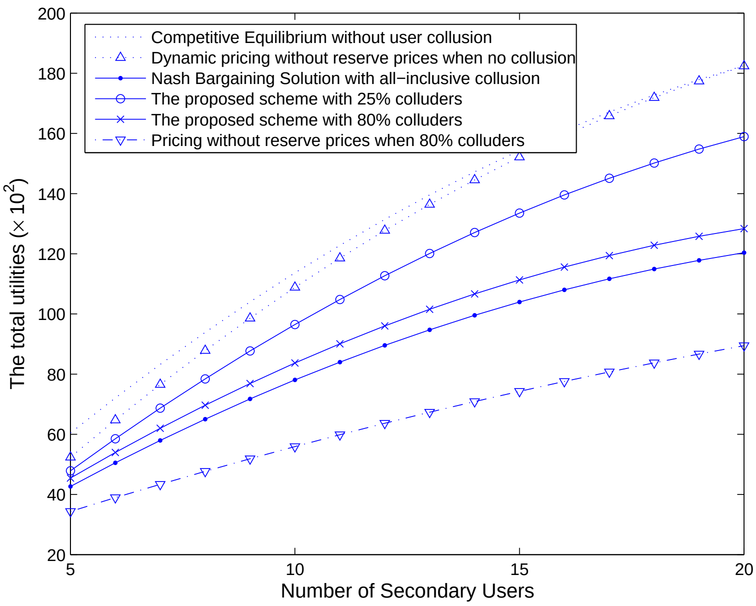

Figure 6.3: Comparison of the total utilities of the CE, pricing scheme without reserve prices, and the proposed scheme with different user collusion.

6.4 Simulation Studies

In this section, we evaluate the performance of the proposed belief-assisted dynamic spectrum sharing approach in wireless networks with user collusion. The simulation setup is the same as in Chapter 5

In Figure 6.3, we compare the total utilities of the competitive equilibrium, our dynamic pricing scheme with reserve prices, and our dynamic pricing scheme without reserve prices under various situations of user collusion. It can be seen from the figure that when there is no user collusion, the dynamic pricing scheme without reserve prices is able to achieve similar performance compared to the theoretical CE outcomes. Moreover, with the presence of user collusion, the proposed scheme with reserves prices achieves much higher total utilities than those of the scheme without reserve prices. Note that the total utilities increase when the number of secondary users increases. It is because that the competition among more secondary users helps to increase the spectrum efficiency. However, under the scenarios of user collusion, the performance gap between the proposed scheme with reserve price and the CE becomes greater when the number of secondary users increases. The reason is that the proposed scheme with reserve prices needs to set more strict reserve prices to combat severe user collusion when there are more secondary users. Further, the lower bound of the proposed collusion-resistant scheme shown in Figure 6.3 provides an efficient measurement for the maximal possible performance loss due to user collusion.

Now we study the overhead of the proposed scheme using the average number of bids and asks for each stage. In Figure 6.4, the overheads of the proposed scheme with or without reserve prices are compared to those of the traditional continuous double auction when the same total utility is achieved. Assume the minimal bid/ask step δ of the continuous double auction to be 0.01. It can be seen from the figure that our approach substantially decreases the pricing communication overhead under either the situations with user collusion or without user collusion. Note that while decreasing the overhead, our proposed approach may introduce extra complexity to update the beliefs and optimal reserve prices.

Then, we study the effect of user collusion for dynamic spectrum allocation when each secondary user is constrained by his/her monetary budget like we discuss in Chapter 5. For comparison, we define a static scheme in which the secondary users make their spectrum-leasing decisions without considering their budget limits. Without loss of generality, we assume that the budget constraints for all secondary users are the same. By applying our proposed scheme with reserve prices to the dynamic programming approach in [42] considering budget constraints, we are

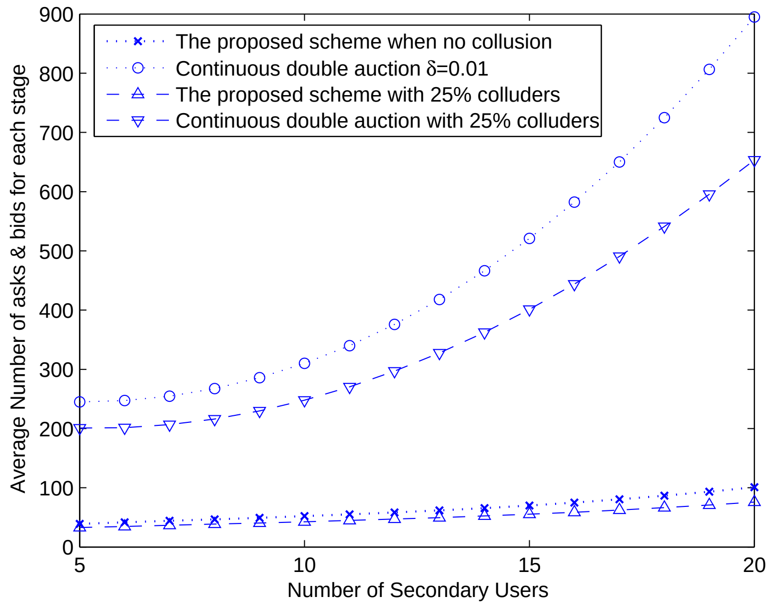

Figure 6.4: Comparison of the overhead between the proposed scheme and continuous double auction scheme.

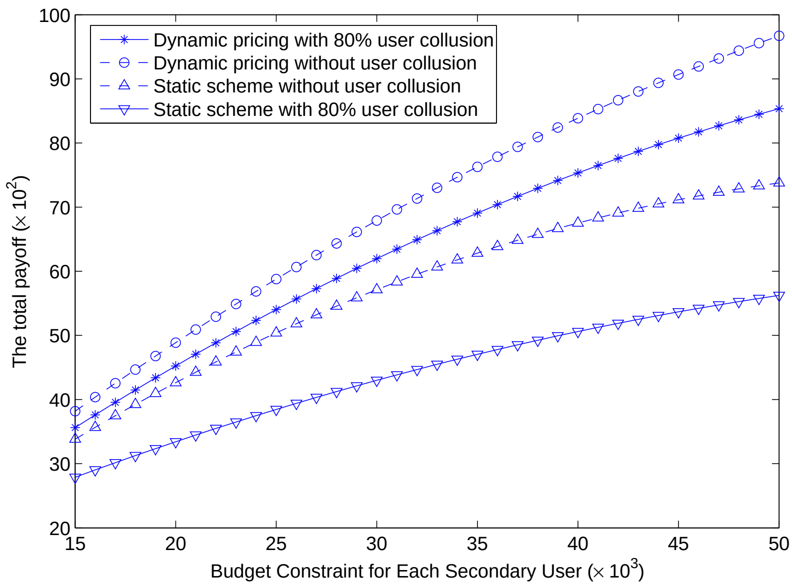

Figure 6.5: Comparison of the total utilities of the proposed scheme with those of the static scheme.

able to similarly obtain the performance of the proposed collusion-resistant scheme when optimal spectrum allocation needs to be considered over time. In Figure 6.5, we compare the total utilities of our proposed scheme with those of the static scheme for different budget constraints when the user collusion is present. Note that the proposed collusion-resistant scheme is applied to both dynamic and static pricing considering budget constraints. It can be seen from the figure that with the presence of user collusion, our proposed scheme with reserve prices achieves significant performance gains over the static scheme when the budget constraints are taken into consideration. That's because the performance loss due to the setting of reserve prices can be partly offset by exploiting the time diversity of spectrum resources.

6.5 Summary

Dynamic spectrum allocation is promising for enhancing the spectrum efficiency for wireless networks. However, user collusion among selfish users severely deteriorates the efficiency of spectrum sharing. In this chapter, we model the dynamic spectrum allocation as a multi-stage pricing game and propose a collusion-resistant dynamic pricing approach to maximize the users' utilities while combating their collusive behaviors using the derived optimal reserve prices. Further, the lower bound of the proposed scheme is analyzed using Nash Bargaining Solution. Simulation results show that the proposed scheme can achieve high spectrum efficiency by only using limited overhead under various situations of user collusion.

Chapter 7

Conclusion and Future Work

In this dissertation we have carried out the game theoretical analysis of cooperation in autonomous wireless networks. We focus on studying the impact of imperfect observation, networks dynamics and collusive behaviors on the efficient and robust game theoretical design of cooperation formation and evolvement among the selfish users in autonomous wireless networks.

First, we have studied the cooperation enforcement in autonomous wireless networks under noise and imperfect information. Most existing works on cooperation in autonomous wireless networks assume perfect or complete information for each network user. In this dissertation, we study the cooperation in a game theoretical framework and propose a set of belief-assisted or pricing-based approaches to ensure cooperation among selfish users under various network scenarios. With the aid of the belief system or pricing interactions, the network users are able to infer other users' private information through their observed imperfect information. Therefore, efficient cooperation can be achieved among selfish users in wireless networks under noise and imperfect information. Specifically, in autonomous MANETs, the belief-based packet forwarding approach is proposed to stimulate the packet forwarding between the network nodes only based on the privately observed imperfect information at each node. In autonomous DSANs, we propose a belief-assisted approach to achieve efficient dynamic spectrum sharing among primary and secondary users based on double auction rules. The network users build up its belief on spectrum demand and supply using their observed local bidding information, which assists them to make optimal decisions on the corresponding pricing actions.

Second, we have investigated the effect of network dynamics on game theoretical cooperation stimulation/enforcement in autonomous wireless networks. In order to have efficient cooperation in dynamic networks scenarios, not only the current moves of network users but also the past moves need to be taken into consideration for developing efficient distributive game theoretical mechanisms. The impact of network dynamics such as mobility, wireless channel fading, or network traffic variations on the users' behaviors also needs to be incorporated. In this dissertation, we model the interaction among users as multi-stage dynamic games and study the effect of reputation and retribution in long-run scenarios. We propose an optimal dynamic pricing approach to dynamically maximize the sender/receiver' payoffs over multiple routing stages considering the dynamic nature of MANETs, meanwhile, keeping the forwarding incentives of the relay nodes by optimally pricing their packet-forwarding actions. For DSANs, by modeling the spectrum sharing as a dynamic pricing game, we propose a distributed pricing approach to optimize the spectrum allocation based on the double auction rules.

Third, we have further investigated the collusive selfish behaviors in autonomous wireless networks in a non-cooperative game theoretical framework. Although the selfish behaviors of individual network users have been studied to ensure cooperation, the collusive selfish behaviors from multiple selfish users have not been fully exploited. In this dissertation, we analyze the collusive behaviors in auction-based cooperation stimulation scenarios and propose a collusion-resistant dynamic pricing mechanism with optimal reserve prices designed to combat or alleviate collusive behaviors. Moreover, the performance bounds of the autonomous networks with collusive users are also derived by using appropriate equilibrium concepts from game theory.

Although in this dissertation we have thoroughly addressed several critical issues in the game theoretical framework for cooperation in autonomous wireless networks, there still exist many issues that need further investigation. In the following of this chapter, we will discuss several avenues for future research.

The first issue we would like to address is about the belief/trust propagation in autonomous wireless networks. In previous chapters, we have studied belief formation in various network scenarios, which helps the selfish users to make optimal decisions of their future moves based on others' behaviorial history. As we have discussed, the network users in autonomous wireless networks may only have incomplete and imperfect information of others' actions and strategy spaces. Therefore, in order to have efficient cooperation through a entire autonomous network, the network users should be able to update their beliefs/trusts based upon the reputation propagation involving multiple network users. Our focus will be on studying the belief/trust propagation using Bayesian game models and deriving formal game theoretical approaches for the belief/trust built-up, update, propagation and evaluation. Moreover, we would like to incorporate the characteristics of different autonomous wireless networks while developing the belief propagation systems. We will also be interested in analyzing the optimality of the derived belief propagation systems using well-defined equilibrium criteria from the dynamic game theory.

In this dissertation, we focus our efforts on selfish behaviors of network users and cooperation stimulation/enforcement among them in autonomous wireless networks. The impacts of the malicious users on autonomous wireless networks need to be further considered and studied. Different from selfish users, the malicious users aim to cause as much damage to the networks as possible. They are also intelligent and even launching attacks in a coordinated way. In order to have robust autonomous wireless networks, not only the attacks on traditional network functionalities should be considered, but also the attacks on the cooperation paradigms or belief systems must be combatted. Further, considering the scenarios that various types of users coexist including cooperative users, selfish users and malicious users, the game theoretical study requires comprehensive understanding of conflicts and cooperation among different types of users. We would like to investigate the game models incorporating various types of users for autonomous networks and devise efficient mechanisms to maximize the system performance while limiting the damage caused by malicious users.

As we mentioned before, smart wireless devices such as cognitive radios enable more intelligent actions at network users equipped with those devices. For example, cognitive radios provide the wireless users with various cognitive capabilities such as frequency agility, adaptive modulation, transmit power control and scheduling management. More importantly, the cognitive engine in a cognitive radio is able to make intelligent decisions based on the observed information. In our future work, we would like to investigate our game theoretical approaches for autonomous wireless networks by considering the ability of cognitive radios and the cognitive interactions between the wireless environments and radio devices. Note that there are powerful open-source cognitive radio softwares such as GNU Radio [84] and OSSIE [85] as well as flexible FPGA-based hardware platforms such as USRP boards [86], which make it possible for the network users to intelligently configure its communication parameters in software. Therefore, by studying game theoretical cooperation stimulation/enforcement on the cognitive radio platforms in practical wireless environments, we will be able to develop practical network protocols for different applications of autonomous wireless networks based upon the theoretical approaches and corresponding field results.

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