Game Theoretic Models for Multiple Access and Resource Allocation in Wireless Networks

by

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ABSTRACT

In wireless communications, when available radio resources are insufficient compared to the total demand from mobile nodes, the resources need to be allocated among the nodes optimally. Game theory is a mathematical tool which can be applied for design, analysis, and optimization of multiple access and resource allocation in wireless networks. We first present a noncooperative auction game model to solve the bandwidth allocation problem for noncooperative channel access in a wireless network. In this model, we assume that the mobile nodes have information about other mobile nodes. Nash equilibrium is obtained as the solution of the auction game which gives the bandwidth share for each group of nodes. To address the problem of bandwidth sharing under unknown information about the opponent mobile nodes, we further develop a Bayesian auction game model. Bayesian Nash equilibrium is obtained as the solution of the auction game with incomplete information.

Next, we present a framework based on coalitional game for cooperative carry-and-forward-based data delivery in a wireless network. Each mobile node helps others to carry and then forward their data due to the limited coverage of wireless access points and to improve the transmission delay performance. A coalitional game is proposed to find a stable coalition structure for this cooperative data delivery. We next present a coalitional game for carry-and-forward-based data delivery in a wireless network under uncertainty. Each mobile node has incomplete information about types of other mobile nodes. A static Bayesian coalitional game is formulated to investigate how cooperative groups can be formed under the uncertainty of mobile nodes' types. Moreover, the static Bayesian game is extended to a dynamic Bayesian coalitional game. In this dynamic game, each mobile node can update its beliefs about other mobile nodes' types when the coalitional game is played repeatedly. As the game evolves, the payoff obtained from the Bayesian coalitional game can converge to the payoff obtained from the coalitional game with complete information.

Finally, we summarize the contributions of this thesis and present future research directions.

Table of Contents

Abstract **ii**

Table of Contents **iii**

List of Figures **ix**

List of Tables **xiii**

Acknowledgement **xv**

Dedication **xvi**

1 Introduction **1**

1.1 Overview of Multiple Access and Resource Allocation 3

1.1.1 General Concepts 3

1.1.2 Performance Issues in Multiple Access and Resource Allocation for Wireless Networks 5

1.1.3 Multiple Access and Resource Allocation Under Uncertainty . 5

1.2 Game Theory for Multiple Access and Resource Allocation 6

1.3 Objectives and Scope of this Research 8

1.4 Organization of the Thesis 9

1.5 Chapter Summary 14

2 Game Theory and Its Application to Multiple Access **15**

2.1 Overview of Game Theory Models 15

2.1.1 General Concepts 15

2.1.2 Game Theoretic Models 16

2.1.2.1 Noncooperative games 16

2.1.2.2 Cooperative games 19

2.2 Game Models for Contention-Free Channel Access 20

2.2.1 Channel Access Games in TDMA 21

2.2.1.1 Auction game-theoretic approach 21

2.2.1.2 Dynamic game-theoretic approach 22

2.2.1.3 Repeated game-theoretic approach 23

2.2.2 Channel Access Games in FDMA 24

2.2.2.1 Noncooperative static game-theoretic approach . . . 24

2.2.2.2 Auction game-theoretic approach 24

2.2.2.3 Cooperative game-theoretic approach 26

2.2.3 Channel Access Games in CDMA 27

2.2.3.1 Noncooperative static game-theoretic approach . . . 27

2.2.3.2 Cooperative static game-theoretic approach 29

2.3 Game Models for Random Channel Access 29

2.3.1 Channel access games in ALOHA-like protocols 29

2.3.1.1 Noncooperative game-theoretic approach 29

2.3.1.2 Evolutionary game-theoretic approach 31

2.3.1.3 Stackelberg game-theoretic approach 32

2.3.2 Channel Access Games in CSMA/CA Systems 32

2.3.2.1 Noncooperative static game-theoretic approach . . . 33

2.3.2.2 Noncooperative dynamic game-theoretic approach . 33

2.3.2.3 Incompletely-cooperative game-theoretic approach . 34

2.3.2.4 Incompletely-cooperative repeated game-theoretic approach 36

2.4 Chapter Summary 36

3 Distributed Noncooperative Channel Access: An Auction Game Model 39

3.1 Introduction 39

3.2 System Model and Assumptions 41

3.3 Auction Model 43

3.3.1 Bandwidth Allocation Strategy 43

3.3.2 Bidding Strategy 44

3.3.3 Nash Equilibrium 46
3.3.4 Procedure of the Auction Game 47
3.4 Numerical Study 48
3.4.1 Parameter Setting 49
3.4.2 Payoff and Best Response 49
3.4.3 Nash Equilibrium 50
3.4.4 Bidding Iteration and Bandwidth Allocation 50
3.5 Chapter Summary 53

4 Distributed Resource Allocation in Wireless Networks Under Uncertainty and Application of Bayesian Game 54

4.1 Introduction 54
4.2 Distributed Resource Allocation in Wireless Networks Under Uncertainty 55
4.2.1 Resource Allocation with Uncertainty 55
4.2.2 Approaches to Solve the Resource Allocation Problem Under Uncertainty 56
4.2.3 Game-theoretic Model with Incomplete Information 59
4.3 Bayesian Game Model for Distributed Resource Allocation Under Uncertainty 60
4.4 System Model and Assumptions 62
4.4.1 A Public Wireless Network 62
4.4.2 Queueing Analysis for a Mobile Node's Buffer Occupancy . . 63
4.4.2.1 Transition Matrix 64
4.4.2.2 Buffer Underrun Probability 65
4.5 Noncooperative Game Formulation for Bandwidth Auction 67
4.5.1 Bandwidth Allocation Strategy 67
4.5.2 Bidding Strategy 68
4.5.3 Optimal Bidding Strategy and Bayesian Nash Equilibrium . . 70
4.5.4 Distributed Algorithm for Bandwidth Auction Game 71
4.6 Numerical Study 71
4.6.1 Application Scenario 71

4.6.2 Parameter Setting 73
4.6.3 Required Transfer Rate 74
4.6.4 Bayesian Nash Equilibrium and Payoff 74
4.7 Chapter Summary 77

5 Distributed Cooperative Channel Access: A Coalitional Game Model 80
5.1 Introduction 80
5.2 System Model and Assumptions 84
5.2.1 Models for Mobile Node Encounter, Node Mobility, and Cooperative Packet Transmission 84
5.2.2 Hierarchical Structure of Cooperative Data Delivery 88
5.3 Social Network Analysis-Based Mobile Node Grouping 89
5.4 Formulation of Bargaining Game for Cooperative Packet Delivery . . 92
5.4.1 Markov Chain Model for Cooperative Packet Delivery 93
5.4.2 Nash Bargaining Game Model 97
5.4.3 Nash Bargaining Solution 98
5.5 Formulation of Coalitional Game for Cooperative Packet Delivery . . 99
5.5.1 Rational Coalition Formation 99
5.5.2 Stable Coalitional Structure 100
5.5.2.1 Distributed Merge-and-Split-Based Algorithm 101
5.5.2.2 Markov Chain-Based Analysis of the Coalitional Structure 101
5.5.3 Optimal Social Welfare Solution 104
5.6 Performance Evaluation 105
5.6.1 Simulation Parameters 105
5.6.2 Encounter Rate 107
5.6.3 Stable and Optimal Coalitional Structures 108
5.6.4 Payoff of the Vehicles and Coalition Formation 110
5.6.5 Packet Delivery Delay 113
5.7 Related Work 114
5.8 Chapter Summary 116

6 Distributed Cooperative Channel Access Under Uncertainty: A Dynamic Bayesian Coalitional Game 119

6.1 Introduction . . . 119
6.2 System Model and Assumptions . . . 122
6.2.1 Network and Communication Model . . . 122
6.2.2 Uncertainty in Node Behavior for Cooperative Packet Delivery 124
6.2.3 Cooperative Packet Delivery Protocol . . . 126
6.3 Formulation of the Bayesian Coalitional Game Model . . . 127
6.3.1 Bayesian Coalitional Game with Non-Transferable Utility . . 127
6.3.2 Coalition Formation . . . 130
6.3.3 Coalition Formation Algorithm . . . 131
6.4 Analysis of the Bayesian Coalitional Game . . . 132
6.4.1 Bayesian Nash-Stability . . . 134
6.4.2 Discrete-Time Markov Chain-Based Analysis of Coalition Formation . . . 135
6.4.3 Bayesian Core . . . 137
6.5 Dynamic Bayesian Coalitional Game . . . 140
6.5.1 Belief Update Mechanism . . . 141
6.5.2 Distributed Algorithm . . . 143
6.6 Performance Evaluation . . . 144
6.6.1 Simulation Parameters and Assumptions . . . 145
6.6.2 Numerical Results . . . 146
6.6.2.1 Nash-stable Coalitional Structure . . . 146
6.6.2.2 Payoffs of the Nodes . . . 149
6.6.2.3 Dynamic Bayesian coalitional game . . . 153
6.7 Related Work . . . 154
6.8 Chapter Summary . . . 156

7 Discussions and Summary 157

7.1 Discussions . . . 158
7.1.1 Complexity and Scalability of the Proposed Algorithms . . . 158
7.1.2 Core Solution in Coalitional Games . . . 159

7.2 Summary of Contributions 160
7.3 Open Problems and Future Directions 163

Bibliography **166**

Appendix A **177**
A.1 Proof of the Uniqueness of Bayesian Nash equilibrium 177

Appendix B **181**
B.1 Markov Chain Model for Cooperative Packet Delivery 181
B.1.1 Formulation of the CTMC 181
B.1.2 Average Utility 184
B.1.3 Average Cost 185

Appendix C **186**
C.1 Result of Running Algorithm 2 with Ten Vehicles 186

List of Figures

Figure 2.1 Coalitions of players are formed following the game model by F. Shams, G. Bacci, and M. Luise [28] when there are 3 mobile nodes and 3 subchannels. 26

Figure 3.1 Schematic diagram shows mobile nodes connected to a wireless access point. 42
Figure 3.2 Payoff function and best response of Group 2 under different bidding prices of Group 1. 50
Figure 3.3 Nash equilibrium for the auction game between Group 1 and Group 2. 51
Figure 3.4 Bidding prices of both groups at each bidding iteration. 51
Figure 3.5 Amount of bandwidth given to Group 2 and then divided to each member when Group 1's bid price is 8 mu/Mbits and Group 2's bidding price varies. 52
Figure 3.6 Amount of bandwidth given to each group and its members at each bidding iteration. 52

Figure 4.1 Schematic diagram of a public wireless network. A mobile node caches the streaming content when connected to a wireless access point. 62
Figure 4.2 Diagram showing the interaction between queueing model and bandwidth auction. 66
Figure 4.3 Minimum transfer rate of vehicle 1 when t_{on} and t_{off} are varied with the target buffer underrun probability $P_{\text{under},1} = 0.25$. 74
Figure 4.4 Bayesian Nash equilibrium in the bandwidth auction game among three vehicles. 75
Figure 4.5 Bidding price and amount of bandwidth for the three vehicles at each bidding round. 76

Figure 4.6 Comparison between the payoffs of (a) vehicle 1 and (b) vehicle 2 from Bayesian Nash equilibrium (BNE), Nash equilibrium (NE) in an incomplete information environment, and Nash equilibrium (NE) in a complete information environment when the expected speed and its variance of vehicle 3 observed by other vehicles is varied. 79

Figure 5.1 In a hybrid wireless network, the mobile nodes can form coalitions to help forward data from a base station to other mobile nodes which are out of the transmission range of the base station. 81

Figure 5.2 Diagram showing the interrelationship among the three steps, namely, mobile node grouping using social network analysis (SNA), bargaining game, and coalitional game. 82

Figure 5.3 Diagram showing the relation between social groups and coalitions. There can be multiple coalitions within a social group. 93

Figure 5.4 The CTMC model for cooperative packet delivery from the BS to a destination mobile node. In this scenario, there are 3 mobile nodes in the same coalition. Mobile nodes 1 and 2 help the BS to deliver a packet to mobile node 3. 95

Figure 5.5 A grid road network used in the simulation. 106

Figure 5.6 Cumulative distribution function of the time interval between two consecutive encounters of a pair of vehicles. 108

Figure 5.7 Encounter rate between vehicle 1 and other vehicles when the transmission range of vehicles is varied. 109

Figure 5.8 Stationary probability of stable rational and optimal structures. 110

Figure 5.9 Probability that each vehicle will help deliver other vehicles' packets. 110

Figure 5.10 Stable coalitional structure obtained from the merge-and-split algorithm when the number of coalitions that can be merged and split at a time is 2. 111

Figure 5.11 Total payoff of all the vehicles under different cost-coefficient. 111

Figure 5.12 Expected payoff of each vehicle under different values of cost-coefficient. The coalitional structure changes when the cost-coefficient is varied. 112

Figure 5.13 Expected total payoff of all the vehicles under different transmission range of vehicles. 113
Figure 5.14 Expected packet delivery delay of each vehicle under different values of cost-coefficient. 114

Figure 6.1 In a wireless network, mobile nodes can form coalitions to help forward data from a base station to other mobile nodes which are out of the transmission range of the base station. 120
Figure 6.2 State transition diagram of the discrete-time Markov chain (DTMC) for coalition formation among 3 players. 136
Figure 6.3 Stationary probability of the Nash-stable rational coalitional structures with incomplete and complete information and optimal coalitional structure. 147
Figure 6.4 Nash-stable coalitional structure obtained from the individual preference-based algorithm. 147
Figure 6.5 (a) Nash-stable coalitional structures with incomplete information, (b) Nash-stable coalitional structures with complete information, and (c) optimal coalitional structures under different values of cost-coefficient. 148
Figure 6.6 Total payoff of all the vehicles under different values of cost-coefficient. 149
Figure 6.7 Average payoffs obtained from the proposed coalitional game with incomplete information (i.e., both expected and actual payoffs), with complete information, and without coalition: (a) for vehicle 1, (b) for vehicle 2, (c) for vehicle 3, and (d) for vehicle 4. 151
Figure 6.8 (a) Vehicle 4's belief probabilities that vehicles 1, 2, and 3 are well-behaved (i.e., p_{41}, p_{42}, p_{43}), and (b) vehicle 4's belief probabilities that vehicles 1, 2, and 3 will refuse to deliver a packet (i.e., ς_{41}, ς_{42}, ς_{43}). 152
Figure 6.9 Nash-stable coalitional structure during each period of coalition formation. 153

Figure B.1 DTMC for cooperative packet delivery from a base station to the destination mobile nodes. 182

Figure C.1 Bid price and amount of bandwidth for ten vehicles at each bidding round. 187

List of Tables

Table 1.1 List of abbreviations 13

Table 2.1 Summary of channel access games 38

Table 3.1 List of symbols used in Chapter 3 41

Table 4.1 List of symbols used in Chapter 4 61
Table 4.2 Required SNR and transmission rate using adaptive modulation and convolutional coding [66]. 66

Table 5.1 List of symbols used in Chapter 5 85
Table 5.2 List of symbols used in Chapter 5 (continued) 86
Table 5.3 Default values of simulation parameters 107
Table 5.4 Rates (r_{ij}) per second that each vehicle meets other vehicles and a base station on a road 108
Table 5.5 15 different coalitional structures for 4 vehicles 109
Table 5.6 Summary of Related Work 117

Table 6.1 List of symbols used in Chapter 6 123
Table 6.2 List of symbols used in Chapter 6 (continued) 124
Table 6.3 Solution concepts and the corresponding conditions for the proposed cooperative packet delivery game 140
Table 6.4 Default values of parameters 145
Table 6.5 Rates (r_{ij}) per second that each vehicle meets other vehicles and an RSB on a road 145
Table 6.6 15 different coalitional structures for 4 vehicles 146

Table 7.1 Approaches to find the existence of the core and the payoffs that lie in the core of a coalitional game [20] 160

Table C.1 Parameter Setting 186

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To my family

Chapter 1

Introduction

Wireless communications and networking technology has become an important part of our daily life. It provides flexibility in communications and improve productivity of users. Nowadays, wireless devices such as laptops, smart phones have become essential elements in our life to connect with people, exchange information, and enjoy different infotainment services. In a wireless network, mobile users may have different quality-of-service (QoS) requirements which need to be satisfied using the limited available radio resources (e.g., radio bandwidth, transmission power). Also, due to the limited coverage area of the wireless access points (depending on the location and mobility of the users) and limited amount of radio resources, the wireless connectivity may not be fully available for all the users throughout an entire service area. Therefore, the users may have to share their connectivity with other users. Hence, resource allocation mechanisms need to be optimized considering different performance measures for the users, such as throughput, delay, and fairness. While throughput and delay are measured from the individual node's perspective, fairness is measured from the network perspective. The network must be able to allocate the resources to all active nodes in a fair manner.

Radio resources in a wireless network can be allocated to the users either in a centralized fashion or a distributed fashion. With centralized resource allocation, a centralized controller (e.g., a base station) collects information about the QoS requirements of the mobile nodes and then allocates the network resources to the mobile nodes accordingly. Although centralized radio resource allocation schemes can achieve optimal network performance, they suffer from the computational complexity, signaling overhead, and scalability problems since all the information of all the mobile nodes or users needs to be analyzed only at the centralized controller. Alternatively, since the decisions can be made locally without exchanging all information among the nodes and the network controller, distributed resource allocation schemes are more scalable, and are viable for networks without any centralized controller (e.g., an ad hoc network). Nevertheless, distributed resource allocation has to address the incomplete information and uncertainty issues for decision making.

The mobile nodes sharing the limited radio resources in a wireless network may have different behaviors. We can describe the mobile nodes' behaviors using two main scenarios. The first one is a scenario of *group rationality* in which all mobile nodes can be cooperative to meet their social welfare requirements, i.e., achieve optimal network performance. The second one is a scenario of *self-interest* in which the mobile nodes are noncooperative and compete with each other for the radio resources. These two types of scenarios can be modeled as games. Game theory has become a very useful mathematical tool to model and analyze multiple access schemes in wireless networks, and to obtain solutions for resource allocation, channel assignment, power control, and cooperation enforcement among the nodes.

Game theory is a branch of applied mathematics which is concerned with how rational entities make decisions in a situation of conflict [1]. It provides a rich set of mathematical tools to model and analyze interactions among the rational entities, and the rationality is based on gains or payoffs perceived by these entities. Game theory has been primarily used in Economics. It has also been used in other disciplines such as Biology, Political Science, Engineering, and Philosophy. One of the major areas in Engineering where game theory has been used is data communication networking. In particular, it has been used to model and analyze routing and resource allocation problems in a competitive environment, and more recently to model security problems in wireless networks. Applicability of game theory tools to analyze power control, waveform adaptation, medium access, routing, and node participation was discussed in [2] from a layered perspective.

In this research, we address the problem of designing distributed multiple access and resource allocation methods for wireless networks using game theory. Game theory can model a multi-player decision making process and analyze how players interact with each other during the process. There can be different solution concepts for a game. Most of the solution concepts deal with finding an equilibrium point. The well-known equilibrium concepts are Nash equilibrium and Pareto efficiency [1]. A player will receive an optimal or fair payoff given other players' strategies if the equilibrium point is reached.

1.1 Overview of Multiple Access and Resource Allocation

In this section, the general concepts of channel access and resource allocation and performance issues related to multiple access design in wireless networks are discussed.

1.1.1 General Concepts

Channel access methods in wireless networks can be divided into two main groups, namely, contention-free channel access and contention-based random channel access schemes. In contention-free schemes, multiple nodes are allocated with the radio resources (e.g., time slot, channel, and code) by a central entity and the nodes use the allocated resources for data transmission [3]. Contention-free channel access can be used in time-division, frequency-division, and code-division multiple access networks.

- *Time-division multiple access (TDMA)*: In TDMA, time is divided into fixed-length frames and each frame is divided into multiple time slots. Time slots are allocated to the nodes for data transmission. In TDMA, synchronization among the nodes is required to avoid interference [4].
- *Frequency-division multiple access (FDMA)*: In FDMA, radio frequency band is divided into multiple channels. The channels are allocated to the nodes for data transmission. Orthogonal frequency-division multiple access (OFDMA) is an improved version of FDMA which is based on the orthogonal frequency-division multiplexing (OFDM) modulation in the physical layer. In OFDMA, frequency band is divided into multiple subcarriers which are shared among the nodes. OFDMA is used in the IEEE 802.16-based WiMAX networks [5].
- *Code-division multiple access (CDMA)*: In CDMA, multiple nodes can transmit data on the same channel simultaneously. The transmitted data by each node is

encoded by using a unique spreading code. The spreading codes for the different users are orthogonal/near-orthogonal to each other. The receiver of each node can decode the original data correctly if the signal-to-interference-plus-noise ratio (SINR) is maintained above a threshold.

For contention-based random access schemes, a node has to compete with other nodes to transmit data over the wireless channel. A packet transmitted by a node will be received successfully if there is no collision. A collision occurs when multiple nodes transmit data simultaneously and the SINR at the receiver is lower than the minimum SINR required to decode the original packet correctly. If collision occurs, a node may attempt to retransmit the packet, and the specifics of the retransmission method depend on the protocol used. The most common contention-based channel access schemes are as follows [6]:

- *ALOHA*: In ALOHA, if a node has a packet to send, it will attempt to transmit the packet immediately. If the packet collides with packets from other nodes, the node will retransmit the packet later. The ALOHA protocol can be operated in a slotted fashion, in which case, time is divided into slots, and packet transmissions are aligned with the time slots.
- *Carrier sense multiple access (CSMA)*: CSMA is a probabilistic medium access method in which a node senses the status of the channel before attempting transmission. If the channel is idle, the node initiates a transmission attempt. If the transmission is unsuccessful due to a collision, the node waits for a packet retransmission interval and transmits again. Two of the improved variants of CSMA are CSMA with collision detection (CSMA/CD) and CSMA with collision avoidance (CSMA/CA). In CSMA/CD, assuming that a node is able to detect a collision, a transmission is terminated as soon as a collision is detected. The collision can be avoided by expanding the retransmission interval (i.e., backoff period) for the node to wait before a new transmission. In CSMA/CA, if the channel is sensed busy before transmission, to decrease the probability of collisions on the channel, transmission is postponed for a random backoff period of time between 1 and CW where CW is contention window in units of slot time.

1.1.2 Performance Issues in Multiple Access and Resource Allocation for Wireless Networks

The key requirements for the design and optimization of multiple channel access and resource allocation schemes for wireless networks are as follows [7]:

- *Maximize network throughput*: Throughput refers to the amount of data successfully transmitted by the nodes over a time period. Maximizing the overall system throughput is a key objective of most of the multiple access schemes. This in turn improves the spectrum efficiency in wireless networks.
- *Minimize delay*: Delay refers to the time required for a packet to be transmitted successfully since it has been received at the transmission buffer from the upper layer. Delay is a key performance metric for real-time traffic (e.g., voice and video). Multiple channel access schemes for such traffic have to minimize delay.
- *Guarantee fairness*: Fairness is a measure of whether the nodes are receiving an equal (or fair) share of radio resources. Multiple channel access schemes must guarantee a certain level of fairness to all nodes in the network.
- *Improve power efficiency*: Power efficiency is an important performance metric for battery-powered wireless nodes. There is a tradeoff between power efficiency and network performance. To reduce power consumption, a node can be put in standby mode during which the node cannot transmit and/or receive packets. Consequently, the throughput reduces.

1.1.3 Multiple Access and Resource Allocation Under Uncertainty

In a wireless and mobile communications environment, uncertain or unknown network parameters, which are involved in distributed resource allocation, include channel state information, number of competing mobile nodes, bandwidth and QoS requirements of the mobile nodes, and mobility patterns. The parameters are uncertain or unknown due to the lack of any information collector, and/or selfish behavior of the mobile nodes, and/or the random nature of the system. As an example, consider the uplink transmission scenario in a cellular wireless system in a fading environment, where multiple mobile nodes transmit in the uplink direction to the same base station simultaneously. The objective of each mobile node is to maximize its transmission rate subject to the power constraint. However, information of other nodes (e.g., number of mobile nodes competing for the resources, channel quality, QoS requirements, and mobility patterns) is private. Therefore, to achieve the optimal or nearly optimal solution of the resource allocation, the values of unknown or uncertain parameters have to be estimated. Different mathematical and statistical techniques can be used to estimate the values of unknown system parameters, and subsequently, decisions can be made in a distributed manner.

1.2 Game Theory for Multiple Access and Resource Allocation

The notion of *multiple access game* can be illustrated by the following example [8, 9]. Suppose that there are two mobile nodes tx_1 and tx_2 who want to access a shared wireless channel to send information to the corresponding receivers $rcvr_1$ and $rcvr_2$. Both the receivers are within the transmission range of both the transmitters. Each transmitter has one packet to transmit in each time step and it can either choose to transmit during a time step or wait. If tx_1 transmits, the packet is successfully transmitted if tx_2 chooses not to transmit during that time step (and hence there is no collision). For successful packet transmission, tx_1 obtains a benefit while its transmit power is considered as the cost of this transmission. It is of interest to analyze the interactions between the transmitters under different network settings and performance objectives.

Different game models (e.g., noncooperative/cooperative, static/dynamic, and complete/incomplete information games) have been developed to study the behavior of transmitting nodes to access the wireless channel(s) and obtain the multiple access solution (or equilibrium) [8, 10]. Various game models are considered under different scenarios, perspectives, or assumptions on transmitting nodes' behavior. Nevertheless, the common aim of these models is to improve network performance (e.g., throughput maximization, resource consumption minimization, and QoS guarantee) given self-interest or group-rationality of transmitting nodes.

The motivations of using game models for design, analysis, and optimization of multiple access and resource allocation in wireless networks are as follows:

- *Theoretical foundation for multiple access schemes*: Game theory, which is most notably used in Economics, usually considers a multiplayer decision problem. A success or benefit of an individual in making decisions depends on the decisions of others. Game theory provides a theoretical basis to analyze interactions in multiplayer systems including human as well as non-human players (e.g., computers, animals, and plants) [11]. Therefore, it can be applied to a wireless communication network in the context of resource sharing where the players are the nodes (e.g., mobile stations, base stations, access points) in the network. Cooperation or competition among mobile nodes for channel access in a wireless network is a multiplayer decision problem that can be modeled as a game. The benefit of a node as a result of its chosen action (i.e., strategy or move) can be measured in terms of performance metrics such as throughput or delay. An equilibrium solution of the game model defines the actions of the different nodes (e.g., transmission power) for which the chosen performance objective is optimized.
- *Modeling selfish/malicious behavior of nodes*: The transmitting nodes in a wireless network may behave selfishly in order to reap performance advantage over other nodes, as a result of which the overall network performance may degrade. To make the network robust against the selfish behaviors (or attacks) by these malicious nodes, efficient defense mechanisms have to be built into the system. Game theory can be used to model and analyze the selfish behavior of nodes and design the defense mechanisms for robust multiple access in wireless networks.
- *Distributed protocols*: In many scenarios, wireless nodes make their decisions in an individual (or distributed) manner rather than in a centralized manner. Then, game theory, which is a suitable tool to optimize wireless access distributively [12], can be used to solve problems of individual decision making. In a centralized scheme, solving the problem of multiple access may become computationally expensive when the network size increases. Also, the network control overhead could be prohibitive. In contrast, efficient distributed algorithms can be designed based on game theory which can reduce the communication and

computation overhead significantly. Therefore, game theory is a useful tool to develop efficient distributed protocols for wireless networks. With an appropriate game formulation, cross-layer optimization can be also performed in a distributed way.

- *Mechanism design*: The parameters of a game can be designed (or varied) such that it leads the independent and self-interested wireless nodes toward a system-wide desirable outcome. Pricing is one technique that can be used for such mechanism design (or incentive scheme) to regulate the usage of radio resources by the wireless nodes.

1.3 Objectives and Scope of this Research

The primary objective of this research is to develop and analyze game theoretic models for multiple access and resource allocation in wireless networks. We consider both noncooperative and cooperative scenarios where rational mobile nodes share the limited radio resources in a wireless network. We aim at

(i) designing, analyzing, and solving the problem of multiple access and resource allocation among rational mobile nodes in wireless communications networks using game theoretic models,

(ii) considering both noncooperative and cooperative game models for different scenarios of multiple access and resource allocation problems,

(iii) considering uncertainty in system parameters while performing resource allocation,

(iv) developing decentralized algorithms to optimize resource allocation in multi-access wireless networks based on the theoretical basis of game theory.

We primarily focus on modeling, analysis, and simulation of the game theoretic models. We consider realistic system parameters to define the utility and cost functions for the players in the game models. The developed game models are evaluated considering practical application scenarios such as vehicle-to-roadside communications in a vehicular network. The research thus contributes to the field of applied game theory as well as the field of wireless communications systems design.

1.4 Organization of the Thesis

In this thesis, we focus on two main scenarios in multiple access and resource allocation for wireless networks as follows:

- *Single-hop transmission*: a mobile node can be directly connected to a base station/access point. Then, when several mobile nodes are connected to the wireless access point at the same time, the bandwidth allocation problem in the multi-access wireless network happens. The bandwidth of the link to the wireless access point has to be shared among these mobile nodes. Then, each mobile node competes with others to obtain an amount of bandwidth when the total demand of the bandwidth is greater than its available quantity. This scenario will be considered in *Chapter 3* and *Chapter 4*.
- *Multi-hop transmission*: a base station has packets to transmit to a mobile node. However, this mobile node may not be in the transmission range of the base station. Then, other mobile nodes can help store and forward packets to the mobile node. This problem is related to the concept of delay-tolerant networks. When the mobile nodes encounter each other, they can then connect and forward packets. Then, a cooperative game can analyze the behavior of mobile nodes which helps each other to forward data packets based on their individual selfishness. This scenario will be considered in *Chapter 5* and *Chapter 6*.

Motivated by these two key problems, we propose noncooperative and cooperative game-theoretic models. Moreover, we consider the game models with either complete or incomplete information (i.e., uncertain parameters) while we are solving the problems. The organization of this thesis is shown as follows.

In *Chapter 2*, we provide an overview of different game theoretic models and their applications.

In *Chapter 3*, we deal with the bandwidth allocation problem in a multi-access wireless network where several mobile nodes are connected to a wireless access point at the same time, and the bandwidth of the link to the wireless access point has to be shared among these mobile nodes. We propose a noncooperative auction game model, where mobile nodes in a neighborhood (e.g., users in a vehicle) form a group. In order to obtain its required amount of bandwidth, each group has to compete with other groups by offering bid prices to the wireless access point. Each group of mobile nodes tries to maximize its payoff which is calculated by the allocated amount of bandwidth and the price to be paid for bandwidth sharing. The bandwidth allocation to all the groups is performed by the wireless access point using a fair allocation strategy. Based on the solution of the game model, we present a distributed iterative algorithm to solve the bandwidth allocation problem. Then, the Nash equilibrium [1] (i.e., bid prices and corresponding allocated bandwidth), which is the solution of the proposed game model, is obtained.

In *Chapter 4*, we also deal with the bandwidth allocation problem in a multi-access wireless network. However, in this case, we consider the case that information of a mobile node is not known completely by other nodes. That is, individual wireless nodes have to make a decision without having complete information about the other nodes (e.g., speed of movement, bandwidth demand) in the network. Our objective is to analyze a conflicting situation among multiple mobile nodes competing for the shared bandwidth from a wireless access point in its coverage area. The mobility and application QoS parameters of the mobile nodes are considered to obtain the required amount of bandwidth for a mobile node. A noncooperative game model with incomplete information, namely, a Bayesian game model is developed to solve the problem. The Bayesian Nash equilibrium [1], which is the solution of the proposed game model, is then compared to the Nash equilibrium solution with incomplete information. Also, a distributed algorithm is presented that achieves the solution. An example scenario of this game model is presented for vehicle-to-roadside communications in a public transportation system.

In *Chapter 5*, we deal with cooperative channel access problem in downlink data transmission from a wireless access point to mobile nodes. Wireless access points act as gateways between mobile nodes and other terrestrial networks such as the Internet for data transfer. Some mobile applications and services such as safety and emergency, infotainment, and real-time traffic applications require short communication time. For these applications, mobile nodes may be able to receive information in a timely manner if they are connected to the wireless access points. However, the transmission range of the wireless access points is limited, and the data from an wireless access point cannot be transferred to the mobile nodes outside its transmission range. A wireless access point can transfer data to mobile nodes in its transmission range only. Once these mobile nodes carrying data move and meet other mobile nodes (i.e., destination mobile nodes) outside the transmission range of the wireless access point, the data is forwarded to the destination mobile nodes. This carry-and-forward-based cooperative data delivery is useful for various mobile applications (e.g., vehicle safety and infotainment applications). We develop such a carry-and-forward-based cooperative data delivery scheme. To study the behavior of the proposed scheme, a social network analysis (SNA)-based approach and a cooperative game model (which is a combination of a coalition formation game and a Nash bargaining game) are used. A Nash-stable coalitional structure, which is a solution of the coalitional game that no mobile node has an incentive to move from its coalition to another coalition, is then obtained. A comprehensive performance evaluation is carried out for the proposed framework.

In *Chapter 6*, we deal with cooperative channel access problem under uncertainty in downlink data transmission from a wireless access point to mobile nodes. Cooperative packet delivery can improve the data delivery performance in wireless networks by exploiting the mobility of the nodes, especially in networks with intermittent connectivity, high delay and error rates such as wireless mobile delay-tolerant networks (DTNs). For such a network, we study the problem of rational coalition formation among mobile nodes to cooperatively deliver packets to other mobile nodes in a coalition. Such coalitions are formed by mobile nodes which can be either well-behaved or misbehaving in the sense that the well-behaved nodes always help each other for packet delivery, while the misbehaving nodes act selfishly and may not help the other nodes. A Bayesian coalitional game model is developed to analyze the behavior of mobile nodes in coalition formation in presence of this uncertainty of node behavior (i.e., *type*). Given the beliefs about the other mobile nodes' *types*, each mobile node makes a decision to form a coalition, and thus the coalitions in the network vary dynamically. A solution concept called Nash-stability is considered to find a stable coalitional structure in this coalitional game with incomplete information. We present a distributed algorithm and a discrete-time Markov chain (DTMC) model to find the Nash-stable coalitional structures. We also consider another solution concept, namely, the Bayesian core, which guarantees that no mobile node has an incentive to leave the grand coalition. The Bayesian game model is extended to a dynamic game model for which we propose a method for each mobile node to update its beliefs about other mobile nodes' *types* when the coalitional game is played repeatedly. The performance evaluation results show that, for this dynamic Bayesian coalitional game, a Nash-stable coalitional structure is obtained in each subgame. Also, the actual payoff of each mobile node is close to that when all the information is completely known. In addition, the payoffs of the mobile nodes will be at least as high as those when they act alone (i.e., the mobile nodes do not form coalitions).

Finally, *Chapter 7* summarizes the research contributions presented in this thesis, and points out interesting avenues for future research.

We provide the list of abbreviations that are commonly used throughout this thesis as shown in Table 1.1. More specific symbols and their definitions used in our game models will be listed later in each chapter.

Table 1.1. *List of abbreviations*

Abbreviation	Definition
AP	Access point
BER	Bit error rate
BNE	Bayesian Nash equilibrium
BS	Base station
CDMA	Code-division multiple access
CRISP	cooperation via randomized inclination to selfish/greedy play
CSMA	Carrier sense multiple access
CSMA/CA	Carrier sense multiple access with collision avoidance
CSMA/CD	Carrier sense multiple access with collision detection
CTMC	Continuous-time Markov chain
CW	Contention window
DTMC	Discrete-time Markov chain
DTN	Delay-tolerant network
EMA	Exponential moving average
ESS	Evolutionarily stable strategy
FDMA	Frequency-division multiple access
FIFO	First in, first-out
ITS	Intelligent transportation systems
KKT	Karush-Kuhn-Tucker
MAC	medium access control
MANET	Mobile ad hoc network
MDP	Markov decision process
MKPAR	Multiple knapsack problem with assignment restrictions
NE	Nash equilibrium
NTP	Non-transferable payoff
OFDMA	Orthogonal frequency-division multiple access
PBE	Perfect Bayesian equilibrium
PDF	Probability density function
POMDP	Partially observable Markov decision process
QoS	Quality-of-service
RSB	Roadside base station
SINR	Signal-to-interference-plus-noise ratio
SDSE	Strongly dominant strategy equilibrium
SNA	Social network analysis
SNR	Signal-to-noise ratio
SPRING	Social-based privacy preserving packet forwarding protocol
SUMO	Simulation of Urban MObility
TDMA	Time-division multiple access
TSP	Transportation service provider
TTl	Time-to-live
V2R	Vehicle-to-roadside
VDTN	Vehicular delay-tolerant network
WiFi	Wireless fidelity
WiMAX	Worldwide interoperability for microwave access

1.5 Chapter Summary

We have provided an introduction to the multiple access problem in wireless networks and discussed the motivations of using game theoretic models to solve the problem. The objectives of the research and the outline of the rest of the thesis have been provided.

Chapter 2

Game Theory and Its Application to Multiple Access

In this chapter, we review the existing literature on game theoretic approaches for channel access and resource allocation in a multi-user wireless network. In this context, different types of game models are reviewed for both contention-free and random channel access schemes. For contention-free channel access, time-division multiple access (TDMA), frequency-division multiple access (FDMA), and code-division multiple access (CDMA)-based wireless networks are considered. For contention-based channel access, game models for ALOHA and carrier sense multiple access (CSMA)-based channel access methods are reviewed.

2.1 Overview of Game Theory Models

In this section, the basic concepts used in game theory are discussed and different game models are briefly introduced. The issues pertinent to using game theory to analyze multiple access schemes in wireless networks are also discussed.

2.1.1 General Concepts

A game is defined by a set of players, a set of actions for each player, and the payoffs for the players. A player chooses an action and the complete plan of action is referred to as the strategy. When the action is chosen deterministically, it is called a pure strategy. On the other hand, when the action is chosen probabilistically according to a certain probability distribution, it is called a mixed strategy. Based on the strategies of the players, their payoffs are determined. Depending on the nature of the game, there are different solution concepts, e.g., Nash equilibrium, subgame perfect equilibrium, and perfect Bayesian equilibrium. However, almost all of them rely on the equilibrium concept which ensures that a player will gain a fair or optimal payoff given the strategies of other players in the game. Pareto optimality or Pareto efficiency [1] is another well-known concept in a game. A strategy is called Pareto optimal if it is impossible to make one player better off without necessarily making other players worse off.

2.1.2 Game Theoretic Models

Two major game-theoretic approaches which can be used to model multiple access schemes are noncooperative and cooperative game approaches. In a noncooperative game, the players make rational decisions by considering only their individual payoffs. In a cooperative game, players are grouped together and establish an enforceable agreement in their group.

2.1.2.1 Noncooperative games

Self-interested players in a noncooperative game make decisions independently. The players are unable to make enforceable contracts but it does not mean that players do not cooperate. Any cooperation in the games must be self-enforcing. Noncooperative game theory has been used extensively to study various issues in wireless networks (e.g., medium access control (MAC) game, time slot competition, and power control in CDMA). The goal of a noncooperative game model is to find the equilibrium solution for networks with self-interested nodes. A well-known solution concept for a noncooperative game is *Nash equilibrium* [1]. A Nash equilibrium is a set of strategies for the players such that no player has any intention to change his/her strategy to gain a higher payoff given that all the other players do not change their strategies.

Let i be an index of a player, $i \in \mathbb{M} = \{1, \ldots, M\}$ where $\mathbb{M}$ is a set of players and M is the total number of players. Let $\mathbb{S}_i$ denote a set of strategy of player i. $s_i \in \mathbb{S}_i$ is any possible strategy of player i. The Nash equilibrium satisfies the following condition [1]:

$$u_i(s_i^*, \mathbf{s}_{-i}^*) \geq u_i(s_i, \mathbf{s}_{-i}^*), \quad \forall i \in \mathbb{M}, \quad \forall s_i \in \mathbb{S}_i \tag{2.1}$$

where $u_i(\cdot)$ is the payoff function of player i, s_i^* is a Nash equilibrium strategy of player i, and $\mathbf{s}_{-i}^*$ is a Nash equilibrium strategy vector of all players except player i. However, a Nash equilibrium may not exist in a game. Also, even if a Nash equilibrium exists, it may not be unique.

Another solution concept which is more general than the Nash equilibrium is known as *correlated equilibrium* [13]. In this concept, a strategy profile is chosen according to the joint distribution instead of the marginal distribution of players' strategies as in the Nash equilibrium solution. The definition of correlated equilibrium is given below. Let $\mathbb{S}_i$ denote a set of strategies of player i. A probability distribution π over $\mathbb{S}_1 \times \cdots \times \mathbb{S}_M$ is a correlated equilibrium if for every strategy $s_i^* \in \mathbb{S}_i$ such that $\pi(s_i^*, \mathbf{s}_{-i}) > 0$, and every alternative strategy $s_i \in \mathbb{S}_i$, it holds that,

$$\sum_{\mathbf{s}_{-i} \in S_{-i}} \pi(s_i^*, \mathbf{s}_{-i})[u_i(s_i^*, \mathbf{s}_{-i}) - u_i(s_i, \mathbf{s}_{-i})] \geq 0, \qquad \forall i \in \mathbb{M}, \quad \forall s_i \in \mathbb{S}_i. \tag{2.2}$$

To interpret this definition, given a recommendation (i.e., a recommended strategy according to the distribution π) to player i, a distribution π is defined to be a correlated equilibrium if no player i can choose a strategy s_i instead of s_i^* which results in a higher expected payoff.

A noncooperative game can be classified as either a complete or an incomplete information game. In a complete information game, information such as the payoffs and strategies of the players can be observed by all the players. On the other hand, in an incomplete information game, the information is unknown by other players. An incomplete information game can be modeled as a Bayesian game [1] in which Bayesian analysis is used to predict the outcome of the game. The equilibrium solution of such a game is called *Bayesian Nash equilibrium* [1]. Similar to the Nash equilibrium in a complete information game, a Bayesian Nash equilibrium can be obtained in which each player seeks for a strategy profile that maximizes its expected payoff given its beliefs about the *types* and strategies of other players.

Moreover, a game can be classified as either a static game or a dynamic game. A static game is a one-shot game where all players make decisions without knowledge of the strategies that are being chosen by other players. The one-shot game ends when actions of all players are chosen and payoffs are received. In contrast, in a dynamic game, a player chooses an action in the current stage based on the knowledge of the actions chosen by the other players in the current or previous stages. This dynamic game can be called a sequential game since players play a static game repeatedly. The common equilibrium solution in dynamic games is a subgame perfect Nash equilibrium [14]. A subgame perfect Nash equilibrium represents a Nash equilibrium of every subgame of the original game. A common method to obtain subgame perfect equilibria is backward induction.

A dynamic game with incomplete information can be described as a multi-stage game when information is unknown to other players [1]. It is similar to a dynamic game with complete information in that the players take turns sequentially rather than simultaneously but information is incompletely known to others. The players follow their beliefs and dynamically update their beliefs by using the Bayes' rule. In a dynamic game with incomplete information, perfect Bayesian equilibrium is the solution concept which can be considered as a combination of the Bayesian Nash equilibrium and subgame perfect equilibrium concepts.

Repeated game [1] is a special kind of dynamic game in which the same set of players plays the same stage game or one-shot game repeatedly over a long time period. Repeated games can be divided into two key types, namely, finite and infinite repeated games, depending on whether the period of time during which the game is played is finite or infinite. Most repeated games are typically infinite repeated games and a player takes into account the effect of his/her current action on the future actions of other players.

Markovian game (i.e., Markovian dynamic game or Markov game) [15, 16] is an extension of game theory to Markov Decision Process-like environments . A Markovian game can be defined as a type of stochastic game which can be regarded as a multiagent extension of Markov decision process [17]. The key difference between a Markov game and a Markov decision process is that a transition depends on the current state and the action profile of the players. Also, each player may receive different reward as a result of the action profile. Each player has a reward function (i.e., payoff function) and tries to maximize its expected sum of discounted reward. A more specific type of Markovian game is a *switching controlled Markovian game* where the transition probability in any given state depends on the action of only one player. The Nash equilibrium for such a game can be computed by solving a sequence of Markov decision processes.

Auction game is a game theoretic approach in which an object or service is exchanged on the basis of bids submitted by the bidders to an auctioneer [18]. There are two main auction mechanisms, namely, the first and second price auctions. In first price auction, an object or service is given to a bidder who submitted the highest bid and pays a price equal to the amount of bid. In second price auction, an object or service is given to a bidder who submitted the highest bid and pays a price equal to the second highest amount of bid.

Stackelberg game or leader-follower game [1] is a strategic game in which the player acting as a leader moves first and then the rest acting as followers move afterward. Then, the problem is to find an optimal strategy for the leader, assuming that the followers react in such a rational way that they optimize their objective functions given the leader's actions. The Stackelberg game model can be solved by subgame perfect Nash equilibrium.

Evolutionarily stable strategy (ESS) [19] is a solution concept in the evolutionary game theory. In this game, the evolution of social behaviour of animals in a population is considered. In a wireless network, a population can be a group of mobile nodes sharing the channels. A strategy is called an ESS if in a fixed population, the entire population using ESS cannot be invaded by mutant strategies of a small group.

2.1.2.2 Cooperative games

In a cooperative game, players are able to make enforceable contracts. The players in a coalition cooperate to maximize a common objective of a coalition. In this case, players can coordinate strategies and agree on how the total payoff is to be divided among players in a coalition. Nash bargaining game is one type of cooperative games where the players maximize the product of their gains given what each player would receive without cooperation (i.e., threat point). This is referred to as the Nash bargaining solution which can be defined as follows:

$$\mathbf{s}^* = \arg\max_{\mathbf{s}} \prod_{i \in \mathbb{M}} (u_i(s_i) - u_i^{\mathrm{d}}) \tag{2.3}$$

where $u_i(\cdot)$ is the payoff function of player i, s_i is a strategy of player i, and $\mathbf{s}^*$ is a Nash bargaining solution strategy vector of all players, and u_i^{d} is the threat point (i.e., the utility gained if player i decides not to cooperate and bargain with the other players).

Coalition formation game is a cooperative game involving a set of players who are looking for cooperative groups (i.e., coalitions). A coalition $\mathcal{S}$, which represents an agreement among the players to act as a single entity, can be formed by players in a set $\mathbb{M}$ to gain a higher payoff, and the worth of this coalition, denoted by v is called the *coalitional value*. Two common forms of coalitional games are *strategic form* and *partition form*. In the former case, the value of a coalition $\mathcal{S}$ depends on the members of that coalition only (i.e., independent of how the players in $\mathbb{M}\backslash\mathcal{S}$ are structured). In the latter case, the value of a coalition $\mathcal{S}$ strongly depends on how the players in $\mathbb{M}\backslash\mathcal{S}$ are structured. Coalitional game models can be developed with either transferable payoff or non-transferable payoff. In a transferable payoff coalitional game, there is no restriction on how the total payoff will be divided among the members of a coalition. In a non-transferable payoff coalitional game, the payoff that each player in a coalition obtains depends on the joint actions that the players of a coalition select [20]. A stable solution for a coalition formation game ensures that the outcome is immune to deviations by groups of players (i.e., no player has an incentive to move from its current coalition to another coalition).

2.2 Game Models for Contention-Free Channel Access

In this section, game models for contention-free channel access based on TDMA, FDMA, and CDMA are reviewed.

2.2.1 Channel Access Games in TDMA

Since the nodes have to transmit data during their allocated time slots, in TDMA-based channel access games, the nodes compete for time slots to achieve their performance objectives (i.e., QoS requirements). Three different game models, namely, *auction game*, *dynamic game*, and *repeated game* models are discussed.

2.2.1.1 Auction game-theoretic approach

A. T. Hoang and Y.-C. Liang[21] proposed a second price and sealed bid auction for time slot competition in a dynamic spectrum access scenario. In dynamic spectrum access, each node i (i.e., the bidder/player in a game) submits its bid to the base station. The value of the submitted bid is the portion of the time slot (i.e., between 0 and 1) that will be used to help the base station relaying data to another distant node. The bidding value b_i of node i is a non-decreasing function of the channel condition x_i. The base station (i.e., the auctioneer) allocates the downlink channel to a node offering the highest bid. The price that this winning node pays is equal to the second highest bid. The amount of transmitted data of winning node j is denoted as $d_j = x_j(1 - \max_{i \in \mathbb{M}, i \neq j} b_i(x_i))$, where x_j is the channel condition of the winning node which is assumed to be the amount of data received per unit time, and $b_i(x_i)$ is the bid submitted by a node. A node chooses a value of bid which maximizes its expected amount of transmitted data under its budget constraint given the probability distributions of the channel conditions of all the nodes. The budget constraint of node i represents the amount of time that the node is able to provide to the base station for data relaying. Nash equilibrium is considered as the solution. It is found that, for pure strategy, a Nash equilibrium exists in the two-node case, but in a general multiple-node case, a Nash equilibrium may not exist. A distributed algorithm is proposed for updating the bids which converges to the Nash equilibrium. The results show that to avoid zero throughput (i.e., maximum bid), the budget constraint has to be smaller than one. Also, the higher the budget constraint, the lower is the throughput for each node.

2.2.1.2 Dynamic game-theoretic approach

J. W. Huang and V. Krishnamurthy [22] formulated a Markovian dynamic game to solve the transmission rate adaptation problem in a dynamic spectrum access-based cognitive radio network. In such a network, the secondary users (or cognitive radio users) opportunistically access the radio spectrum, which is licensed to the primary (or licensed) users, without causing harmful interference to the primary users. The players of the game are secondary nodes competing for the channel or time slot in a TDMA scenario (e.g., in the IEEE 802.16-based network). In a TDMA cognitive radio system, the system has a predefined decentralized access rule that allows only one secondary node to access the channel at a time. The access rule is defined as a function of channel quality and transmission delay. This transmission rate control problem is formulated as a general-sum switching control Markovian dynamic game.

In this dynamic game, the system state transition probability at each time slot depends only on the active secondary node. Node i (i.e., secondary node i) follows a decentralized access rule to try to occupy a time slot at time n after a period of time $t_i^n = \frac{\gamma_i}{q_i^n h_i^n}$ where γ_i is the QoS parameter of node i, q_i^n is the buffer occupancy state of user i, and h_i^n is the channel state of node i. The composite variable $\mathbf{x}_i^n = [q_i^n, h_i^n]$ denotes the state of user i at time n. If there are more than one node having the same waiting period, a node will be randomly picked with equal probability. After node j is selected to transmit data, this node chooses action a_j^n (i.e., transmission rate in bits/symbol) assuming an M-ary quadrature amplitude modulation. The transmission cost of the selected node j, $c_j(\mathbf{x}^n, a_j^n)$, is defined as its transmission bit error rate (BER), and the cost of node i, $d_i(\mathbf{x}^n, a_j^n)$, is defined as its delay constraint (i.e., QoS constraint) which is a function of the buffer state q_i^n. The transition probabilities depend only on the action of active node; hence, a Markovian dynamic game can be formulated. The strategy of node i denotes the transmission policy s_i. The Nash equilibrium policy s_i^* is computed by minimizing the expected total discounted cost function subject to the expected total discounted delay constraint as follows:

$$s_i^{*(n)} = \{s_i^n : \min_{s_i} C_i^n(s_i)\} \quad \text{subject to} \quad D_i^n(s_i) \leq \hat{D}_i \tag{2.4}$$

where $C_i^n(s_i)$ is the infinite expected total discounted transmission cost calculated from $c_j(\mathbf{x}^n, a_j^n)$. $D_i^n(s_i)$ is the infinite expected total discounted delay which is calculated from $d_i(\mathbf{x}^n, a_j^n)$ and cannot be greater than threshold $\hat{D}_i$.

The value iteration algorithm is used to obtain a Nash equilibrium policy. The Nash equilibrium policy of any node i is observed to be a randomized mixture of pure policies and the pure policies are non-decreasing on the buffer occupancy state. A stochastic approximation algorithm exploiting this structure is presented to efficiently estimate the Nash equilibrium policy by computing parameters such as buffer state thresholds and randomization factors.

2.2.1.3 Repeated game-theoretic approach

Y. Wu, B. Wang, and K. J. R. Liu [23] presented a repeated game model for spectrum sharing in a cognitive radio network. The game enforces the nodes to tell their true channel conditions and to cooperate with each other. Data transmission over a long time period is considered. Therefore, spectrum sharing can be formulated as a repeated game where the nodes are concerned about their payoffs (e.g., throughputs) in the future. The actions of the nodes are the power allocation according to the power constraint and channel condition. In this game, the power constraint is assumed to be identical for all nodes. If all the nodes make an agreement and share the spectrum in an orderly fashion, every node gains benefit from the cooperation. However, some nodes may violate the agreed upon rule and deviate from cooperation. Then, the game model provides a punishment mechanism which will be triggered and applied to the deviating node for a certain period of time. The period of time for punishment is chosen such that the expected payoff from cooperation is greater than the expected payoff from deviation.

To design a cooperation rule, an opportunistic time slot allocation method is developed which maximizes the total throughput. The node informing the best channel gain will be allocated time slots for transmission. However, in the incomplete information case, the channel gain of one node may not be known to other nodes, and some node may falsely inform its channel gain information. Therefore, a Bayesian mechanism is introduced to enforce all the nodes to tell the true values of their channel gains.

2.2.2 Channel Access Games in FDMA

In FDMA, the nodes compete for available channels in the network and the solutions of the game models (i.e., equilibria) can be obtained in the complete and incomplete information cases. We consider three different game models, namely, *noncooperative static game*, *auction game*, and *cooperative game* models.

2.2.2.1 Noncooperative static game-theoretic approach

F. Wu, S. Zhong, and C. Qiao [24] studied the optimal FDMA channel assignment problem for noncooperative wireless networks. It is assumed that the nodes can be equipped with either single or multiple radio interfaces. The available frequency band is divided into orthogonal channels. The authors introduce a payment formula to ensure the existence of a strongly dominant strategy equilibrium (SDSE) [25], which is a stronger solution concept than the Nash equilibrium. This payment is used to obtain the globally optimal solution in terms of effective system-wide throughput. The strategy of node i (s_i) is the channel assignment vector which is the number of radio interfaces allocated to each channel. The solution in terms of SDSE can be described as follows:

$$\forall \mathbf{s_{-i}} \in \mathbb{S}_i, \forall s_i \neq s_i^*, u_i(s_i^*, \mathbf{s_{-i}}) \geq u_i(s_i, \mathbf{s_{-i}}) \tag{2.5}$$

$$\exists \mathbf{s_{-i}} \in \mathbb{S}_i, \forall s_i \neq s_i^*, u_i(s_i^*, \mathbf{s_{-i}}) > u_i(s_i, \mathbf{s_{-i}}) \tag{2.6}$$

where $\mathbb{S}_i$ is the set of all possible strategies and $u_i(\cdot)$ is the payoff function of node i. The payoff function is defined as the difference between the throughput and the payment to the system administrator. The payment is a function of the node's throughput plus a penalty (if the node deviates from the globally optimal solution) or a bonus (if the node does not deviate). An algorithm to obtain the SDSE is proposed. It is proved that the algorithm converges to the SDSE.

2.2.2.2 Auction game-theoretic approach

W. Noh [26] presented a distributed resource control scheme to achieve fairness in OFDMA systems. Specifically, an auction game-theoretic resource allocation scheme based on iterative multi-unit second price auction was applied. A base station controls transmission power and bidding to maximize system capacity and node fairness. From an information-theoretic point of view, the medium access control (MAC)-layer throughput capacity region is achievable by successive decoding [27] when at each subchannel k, the first node's decoded signal is subtracted from the sum signal, then the next node's signal is decoded, and so on.

In this auction, first each node i submits bid b_i which includes power control variable and bid value. Each node calculates its bid by maximizing the expected Shannon capacity, and each node submits its bid and waits to be assigned the decoding priority for each sub-channel from the base station. After the bids are received by the base station, the decoding priority is assigned to each node following the weighted sum-rate capacity maximization of the base station. The cost that each node i pays is the cost for winning the lth decoding priority at subchannel k. Then, transmission power will be allocated based on the optimal and fair water-filling allocation according to the result of the decoding order. Also, the cost that the nodes have to pay will be announced.

To obtain the Nash equilibrium for bidding in this auction, an iterative update algorithm is proposed. The key concept is to update the bid value based on the difference between the current bidding efficiency and the target bidding efficiency at each time slot t. Bidding efficiency is computed by a node's achievable transmission rate divided by the cost of the node. Also, the bidding control variable is updated using the subgradient algorithm as follows:

$$x^{(t+1)} = x^{(t)} + \alpha_t g^{(t)} \tag{2.7}$$

where $x^{(t)}$ is the bidding control variable at time t, α_t is a constant step size, and $g^{(t)}$ is a subgradient which is a function of the total cost that node has to pay for and the total bid money that node can use during the game. The analytical and simulation results show that this iterative update algorithm can converge to the stable and optimal equilibrium which can achieve fairness among users when the channel conditions of the subchannels for the different nodes are uniformly distributed.

2.2.2.3 Cooperative game-theoretic approach

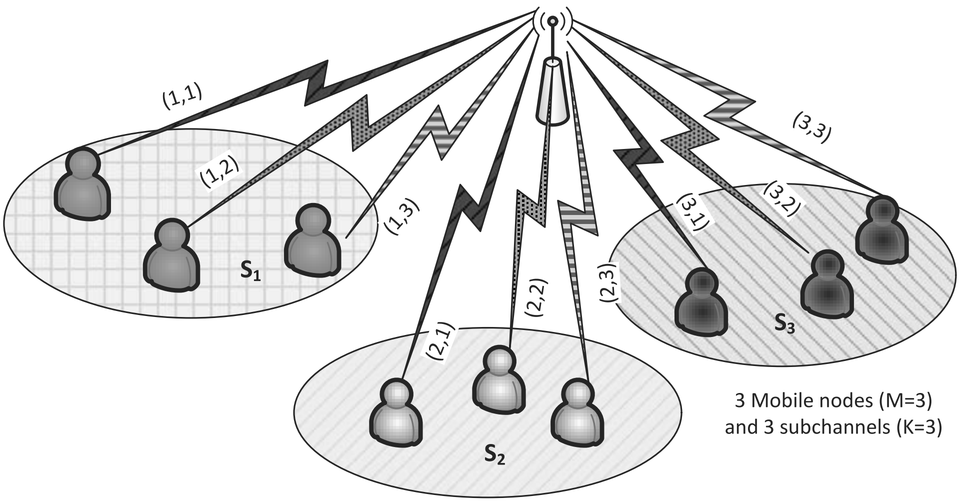


Figure 2.1. *Coalitions of players are formed following the game model by F. Shams, G. Bacci, and M. Luise [28] when there are 3 mobile nodes and 3 subchannels.*

A coalitional game for transmission power allocation and subchannel assignment in the uplink channel of an OFDMA system was presented by F. Shams, G. Bacci, and M. Luise [28]. In the considered system model, there are M nodes located in the coverage area of a same base station. The base station provides K subchannels to node $i \in \mathbb{M} = \{1, \ldots, M\}$ to guarantee the target rate requirement. Let k denote each subchannel $k \in \mathbb{K} = \{1, \ldots, K\}$. Let R_i be the target rate requirement of node i. Suppose that the total bandwidth is B, then the carrier spacing of every subchannel is $\triangle f = B/K$. A player defined in this game is a pair of one subchannel and one node. Hence, MK players are considered in this game. The strategy of each player is the transmission power assigned to subchannel p_{ik}. Then, there are M coalitions $\zeta = [\mathcal{S}_1, \ldots, \mathcal{S}_i, \ldots, \mathcal{S}_M]$ to be assigned to the M nodes and each coalition $\mathcal{S}_i$ contains K players (e.g., shown in Figure 2.1).

In this game, the members in each coalition do not change during the game. Consequently, the coalition $\mathcal{S}_i$ achieves its rate $C_i = \sum_{k \in \mathbb{K}} C_{ik}$ where $C_{ik} = \triangle f \log_2(1+\gamma_{ik})$ is the Shannon capacity achieved by node i on subchannel k. γ_{ik} is the SINR at the base station. The payoff that each coalition will obtain is defined as follows:

$$u(\mathcal{S}_i) = \frac{1}{C_k/R_k - 1} - \alpha.t(1 - C_k/R_k) \tag{2.8}$$

where $t(\cdot)$ is the step function with $t(y) = 1$ if $y \geq 0$ and $t(y) = 0$ if $y < 0$, and α is a positive constant. A coalition will achieve the highest payoff (i.e., positive infinite) when $C_k = R_k$. An iterative algorithm based on Markov modeling of the TU coalitional game is proposed to update the best-responses. The analytical and numerical results show that the algorithm can be considered as a Markov process. The process can quickly converge to an absorbing state which is also a Nash equilibrium solution with probability of one.

2.2.3 Channel Access Games in CDMA

CDMA systems use spread-spectrum technology in which each node is assigned with a different code to allow multiple users to be multiplexed over the same channel at the same time. Power control for multiple access is crucial for CDMA to ensure that the received signal can be decoded correctly. In a CDMA system with self-interested nodes, the transmission power control problem can be modeled as both the complete and incomplete information noncooperative games. Also, cooperative game models can be used for group-rational nodes in a CDMA system to achieve a Pareto optimal power control strategy.

2.2.3.1 Noncooperative static game-theoretic approach

F. Meshkati et al. [29] presented a noncooperative game model for power control. Each node has an objective to maximize its own utility. The game considers a multi-carrier direct-sequence CDMA system in which the data stream for each node is divided into multiple parallel streams. Each stream is first spread using a spreading sequence and then transmitted on a carrier. The strategy of each node is to choose its transmission power. A high transmission power may yield high SINR and high transmission rate. However, it may also cause high interference to the other nodes in the network. The utility of a node is defined as the ratio of the total throughput and the total transmission power for all K carriers.

Assuming that all the nodes use equal transmission rates, the utility function of a node can be expressed as the ratio of the summation of the efficiency functions and the summation of transmission powers for all K carriers. The efficiency function $(f(\gamma))$ represents packet success probability. The utility is a non quasi-concave function of the transmission power of the node. Nash equilibrium is considered as a solution. At the Nash equilibrium, each node transmits only on the carrier with the best effective channel. This best effective channel is the channel that requires the least amount of transmission power to achieve optimal SINR γ^* at the output of the uplink receiver. Optimal SINR $\gamma^* = \gamma f^{'}(\gamma)$ is the solution to the efficiency function. A unique Nash equilibrium in this game can be achieved under a certain set of conditions.

Also, an iterative and distributed algorithm based on best-response update is proposed to obtain the Nash equilibrium. The results show that, at the Nash equilibrium, the total network utility of this multicarrier system is higher than that of a single carrier system. Also, it is higher than that of a multicarrier system with the nodes choosing their transmission powers to maximize their utilities over each carrier independently.

C. A. St Jean and B. Jabbari [30] presented a noncooperative static Bayesian game for uplink power control in a CDMA network. Each node chooses its transmission power by . The payoff is a function of the difference between throughput and power consumption. The throughput part in the payoff function is composed of the gain from achievable bit rate and a ‘success function’. The ‘success function’ is a Sigmoid function of SINR. Since the path loss information for the other nodes is not completely known, each node uses path loss probability density functions to estimate the SINR (and hence payoff) of the other nodes.

The solution of this incomplete information game is the Bayesian Nash equilibrium (BNE), which can be obtained from the best-response dynamics. This dynamics represents the strategy update rules based on the expected utility when path loss information is not completely known to the other nodes. The existence of the Bayesian Nash equilibrium is proved and it can be obtained in a distributed way.

2.2.3.2 Cooperative static game-theoretic approach

A. Feiten and R. Mathar applied [31] a cooperative game to obtain the optimal power allocation in a CDMA system. A multiuser CDMA system with perfectly known channel information and fixed signature and linear sequences is considered. The objective is to minimize power consumption given minimum SINR of each node. It is shown that the power region (i.e., a feasible set of power allocation such that the SINR requirement of each node is met) is convex and log-convex. If the power region is not empty, then there is a unique power allocation that satisfies the SINR requirements of all nodes. To obtain the unique, Pareto optimal, and proportional fair solution, a bargaining game similar to that in (2.3) is formulated and solved. In this case, a node's strategy is its transmission power. The results show that the utility should be appropriately selected as a function of transmission power. The payoff function can be chosen to be $u_i(s_i) = -e^{s_i}$, where s_i, node i's strategy is the choice of transmission power.

2.3 Game Models for Random Channel Access

In this section, the game models for random channel access are reviewed. In particular, channel access based on ALOHA and CSMA/CA protocols are considered.

2.3.1 Channel access games in ALOHA-like protocols

In the literature, different game models, namely, noncooperative game, cooperative game, evolutionary game, and Stackelberg game models have been used for analyzing ALOHA-like channel access schemes with (and without) power control and rate adaptation.

2.3.1.1 Noncooperative game-theoretic approach

H. Inaltekin and S. Wicker [32] applied a noncooperative static game analysis to the slotted ALOHA protocol with M selfish nodes. Actions of nodes are "To transmit" and "Not to transmit". A node has the objective to maximize its expected payoff given other nodes' transmission probabilities. The payoff is zero when a node chooses not to transmit, one when a node chooses to transmit and it is successful, and $-c_i$ when a node chooses to transmit but it is unsuccessful (here c_i is the cost of unsuccessful transmission for node i). Mixed strategy Nash equilibria are considered as the solutions which can be described as the transmission probability (i.e., the probability to perform action "To transmit" and "Not to transmit") of the nodes.

In a noncooperative ALOHA game, the Bayesian Nash equilibrium is always the threshold strategy of a channel gain. That is, a node will transmit if its channel gain is not lower than the threshold. The threshold strategy enables the system to exploit multiuser diversity by giving more chance of transmission to the node with better channel gain. To find the optimal strategy, the optimal threshold strategy has to be obtained first. In this model, only a symmetric case is considered where the cumulative distribution function (CDF) of channel gains and weights of the payoff function are identical for all nodes. The existence of a unique symmetric Bayesian Nash equilibrium is proved.

Noncooperative Bayesian static ALOHA games were also presented in the research papers of Y. Cho, C. S. Hwang, and F. A. Tobagi [33] and H. Lee et al. [34]. Both the game models consider interference. As in [32], a fixed power is assumed in both the MAC games. The nodes do not know others' channel states (i.e., signal-to-noise ratio (SNR)). Each node decides to transmit or not to transmit the data (i.e., strategies) based on the SNR. In [33] and [34], each node will then obtain its payoff which is the difference between the utility function of SNR and the cost function if its transmission is successful.

D. Wang et al. [35] presented a pricing-based noncooperative slotted ALOHA MAC game. The key idea of this game is to motivate the nodes to cooperate with each other by using a pricing mechanism in the payoff function so that the multiuser diversity gain can be achieved. A static game is proposed in which the actions of each player $i \in \mathbb{M} = \{1, \ldots, M\}$ are "To transmit" and "Not to transmit". If a player successfully transmits its packet(s), the payoff is $1 - c_i - \mu_i$, where c_i is the cost of transmission and μ_i is the price charged per successful packet transmission. If the transmission is unsuccessful, the payoff is $-c_i - v_i$. If a player chooses not to transmit and it waits, the payoff is $-v_i$, where v_i is the waiting cost which is defined as $1 - c_i - \mu_i$.

In this game, each node maximizes its payoff given the medium access probabilities of all nodes. The probabilities of medium access are identical for all nodes since a fair game is considered. To maximize the expected payoff, a node will choose "To transmit" when the expected utility of "To transmit" action is not lower than that of "Not to transmit" action. Nash equilibrium, which is considered as a solution, can be found to be of threshold type. The equilibrium threshold is the cost of the corresponding action. Therefore, the transmission is successful only if there is exactly one transmitting node and transmission cost is smaller than the equilibrium threshold.

2.3.1.2 Evolutionary game-theoretic approach

H. Tembine, E. Altaian, and R. El-Azouzi [36] formulated an evolutionary game-theoretic model for ALOHA protocol. An evolutionary game is a dynamic game where players interact with other players and adapt their strategies based on payoff (fitness). The dynamics (i.e., stability) of the population adopting different strategies is studied. Also, an evolutionary stable strategy (ESS) is considered. In the evolutionary game model, if an ESS is reached, the proportions of population adopting different strategies do not change over time. In particular, the population with ESS is immune from being invaded by a population with non-ESS strategy. The effect of time delay on the dynamics of the evolutionary game model is studied. Similar to the other ALOHA games, each player has two possible strategies (i.e., "To transmit" and "Not to transmit").

For the two-player case, if a player transmits a packet, it incurs a transmission cost ($c \in (0, 1)$) irrespective of whether the transmission is successful or not. The payoffs are $1 - c$, 0, and $-c$ if the player has a successful transmission, no transmission, and collision, respectively. It is found that this game has two pure Nash equilibria (i.e., (Player I - Transmit, Player II - Not to transmit) and (Player I - Not to transmit, Player II - Transmit)) and one mixed Nash equilibrium ($1 - c$, c) where $1 - c$ and c represent proportions of individuals which transmit and do not transmit, respectively. The strategy ($1 - c$, c) can also be an ESS since this strategy is a unique symmetric Nash equilibrium.

2.3.1.3 Stackelberg game-theoretic approach

R. T. B. Ma, V. Misra, and D. Rubenstein [37] analyzed slotted ALOHA protocols using game theory. The model considers throughput of the system when nodes are of self-interest and compete for bandwidth using a generalized version of slotted-ALOHA protocols. First, an analysis based on a two-state Markov model is presented when the nodes cooperate to equally share the bandwidth and maximize the system throughput. The states are "Free state" when the most recent transmission of node is successful, and "Backlogged state" when the most recent transmission is unsuccessful due to collision. The results show that the lower bound of aggregated throughput is one half and this bound is independent of the number of nodes. Next, an analysis is presented for the case when the nodes are selfish to maximize their own throughputs. Since in this case all nodes transmit with probability one, the system throughput will be zero.

Next, a Stackelberg game model is presented. A leader is any node that takes the selfish nodes (i.e., the followers) into account. The follower and leader nodes choose their best strategies (i.e., transmission probabilities in both states) by maximizing their throughputs (i.e., payoffs) subject to constraints on the *budgets* of the nodes. The budget should be higher than the cost of transmission. The followers maximize their throughputs based on the leader's strategy while the leader maximizes its own throughput according to the best response strategies of followers. Backward induction is used to find the Stackelberg equilibrium. The leader achieves a higher throughput than that of the followers when the budget is large.

2.3.2 Channel Access Games in CSMA/CA Systems

In this section, the game models formulated for analyzing CSMA/CA-based channel access are reviewed. The solution of a CSMA/CA game describes how the nodes in the network should choose their backoff windows so that the equilibrium point can be reached. Noncooperative static game-theoretic approach, noncooperative dynamic game approach, and repeated game approach can be used to model and analyze CSMA/CA systems. Since the nodes are selfish, to maximize their payoffs, the nodes may set the backoff windows to the smallest value. However, if all the nodes do so, the network throughput will be zero due to collision. To avoid this problem, incompletely-cooperative game models are used in which the nodes are enforced to cooperate in the system by using a penalizing mechanism.

2.3.2.1 Noncooperative static game-theoretic approach

Y. Cho, C. S. Hwang, and F. A. Tobagi [33] formulated a medium access contention game model for the CSMA protocol. Similar to the slotted ALOHA protocol, the possible results from transmission attempts of each node are successful transmission, collision, and no-transmission. Transmission after k backoff slots is added to the action space of each node. The action set is $\mathbb{A} = \{1, \ldots, K, K+1\}$, where $k \in \mathbb{K} = \mathbb{A} \setminus \{K+1\} = \{1, \ldots, K\}$ denotes transmitting at slot k and index $K+1$ denotes the action of not-transmitting a packet. The payoff function of node i is the difference between the utility and the cost of transmission if this node selects a backoff slot number which is less than the backoff slot number of each of the other nodes. Node i incus a cost of transmission if a collision occurs, that is, when the earliest backoff slot chosen by one (or more) of the other nodes is the same as that of node i. Node i gains nothing if it selects a backoff slot number greater than the lowest backoff slot number among the other nodes. The nodes play the game by maximizing their expected payoffs (similar to the ALOHA game models discussed in Section 2.3.1.1 before) given the type spaces (i.e., channel SNR, $\mathbf{h}$) and beliefs (i.e., probabilities of channel states of other nodes, $\mathbf{P}_{-i}(\mathbf{h}_{-i})$). A symmetric mixed strategy (in terms of the probability that the node will not transmit at the first $k \in \mathbb{K}$ slots) Bayesian Nash equilibrium is found for this single-stage (static) Bayesian game.

2.3.2.2 Noncooperative dynamic game-theoretic approach

The single-stage CSMA Bayesian game in the work of Y. Cho, C. S. Hwang, and F. A. Tobagi [33] described before was extended to a dynamic game where the static one-stage game is played repeatedly. The action of node i can be either to transmit a packet or not to transmit a packet based on node i's channel gain h_i and node i's type. K stages associated with K backoff slots are considered in this Bayesian dynamic game. At stage $k \in \{1, \ldots, K\}$, if node i successfully transmits its packet, it will obtain the payoff function, $\mu_i(h_i) - c_i(h_i)$ where μ_i is the utility function and

$c_i(h_i)$ is the cost function. If node i unsuccessfully transmits its packet, it will pay $-c_i(h_i)$ as a cost of transmission; otherwise, node i gains nothing (i.e., zero payoff). If there is no transmission, the stage of the game increases from k to $k+1$. When there is at least one transmission at any stage k, the game ends. Each node maximizes its expected payoff from stage 1 to k to obtain the perfect Bayesian equilibrium (PBE).

A symmetric PBE is considered since it is a proper operating point of a distributed protocol for the following reasons. First, it might not be possible to distinguish among nodes in the random access network. Second, asymmetric PBE is not sustainable since it causes unfairness problem by assigning unequal shares of channel to the nodes. Third, it is much simpler to operate a network with a single strategy in a symmetric equilibrium for all nodes than to operate a network with different strategies for different nodes. The symmetric PBE is shown to be a threshold strategy. That is, any node i decides to transmit at stage k when its SNR is greater than SNR threshold h_{th}^k (i.e., $h_i > h_{th}^k$). The numerical results show that the proposed protocols provide better robustness and higher multi-user diversity gain than those of conventional random access protocols.

2.3.2.3 Incompletely-cooperative game-theoretic approach

M. Felegyhazi, M. Cagalj, and J.-P. Hubaux [38] presented a CSMA/CA-based MAC game model for dynamic spectrum access in a cognitive radio network. This game model can be divided into two sub-games. The first sub-game is a channel allocation game in which the nodes compete to allocate radio interfaces to the channels. The second sub-game is a multiple access game among the nodes contending to transmit packets in the same channel. The available frequency band is divided into K channels of the same bandwidth. Each node is equipped with l radio interfaces (for $l < K$). Each node can hear other nodes' transmissions if the same channel is used. Each node determines the number of interfaces to be used in each channel. This is the action of nodes in the first sub-game of channel allocation. Each node maximizes its utility function which is the sum of throughputs achieved by the node in all allocated channels. Each node can observe other nodes' information perfectly. The solution of the channel allocation game is the Nash equilibrium if the difference between the number of interfaces in any channel x and that in any other channel y is lower than or equal to 1. Also, the number of interfaces allocated to any channel x by node i is lower than or equal to 1 for any channel y. It is found that if the rate function of each channel is independent of the number of interfaces in any channel, then any Nash equilibrium of channel allocation is Pareto optimal. The existence of Nash equilibrium is shown and its efficiency (i.e., price of anarchy) is studied. It is found that the price of anarchy is close to one (i.e., Nash equilibrium yields a payoff close to that of the socially optimal solution).

Next, the second sub-game for CSMA/CA channel contention is formulated. This sub-game aims not only to optimize the network performance, but also to provide incentives to the nodes to behave optimally. The actions of the nodes are "To transmit", "Not to transmit", and "To backoff" in which a contention window value between one and the maximum value is chosen by a node. Node i selects the value of contention window on each channel c to maximize its throughput (i.e., payoff). The static CSMA/CA game shows that the Nash equilibrium (i.e., contention window is chosen to be one) is inefficient and unfair.

A desirable solution for the CSMA/CA game should have three properties: uniqueness, per-radio fairness, and Pareto optimality. Using the Nash bargaining framework from the cooperative game theory, these three properties can be achieved. However, in the noncooperative regime, the Nash bargaining solution is not a Nash equilibrium and might not be stable. Therefore, a penalizing mechanism is introduced by which the node deviating from Nash bargaining solution will be punished. A jamming mechanism is presented to penalize the deviating node. The deviating node is selectively jammed for a short duration by other nodes using the same channel when the deviating node is detected doing selfishly for its transmission. Using the penalty function and the jamming mechanism, the game can reach a Nash equilibrium unilateral deviation from which is not profitable. A distributed algorithm is proposed to obtain the Pareto-optimal Nash equilibria. The algorithm can converge to the equilibrium point even in case of imperfect information. The algorithm is based on a round-based distributed algorithm [39]. Also, a coordination algorithm is proposed for CSMA/CA in which one node acts as a coordinator for the observed channel by inflicting penalties to the other nodes which receive a higher throughput.

2.3.2.4 Incompletely-cooperative repeated game-theoretic approach

J. Konorski [40] presented a game-theoretic study of CSMA/CA under a backoff attack. An enforcement mechanism is introduced for the misbehaving nodes in the network. Although this enforcement mechanism is similar to that in the work of M. Felegyhazi, M. Cagalj, and J.-P. Hubaux [38], here it is used in the context of a mobile ad hoc network and the game formulation is for a repeated game in which a long-term utility is to be maximized. First, a noncooperative game is formulated for a finite number of nodes. Each node chooses an action which is a backoff configuration from a feasible set. The payoff function is defined to be the bandwidth share function depending on the backoff configuration profile ($\mathbf{s} = (s_1, \ldots, s_i, \ldots, s_M)$). Nash equilibrium is the solution of this one-shot noncooperative game which might be unfair or inefficient. Therefore, to obtain a better solution, a repeated game is proposed in which a node takes into account the effect of its current action on the future actions of other nodes. The number of stages is finite and should be large enough to approach the steady state values. Nodes can switch between standard or non-standard backoff configuration (i.e., fair or more-than-fair bandwidth share, respectively) to maximize their own long-term payoffs.

To prevent the backoff attack and to obtain a fair Pareto optimal and sub-game perfect Nash equilibrium, a strategy profile called cooperation via randomized inclination to selfish/greedy play (CRISP) is introduced. This optimal solution is a probability distribution over the selected backoff configuration at stage k (s_i^k). An invader node deviating from CRISP will experience lower bandwidth than that of nodes playing CRISP.

2.4 Chapter Summary

Table 2.1 summarizes the game models formulated for the key multiple access mechanisms. In the channel access games for TDMA, nodes compete with each other to obtain time slots for their transmissions. Time slot allocation among the nodes is performed by using various game models. In the auction game models, the nodes bid for time slots and they have to pay to the base stations for the allocated time slots. Game models can be formulated in which the nodes are able to choose transmission power in their allocated time slots. To enforce cooperation among the nodes, a punishment and truth-telling mechanism can be used.

In the channel access games for FDMA, most of the models consider how nodes (with single or multiple radio interfaces) choose channels for transmission. In these game formulations, the number of radios, transmit rate, and power rate assigned to each channel correspond to nodes' actions. In the channel access games for CDMA, power control is the key objective of all the proposed games. Both cooperative and noncooperative games can be formulated. Nodes select their transmission powers to meet their requirements in terms of SINR and transmission cost.

In most of the ALOHA-like game models, the nodes can choose either "To transmit" or "Not to transmit" as their possible actions and the transmission powers of the nodes are assumed to be fixed. Then, the games have mixed strategy solutions. Some of the games can be shown to have solutions which are threshold strategies. In some of the CSMA/CA game models, the actions are "To transmit" and "To wait for k backoff time slots". The solutions of these game models are mixed strategies (i.e., the transmitting probability of nodes at the first k time slots). In some CSMA/CA-like MAC game models, the action set of nodes is defined as transmission probabilities. In addition, most of the CSMA/CA-like MAC game models consider only the symmetric strategy case by assuming that all nodes are identical and throughput maximization is the key objective. Since in random access schemes, nodes access the channel(s) in a distributed manner, some nodes may misbehave. A penalizing mechanisms is required to address this problem.

In the following chapters of this thesis, we present novel game theoretic models for distributed channel access by mobile nodes which consider mobility of the nodes, QoS performance of the users, and channel uncertainty. Performances of these developed game models are evaluated considering practical application scenarios (e.g., vehicle-to-roadside communications in a vehicular network). These game models complement the existing literature on game theoretic modeling of wireless network protocols.

Table 2.1. *Summary of channel access games*

Access Scheme	Summary
TDMA	In TDMA access games nodes compete for time slots to achieve their objectives and meet QoS requirements. Noncooperative static game, auction game, dynamic game, and repeated game models can be applied for TDMA.
FDMA	In FDMA, nodes compete for the available channels in the network (e.g., through an auction mechanism). The solution in terms of equilibrium can be achieved for the complete and incomplete information cases. Noncooperative static game, auction game, and cooperative game models can be used for FDMA.
CDMA	In a CDMA system, each node is assigned with a different code to allow multiple users to be multiplexed over the same channel at the same time. Power control is crucial for CDMA to ensure that the received signal can be decoded correctly. In a CDMA system with self-interested nodes, the transmission power control can be modeled as complete and incomplete information noncooperative games. Also, cooperative game model for group-rational nodes can be used to achieve a Pareto optimal power control strategy.
ALOHA	Noncooperative game, cooperative game, evolutionary game, and Stackelberg game models can be used for ALOHA-like channel access. For the majority of the models, the solution is a threshold strategy. Along with channel access, power control and rate adaptation are also considered in the models.
CSMA/CA	In CSMA/CA games, the nodes in the network choose their backoff windows so that the equilibrium point can be achieved. Noncooperative static game, noncooperative dynamic game, and repeated game models can be applied for CSMA/CA. Since the nodes can be selfish (i.e., to maximize their payoffs, they may set the backoff windows to be the smallest value), a penalizing mechanism is required for the misbehaving nodes.

Chapter 3

Distributed Noncooperative Channel Access: An Auction Game Model

3.1 Introduction

In a public wireless network, wireless services can be provided through wireless access points installed at the selected points. Due to the non-continuous network coverage of the wireless access points, which are deployed at the selected locations, wireless connectivity becomes sporadic for mobile nodes. For streaming media applications, the mobile nodes require high bandwidth [41]. To ensure smooth infotainment streaming service, a mobile node needs to obtain sufficient bandwidth to download and cache the multimedia data [42, 43]. When there are multiple mobile nodes connected to a wireless access point at the same time, the transmission bandwidth has to be shared among the mobile nodes. The wireless access point must be able to allocate the available bandwidth to different mobile nodes optimally.

Multiuser bandwidth allocation problem in communication networks can be solved by game-theoretic mechanisms. C. Wu, B. Li, and Z. Li [44] presented a model of bandwidth auction game for multi-overlay peer-to-peer streaming applications. This auction model uses decentralized strategies in order to allocate bandwidth to peers and to minimize the streaming cost of the system. An auction model with a varying reserve price was proposed by S. Baskar et al. [45]. This auction model is based on the progressive second price model [46]. The variation of the reserve price depends on the demand for Internet bandwidth of the buyers. This mechanism was shown to result in increased revenue for the Internet service provider.

In this chapter, we present a game-theoretic auction mechanism to solve the problem of bandwidth allocation among mobile nodes in wireless networks. In the proposed game, we consider both cooperative and noncooperative behaviors among mobile nodes. Neighboring mobile nodes owned by the same owners (i.e., in Intelligent Transportation Systems (ITS), buses equipped with proxy gateways for data transfer are owned by the same transportation service provider (TSP)) form mobile node groups. The base station or wireless access point allocates its available bandwidth based on bids from the mobile node groups. Each mobile node group is rational and selfish to maximize its profit. They are allowed to submit bids in each round of bidding if they are not satisfied with their current allocated portions of bandwidth. The auction ends when all mobile node groups are satisfied with their allocated amount of bandwidth.

The organization of the rest of the chapter is as follows. Section 3.2 describes the system model and assumptions. The auction model is presented in Section 3.3. Section 3.4 presents numerical study on the proposed auction game and Section 3.5 concludes this chapter. Note that the list of symbols used in this chapter is shown in Table 3.1.

3.2 System Model and Assumptions

Table 3.1. *List of symbols used in Chapter 3*

Symbol	Definition
B	The amount of data (Mbits) currently available in the gateway of a mobile node
B_{ij}	The amount of data (Mbits) currently available in the gateway of mobile node j in group i
$BR_i(.)$	The best response function for mobile node group i
$\vec{\mathbf{b}}$	The vector containing the bids (b_i) from all mobile node groups
$\vec{\mathbf{b}}_{-i}$	The vector containing the bids offered by all mobile node groups except mobile node group i
$\vec{\mathbf{b}}^*$	The vector containing the Nash equilibrium (i.e., the bids) of the bandwidth allocation game
b_i	The bid from mobile node group i
$C_{ij}(.)$	The cost function for mobile node j in group i
$\vec{\mathbf{g}}$	The vector containing the allocated amounts of bandwidth to all mobile node groups
g_i	The allocated amounts of bandwidth to mobile node group i
i	The index of a group of mobile nodes
j	The index of a mobile node in each group
$\mathbb{M}$	The set of indices of mobile node groups
M	The number of mobile node groups connected to a wireless access point
$\mathbb{N}_i$	The set of indices of mobile nodes in group i
n_i	The number of members in group i
P_i	The payoff for mobile node group i
P_{ij}	The payoff for mobile node j in group i
p_i	The price per unit of downloaded data (monetary units (mu)/Mbits)
q_i	The total required amount of bandwidth from group i
r_{u}	The total playout rate
r_{ij}^{u}	The total playout rate of mobile node j in group i
r_{p}	The physical data rate
$r_{\mathrm{w}})$	The required rate of a mobile node
r_{ij}^{w}	The requested rate by mobile node j in group i
$S(.)$	The user's satisfaction function, given an service interruption interval
t_{on}	The mean time intervals during which a mobile node remains in state "online"
t_{ij}^{on}	The mean time interval during which mobile node j in group i in state "online"
t_{off}	The mean time intervals during which the mobile node remains in state "offline"
t_{ij}^{off}	The mean time interval during which mobile node j in group i in state "offline"
t_{ij}^{out}	The time interval during which the service interruption of mobile node j in group i occurs
$U(.)$	The utility function for a mobile node
$V_{ij}(.)$	The valuation function for mobile node j in group i
W	The transmission bandwidth available at a wireless access point (Mbps)
ϵ	The initial price of downloaded data (mu/Mbits)
δ_i	The weight corresponding to the cost function for mobile node group i
α and γ	The constants indicating the scale and the shape of the utility function
σ_i	The constant indicating the scale of the user dissatisfaction function of mobile node group i
μ	The steepness of the Sigmoid function (i.e., the user's satisfaction function)
β	The acceptable region of operation of the Sigmoid function (i.e., the user's satisfaction function)

Consider a public wireless network which offers Internet access to the commuting customers (Figure. 3.1). The Internet connection is available at wireless access points sporadically deployed throughout the city (e.g., at traffic lights, bus stations, or bus transfer points). The mobile nodes are divided into groups and the mobile nodes in a group are owned by the same owner. To ensure smooth uninterrupted Internet access, a caching system and a WiFi transceiver is installed in each mobile node. The data stored in the caching system is unique and is retrieved in a FIFO manner. The mobile node downloads and caches data from a wireless access point when the mobile node is connected to the wireless access point and retrieve data from the caching system when the mobile node is in either "online" or "offline" to a wireless access pointstate. The mean time intervals during which the mobile node remains in each state are represented by variables t_{on} and t_{off}, respectively.

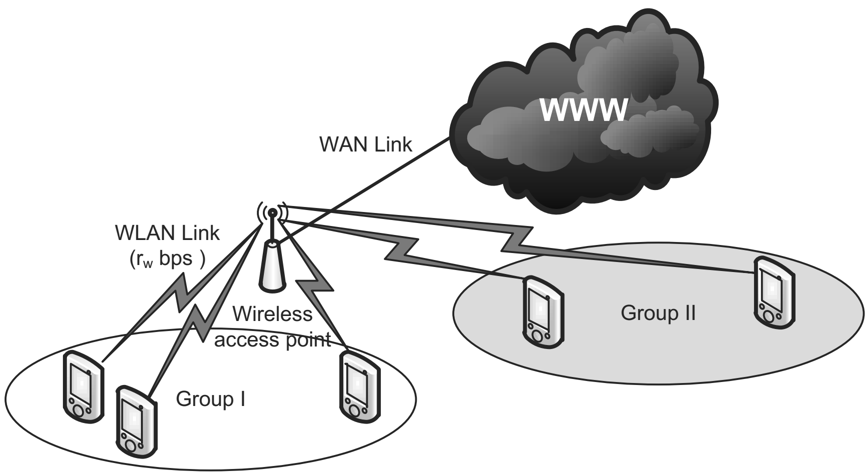


Figure 3.1. *Schematic diagram shows mobile nodes connected to a wireless access point.*

We assume that the data stored in the buffer is retrieved at a total playout rate r_{u} during the time period $t_{\mathrm{on}} + t_{\mathrm{off}}$. Let r_{p} denote the physical data rate (e.g., 2 Mbps, 11 Mbps, or 54 Mbps for IEEE 802.11-based radio). At the wireless access point , the rate (r_{w}) at which each mobile node needs to download and cache the data without any service interruption during time period $t_{\mathrm{on}} + t_{\mathrm{off}}$ is calculated as follows:

$$r_{\mathrm{w}} \geq \min\left(r_{\mathrm{p}}, \max\left(0, r_{\mathrm{u}} + \frac{r_{\mathrm{u}} t_{\mathrm{off}} - B}{t_{\mathrm{on}}}\right)\right) \tag{3.1}$$

where B is the amount of data (Mbits) currently available in the proxy buffer when the mobile node begins downloading and caching data from the wireless access point.

3.3 Auction Model

Our main interest is the competition among mobile nodes to download data at the wireless access point when the total amount of requested bandwidth from all mobile nodes is greater than the link capacity. We can solve this problem by formulating it as an auction game. Each mobile node tries to compete with other mobile nodes to obtain its required amount of bandwidth. Then, the wireless access point allocates the bandwidth by using its allocation strategy.

In a realistic scenario as shown in Figure. 3.1, some mobile nodes connected to the same wireless access point could be owned by the same owner. Then, a mobile node should pay the same price per unit of bandwidth as other mobile nodes owned by the same owner. Moreover, each mobile node should be able to prorate the allocated bandwidth among the group members in order to maximize the profit of the group. In the auction model considered in this chapter, a wireless access point allows a mobile node to cooperate with other mobile nodes owned by the same owner.

3.3.1 Bandwidth Allocation Strategy

The transmission bandwidth available at a wireless access point is W Mbps. Let i be an index of a group of mobile nodes, $i \in \mathbb{M} = \{1, \cdots, M\}$, where $\mathbb{M}$ is the set of indices of mobile node groups and M is the number of mobile node groups connected to a wireless access point. Let $\vec{\mathbf{b}}$ be a vector containing the bids (b_i) from all mobile node groups sent to the wireless access point. This vector is defined as follows: $\vec{\mathbf{b}} = [b_1 \ \cdots \ b_i \ \cdots \ b_M]^T$. Assume that a leader mobile node is selected for each group. The leader of each mobile node group sends the first bid to the wireless access point who is the auctioneer. The first bid is composed of the total required amount of bandwidth from the group (q_i) and the price per unit of downloaded data (p_i monetary units (mu)/Mbits), and the number of members in the group (n_i):

$$b_i^1 = (q_i, p_i, n_i) \tag{3.2}$$

where $0 < q_i \leq W$, $p_i \geq \epsilon$, $n_i > 0$, $q_i = \sum_{j=1}^{n_i} r_{ij}^{\mathrm{w}}$. Let ϵ be the initial price of downloaded data (mu/Mbits) defined by the wireless access point. Here j denotes the index of a mobile node in group i, $j \in \mathbb{N}_i = \{1, \cdots, n_i\}$, where $\mathbb{N}_i$ is the set of indices of mobile nodes in group i. r_{ij}^{w} is the requested amount of bandwidth by mobile node j in group i.

The wireless access point defines its allocation strategy to be proportionally fair by weight [47]. After all bids are reported to the wireless access point, then the wireless access point determines an allocation $\vec{\mathbf{g}} = [g_1 \ \cdots \ g_i \ \cdots \ g_M]^T$, where $\vec{\mathbf{g}}$ is the vector containing the allocated amounts of bandwidth to the mobile node groups. That is,

$$g_i = \min\left(q_i, \frac{n_i p_i}{\sum_{i=1}^{M} n_i p_i} W\right). \tag{3.3}$$

3.3.2 Bidding Strategy

The bidders who obtain their required bandwidth will not submit new bids in the next round of bidding. If all the bidders are satisfied, the game stops. However, if some of them are not satisfied, they can submit new bids in the next round. Only new "willing-to-pay" prices are reported to the auctioneer (i.e., $b_i = (p_i)$).

After this point, their payoffs are considered in order to make the decision whether to further bid or not. The payoff function is found as the difference between the valuation of the object and the cost of the object. For an allocated amount of bandwidth g_{ij} from the wireless access point, the payoff for mobile node j in group i is given by

$$P_{ij}(b_i, \vec{\mathbf{b}}_{-i}) = V_{ij}(g_{ij}(\vec{\mathbf{b}})) - \delta_i C_{ij}(g_{ij}(\vec{\mathbf{b}}), p_i) \tag{3.4}$$

$$P_i(b_i, \vec{\mathbf{b}}_{-i}) = \max \sum_{j=1}^{n_i} P_{ij}(b_i, \vec{\mathbf{b}}_{-i}) \tag{3.5}$$

subject to

$$g_i = \sum_{j=1}^{n_i} g_{ij}$$

$$0 \leq g_{ij} \leq r_{ij}^{\mathrm{w}}$$

and

$$0 \le g_{ij} \le g_i, \ \forall i \in \mathbb{M}, \forall j \in \mathbb{N}_i$$

where the vector $\vec{\mathbf{b}}_{-i}$ contains the bids offered by all mobile node groups except mobile node group i, $V_{ij}(.)$ is the valuation function, the constant δ_i denotes the weight corresponding to the cost function for mobile node group i, and $C_{ij}(.)$ is the cost function for mobile node j in group i. From (3.4) and (3.5), the bandwidth assigned to mobile node j in group i (g_{ij}) is computed by maximization of the total payoff of the group, which can be done numerically.

The cost function, which is the price paid for downloading data, is given by

$$C_{ij}(g_{ij}, p_i) = t_{ij}^{\text{on}} g_{ij} p_i \tag{3.6}$$

where t_{ij}^{on} is the time interval during which mobile node j in group i is connected to the wireless access point. The valuation function is given by

$$V_{ij}(g_{ij}) = t_{ij}^{\text{on}} U(g_{ij}) + \sigma_i S(t_{ij}^{\text{out}}) \tag{3.7}$$

where $U(.)$ the utility function [48], $S(.)$ is the user's satisfaction function [49] which is a Sigmoid function, t_{ij}^{out} is the time interval during which the service interruption of mobile node j in group i occurs, and σ_i is a constant indicating the scale of the user dissatisfaction function of mobile node group i. For an allocated bandwidth of w, the utility function for a mobile node is defined as follows:

$$U(w) = \alpha \log(1 + \gamma w) \tag{3.8}$$

where α and γ are constants indicating the scale and the shape of the utility function. The satisfaction function, which is used to approximate the satisfaction with respect to the interruption time, is defined as follows:

$$S(\tau) = 1 - \frac{1}{1 + \exp(-\mu(t - \beta))} \tag{3.9}$$

where τ is the service interruption interval, μ is the steepness of the Sigmoid function, and β is the acceptable region of operation. In the rest of the chapter β is assumed to be 0.

The service interruption interval during when mobile node j in group i is connected to the wireless access point before it connects to another wireless access point (i.e., a time period of $t_{\text{on}} + t_{\text{off}}$) is computed as follows:

$$t_{ij}^{\text{out}} = \begin{cases} \max\left(0, \left(t_{ij}^{\text{on}} + t_{ij}^{\text{off}}\right) - \left(\frac{B_{ij}}{r_{ij}^{\text{u}}} + \frac{t_{ij}^{\text{on}} g_{ij}}{r_{ij}^{\text{u}}}\right)\right), \\ \qquad t_{ij}^{\text{on}} \leq \frac{B_{ij}}{r_{ij}^{\text{u}}} \\ \max\left(0, t_{ij}^{\text{on}} - \left(\frac{B_{ij}}{r_{ij}^{\text{u}}} + \frac{B_{ij} g_{ij}}{r_{ij}^{\text{u}}}\left(\frac{1}{r_{ij}^{\text{u}} - g_{ij}}\right)\right)\right) + t_{ij}^{\text{off}} - \max\left(0, \frac{B_{ij} + g_{ij} t_{ij}^{\text{on}} - r_{ij}^{\text{u}} t_{ij}^{\text{on}}}{r_{ij}^{\text{u}}}\right), \\ \qquad t_{ij}^{\text{on}} > \frac{B_{ij}}{r_{ij}^{\text{u}}} \;\&\; g_{ij} < r_{ij}^{\text{u}} \\ \max\left(0, t_{ij}^{\text{off}} - \left(\frac{(g_{ij} - r_{ij}^{\text{u}})(t_{ij}^{\text{on}} - B_{ij}/r_{ij}^{\text{u}})}{r_{ij}^{\text{u}}} + \frac{B_{ij} g_{ij}/r_{ij}^{\text{u}}}{r_{ij}^{\text{u}}}\right)\right), \\ \qquad t_{ij}^{\text{on}} > \frac{B_{ij}}{r_{ij}^{\text{u}}} \;\&\; g_{ij} \geq r_{ij}^{\text{u}} \end{cases} \tag{3.10}$$

where t_{ij}^{off} is the time interval during which mobile node j in group i is on the road, B_{ij} is the amount of data currently available in the gateway of mobile node j in group i, and r_{ij}^{u} is the rate at which data is retrieved from the gateway of mobile node j in group i.

3.3.3 Nash Equilibrium

The Nash equilibrium, which is a solution of this auction game, can be obtained by using the best response function. The best response function is the best strategy of one player given others' strategies. That is,

$$BR_i(\vec{\mathbf{b}}_{-i}) = \arg\max_{b_i} P_i(b_i, \vec{\mathbf{b}}_{-i}). \tag{3.11}$$

The auction ends when all bidders obtain their best strategies given others' best strategies. The best strategy of bidder i (b_i^*) is the strategy giving the maximum payoff. Let vector $\vec{\mathbf{b}}^* = [b_1^* \cdots b_i^* \cdots b_M^*]^T$ denote the Nash equilibrium of this bandwidth allocation game. Then

$$b_i^* = BR_i(\vec{\mathbf{b}}_{-i}^*). \tag{3.12}$$

3.3.4 Procedure of the Auction Game

First, the leaders of the mobile node groups submit their first bids to the wireless access point. The bidding price can be set to ϵ which is the given initial price from the wireless access point. In the first bid, the total amount of bandwidth that can be asked as part of the bid can be calculated as the sum of the minimum required bandwidth for the mobile nodes to avoid any service interruption. That is,

$$q_i = \min\left(W, \sum_{j=1}^{n_i} \min\left(r_{\mathrm{p}}, \max\left(0, r_{ij}^{\mathrm{u}} + \frac{r_{ij}^{\mathrm{u}} t_{ij}^{\mathrm{off}} - B_{ij}}{t_{ij}^{\mathrm{on}}}\right)\right)\right). \tag{3.13}$$

After all groups obtain the allocated bandwidth from the wireless access point, if some mobile node groups are not satisfied (i.e., do not have the best bidding strategies yet), they report new bids (i.e., new prices) to the wireless access point. The auction process continues until all mobile nodes are satisfied with their received amount of bandwidth which is an equilibrium point and then the game ends.

In a practical environment, a mobile node may not be able to observe the payoffs of other mobile nodes except mobile nodes owned by the same owner. Also, the current bidding strategy adopted by each group of mobile nodes may be unknown. Hence, each group of mobile nodes should learn the strategy on choosing the bidding price. Therefore, a distributed price adjustment algorithm is required for a mobile node group in order to reach the Nash equilibrium of the auction game.

Let $b_i[t]$ be the bid offered by mobile node group i at iteration t. The vectors $\vec{\mathbf{b}}[t]$ and $\vec{\mathbf{b}}_{-i}[t]$ are defined accordingly. Let us assume that mobile node groups update their bids $b_i[t]$ at time t according to the best response. That is,

$$b_i[t] = BR_i(\vec{\mathbf{b}}_{-i}[t-1]), \forall i \in \mathbb{M}. \tag{3.14}$$

To find the best response, mobile node groups need to know the amount of bandwidth that will be obtained after a bidding price is reported to the wireless access point. Even though the strategies (i.e., bidding prices) used by other mobile node groups may not be known, each mobile node group is able to know the sum of bidding prices of all others by using only local information and the allocation strategy of the wireless access point. Now, rewriting (3.3) as

$$g_i = \frac{n_i p_i}{\sum_{k=1,k\neq i}^{M}(n_k p_k) + n_i p_i} W \tag{3.15}$$

the sum of others' bidding prices at iteration t can be obtained as

$$\sum_{k=1,k\neq i}^{M}(n_k p_k[t]) = \frac{n_i p_i[t] W - n_i p_i[t] g_i[t]}{g_i[t]} \tag{3.16}$$

where $g_i[t]$ denotes the amount of bandwidth offered by the wireless access point to mobile node group i after bid $b_i[t]$ is submitted at iteration t. After that, the best response $BR_i(\vec{\mathbf{b}}_{-i}[t])$ can be found.

Algorithm 1 Bidding algorithm.

$t = 1$.
$b_i^1[t] = (q_i, p_i[t], n_i),\ \forall i \in \mathbb{M}$ is submitted to the wireless access point.
$g_i[t]$ is allocated to each group.
repeat
    if $g_i[t] < q_i$
        each group updates $\sum_{k=1,k\neq i}^{M}(n_k p_k[t])$.
        $t = t + 1$.
        $b_i[t] = (BR_i(\vec{\mathbf{b}}_{-i}[t-1]))$.
    else
        $t = t + 1$.
        $b_i[t] = b_i[t-1]$.
    end
$g_i[t]$ is allocated to each group.
until $b_i[t] = b_i[t-1],\ \forall i \in \mathbb{M}$.
g_{ij} of $g_i[t]$ is allocated to each mobile node of the group.

3.4 Numerical Study

In this numerical study, we apply this auction game model to the bandwidth allocation in vehicle-to-roadside (V2R) communications as an example. In V2R communications, data is transferred through the roadside base stations (RSBs), i.e., wireless access points. That is, the mobile nodes shown in Figure. 3.1 are vehicles. The transportation service provider (TSP) installs a proxy gateway equipped with WiFi transceiver in its vehicles. The streaming proxy gateway downloads data when the vehicle is connected to the RSB.

3.4.1 Parameter Setting

We consider two groups vehicles (Group 1 and Group 2) with 2 vehicles in each group. The time intervals during which the vehicles are connected to the RSB have average values of $t_{11}^{\mathrm{on}} = 30$, $t_{12}^{\mathrm{on}} = 30$, $t_{21}^{\mathrm{on}} = 25$, and $t_{22}^{\mathrm{on}} = 20$ seconds. The time intervals during which the vehicles are on the road have average values of $t_{11}^{\mathrm{off}} = 90$, $t_{12}^{\mathrm{off}} = 75$, $t_{21}^{\mathrm{off}} = 90$, and $t_{22}^{\mathrm{off}} = 80$ seconds. The physical data rate of the all mobile nodes is r_{p} = 11 Mbps and the available bandwidth at the RSB is $W = 12$ Mbps. The playout rate of Group 1 is $r_{11}^{\mathrm{u}} = r_{12}^{\mathrm{u}} = 1$ Mbps and the playout rate of Group 2 is $r_{21}^{\mathrm{u}} = r_{22}^{\mathrm{u}}$ = 1.2 Mbps. Assume that the buffers at the gateways are empty for all vehicles, i.e., $B_{11} = B_{12} = B_{21} = B_{22} = 0$ Mbits. The values of the parameters α and γ in the valuation function are assumed to be 15 and 5, respectively, for all the vehicles. The values of μ and β in the satisfaction function are assumed to be 0.1 and 0, respectively. The weights of the satisfaction function of both groups are $\sigma_1 = \sigma_2 = 20$. The weights corresponding to the cost function of both groups are $\delta_1 = \delta_2 = 0.1$. The initial price ϵ is 5 mu/Mbits. The first bidding price of both groups is ϵ mu/Mbits. The requested amount of bandwidth of both groups, as computed using (3.13), is $q_1 = 7.50$ Mbps and $q_2 = 11.52$ Mbps.

3.4.2 Payoff and Best Response

Figure. 3.2 shows the payoff and best response of Group 2 under different strategies adopted by Group 1. When the Group 2 vehicles offer high price to the RSB, as expected, the payoff increases. However, after a certain point this payoff decreases. This is due to the fact that, the total cost to be paid is higher than the valuation of the obtained bandwidth. The maximum payoff can be found and the strategy (i.e., bidding price) corresponding to this maximum payoff is defined as the best response for Group 2. When the bidding price of Group 1 increases, the bidding price of Group 2 becomes higher as well in order to obtain the best response and also the

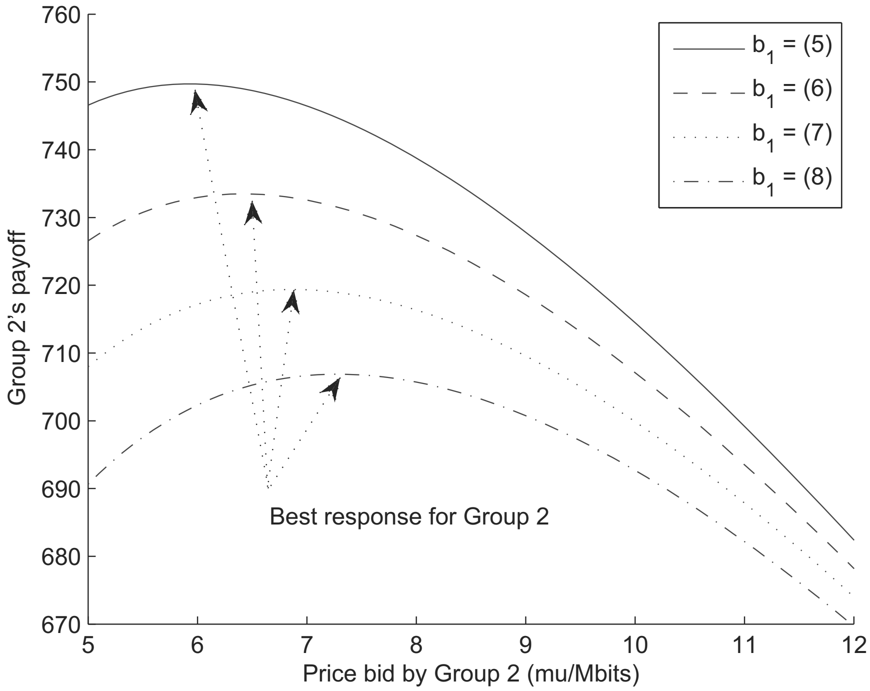


Figure 3.2. *Payoff function and best response of Group 2 under different bidding prices of Group 1.*

payoff decreases since the cost of bandwidth sharing increases.

3.4.3 Nash Equilibrium

Figure. 3.3 shows the best response functions of Group 1 and Group 2. The Nash equilibrium is located at the point where the best response functions of the two groups intersect.

3.4.4 Bidding Iteration and Bandwidth Allocation

We apply the iterative algorithm in Section 3.3.4 to obtain the Nash equilibrium in this two-group auction game. Each vehicle group increases its bidding price in each bidding iteration. As shown in Figure. 3.4, the bidding prices of both the groups converge to the solution within a few iterations. At the equilibrium, Group 1 bids with a price of 7.46 mu/Mbits and obtains 6.17 Mbps of bandwidth while Group 2 bids with a price of 7.06 mu/Mbits and obtains 5.83 Mbps of bandwidth.

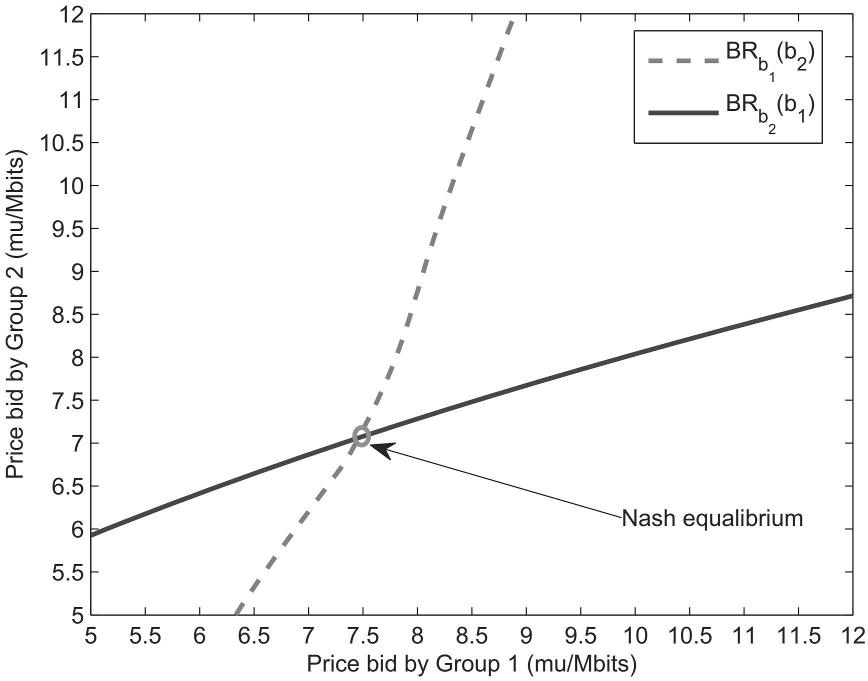


Figure 3.3. *Nash equilibrium for the auction game between Group 1 and Group 2.*

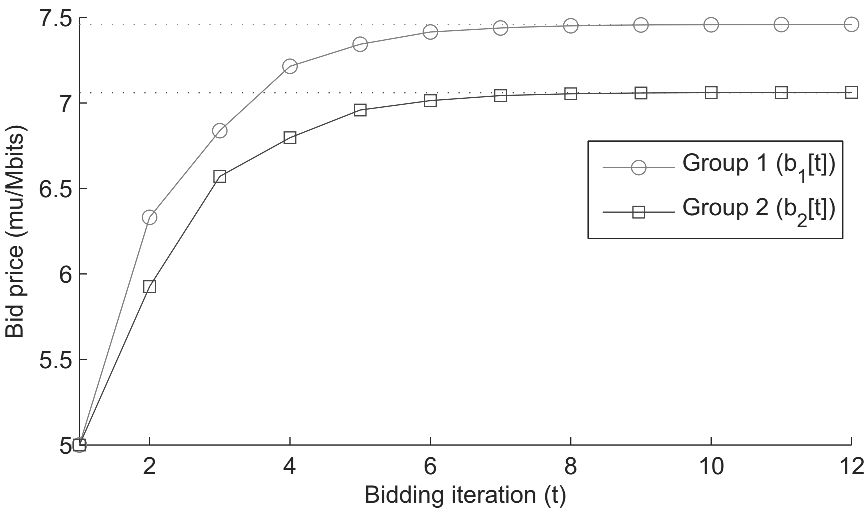


Figure 3.4. *Bidding prices of both groups at each bidding iteration.*

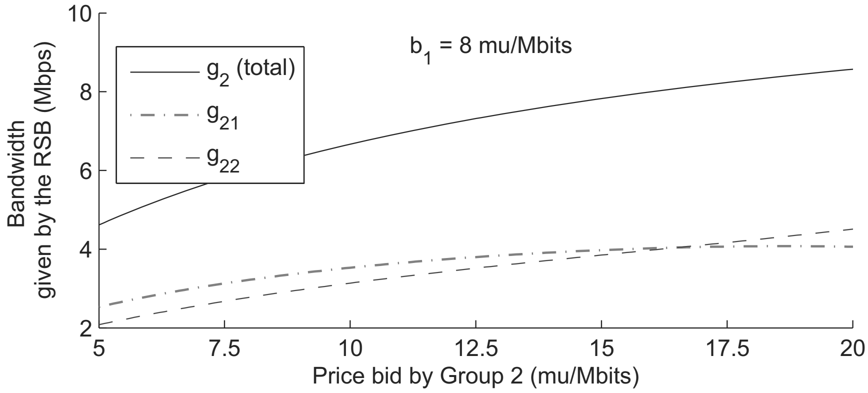


Figure 3.5. *Amount of bandwidth given to Group 2 and then divided to each member when Group 1's bid price is 8 mu/Mbits and Group 2's bidding price varies.*

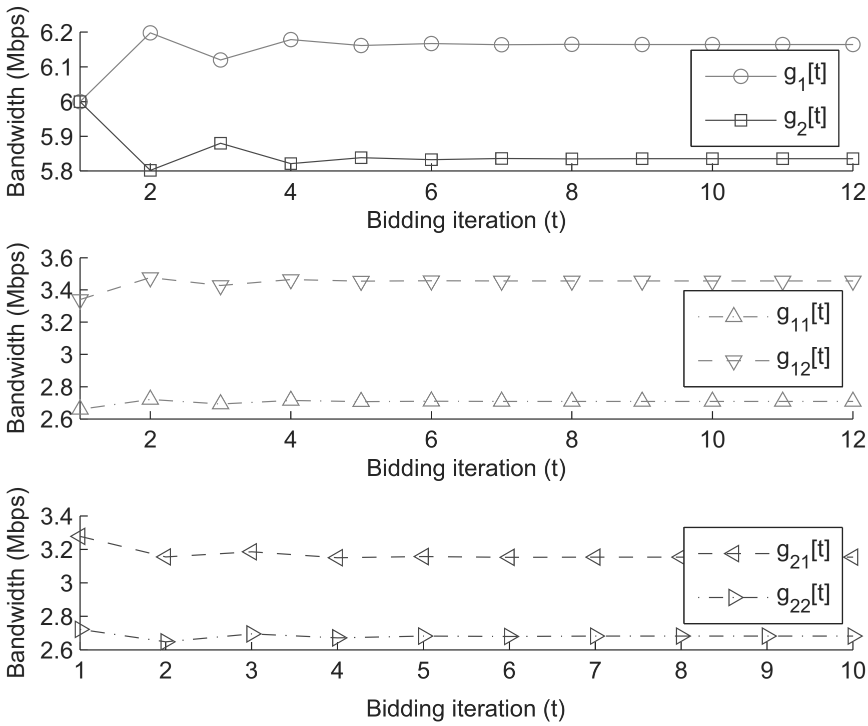


Figure 3.6. *Amount of bandwidth given to each group and its members at each bidding iteration.*

Figure. 3.5 shows that the amount of bandwidth offered by the RSB to Group 2 increases when the bidding price of Group 2 increases. We observe that the amount of bandwidth is unequally divided to each member since the allocation is based on maximization of payoff. Next, we show the allocation of bandwidth at each bidding iteration. As the bidding prices of both the groups vary, the offered amount of bandwidth by the RSB also vary (Figure. 3.6).

3.5 Chapter Summary

We have presented an auction mechanism for bandwidth allocation among mobile nodes for downlink communications. The auction game allows a mobile node to cooperate with others mobile nodes owned by the same owner. Each group of mobile nodes tries to maximize its payoff. On the contrary, each group tries to compete with other groups by offering "willing-to-pay" prices to the wireless access point in order to obtain its required amount of bandwidth. The wireless access point then manages the groups' requirements by using a fair allocation strategy. The Nash equilibrium is a solution of the game and a distributed iterative algorithm has been presented to obtain the solution.

Chapter 4

Distributed Resource Allocation in Wireless Networks Under Uncertainty and Application of Bayesian Game

4.1 Introduction

Differently from the previous chapter, we present a game-theoretic Bayesian auction mechanism (also referred to as Bayesian auction game) for bandwidth allocation among mobile nodes taking the mobility parameters and application quality-of-service (QoS) requirements into account. First, problem of resource allocation with uncertainty and different approaches to estimate and predict the values of uncertain parameters and their applications are briefly reviewed. Then, we focus on the game theoretic approach to address the problem of resource sharing among multiple mobile nodes. Different game theoretic models for resource allocation in wireless networks and the related work in the literature are briefly discussed. To this end, we present a game-theoretic Bayesian auction mechanism (also referred to as Bayesian auction game) for bandwidth allocation among mobile nodes taking the mobility parameters and application quality-of-service (QoS) requirements into account. In this game model, a wireless access point allocates available bandwidth among mobile nodes based on the bids from these nodes, while the mobile nodes make decisions on the bids in a noncooperative and incomplete information environment. With incomplete information about other nodes (e.g., their bandwidth and QoS requirements, and mobility pattern), each rational mobile node will aim at maximizing its expected utility. In this bandwidth auction game, a node determines its bidding strategy based on the minimum bandwidth required to satisfy the target QoS requirements given that the node does not know the exact values of related parameters for other nodes. The solution of this game model is the Bayesian Nash equilibrium (BNE) which has the property that with incomplete information, none of the nodes can improve its utility given that the other nodes do not change their bidding strategies. A distributed algorithm to obtain the BNE is presented.

The organization of the rest of the chapter is as follows. Section 4.2.2 describes different approaches to solve the resource allocation problem in wireless networks under uncertainly. Section 4.3 provides an overview of the Bayesian game model. Section 4.4 describes the system model and assumptions. The auction model is presented in Section 4.5. Section 4.6 presents numerical results on the proposed auction game and Section 4.7 concludes the chapter. Note that the list of symbols used in this chapter is shown in Table 4.1.

4.2 Distributed Resource Allocation in Wireless Networks Under Uncertainty

4.2.1 Resource Allocation with Uncertainty

In a wireless network, mobile users may have different QoS requirements which need to be satisfied using the limited available radio resources (e.g., radio bandwidth). Therefore, resource allocation mechanisms need to be optimized. Radio resources in a wireless network can be allocated either in a centralized or distributed fashion. With centralized resource allocation, a centralized controller (e.g., a base station) collects information about the QoS requirements of the mobile nodes and then allocates the network resources to the mobile nodes accordingly. Although centralized radio resource allocation schemes can achieve optimal network performance, they suffer from high computational complexity, signaling overhead, and scalability problems. Alternatively, since the decisions can be made locally without exchanging all the information among the nodes and the network controller, distributed resource allocation schemes are more scalable, and are viable for networks without any centralized controller (e.g., an ad hoc network). Nevertheless, distributed resource allocation has to address the incomplete information and uncertainty issues for decision making.

In a wireless and mobile communication environment, uncertain or unknown network parameters, which are involved in distributed resource allocation, include channel state information, number of competing mobile nodes, bandwidth and QoS requirements of the mobile nodes, and mobility patterns etc. The parameters are uncertain or unknown due to the lack of any information collector, and/or selfish behaviors of the mobile nodes, and/or the random nature of the system. As an example, consider the uplink transmission scenario in a cellular wireless system in a fading environment where multiple mobile nodes transmit in the uplink direction to the same base station simultaneously. The objective of each mobile node is to maximize its transmission rate subject to the power constraint. However, information of other nodes (e.g., number of mobile nodes competing for the resources, channel quality, QoS requirements, and mobility patterns) is private. Therefore, to achieve the optimal or nearly optimal solution of the resource allocation problem, the values of unknown or uncertain parameters have to be estimated. Different mathematical and statistical techniques can be adopted for this estimation, and subsequently, decisions can be made in a distributed manner.

4.2.2 Approaches to Solve the Resource Allocation Problem Under Uncertainty

In the following, we discuss different approaches to address the uncertainty and to support decision making process in resource management in multi-access wireless networks.

- *Kalman Filter*

  Kalman filter measures the value of an unknown parameter which could be noisy, and then makes the estimation using the previous original measured value and the previous estimated value [52]. It can be used for linear dynamic systems, and sequential measurements are required for this. A Kalman filter is used to estimate the number of competing nodes in the IEEE 802.11 wireless local area networks in both saturated and non-saturated conditions [53]. Since performance of the IEEE 802.11 protocol is sensitive to the number of contending mobile nodes, to maximize the network performance, the backoff window can be adjusted optimally according to the number of contending mobile nodes. An extended Kalman filter is built based on the relationship between the number of contending mobile nodes and the packet collision probability. A measurement model is used to estimate the number of contending mobile nodes at each time step while mobile nodes that have been activated and/or terminated are considered as noise. In most of the Kalman filter applications, the noise is assumed to be a stationary process with a constant variance. The Kalman filter can estimate the number of contending mobile nodes close to the actual number.

- *Maximum Entropy Principle*
  The principle of maximum entropy is used to obtain least-biased statistical inference when information available about the possible outcomes or data are insufficient. The principle of maximum entropy is a general, flexible, and efficient technique to assign probability distribution to any problem of inference when information is incomplete. Hence, it has been widely used in many different disciplines including wireless communications [54]. The probability distribution is chosen to maximize information entropy (i.e., a measure of the uncertainty). However, finding the probability distribution maximizing information entropy subject to the information constraints is normally complex. M. Johansson and M. Sternad [54] developed a channel allocation to maximize system throughput for multiple mobiles nodes while the QoS requirements (i.e., minimum rate constraints and priorities of mobile nodes) are satisfied. However, the bit rates of users sharing the channels and transmission capacities of the available channels are uncertain. The maximum entropy principle is applied to this channel allocation problem to find the optimal solution given partial statistical knowledge of both the bit rates and capacities.
- *Bayesian Learning* Bayesian learning is a statistical learning approach based on Bayes' theorem in which the probability is used to describe uncertainty of data being learned [55]. The prior probability distribution about the uncertain

data is first initialized. After the data has arrived and been observed, the *a priori* distribution is updated to be a *posterior* distribution using Bayes' Rule. Then, the estimate of unknown data can be expressed as its expected value given the posterior distribution or the value with the highest probability. The Bayesian method can be used to provide solutions to predict future value after the data is learned. D. H. T. Huang, S. H. Wu, and P. H. Wang [56] applied the concept of Bayesian learning for cooperative spectrum sensing and locating the primary users in a cognitive radio network. The number of primary users, the locations of the primary users, and their power profiles are used for radio resource management in the cognitive radio network; however, these parameters are imperfectly known in a real scenario. The transmit power and location information of primary users (e.g., TV transmitters) used to build the probability model are assumed to be measured and reported to the cognitive radio base stations by customer premise equipments. Then, a Bayesian-based sensing approach estimates the unknown parameters of the primary users and updates the beliefs at each time step. Bayesian learning approach is suitable to estimate unknown parameters when some information about the uncertain parameters can be made available over time.

- *Partially Observable Markov Decision Process* In a wireless network, some parameters (e.g., the number of users, power, and channel occupancy) dynamically vary over time. Therefore, dynamic optimization is essential for a wireless network to maximize long-term utility (e.g., defined as the function of throughput and delay) of the users (or the system). Partially observable Markov decision process (POMDP) [57] is an extension of Markov decision process (MDP) which considers the uncertainty of system states from the perspective of a decision maker to maximize the long-term utility of the decision maker. In a POMDP, the current state (which is not completely observable) changes to another state based on a transition probability estimated from observations. Q. Zhao et al [58] applied POMDP to find the optimal channel sensing and access strategy of secondary users in a multi-channel cognitive radio system. The availability of each sensed channel (i.e., idle or occupied) is considered as a state which is incompletely observed but the state transition probability is assumed to be known. Each user obtains the optimal proportion of bandwidth maximizing her long-term utility based on its belief of channel availability and past observations.

All of the above statistical methods are suitable for a system with single player and one objective. Bayesian learning is suitable to estimate parameters in dynamic systems when some information can be obtained over time. Kalman filter is typically suitable for multiple sequential measurements in a linear dynamical system rather than a single measurement. Maximum entropy principle is more general framework used to assign probability distributions to unknown random variables. Bayesian learning, Kalman filter, and maximum entropy principles provide only methods to estimate the value of unknown parameters, but they do not provide any mechanisms to obtain the optimal solutions for a system with individual agent or multiple agents. In addition, the above approaches have their own limitations. For example, POMDP requires the system to have Markov property. Also, POMDP suffers from the curse of dimensionality problem in which the complexity of the model grows rapidly with the number of states and actions.

4.2.3 Game-theoretic Model with Incomplete Information

Game theory can be used in a situation where information about characteristics of the other nodes is incompletely known to a node. A game is called *complete information game* if the payoffs and set of strategies of the players are completely known by all the players. On the other hand, in an *incomplete information game*, the information is unknown or partly known by other players. An incomplete information game can be modeled as a *Bayesian game* in which the outcome of the game can be predicted by using Bayesian analysis. A game-theoretic model with incomplete information can be seen as an extension of the Bayesian learning approach. In this case, a probability distribution is used to express the belief about uncertain or unknown information of the players or nodes, which is referred to as the *type* of the player. Then, the solution in terms of equilibrium is obtained. Game theory has many applications for resource allocation in distributed wireless networks (e.g., ad hoc networks [60]).

4.3 Bayesian Game Model for Distributed Resource Allocation Under Uncertainty

Most of game theoretic approaches for radio resource management assume that, in a game, all information needed by any player to make a decision, is known correctly. However, in a real situation, this assumption may not be true. Some important information may be uncertain or unknown by the decision makers (i.e., players). An incomplete information game can be modeled as a Bayesian game in which Bayesian analysis is used to predict the outcome of the game. The advantages of using a Bayesian game to solve the problem of distributed resource allocation, when information is incomplete, are as follows: i) A Bayesian game can relax the assumption that all key required information are completely known. Bayesian game allows players to have beliefs over the uncertainty of the other players' types. This is the main advantage of a Bayesian game over other game models. ii) A Bayesian game inherits the theoretical basis of game theory. Therefore, it is a suitable tool to design a distributed resource allocation mechanism.

A Bayesian game is generally composed of a set of *players*, a set of *actions*, *types* of players, *payoff* function for each player, and *probability distributions* associated with the types. The equilibrium solution of such a game is called *Bayesian Nash equilibrium* (BNE). Similar to the Nash equilibrium in a complete information game, a Bayesian Nash equilibrium can be obtained in which each player seeks for a strategy profile that maximizes its expected payoff given its beliefs about the *types* and strategies of other players.

To illustrate the application of Bayesian game for distributed resource allocation under uncertainty, we consider the problem of radio resource sharing in a public wireless network.

Table 4.1. *List of symbols used in Chapter 4*

Symbol	Definition
B	The maximum number of packets of a queue (i.e., buffer)
$\mathbb{B}_i$	The action set (i.e., possible bids) for player or mobile node i
$BR_i(.)$	The best response function of mobile node i
$\vec{\mathbf{b}}$	The vector containing the bids (b_i) from all mobile nodes
$\vec{\mathbf{b}}_{-i}$	The vector containing the bids offered by all mobile nodes except mobile node i
b_i	The bid from mobile node i
C	The amount of bandwidth available at a wireless access point
d_i	The distance between vehicle i and the RSB in meters
$f_T(.)$	The probability function of the type profile of a player
$f_S(.)$	The speed of a vehicle can be modeled as a random variable with normal distribution
$\vec{\mathbf{g}}$	The vector containing the allocated amounts of bandwidth to all mobile nodes
g_i	The allocated amounts of bandwidth to mobile node i
i	The index of each mobile node
L	The packet length
l	The transmission range in meters
M	The number of mobile nodes connected to a wireless access point
$\mathbf{P}$	The finite state transition matrix of a queue
P_{under}	The required buffer underrun probability
p_{bu}	The buffer underrun probability
P_i	The payoff for mobile node i
p_i	The offered price per unit of bandwidth per unit of time (monetary unit (mu)/s/MHz)
q_i	The required bandwidth of mobile node i
$\mathbf{Q}$	The inner square matrix of $\mathbf{P}$ representing the transitions between the online state and the offline state
r_{p}	The maximum physical rate of the transmitter
r_{u}	The total playout rate (packets/second)
r_{w}	The required rate of a mobile node (packets/second)
r_{on}	The rate for which a mobile node remains in state "online"
r_{off}	The rate for which a mobile node remains in state "offline"
S	The mobile node's state (i.e., either online or offline)
s	The speed of a vehicle
$\mathbb{T}_i$	Player or mobile node i's type set which is the time interval during which the player wants to connect to the wireless access point
t_i	The time interval that mobile node i requests to connect to wireless access point
$\vec{\mathbf{t}}_{-i}$	The vector of time intervals for all mobile nodes except mobile node i to be in state "online"
t_{on}	The mean time intervals during which a mobile node remains in state "online"
$t_{\text{on},i}$	The mean time for mobile node i to be in state "online"
t_{off}	The mean time intervals during which a mobile node remains in state "offline"
t_{bu}	The proportion of service interruption time during period $t_{\text{on}} + t_{\text{off}}$
$U_i(\cdot)$	The utility function for mobile node i
X	The buffer occupancy state
$\vec{\boldsymbol{\pi}}$	The stationary probability vector
$\vec{\boldsymbol{\pi}}_{(x)}$	The probability vector composed of two stationary probabilities that there are x packets in system
α and γ	The constants indicating the scale and the shape of the utility function
$\pi_{(x,0)}$	The probability that there are x packets in system when a mobile node is in the offline state
$\pi_{(x,1)}$	The probability that there are x packets in system when a mobile node is in the online state
ϕ	The spectral efficiency
τ	The minimum price for a unit of bandwidth which is acceptable to the wireless access point
ϵ	The reserved price (mu/MHz) defined by the wireless access point
δ_i	The weight corresponding to the cost for mobile node i

4.4 System Model and Assumptions

4.4.1 A Public Wireless Network

We consider a public wireless network which supports streaming applications for mobile users through the wireless access points sporadically deployed throughout the city (e.g., at shops or bus transfer points). To ensure seamless playback, a proxy caching system, (e.g., data buffering mechanism) is installed in the mobile devices (Figure 4.1). The pre-fetched data stored in the caching system in a mobile node is unique and is retrieved by the user in a FIFO fashion. A mobile node is equipped with WiFi transceiver to download data when it is connected to the wireless access point. This cached data is used when the mobile node is not in the coverage of wireless access point. A mobile node can be in either "online" (i.e., connected to the wireless access point) or "offline" (i.e., not connected to the wireless access point) state. The time intervals during which the mobile node remains in each state are assumed to be random with means t_{on} and t_{off}, respectively [43].

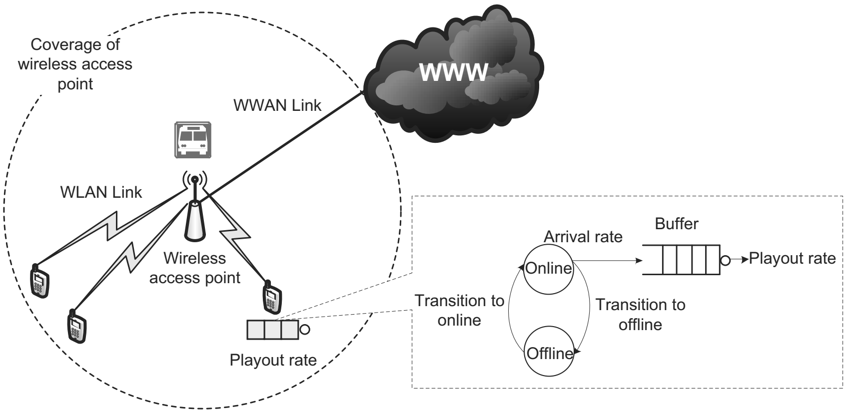


Figure 4.1. *Schematic diagram of a public wireless network. A mobile node caches the streaming content when connected to a wireless access point.*

We assume that the data stored in the buffer is retrieved at a total playout rate r_{u} packets/second during the time period $t_{\text{on}} + t_{\text{off}}$. At the wireless access point, the minimum rate (r_{w} packets/second) at which each mobile node needs to download the data given the target buffer underrun probability, can be obtained analytically from the queuing model which will be presented later in this chapter.

We consider the competition among nodes to download continuous data from a wireless access point when the total amount of requested bandwidth from all mobile nodes is greater than the link capacity. We analyze this competitive situation among nodes in bandwidth auction using the Bayesian noncooperative game. The Bayesian Nash equilibrium (BNE) is obtained from this game model. Note that each node acts noncooperatively. Intuitively, the BNE might not be optimal from a centralized utility perspective but BNE ensures that none of the nodes changes its strategy to improve the payoff as long as the other nodes do not do so. In addition, BNE can be obtained in the decentralized fashion.

4.4.2 Queueing Analysis for a Mobile Node's Buffer Occupancy

For the proxy caching system, a queueing model based on continuous-time Markov chain can be formulated [43, 65]. This queueing model is used to obtain the minimum transfer rate from a wireless access point to a mobile node, which is equivalent to the minimum arrival rate to the queue. This minimum transfer rate is obtained to satisfy the target buffer underrun probability. This minimum transfer rate will be used by the mobile node to bid for bandwidth from the wireless access point.

The state space of the queueing model can be expressed as a two-dimensional state space as follows:

$$\Psi = \{(X, S); X \in \{0, \cdots, B+1\}, S \in \mathbb{S}\} \tag{4.1}$$

where S denotes the mobile node's state (i.e., either online or offline) and X is the buffer occupancy. The maximum number of packets in the system is $B+1$ packets including one packet in service (i.e., being downloaded by user). The mobile node is in the online state, the mean duration of which is t_{on} seconds, when it is in the transmission range of an wireless access point. Therefore, the state transition rate from online state to offline state is $r_{\text{off}} = 1/t_{\text{on}}$. The mobile node is in the offline state, the mean duration of which is t_{off} seconds, when it is not in the transmission range of an wireless access point. Therefore, the state transition rate from offline to online is $r_{\text{on}} = 1/t_{\text{off}}$. When the mobile node is in the online state, data is downloaded from the wireless access point to the buffer of the mobile node following a Poisson process with average rate r_{w} packets/second. The packets stored in the proxy caching system are played back by user's media applications a with rate r_{u} packets/second.

4.4.2.1 Transition Matrix

Let $\mathbf{P}$ denote the finite state transition matrix of the queue defined as follows:

$$\mathbf{P} = \begin{bmatrix} \mathbf{B}_0 & \mathbf{E}_0 & & & & \\ \mathbf{C}_0 & \mathbf{A}_1 & \mathbf{A}_0 & & & \\ & \mathbf{A}_2 & \mathbf{A}_1 & \mathbf{A}_0 & & \\ & & \ddots & \ddots & \ddots & \\ & & & \mathbf{A}_2 & \mathbf{A}_1 & \mathbf{E}_1 \\ & & & & \mathbf{C}_1 & \mathbf{B}_1 \end{bmatrix}. \tag{4.2}$$

The dimension of the square matrix $\mathbf{P}$ is $(B+2) \times (B+2)$ and matrix $\mathbf{P}$ has a block-tridiagonal structure. Let $\mathbf{Q}$ denote the inner square matrix of $\mathbf{P}$. $\mathbf{Q} \in \{\mathbf{B}_0, \mathbf{E}_0, \mathbf{C}_0, \mathbf{A}_0, \mathbf{A}_1, \mathbf{A}_2, \mathbf{E}_1, \mathbf{C}_1, \mathbf{B}_1\}$ represents the transitions between the online state and the offline state. These inner square matrices can be defined as follows:

$$\begin{aligned} \mathbf{B}_0 &= \begin{bmatrix} -r_{\mathrm{on}} & r_{\mathrm{on}} \\ r_{\mathrm{off}} & -r_{\mathrm{w}} - r_{\mathrm{off}} \end{bmatrix} \\ \mathbf{E}_0 &= \mathbf{A}_0 = \mathbf{E}_1 \begin{bmatrix} 0 & 0 \\ 0 & r_{\mathrm{w}} \end{bmatrix} \\ \mathbf{C}_0 &= \mathbf{A}_2 = \mathbf{C}_1 \begin{bmatrix} r_{\mathrm{u}} & 0 \\ 0 & r_{\mathrm{u}} \end{bmatrix} \\ \mathbf{A}_1 &= \begin{bmatrix} -r_{\mathrm{u}} - r_{\mathrm{on}} & r_{\mathrm{on}} \\ r_{\mathrm{off}} & -r_u - r_w - r_{\mathrm{off}} \end{bmatrix} \\ \mathbf{B}_1 &= \begin{bmatrix} -r_{\mathrm{u}} - r_{\mathrm{on}} & r_{\mathrm{on}} \\ r_{\mathrm{off}} & -r_{\mathrm{u}} - r_{\mathrm{off}} \end{bmatrix}. \end{aligned}$$

Given transition matrix $\mathbf{P}$ of the queue, the stationary probability vector $\vec{\boldsymbol{\pi}}$ can be obtained by solving the following equation:

$$\vec{\boldsymbol{\pi}}^T \mathbf{P} = \vec{\mathbf{0}}^T \tag{4.3}$$

where $\vec{\boldsymbol{\pi}}^T \vec{\mathbf{1}} = 1$ and $\vec{\boldsymbol{\pi}} = \begin{bmatrix} \vec{\boldsymbol{\pi}}_{(0)} & \cdots & \vec{\boldsymbol{\pi}}_{(x)} & \cdots & \vec{\boldsymbol{\pi}}_{(B+1)} \end{bmatrix}^T$. $\vec{\mathbf{0}}$ is a vector of zeros, and $\vec{\mathbf{1}}$ is a vector of ones. $\vec{\boldsymbol{\pi}}_{(x)}$ is the probability vector composed of two stationary probabilities $\pi_{(x,0)}$ and $\pi_{(x,1)}$ which are the probabilities that there are x packets in system when the mobile node is in the offline state and in the online state, respectively.

4.4.2.2 Buffer Underrun Probability

Let p_{bu} denote the buffer underrun probability and t_{bu} denote the proportion of service interruption time during period $t_{\mathrm{on}} + t_{\mathrm{off}}$. Then, we obtain

$$p_{\mathrm{bu}} = \pi_{(0,0)} + \pi_{(0,1)}. \tag{4.4}$$

Let the buffer underrun probability be defined as a function of packet arrival rate (i.e., required transfer rate from wireless access point to mobile node in packets/second) as follows: $p_{\mathrm{bu}}(r_{\mathrm{w}})$ where $p_{\mathrm{bu}}(r_{\mathrm{w}})$ can be found by (4.4). To maintain the buffer underrun probability at the target level P_{under}, an optimization problem can be formulated to obtain the minimum transfer rate as follows:

$$\min \quad r_{\mathrm{w}} \tag{4.5}$$

$$\text{subject to} \quad p_{\mathrm{bu}}(r_{\mathrm{w}}) \leq P_{\mathrm{under}} \tag{4.6}$$

where the decision variable is r_{w}. The optimal solution r_{w}^* (i.e., minimum transfer rate) can be obtained numerically by using a search method.

With the adaptive modulation and coding as shown in Table 4.2 [66], the amount of required bandwidth can be obtained from

$$q = \min\left(\frac{r_{\mathrm{w}}^* L}{\phi}, \frac{r_{\mathrm{p}}}{\phi}\right) \tag{4.7}$$

where ϕ is the spectral efficiency and q is the required bandwidth. We assume that

Table 4.2. *Required SNR and transmission rate using adaptive modulation and convolutional coding [66].*

Mode	Rate	Modulation	Convolutional Coding Rate	SNR (dB) for BER $\leq 10^{-5}$
1	$1BW$	QPSK	1/2	4.09
2	$1.33BW$	QPSK	2/3	5.86
3	$1.5BW$	QPSK	3/4	6.84
4	$1.75BW$	QPSK	7/8	8.44
5	$2BW$	16QAM	1/2	10.04
6	$2.66BW$	16QAM	2/3	12.13
7	$3BW$	16QAM	3/4	13.29
8	$3.5BW$	16QAM	7/8	15.01
9	$4BW$	64QAM	2/3	17.70
10	$4.5BW$	64QAM	3/4	18.99
11	$5.25BW$	64QAM	7/8	21.06

all packets have the same length L, and r_{p} is the maximum physical rate of the transmitter.

The required bandwidth is used to determine the bidding strategy in the bandwidth auction game as shown in Figure 4.2.

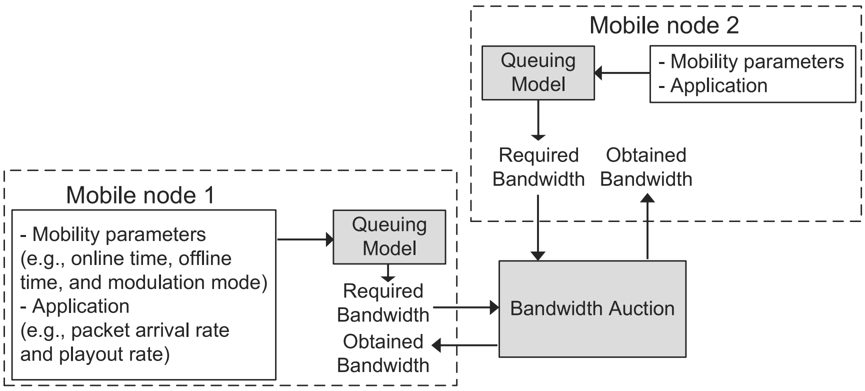


Figure 4.2. *Diagram showing the interaction between queueing model and bandwidth auction.*

4.5 Noncooperative Game Formulation for Bandwidth Auction

We present a noncooperative game with incomplete information for bandwidth auction. In this game, a mobile node competes with other mobile nodes to obtain the required amount of bandwidth by optimizing the bidding strategy. A distributed algorithm to obtain the Bayesian Nash equilibrium, which is the solution of this game, is also presented.

4.5.1 Bandwidth Allocation Strategy

The amount of bandwidth available at a wireless access point is denoted as C MHz. Let i denote an index of a mobile node, $i \in \mathbb{M} = \{1, \ldots, M\}$, where $\mathbb{M}$ is the set of mobile nodes and M is the total number of mobile nodes connected to an wireless access point. Let $\vec{\mathbf{b}}$ denote a vector of bids from all mobile nodes submitted to the wireless access point. This vector is defined as follows: $\vec{\mathbf{b}} = \begin{bmatrix} b_1 & \cdots & b_i & \cdots & b_M \end{bmatrix}^T$. Each mobile node sends the first bid to the wireless access point (i.e., auctioneer). The first bid is defined as: $b_i^1 = (p_i, t_i)$, for $p_i \geq \tau$, where p_i is the offered price per unit of bandwidth per unit of time (monetary unit (mu)/s/MHz), and t_i is the time interval that the mobile node requests to connect to wireless access point (i.e., $t_i > 0$). τ is the minimum price for a unit of bandwidth which is acceptable to the wireless access point.

Assume that mobile node i submits $t_i = t_{\text{on},i}$ where $t_{\text{on},i}$ is the average time for the mobile node to be in online state. Let ϵ be the reserved price (mu/MHz) defined by the wireless access point. The access point will adjust its reserved price due to the variation of bandwidth demand. The bandwidth allocation policy based on proportional fairness [47] is used by the wireless access point where the weight is the price per unit of bandwidth. After all the bids are submitted to the wireless access point, the wireless access point determines the bandwidth allocation vector $\vec{\mathbf{g}} = \begin{bmatrix} g_1 & \cdots & g_i & \cdots & g_M \end{bmatrix}^T$, where g_i is the amount of allocated bandwidth to mobile node i. This allocated bandwidth is obtained from

$$g_i(t_i, \vec{\mathbf{t}}_{-i}) = \frac{p_i t_i}{\sum_{j=1}^{M} (p_j t_j) + \epsilon} C \tag{4.8}$$

where $\vec{\mathbf{t}}_{-i}$ is the vector of time intervals for all mobile nodes except mobile node i to be in online state, i.e., $\vec{\mathbf{t}}_{-i} = \begin{bmatrix} \cdots & t_j & \cdots \end{bmatrix}^T$ for $j \neq i$.

4.5.2 Bidding Strategy

The mobile nodes (i.e., bidders) which are previously allocated with the required bandwidth will not submit new bids in the new bidding round. If all the bidders are satisfied (i.e., reaching the equilibrium solution), the game stops. However, if some mobile nodes are not satisfied with the allocated bandwidth, they can submit new bids in the next round. Only new "willing-to-pay" prices are reported to the auctioneer (i.e., $b_i = (p_i)$). A Bayesian noncooperative game for bandwidth auction can then be formulated as follows:

- *Players* are M mobile nodes. A set of player is $\mathbb{M} = \{1, \ldots, M\}$.
- *Action* set is $\mathbb{B} = \mathbb{B}_1 \times \cdots \times \mathbb{B}_M$ ('$\times$' is the Cartesian product), where $\mathbb{B}_i = \{\tau, b_i^{max}\}$ denotes the action set (i.e., possible bids $b_i \in \mathbb{B}_i$) for player i. The bids have nonnegative values in the range τ and b_i^{max}. τ is the minimal bidding price defined by the wireless access point and b_i^{max} is the maximum bidding price that mobile node i can pay.
- *Type set* is $\mathbb{T} = \mathbb{T}_1 \times \cdots \times \mathbb{T}_M$, where $\mathbb{T}_i = \{t_{min}, t_{max}\}$ denotes a player's type set which is the time interval during which the player wants to connect to the wireless access point (i.e., $t_i \in \mathbb{T}_i$). Since a time slot-based allocation is considered, mobile nodes' types are discrete values between t_{min} and t_{max}, where $0 < t_{min} < t_{max}$. t_{min} is the minimum connection period and t_{max} is the maximum connection period before the connection is terminated. Note that each mobile node can observe its own *type* but not the *type*s of other mobile nodes.
- *Probability function* is the conditional probability assigned to the type profile denoted as $f_{T_i}(t_i)$. Let $f_{T_i}(t_i), t_i \in \mathbb{T}_i$ denote the probability function of the type

profile of each player i (i.e., the time interval during which the player wants to connect to the wireless access point).

- *Payoff* is defined as the difference between the utility of allocated bandwidth and the cost paid to wireless access point. For allocated bandwidth g_i from the wireless access point, the payoff of mobile node i is given by

$$P_i(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i}) = t_i U_i(g_i(t_i, \vec{\mathbf{t}}_{-i})) - \delta_i g_i(t_i, \vec{\mathbf{t}}_{-i}) p_i t_i \tag{4.9}$$

where $\vec{\mathbf{b}}_{-i}$ and $\vec{\mathbf{t}}_{-i}$ denote, respectively, the vector of bids and the vector of time intervals to be in online state for all mobile nodes except mobile node i. δ_i is the weight corresponding to the cost for mobile node i. This parameter can be chosen according to the preference of mobile nodes (e.g., according to the application). $U_i(\cdot)$ is the utility function of bandwidth. We assume this utility function to be logarithmic [48], which is given by

$$U_i(g_i(t_i, \vec{\mathbf{t}}_{-i})) = \begin{cases} \alpha \log(1 + \gamma g_i(t_i, \vec{\mathbf{t}}_{-i})), \\ \qquad \text{for} \quad g_i(t_i, \vec{\mathbf{t}}_{-i}) < q_i \\ \alpha \log(1 + \gamma q_i), \\ \qquad \text{for} \quad g_i(t_i, \vec{\mathbf{t}}_{-i}) \geq q_i \end{cases} \tag{4.10}$$

where α and γ are the constants indicating the scale and the shape of the utility function, respectively. For the function defined in (4.10), the utility becomes constant (i.e., saturated) if the allocated bandwidth is equal to or greater than the required bandwidth q_i. Note that $U_i(g_i)$ is also a function of t_i due to the allocation policy of the auctioneer g_i.
The mobile nodes (i.e., bidders) which are previously allocated with the required bandwidth will not submit new bids in the new bidding round. If all the bidders are satisfied (i.e., the equilibrium solution is reached), the game terminates. However, if some mobile nodes are not satisfied with the allocated bandwidth (i.e., allocated bandwidth is smaller than the required bandwidth), they can submit new bids in the next round. Only new "willing-to-pay" prices are reported to the auctioneer.

4.5.3 Optimal Bidding Strategy and Bayesian Nash Equilibrium

To obtain the Bayesian Nash equilibrium (BNE), the best bidding strategy of mobile node i is defined as the strategy yielding the highest expected payoff given the strategies of other players. This BNE is obtained as follows:

$$\begin{aligned} BR_i(\vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i}) &= \arg\max_{b_i} E[P_i(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i})] \\ &= \arg\max_{b_i} \sum_j f_T^{\prime j}(\vec{\mathbf{t}}_{-i}) P_i^j(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i}) \end{aligned} \tag{4.11}$$

where $\vec{\mathbf{t}}_{-i}$ is the vector of time intervals to be in online state by all mobile nodes except mobile node i, and $f_T^{\prime j}(\vec{\mathbf{t}}_{-i})$ is the joint probability for index j of the different events of other mobile nodes' types. Since the best response is obtained based on the joint distribution of the time intervals for the mobile nodes to be in online state, the accuracy of the distribution will affect the best response function. Note that the joint probability can be calculated from the mobility information of nodes (e.g., speed and direction) estimated at the access point. Note that the noncooperative game formulation is a one-shot (single-stage) game in which the outcome of the game is determined only once (i.e., when Bayesian Nash equilibrium is reached). In this case, type t_i of mobile node i is fixed for one stage. This is in contrast to a dynamic game where the players play the one-shot game repeatedly.

Let vector $\vec{\mathbf{b}}^* = \begin{bmatrix} b_1^* & \cdots & b_i^* & \cdots & b_M^* \end{bmatrix}$ denote the BNE of this game. The auction ends when all bidders obtain their best bidding strategies given others' best bidding strategies as follows:

$$b_i^* = BR_i(\vec{\mathbf{b}}^*_{-i}, t_i, \vec{\mathbf{t}}_{-i}) \tag{4.12}$$

where $\vec{\mathbf{b}}^*_{-i}$ is a vector of best bidding strategies of all mobile nodes except mobile node i.

Since a Bayesian Nash equilibrium is a Nash equilibrium when players are expected to be utility-maximizing, the existence of a Bayesian Nash equilibrium is immediately proved by the Nash existence theorem. Since the strategy space b_i is convex, compact, and nonempty for each i, the expected payoff function $E[P_i(\cdot)]$ is continuous in both b_i and $\vec{b_{-i}}$, and $E[P_i(\cdot)]$ is concave for any $\vec{b_{-i}}$. Therefore, it is guaranteed that at least one Bayesian Nash equilibrium (or Nash equilibrium) exists [125]. Furthermore, using the Karush-Kuhn-Tucker (KKT) conditions to (4.12), which yield the necessary and sufficient conditions for BNE in this case, the uniqueness of BNE can be proved as shown in Appendix A.1.

4.5.4 Distributed Algorithm for Bandwidth Auction Game

We assume that the wireless base station announces all the trading prices to the mobile nodes at the end of each bidding round and the mobile nodes know the allocation strategy of the wireless base station. Let k denote the bidding round. A distributed bidding algorithm for a mobile node to reach the BNE of the bandwidth auction game is presented in **Algorithm 2**.

Algorithm 2 Bidding algorithm.

```
Initialize k = 1.
b_i^1[k] = (p_i[k], t_i), ∀i ∈ 𝕄 is submitted to the wireless access point.
Wireless access point allocates bandwidth g_i[k] to each mobile node.
repeat
    Vector b⃗[k] is announced to all mobile nodes by the wireless access point.
    k = k + 1.
    b_i[k] = BR_i(b⃗_{-i}[k − 1], t_i, t⃗_{-i}).
    b_i[k] is submitted to the wireless access point.
    Wireless access point allocates bandwidth g_i[k] to each mobile node.
until b_i[k] = b_i[k − 1], ∀i ∈ 𝕄.
```

4.6 Numerical Study

4.6.1 Application Scenario

In this numerical study, we apply this auction game model to the bandwidth allocation in vehicle-to-roadside (V2R) communications as the example. In V2R communications, data is transferred through the roadside base stations (RSBs), i.e., wireless access points. That is, the mobile nodes shown in Figure 4.1 are vehicles. We assume that network coverage of the roadside base stations (RBSs) is non-continuous. To ensure smooth streaming service, a vehicle needs to obtain sufficient bandwidth to download and cache the continuous data within its limited connection time interval (i.e., due to high mobility of vehicles).

We assume that each vehicle can observe its own *type* but not the *type*s of other vehicles, and the *types* of the vehicles are assumed to be independent. We assume that the probability distribution of connection duration is given as follows [43]:

$$f_T(t) = \frac{1}{\beta} e^{-t/\beta}, \quad t \geq 0 \tag{4.13}$$

where β is the average connection duration. Note that any other probability distribution function (pdf) for connection duration can also be applied in our system model. From [67], the speed of a vehicle can be modeled as a random variable with normal distribution with the pdf expressed as follows:

$$f_S(s) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(s-\mu)^2}{2\sigma^2}} \tag{4.14}$$

where s is the vehicle speed, μ is the average speed, and σ is the standard deviation of speed. Since the speed can be only positive value and it is bounded, we normalize the pdf for vehicle's speed as follows:

$$\tilde{f}_S(s) = \frac{f_S(s)}{\int_{s_{\min}}^{s_{\max}} f_S(v) \quad dv}, \quad s_{\min} \leq s \leq s_{\max} \tag{4.15}$$

where $s_{\min}$ denotes the minimum speed and $s_{\max}$ denotes the maximum speed.

Next, we show the relationship among vehicle's speed, connection duration, and transmission range of the RSB [68]. Let t_{r} denote the time remaining in the transmission range of the RSB in seconds, d denote the distance between the vehicle and the RSB in meters, l denote the transmission range in meters, and s is the vehicle's speed in km/h. We assume that the vehicles connect to the RSB when they are in the RSB's transmission range.

$$t_{\mathrm{r}} = \frac{d+l}{(s \times 10^3)/3600} = \frac{2l}{(s \times 10^3)/3600}. \tag{4.16}$$

Therefore, we can replace β in (4.13) by

$$\beta = E[t_{\mathrm{r}}] = \frac{2l}{10^3/3600} \int_{s_{\min}}^{s_{\max}} \frac{\tilde{f}_S(s)}{s} \quad ds. \tag{4.17}$$

Clearly, if the vehicle knows the statistics of the other vehicles' speed (e.g., observing from the current traffic condition, speed limit of the road, etc.), the probability distributions of the time intervals that other vehicles will connect to the RSB can be obtained by using (4.13).

Since the players' *types* are considered to have discrete values, the probability distribution of the type is discretized into a probability mass function (pmf) of values equally spaced between t_{min} and t_{max}. Then, we obtain this pmf $f_T'(\cdot)$ that can be used in (4.12).

4.6.2 Parameter Setting

We consider three vehicles. The time intervals during which the vehicles have connection to RSB have average values of $t_{\mathrm{on},1} = 30$, $t_{\mathrm{on},2} = 20$, and $t_{\mathrm{on},3} = 50$ seconds for vehicles 1, 2, and 3, respectively. The time intervals during which the vehicles do not have connection to RSB have average values of $t_{\mathrm{off},1} = 60$, $t_{\mathrm{off},2} = 60$, and $t_{\mathrm{off},3} = 70$ seconds for vehicles 1, 2, and 3, respectively. The physical data rate of all the WiFi transceivers equipped in all the vehicles is $r_{\mathrm{p}} = 11$ Mbps. The data transfer rate from the gateway to vehicle 1 is $r_{\mathrm{u},1} = 20$ packets/second, to vehicle 2 is $r_{\mathrm{u},2} = 15$ packets/second, and to vehicle 3 is $r_{\mathrm{u},3} = 25$ packets/second, where all packets have the same length $L = 0.1$ Mbits. Buffers at the gateways of all the vehicles have the same size $B_1 = B_2 = B_3 = 2{,}000$ packets. The target buffer underrun probabilities of vehicles 1, 2, and 3 are $P_{\mathrm{under},1} = 0.25$, $P_{\mathrm{under},2} = 0.20$, and $P_{\mathrm{under},3} = 0.40$, respectively. Vehicles 1, 2, and 3 use transmission modes 5, 4, and 6, respectively, as given in Table 4.2 [66].

In the utility function, we set $\alpha = 9$ and $\gamma = 5$ for all the vehicles. The weights corresponding to the cost function of the three vehicles are $\delta_1 = \delta_2 = \delta_3 = 0.05$. We assume that the currently available bandwidth at the RSB is $C = 5$ MHz and the transmission range of the RSB is $l = 250$ m. The reserved price and minimum price defined by the RSB are $\epsilon = 5$ mu/MHz and $\tau = 5$ mu/s/MHz, respectively. The maximum bidding price for all the vehicles is 50 mu/MHZ. The speed of vehicles 1, 2, and 3 as observed by other vehicles follows normal distribution with parameters $N(70, 21)$, $N(90, 27)$, and $N(90, 27)$, respectively. We assume $s_{\max} = \mu + 3\sigma$ km/h [70].

4.6.3 Required Transfer Rate

Figure 4.3 shows the minimum transfer rate of vehicle 1 when the target buffer underrun probability is 0.25 and t_{on} and t_{off} are varied. Vehicles can calculate their required transfer rates to meet their performance requirements so that the bidding strategy can be adapted accordingly.

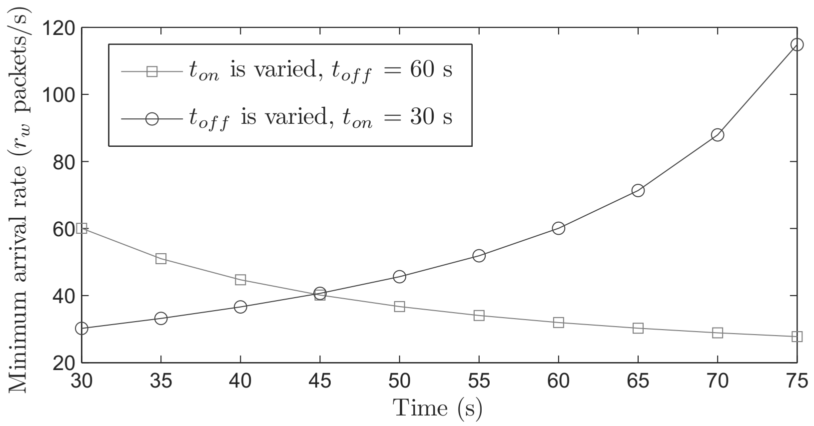


Figure 4.3. *Minimum transfer rate of vehicle 1 when t_{on} and t_{off} are varied with the target buffer underrun probability $P_{\text{under},1} = 0.25$.*

4.6.4 Bayesian Nash Equilibrium and Payoff

Figure 4.4 shows the best bidding strategies of all the vehicles. The Bayesian Nash equilibrium is located at the point where the best bidding strategies of the three vehicles intersect.

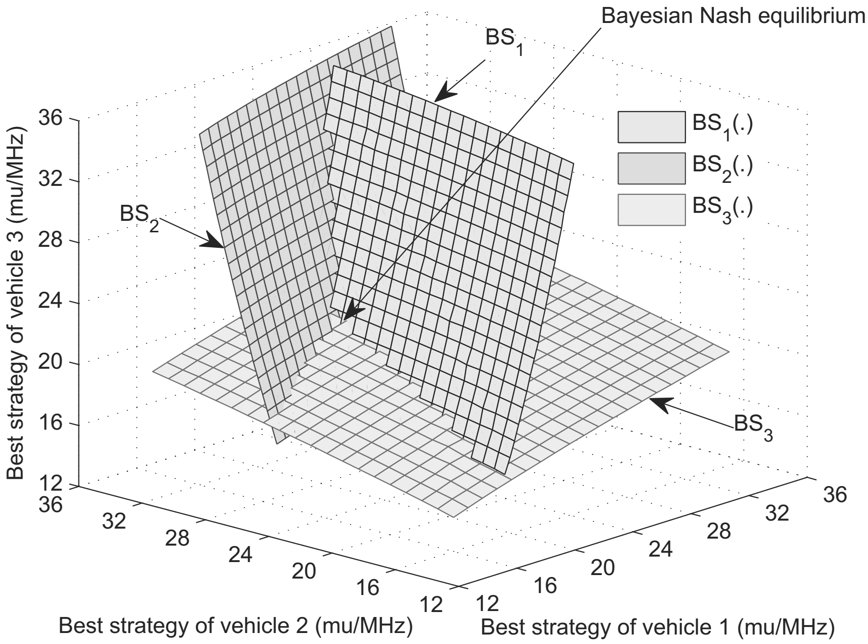


Figure 4.4. *Bayesian Nash equilibrium in the bandwidth auction game among three vehicles.*

Since a Bayesian Nash equilibrium is a Nash equilibrium when players are expected to be utility-maximizing, the existence of a Bayesian Nash equilibrium is immediately proved by the Nash existence theorem [1]. Since this game has a finite number of players each of whom has a finite number of pure strategies (b_i), this game of incomplete information possesses at least one Bayesian Nash equilibrium.

Using the distributed algorithm based on the best response bidding strategy, the equilibrium point will be reached [69]. Then, we apply the distributed algorithm to obtain the solution of the bandwidth auction game. Each vehicle adjusts its bidding price in each bidding round. As shown in Figure 4.5, the bidding prices of all the vehicles converge to the solution within a few rounds. At the equilibrium, vehicle 1 bids with a price of 24.67 mu/MHz and obtains 1.97 MHz of bandwidth, vehicle 2 bids with a price of 31.29 mu/MHz and obtains 1.66 MHz of bandwidth, and vehicle 3 bids with a price of 20.33 mu/MHz and obtains 1.35 MHz of bandwidth.

Next, we compare the payoffs of vehicle obtained from the BNE, the NEs in an incomplete information environment and a complete information environment, and the optimal social welfare strategy for which the sum of all vehicles' utilities is

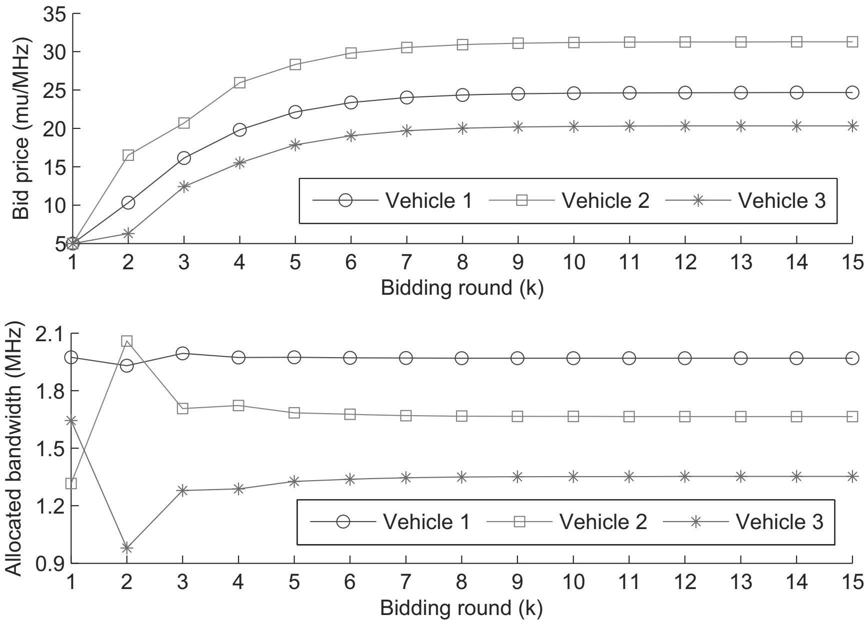


Figure 4.5. *Bidding price and amount of bandwidth for the three vehicles at each bidding round.*

maximized in a centralized environment with complete information (i.e., connection time intervals for all the vehicles are known). The optimal social welfare strategy is given by

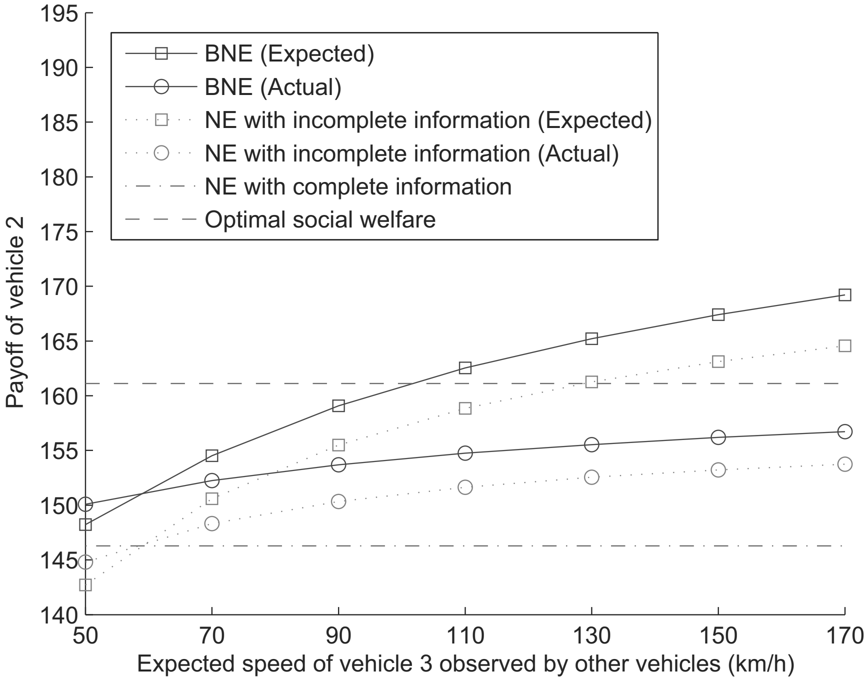
$$\vec{\mathbf{b}}_i^{\star} = \arg\max_{\vec{\mathbf{b}}_i} \sum_{i=1}^{M} P_i(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i}). \tag{4.18}$$

The payoffs of vehicles 1 and 2 obtained from BNE and NEs with complete and incomplete information are shown in Figs. 4.6(a) and (b), respectively. The mean value of vehicle 3's speed is varied in the x-axis, and its variance is varied according to the mean speed based on Table I of [70]. Here, the NE with incomplete information refers to the equilibrium solution when a vehicle does not use any probabilistic belief when information is incomplete. For example, a node uses only single-type beliefs about the types of other nodes. In this game, the connection time interval of each vehicle (i.e., type), which is computed from average speed observed by its competitors, is fixed (i.e., the probability density function for the type built from the observation of speed is a delta function). The NE with complete information refers to the Nash equilibrium solution when the vehicles perfectly know the connection time intervals (i.e., types) of each other. The BNE and the NE in an incomplete information environment are different from the NE in a complete information environment; that is, they represent different equilibrium points. The payoffs corresponding to BNE and NE in an incomplete information environment may be higher or lower than, or equal to the payoff corresponding to the NE in a complete information environment depending on the accuracy of beliefs about opponents' types. The more accurate the belief, the closer will be the actual payoff to the one computed from BNE or NE.

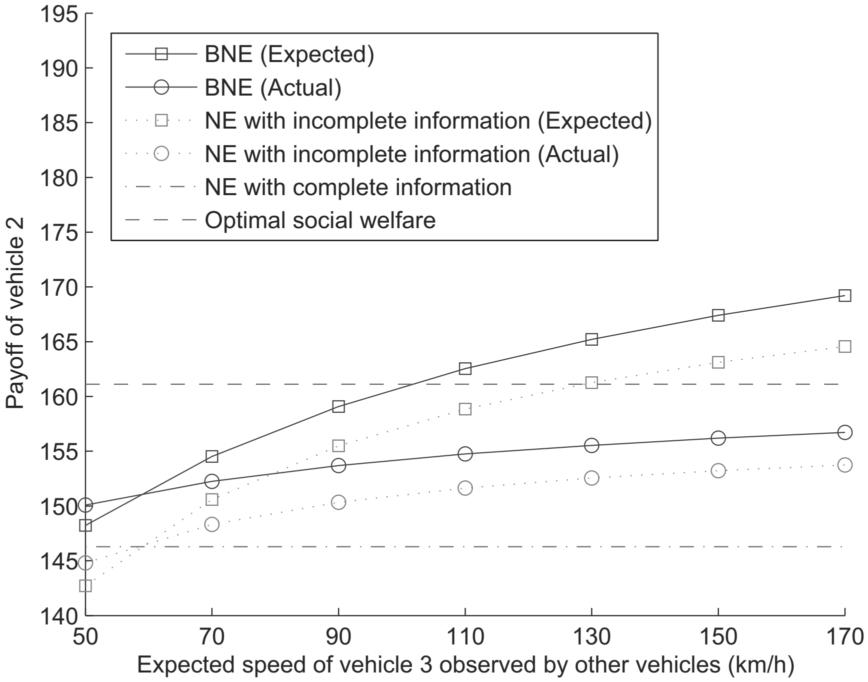
In the incomplete information environment, we observe the difference between the expected and actual payoffs obtained from BNE and NE when the observed speed is varied. Note that the actual payoff is computed from actual allocated bandwidth, actual types, and equilibrium bid prices. In this case, the differences between the expected and actual payoffs for vehicles 1 and 2 obtained from the BNE are lower than those from the NE with incomplete information. The reason is that when a player does not have complete information, using probabilistic beliefs would be better than using a single-type beliefs about other vehicles' types. Moreover, the payoffs of both the vehicles obtained from the BNE and NEs are less than the payoffs obtained from social welfare optimization. This difference is called the price of anarchy which shows how well the players do when they play selfishly in the auction game compared to the centralized social welfare optimization. Note that since the expected payoffs are computed based on the actual bids but not the actual types, it can be higher than the payoff from social welfare optimization, which is computed based on perfect information. In case of social welfare optimization, the players play cooperatively and all the information are known. As a result, the actual payoffs of the players are higher than those from NE.

4.7 Chapter Summary

We have discussed the applications of game theoretic models, and in particular, the application of Bayesian game, to solve the problem of distributed resource allocation under uncertainty in wireless networks. As an example, we have presented a distributed Bayesian auction mechanism for bandwidth allocation among mobile nodes in a public wireless network while considering their QoS requirements for a streaming application. Given the required transfer rate for the streaming application, a Bayesian noncooperative game has been formulated to model the decision making process of mobile nodes to bid for the radio bandwidth in an incomplete information environment. The Bayesian Nash equilibrium has been considered as the solution of this bandwidth auction game. Performance of this game model has been studied for bandwidth allocation in vehicle-to-roadside communications environment. As an extension, advanced models such as coalitional Bayesian game models can be developed for cooperative distributed resource allocation under uncertainty in wireless networks.



(**a**)



(**b**)

Figure 4.6. *Comparison between the payoffs of (a) vehicle 1 and (b) vehicle 2 from Bayesian Nash equilibrium (BNE), Nash equilibrium (NE) in an incomplete information environment, and Nash equilibrium (NE) in a complete information environment when the expected speed and its variance of vehicle 3 observed by other vehicles is varied.*

Chapter 5

Distributed Cooperative Channel Access: A Coalitional Game Model

5.1 Introduction

Since we have considered the bandwidth allocation problem for the single-hop transmission scenario (i.e., a wireless node directly connected to a base station/access point) in Chapter 3 and Chapter 4, here we consider a multiple access problem for the multi-hop transmission scenario. A mobile node may be able to receive information in a timely manner only if it is within the transmission range of a BS and connected to the BS for a sufficient amount of time. However, if a mobile node moves out of the transmission range of a BS (e.g., due to high mobility), data can be forwarded to this node by other nodes carrying data from that BS and meeting this destination mobile node (Figure 5.1). Also, when the wireless link condition between the BS and a mobile node in poor (e.g., the mobile node is inside a tunnel), carry-and-forward-based cooperative data delivery will be useful to reduce the delay of data delivery. A mobile node, which is currently connected to a BS, can help the BS to forward packets to other mobile nodes until the packets reach their destinations. This is an example of hybrid wireless networking model because it uses communications among mobile nodes and BSs as well as communications among mobile nodes.

A few works in the literature proposed communication models for wireless networks with relay-based schemes [72]–[74] to reduce the delay of data delivery. In these schemes, mobile nodes in a group (i.e., cluster) cooperatively deliver data packets among each other. However, the key assumption here is that the mobile nodes in

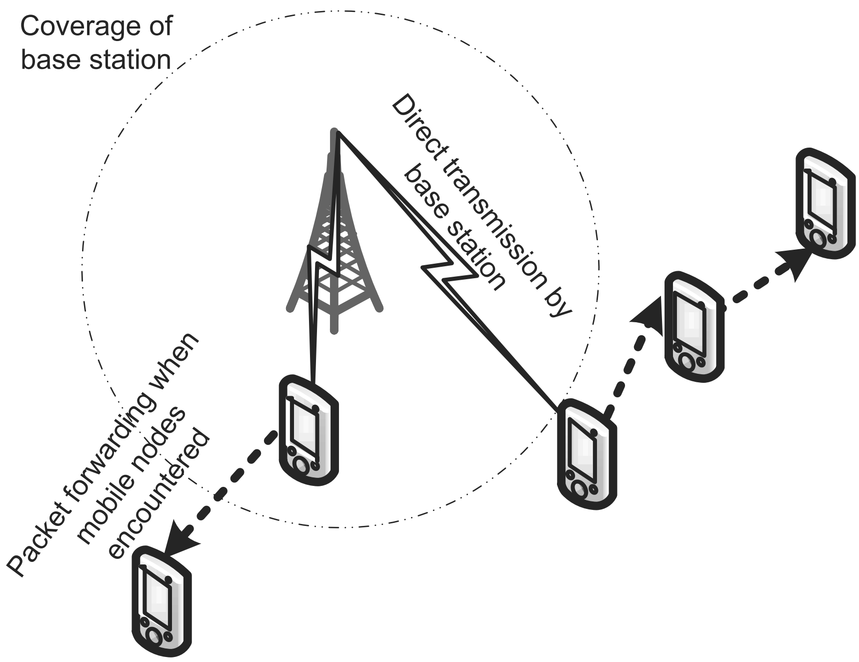


Figure 5.1. *In a hybrid wireless network, the mobile nodes can form coalitions to help forward data from a base station to other mobile nodes which are out of the transmission range of the base station.*

the same group always help each other for data delivery. Since a tradeoff exists between performance improvement (i.e., smaller packet delivery delay) and transmission cost (i.e., bandwidth and energy-consumption) for such cooperative data delivery, this assumption may not be always true. For example, when a mobile node has limited transmission bandwidth and is of self-interest, it may not join a group for cooperative data delivery. In this context, the theory of coalitional game [20] can be applied to analyze the dynamics of coalition (or group) formation among mobile nodes. Coalitional games have been used to model and analyze the resource allocation problem in wireless networks. In the research paper of D. Niyato et al. [75], mobile nodes (e.g., vehicular users) form coalitions and cooperatively share the limited bandwidth of vehicle-to-roadside links to achieve high spectrum utilization. In the research paper of W. Saad et al. [76], roadside BSs form coalitions in which the BSs in the same coalition cooperatively coordinate the classes of data that they transmit to mobile nodes, and thereby, improve their revenue.

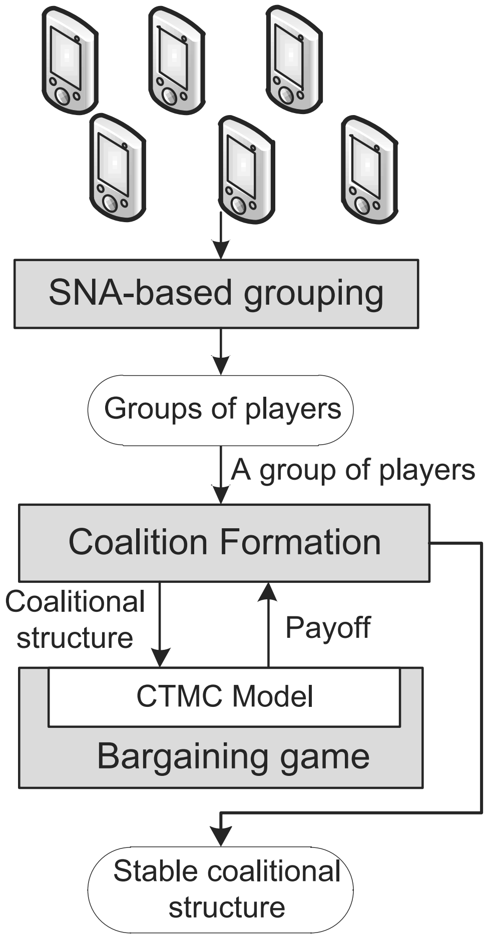


Figure 5.2. *Diagram showing the interrelationship among the three steps, namely, mobile node grouping using social network analysis (SNA), bargaining game, and coalitional game.*

Different from the above works, in this study, we present a cooperative packet delivery scheme in a hybrid wireless networking scenario. In the scenario under consideration, a base station has packets to transmit to a mobile node which may not be in the transmission range of the BS. To reduce the delay of packet delivery, coalitions of mobile nodes can be formed. The social relationship among the mobile nodes can be exploited to reduce the complexity of coalition formation. Mobile nodes in the same coalition help each other to deliver packets sent from the BS to the destination mobile nodes. Based on a coalitional game model, we study the dynamics of the behavior of mobile nodes helping each other to forward data packets based on their individual selfishness with an objective to maximizing their individual payoffs.

The proposed scheme consists of three interrelated steps as shown in Figure 5.2. We first use a social network analysis (SNA)-based approach [77]-[79] to identify which mobile nodes have the potential to help other mobile nodes for data delivery in the same group or coalition. After the SNA-based mobile node grouping is done, the mobile nodes in each group play a coalitional game to obtain a stable coalitional structure. The payoff of each mobile node is a function of cost incurred by the mobile node in relaying packets and the delivery delay for packets transmitted to this mobile node from a BS. A continuous-time Markov chain (CTMC) model is formulated to obtain the expected cost and packet delivery delay for each mobile node in the same coalition. Since the expected cost and packet delivery delay vary with the probability that each mobile node helps other mobile nodes deliver packets, a bargaining game [66, 80] is used to find the optimal helping probabilities for all the mobile nodes in a coalition. For each mobile node, after the optimal probability of helping other mobile nodes is obtained, we can determine the payoff of each mobile node when it is a member of its current coalition. The payoffs obtained from the bargaining game are used to determine the solution of the coalitional game in terms of stable coalitional structure (i.e., a group of stable coalitions). A distributed algorithm is used to obtain the solution of the coalitional game and a Markov chain-based analysis is presented to evaluate the stable coalitional structures obtained from the distributed algorithm.

The major contributions of the proposed work can be summarized as follows.

- We introduce a coalitional game formulation to study how mobile nodes can dynamically form coalitions to cooperatively forward data of other mobile nodes in the same coalition. We apply social network analysis to reduce the computational complexity of coalition formation. Two solution concepts, i.e., *stable coalitional structure* and *core*, are considered for the proposed coalitional game.
- We propose a Nash bargaining game formulation to obtain Pareto-optimal solution for the probabilities that mobile nodes will help other mobiles in the same coalition.
- A distributed coalition formation algorithm is proposed which guarantees that stable coalitional structures can be obtained. We perform a comprehensive

performance evaluation of the proposed method.

Using SNA-based grouping, bargaining game-based optimal data forwarding, and distributed coalition formation in a unified framework for cooperative packet delivery in a hybrid wireless network constitutes the major novelty of this work. The proposed framework will be useful for supporting various mobile applications based on distributed cooperative packet delivery. The rest of this chapter is organized as follows. Section 5.2 describes the system model and assumptions. The social network analysis-based mobile node grouping is presented in Section 5.3. Section 5.4 presents the bargaining game model for cooperative packet delivery. The formulation of the coalitional game is presented in Section 5.5. Section 5.6 presents representative performance evaluation results for the proposed coalitional game framework. The related researches on cooperative data delivery are reviewed in Section 5.7. Section 5.8 concludes the chapter. Note that the list of symbols used in this chapter is shown in Table 5.1 and Table 5.2.

5.2 System Model and Assumptions

5.2.1 Models for Mobile Node Encounter, Node Mobility, and Cooperative Packet Transmission

We are interested in downlink communications from the sporadically deployed BSs/APs (e.g., based on IEEE 802.11) to the mobile nodes.[1] To reduce the delay of packet delivery to a mobile node which is out of the transmission range of a BS (e.g., connectivity lost due to high mobility), a cooperative packet delivery scheme based on carry-and-forward mechanism is used. We assume that the BSs can communicate with each other through the wired network to exchange information about the mobile nodes.

Multiple mobile nodes can cooperate and form coalitions. We assume that each mobile node in the same coalition will carry and forward packets to other mobile nodes when they meet each other. Each mobile node $i \in \mathbb{M} = \{1, \ldots, M\}$ has a transmission range of h_i meters. We consider a period of time and assume that over

[1] The proposed model can also be applied for uplink transmission from mobile nodes to a BS/AP.

Table 5.1. *List of symbols used in Chapter 5*

Symbol	Definition
"0"	The index of any base station
$\mathbf{0}$	The zero matrix
$\mathcal{B}_{\Upsilon,\Upsilon'}$	The set of players who move from its current coalition to a new coalition and the coalitional structure changes from Υ to Υ'
$\mathcal{C}$	The core of the coalitional game
C_i	The total cost of mobile node i for packet delivery to any mobile node j in the same coalition
c^{r}_{ij}	The cost incurred to mobile node i for receiving packet(s) from a BS or from other mobile node j in the same coalition
$c^{\mathrm{f}}_{ij'}$	The cost incurred to mobile node i for forwarding packet(s) to its destination or to another mobile node j' in the same coalition
$c^{\mathcal{X}'}_{ij}$	The expected cost that mobile node i incurs for delivering the packet to mobile node j in state $\mathcal{X}'$
D_N	The number of different coalitional structures for N players
d_i	The packet delivery delay from when the packet is originally transmitted from the base station to when the packet is received by mobile node i
$\mathcal{E}$	The edges of the graph (i.e., edges are the mobile nodes' relationships)
$\mathbf{F}$	The transition probability matrix corresponding to the transitions from the transient states to the absorbing state
$f_{0j}(t)$	The probability density function (PDF) of T_{0j}
$f_{ji}(t)$	The probability density function (PDF) of T_{ji}
h_0	The transmission range in meters of a base station
h_i	The transmission range in meters of mobile node i
$\mathbf{I}$	The identity matrix
i	The index of each mobile node
K	The label of a mobile node which is the final destination for a transmitted packet
M	The number of mobile nodes
$\mathbb{M}$	The set of all mobile nodes
$\mathbf{M}$	The fundamental matrix of the absorbing DTMC
$m_{\mathcal{X},\mathcal{X}'}$	The expected number of times that the transient state $\mathcal{X}'$ will be visited if it starts in transient state $\mathcal{X}$
$\mathbb{N}_k$ and $\mathbb{N}$	The group of mobile nodes in social group k
N	The number of mobile nodes in a social group
n_{ij}	The number of encounters between mobile node i and mobile node j during a period of time
n_{th}	The threshold on the number of encounters
P_{ij}	The probability that the data packet will be delivered from the base station to mobile node i via mobile node j
$\mathbf{P}$	The transition probability matrix of the absorbing DTMC
$\mathcal{P}_i$	The action set of each player which is to choose its optimal probability p_i
$\vec{\mathbf{p}}$	The vector of probabilities that mobile nodes help each other in the same coalition
p_i	The probability that mobile node i is willing to help other mobile nodes to deliver packets
$p_{\mathcal{X},\mathcal{X}'}$	The probability of state transition from state $\mathcal{X}$ to any state $\mathcal{X}'$
$\mathcal{Q}_i$	The vector denoting the relationship of mobile node i with other mobile nodes
$q_{\mathcal{X},\mathcal{X}'}$	The total state transition rate from $\mathcal{X}$, which is a transient state, to another state $\mathcal{X}'$
$q_{\mathcal{X}}$	The summation of state transition rates from state $\mathcal{X}$ to any state $\mathcal{X}'$
R_i	The utility of mobile node i
r_{ij}	The encounter rate between mobile node i and mobile node j during a period of time
r_{i0}	The encounter rate between mobile node i and base station during a period of time
$\mathcal{S}$	The coalition of players (i.e., mobile nodes)

Table 5.2. *List of symbols used in Chapter 5 (continued)*

Symbol	Definition
$\mathbf{T}$	The transition probability matrix corresponding to the transitions among the transient states
T_i	The required delivery time of mobile node i
T_{0j}	The time interval before mobile node j is contacted by the base station
T_{ij}	The time interval before mobile node j is contacted by mobile node i
$t_{\mathcal{X}'}$	The mean sojourn time in state $\mathcal{X}'$
$\vec{\mathbf{u}}^{\mathbb{S}}$	The payoff vector of all mobile nodes in coalition $\mathbb{S}$
u_i	The payoff of mobile node i
u_i^d	The status-quo payoff of mobile node i
$\mathbb{V}$	The vertices of the graph (i.e., vertices are the mobile nodes)
$V(\mathcal{S})$	The characteristic function of coalition $\mathcal{S}$
$v(\mathcal{S})$	The total payoff of coalition $\mathcal{S}$
$\mathcal{X}$	The set of mobile nodes which already have the packet destined to mobile node K in the same coalition
α_i	The positive weight constant of the utility of delivering a packet to other mobile nodes in the same coalition
β_i	The positive weight constant of the cost of delivering a packet to other mobile nodes in the same coalition
γ	The probability that a player will make a decision
Ω	The state space or set of all possible coalitional structures
ω_i	The threshold on probability P_{ij} of mobile node i
Ψ	The state space of the CTMC for the cooperative packet delivery scheme
Ψ_A	The set of absorbing states of the CTMC
Ψ_T	The set of transient states of the CTMC
$\vec{\boldsymbol{\pi}}$	The stationary probability vector of all stable coalitional structures
π_{Υ_x}	The probability that the coalitional structure Υ_x will be formed
$\rho_{\Upsilon,\Upsilon'}$	The probability that the coalitional structure changes from coalitional structure Υ to coalitional structure $\Upsilon^{'}$
τ	The index of time iterattion
Υ	The coalitional structure
$\varphi_i(\Upsilon^{'}\vert\Upsilon)$	The probability that player i decides to move from its current coalition $\mathcal{S}_l^i$ to a new coalition

a period of time (e.g., one hour), we can predict the mobility and inter-encounter time pattern of each mobile node (e.g., based on the technique presented by S. C. Nelson et al. [81]). The effects of speeds and density of mobile nodes may result in a change of encounter-related statistical data [82]. Moreover, the mobility and inter-encounter time pattern of mobile nodes collected during a specific and short time period can be expressed as transient social contact pattern which can be better improve carry-and-forward-based data delivery than cumulative contact pattern (i.e., long time collection of contact pattern) [83]. Let mobile node i meet another mobile node j on the road with rate $r_{ij} = r_{ji}$ per unit of time and the number of encounters between mobile node i and mobile node j during a period of time is $n_{ij} = n_{ji}$. Let r_{i0} and r_{0i} be the rates that mobile node i meets the base station and vice versa. Note that "0" is used as the index of any base station and its transmission range is h_0. The encounter process for each pair of nodes is assumed to follow a Poisson process and the encounter rate is used as the corresponding parameter. For the encounter process, that the stochastic properties can be represented by the Poisson assumption, was justified be the research paper of Z. Xinjuan and X. Bo [84] and the research paper of R. Groenevelt, P. Nain, and G. Koole [85]. It was shown that the encounters between a pair of mobile nodes follow a Poisson distribution if the nodes move in a limited region.

Each mobile node i is willing to help other mobile nodes to deliver packets with probability p_i (i.e., $p_i = 1$ if mobile node i always receives data packets, carries, and forwards them to other mobile nodes). Any mobile node i receives packet(s) from a BS or from other mobile node j in the same coalition at the cost of c^{r}_{ij} per packet. Mobile node i then forwards the packet(s) to its destination or to another mobile node j' in the same coalition (which does not have the packet(s)) at the cost of $c^{\mathrm{f}}_{ij'}$ per packet. Note that the cost of transmission can be defined based on the application (e.g., the cost for delivering a packet for safety message dissemination can be lower than that for an entertainment message) as well as the physical transmission parameters. We assume that each mobile is able to know whether the other mobile nodes have the same packet(s), for example, by applying a point-to-point communication mechanism used in a routing protocol (e.g., encounter-based routing protocols) [81, 82, 86]. The cost of receiving a mobile node's own packets and the cost of packet transmission of a base station are assumed to be zero.

With the cooperative packet delivery scheme, the mobile nodes consider whether they should form a coalition, and if they form coalition which coalition to form. Let d_i denote the packet delivery delay which is the duration from when the packet is originally transmitted from the base station to when the packet is received by its destination. The time delay depends on the number of mobile nodes that help to deliver the packet. The mobile nodes may achieve a lower delay if they join a coalition. However, since they have to use their own resources for packet delivery of other mobile nodes in the same coalition, they will incur a cost. To model this tradeoff in the coalition formation among mobile nodes for cooperative packet delivery, a coalitional game-theoretic approach is applied. We assume that the packets are not immediately discarded from the cache of the BSs or the mobile nodes after they are sent or forwarded. In addition, there is a coordinator at the application server which collects mobility information of the nodes by using the following procedure.

(i) When the mobile nodes encounter each other, they make a record of the time they encounter.

(ii) Given a certain time period (e.g., one hour), the mobile nodes calculate the encounter rate with other nodes by dividing the number of encounters by the length of the time period.

(iii) The mobile nodes provide the encounter rate information to the central coordinator at the application server periodically.

(iv) The coordinator maintains a database of the encounter rate information for all the mobile nodes in the network, and this database is used for social network analysis. Also, the coordinator manages the information exchange among the base stations or access points.

5.2.2 Hierarchical Structure of Cooperative Data Delivery

For the hierarchical model of cooperative data delivery shown in Figure 5.2, given a coalition of mobile nodes (i.e., a coalitional structure in the considered coalitional game), a Markov chain model is formulated to find the expected cost and delay of each mobile node in a coalition. The expected cost and delay depend on the probabilities that the mobile nodes in the same coalition will help each other. To find the optimal probabilities, a bargaining game model is formulated and the Nash bargaining solutions [66] are obtained which are Pareto optimal. Subsequently, these probabilities are used to obtain the payoff of each mobile node which is a function of the expected cost and delay. The payoffs of all the mobile nodes are used to determine whether the current coalitional structure is stable or not. If it is unstable, a new coalitional structure will be formed, and the bargaining game and the Markov chain models will be used to find the payoff of the mobile nodes again until a stable solution is reached.

While the mobile nodes play the coalitional game, the bargaining game is used to find the optimal probabilities of helping other mobile nodes deliver packets, and then each mobile node's payoff is obtained. Therefore, for the purpose of presentation, the SNA-based mobile node grouping is first introduced. Then, the bargaining game model is presented and solved given a coalition of mobile nodes. Lastly, the coalitional game model is presented to obtain the stable coalitional structure.

5.3 Social Network Analysis-Based Mobile Node Grouping

In this section, we present a method for mobile node grouping based on social network analysis (SNA). The main problem of coalition formation is that the computational complexity increases exponentially when the number of nodes increases [20, 87]. Hence, the main objective of the proposed SNA-based mobile node grouping is to reduce the complexity of coalition formation when there are many mobile nodes participating in the cooperative data delivery scheme. The key mechanism of the SNA-based mobile node grouping is to filter out some mobile nodes which will not contribute to the cooperative packet delivery (i.e., to divide the mobile nodes into multiple social groups which mobile nodes in a social group do not cooperate with the mobile nodes in another social group).

A social network or a group is composed of nodes and ties. In this model, each mobile node is a *node* and relationships of mobile nodes are *ties*. Whether or not a tie will be established between two nodes can be determined by using centrality metrics used in graph theory and network analysis. Centrality is a quantification of the relative importance of a vertex within the graph (e.g., how important a node is within a social network). We identify how each node is important to others based on the Poisson modelling of the network which is called Poisson process-based centrality. To identify groups of mobile nodes using their Poisson process-based centrality, we propose an algorithm which ensures that for each mobile node in the same group, the probability that the packet delivery delay remains below a required time interval, can be maintained above a target threshold.

To ensure that mobile node j will deliver a packet received from the base station to mobile node i within the required time T_i (which depends on the application), we consider that if mobile node j is contacted by the base station within a time interval of $T_{0j} = 1/r_{0j}$ and then contacted by mobile node i within an interval of $T_{ji} = 1/r_{0j}$, the probability that the data packet will be delivered from the base station to mobile node i via mobile node j is

$$\begin{aligned} P_{ij}(T_{0j} + T_{ji} < T_i) &= \int_0^{T_i} f_{0j}(t) \otimes f_{ji}(t) dt \\ &= \int_0^{T_i} \int_0^{t} f_{0j}(t') f_{ji}(t - t') dt' dt \end{aligned} \tag{5.1}$$

where $\otimes$ is the convolution operator, and $f_{0j}(t)$ and $f_{ji}(t)$ for $t \geq 0$ are the probability density functions (PDFs) of T_{0j} and T_{ji}, respectively. $f_{0j}(t)$ and $f_{ji}(t)$ are given by exponential PDFs. Hence, the probability density function of random time interval t that mobile nodes i and j will contact each other is given by: $f_{ij}(t) = r_{ij} e^{-r_{ij} t}$, where r_{ij} is the encounter rate between mobile node i and mobile node j. Note that $f_{0j}(t)$ and $f_{ji}(t)$ are general and can be any other PDF rather than the exponential PDF.

Algorithm 3 below identifies the groups of mobile nodes. The nodes in such a group are the players in the bargaining game and the coalitional game. In this algorithm, $\mathbb{M}$ denotes the set of all mobile nodes and $\mathcal{Q}_i$ is a vector denoting the relationship of mobile node i with other mobile nodes.

Mobile node i is said to have a social relationship with mobile node j if they meet each other within a required time T_i (i.e., P_{ij} is greater than threshold ω_i and the number of encounters between mobile node i and mobile node j is greater than

Algorithm 3 Mobile node grouping algorithm based on social network analysis

```
Profile information (i.e., encounter information) of mobile nodes are collected by
  the central coordinator.
Set 𝒦 = ∅. // a temporary variable.
Initialize sets of relationships for all the mobile nodes, i.e., 𝒬_i = ∅, ∀i ∈ 𝕄.
for each mobile node i ∈ 𝕄 = {1, ..., M}
  𝒦 = 𝒦 ∪ {i}
  for each mobile node j ∈ 𝕄 \ 𝒦
    if (P_ij(T_0j + T_ji < T_i) ≥ ω_i and P_ji(T_0i + T_ij < T_j) ≥ ω_j and n_ij > n_th)
      Add mobile node j to mobile node i's set of relationships and vice versa.
      𝒬_i = 𝒬_i ∪ {(i, j)}
      𝒬_j = 𝒬_j ∪ {(j, i)}
    end
  end
end
Use the sets of relationships 𝒬_i of all the mobile nodes to build a graph G(𝕍, ℰ).
Set the vertices of the graph 𝕍 = 𝕄 (i.e., vertices are the mobile nodes).
Set the edges of the graph ℰ = ⋃_{i=1}^{M} 𝒬_i (i.e., edges are the mobile nodes' relation-
  ships)
Identify each group k of mobile nodes, ℕ_k ⊆ 𝕍 where ⋃_k ℕ_k = 𝕄, which is a
  maximal complete clique or subgraph in the graph G(𝕍, ℰ) by using algorithms
  such as those in [88].
```

threshold n_{th}). Each mobile node would like to reduce the expected packet delay by cooperating with the mobile nodes it has strong social ties with. Here both ω_i and n_{th} are design parameters which define the "strength" of the social tie. When ω_i increases, the number of mobile nodes in a social group may decrease due to the tighter requirement for encountering. However, the chances to contact those mobile nodes within the required time interval will be higher. On the other hand, when ω_i decreases, the number of mobile nodes in a social group may increase due to the looser requirement for encountering. However, the chances to contact those mobile nodes within the required time interval will be lower. The threshold n_{th} on the number of encounters is used to ensure that the relationship between a pair of mobile nodes is strong enough. If the value of threshold n_{th} increases, the mobile nodes require stronger relationship to meet the condition. As a result, the number of mobile nodes in a social group may decrease. Conversely, if the value of the threshold n_{th} decreases, the number of mobile nodes in a social group may increase. If the requirement is satisfied, mobile node i adds (i, j) (i.e., its relationship with mobile node j) to $\mathcal{Q}_i$.

After the relationships among all the mobile nodes are created, we can identify the groups of mobile nodes which are complete subgraphs in the graph representing the mobile nodes' relationships. In a complete subgraph, each member has relationships with other mobile nodes in the same group (i.e., the same subgraph). In particular, after the social network analysis is done, multiple groups of mobile nodes are obtained. Mobile nodes in the same social group have social ties (i.e., relationships in term of inter-encounter times). Next, the mobile nodes in the same social group will play the coalitional game in order to form coalitions (i.e., mobile nodes will be members of the same coalition if all of them satisfy their obtained payoffs). Also, to obtain their payoffs, the mobile nodes in the same coalition will play the bargaining game. Clearly, there can be multiple coalitions within a social group as shown in Figure 5.3.

5.4 Formulation of Bargaining Game for Cooperative Packet Delivery

In this section, we first formulate a continuous-time Markov chain (CTMC) to find the expected cost and delay of each mobile node in the same coalition. The expected cost

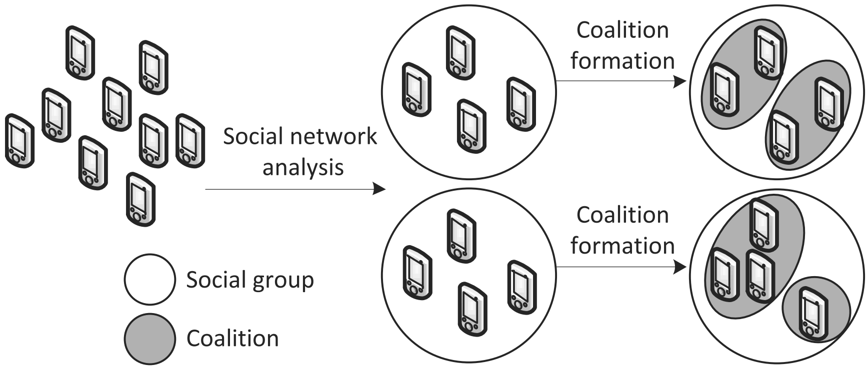


Figure 5.3. *Diagram showing the relation between social groups and coalitions. There can be multiple coalitions within a social group.*

and delay depend on the probabilities that the mobile nodes will help each other to deliver data. Then, we present a Nash bargaining solution to find these probabilities.

5.4.1 Markov Chain Model for Cooperative Packet Delivery

We focus only on a group of mobile nodes $\mathbb{N}_k \subseteq \mathbb{M}$. To simplify the presentation, we omit index k of a group (e.g., $\mathbb{N}_k$ is represented by $\mathbb{N}$). Consider a particular coalition $\mathcal{S} \subseteq \mathbb{N} \in \{1, \ldots, N\}$ of mobile nodes. A CTMC with absorbing states can be formulated for the scenario in which one mobile node in the coalition is considered as the final destination of a packet transmitted from a base station, and the rest of the mobile nodes in the coalition help the base station to deliver the packet to the final destination. The CTMC model is used to obtain the expected packet delivery delay (d_i) for a mobile node which is the final destination of the packet originally transmitted from the BS. Also, it is used to obtain the expected cost of other mobile nodes (c_{ij}) in the same coalition which help the base station to deliver the packet to the final destination.

Let $K \in \mathcal{S}$ denote the label of a mobile node which is the final destination for a packet transmitted from the BS. The state space of the CTMC for the cooperative packet delivery scheme can be expressed as follows:

$$\Psi = \{(\mathcal{X}); \mathcal{X} \subseteq \mathcal{S}, \mathcal{S} \subseteq \mathbb{N}\} \tag{5.2}$$

where $\mathcal{X}$ is the set of mobile nodes which already have the packet destined to mobile node K in the same coalition $\mathcal{S}$. $\mathbb{N}$ is the set of all the mobile nodes. The state space Ψ can be partitioned into Ψ_A (absorbing states) and Ψ_T (transient states), i.e., $\Psi = \Psi_A \cup \Psi_T$. State $\mathcal{X} \in \Psi$ is an absorbing state if mobile node K is a member of $\mathcal{X}$. Otherwise, it is a transient state.

Let $\mathcal{Y} = \mathcal{X} \cup \{0\}$ and $\mathcal{Z} = \mathcal{X} \cap \mathcal{X}'$, where $\mathcal{X}'$ is another state. The total state transition rate from $\mathcal{X}$, which is a transient state, to another state $\mathcal{X}'$ is defined as follows:

$$q_{\mathcal{X},\mathcal{X}'} = \begin{cases} \sum_{i \in \mathcal{Y}, j \in \mathcal{Z}} r_{ij}, & (|\mathcal{Z}| = 1)\&(|\mathcal{X}'| - |\mathcal{X}| = 1)\&(K \notin \mathcal{X}) \\ 0, & \text{otherwise} \end{cases} \tag{5.3}$$

where $|\mathcal{X}|$ and $|\mathcal{X}'|$ denote the cardinalities of sets $\mathcal{X}$ and $\mathcal{X}'$, respectively, and & denotes the logical AND operation. Recall that, r_{ij} denotes the rate that mobile node i meets mobile node j for $i \neq j$ and $r_{i0} = r_{0i}$ is the rate that mobile node i meets the BS. Hence, the state transition rate $q_{\mathcal{X},\mathcal{X}'}$ is the rate that any mobile node in $\mathcal{X}$, or the BS (i.e., any member of set $\mathcal{Y}$) will meet another mobile node which does not have the packet destined to mobile node K. Then, the state changes from $\mathcal{X}$ to $\mathcal{X}'$.

As an example, Figure 5.4 shows the CTMC model of a packet delivery scenario when there are 3 mobile nodes in the same coalition. Mobile nodes 1 and 2 help the BS to deliver the packet to mobile node 3. Given the state transition rate of the CTMC model, the corresponding discrete-time Markov chain (DTMC) (also called the embedded Markov chain [89]) can be derived. Each mobile node may help other mobile nodes deliver data with probability p_i. Note that probability p_i, when mobile node i is a destination node K (i.e., $i = K$), is one (i.e., mobile node i always needs to obtain its own packets). Let $q_{\mathcal{X}} = \sum_{\mathcal{X}' \in \Psi} q_{\mathcal{X},\mathcal{X}'}$ be the summation of state transition rates from state $\mathcal{X}$ to any state $\mathcal{X}'$. Then, the probability of state transition of the

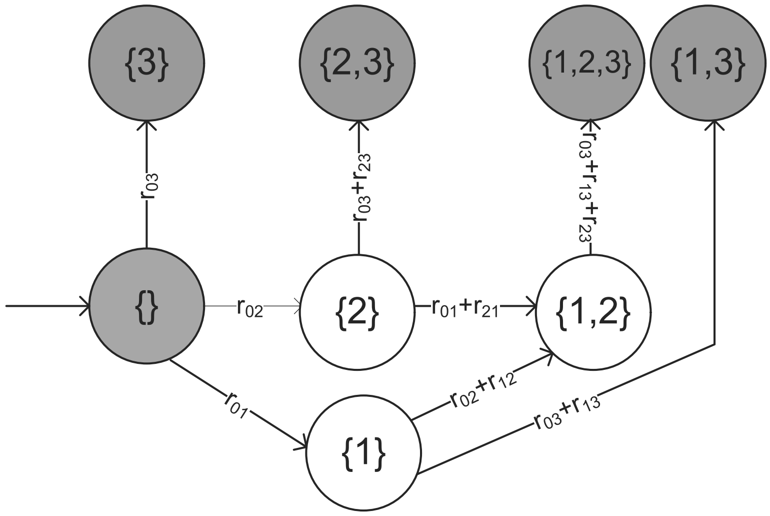


Figure 5.4. *The CTMC model for cooperative packet delivery from the BS to a destination mobile node. In this scenario, there are 3 mobile nodes in the same coalition. Mobile nodes 1 and 2 help the BS to deliver a packet to mobile node 3.*

DTMC can be obtained from

$$p_{\mathcal{X},\mathcal{X}'} = \begin{cases} \frac{\sum_{i\in\mathcal{Y},j\in\mathcal{Z}} p_j r_{ij}}{q_{\mathcal{X}}}, & (q_{\mathcal{X}} \neq 0) \quad \& \quad (|\mathcal{Z}| = 1) \quad \& \quad (|\mathcal{X}'| - |\mathcal{X}| = 1) \quad \& \quad (K \notin \mathcal{X}) \\ 1 - \sum_{\mathcal{X}'\in\Psi} p_{\mathcal{X},\mathcal{X}'}, & (q_{\mathcal{X}} \neq 0) \quad \& \quad (\mathcal{X} = \mathcal{X}') \\ 1, & (q_{\mathcal{X}} = 0) \quad \& \quad (\mathcal{X} = \mathcal{X}') \\ 0, & \text{otherwise.} \end{cases} \tag{5.4}$$

The transition probability matrix of the absorbing DTMC can be partitioned [90] as follows:

$$\mathbf{P} = \left[\begin{array}{c|c} \mathbf{T} & \mathbf{F} \\ \hline \mathbf{0} & \mathbf{I} \end{array} \right] \tag{5.5}$$

where $\mathbf{T}$ is the transition probability matrix corresponding to the transitions among the transient states, $\mathbf{I}$ is an identity matrix, $\mathbf{0}$ is a zero matrix, and $\mathbf{F}$ is the transition probability matrix corresponding to the transitions from the transient states to the absorbing state.

For an absorbing DTMC with transition probability matrix $\mathbf{P}$, the matrix $\mathbf{M} = (\mathbf{I}-\mathbf{T})^{-1}$ is its fundamental matrix. The entry $m_{\mathcal{X},\mathcal{X}'}$ of $\mathbf{M}$ gives the expected number of times that the process is in transient state $\mathcal{X}'$ if it starts in transient state $\mathcal{X}$ before the Markov chain reaches any absorbing state (i.e., the expected number of times that the transient state $\mathcal{X}'$ will be visited). To obtain the packet delivery delay from the BS to mobile node K (i.e., destination of the packet), let state $\mathcal{X} = \emptyset$ be the initial transient state (i.e., the state that no mobile node in coalition $\mathcal{S}$ obtains the packet destined to mobile node K, or only the BS has the packet for mobile node K). Let $t_{\mathcal{X}'}$ be the mean sojourn time in state $\mathcal{X}'$ (i.e., the amount of time spent in state $\mathcal{X}'$ before the process leaves state $\mathcal{X}'$) given as follows:

$$t_{\mathcal{X}'} = \frac{1}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}'\mathcal{X}''}}, \quad \text{where } \mathcal{X}'' \in \Psi. \tag{5.6}$$

Then, the expected packet delivery delay to the final destination (i.e., mobile node K) can be calculated as follows:

$$d_{i=K} = \sum_{\mathcal{X}' \in \Psi_T} t_{\mathcal{X}'} m_{\mathcal{X}=\emptyset,\mathcal{X}'}. \tag{5.7}$$

Next, we find the expected cost (c_{ij}) that incurs to mobile node i for delivering the packet of mobile node $j(= K)$, which is defined as follows [91]:

$$c_{ij} = \begin{cases} \sum_{\mathcal{X}' \in \Psi_T} c_{ij}^{\mathcal{X}'} m_{\mathcal{X}=\emptyset,\mathcal{X}'}, & (i \neq j) \quad \& \quad (j = K) \\ 0, & i = j \end{cases} \tag{5.8}$$

where $c_{ij}^{\mathcal{X}'}$ is the expected cost that mobile node i incurs for delivering the packet to mobile node $j(= K)$ in state $\mathcal{X}'$. If mobile node i is in the set $\mathcal{X}'$ of mobile nodes which already have the packet for mobile node K, there will be an expected cost of forwarding the packet to other mobile nodes. If mobile node i is not in the set $\mathcal{X}'$ of mobile nodes, there will be an expected cost of receiving the packet from the BS or from other mobile nodes, i.e.,

$$c_{ij}^{\mathcal{X}'} = \begin{cases} \sum_{g \in \mathcal{S} \cap \mathcal{X}'} \frac{p_g r_{ig}}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}',\mathcal{X}''}} c_{ig}^{\mathrm{f}}, & i \in \mathcal{X}' \\ \sum_{g \in \mathcal{X}' \cup \{0\}} \frac{p_i r_{gi}}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}',\mathcal{X}''}} c_{ig}^{\mathrm{r}}, & i \notin \mathcal{X}'. \end{cases} \tag{5.9}$$

Again, from the CTMC model shown in Figure 5.4, we can obtain the expected costs of mobile nodes 1 and 2 (i.e., c_{13} and c_{23}) and the delay of mobile node 3 (i.e., d_3). To obtain the packet delivery delays for other mobile nodes (i.e., d_1 and d_2) and the expected costs (i.e., c_{21}, c_{31}, c_{12}, and c_{32}), mobile nodes 1 and 2 are considered as the final destinations (i.e., $K = 1$ and $K = 2$), and the same steps are applied.

5.4.2 Nash Bargaining Game Model

A Nash bargaining game is used to model the interaction among a group of mobile nodes in cooperative delivery of packets. The players of this bargaining game are the mobile nodes in the same coalition. The set of mobile nodes is denoted by $\mathbb{N} = \{1, \ldots, N\}$ and a coalition of players (i.e., mobile nodes) is denoted by $\mathcal{S} \subseteq \mathbb{N}$. The action set of each player is $\mathcal{P}_i = [0, 1]$. The strategy of each player is to choose the optimal probability, $p_i \in \mathcal{P}_i$, that the mobile node will help other mobile nodes in the same coalition to deliver packets. The payoff of each player is a function of expected cost that the player will incur for other players and the packet delivery delay for its own packet, delivery of which is helped by other players.

Consider the expected cost and delay of packet delivery calculated in Section 5.4.1. Any mobile node i can achieve a lower packet delivery delay due to the help from other mobile nodes in the same coalition $\mathcal{S}$. However, an additional cost is incurred to mobile node i due to the packet delivery to other mobile nodes in the same coalition. The total cost of mobile node i for packet delivery to any mobile node j in the same coalition can be expressed as follows:

$$C_i(\mathcal{S}) = \begin{cases} \sum_{j \in \mathcal{S}, j \neq i} c_{ij}(\mathcal{S}), & |\mathcal{S}| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{5.10}$$

where $c_{ij}(\mathcal{S})$ is the expected cost that incurs to mobile node i for delivering the packet of mobile node j in the same coalition $\mathcal{S}$ as defined in (5.8). $|\mathcal{S}|$ is the number of mobile nodes in coalition $\mathcal{S}$.

The utility of mobile node i is defined as a function of $R_i(\mathcal{S})$ as follows:

$$R_i(\mathcal{S}) = \begin{cases} 1 - \frac{d_i(\mathcal{S})}{\hat{d}_i}, & |\mathcal{S}| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{5.11}$$

where $d_i(\mathcal{S})$ is the packet delivery delay for mobile node $i \in \mathcal{S}$, and $\hat{d}_i = 1/r_{0i}$ is the packet delivery delay for mobile node i without any coalition (i.e., mobile node i acts alone).

The objective of each mobile node is to maximize its payoff. The payoff of mobile node i in the coalition $\mathcal{S}$ can be defined as follows:

$$u_i(\mathcal{S}) = \alpha_i R_i(\mathcal{S}) - \beta_i C_i(\mathcal{S}) \tag{5.12}$$

where α_i and β_i denote, respectively, the positive weight constants of the utility and the cost of delivering a packet to other mobile nodes in the same coalition. The solution of the bargaining game is presented in the next section.

5.4.3 Nash Bargaining Solution

Nash axioms specify the conditions for reaching Pareto-optimal Nash bargaining solutions [92, 66]. The payoff of each mobile node depends on the probabilities of the mobile nodes to help other mobile nodes in the same coalition. As a result, for each mobile node, using the bargaining game we find the probability that it will help other mobile nodes in the same coalition deliver a packet transmitted from a BS.

Let $\vec{\mathbf{p}} = [\ldots, p_i, \ldots], \forall i \in \mathcal{S}$ be the vector of the probabilities that the mobile nodes help each other in the same coalition. To find a solution of the Nash bargaining game, all mobile nodes in coalition $\mathcal{S}$ exchange their payoff functions. We assume that the mobile nodes which are members of the same coalition can exchange their information (e.g., payoff function and active status) with the help of the base stations and the coordinator. After a mobile node obtains all other mobile nodes' payoffs, it solves the following optimization problem to obtain the probability of helping other mobile nodes:

$$\begin{aligned} \vec{\mathbf{p}}^* &= \arg\max_{\vec{\mathbf{p}}} \prod_{i \in \mathcal{S}} (u_i(\mathcal{S}, \vec{\mathbf{p}}) - u_i^d(\{i\})) \qquad (5.13) \\ \text{subject to} \quad & p_i \in \mathcal{P}_i = [0,1], \ \forall i \in \mathcal{S} \\ & u_i(\mathcal{S}) \geq 0, \ \text{and} \quad u_i(\mathcal{S}) \geq u_i^d(\{i\}) \end{aligned}$$

where $u_i(\mathcal{S})$ is defined as in (5.12) and can be calculated as shown in Section 5.4.1 and

u_i^d is the status-quo payoff (i.e., the payoff obtained if mobile node i decides not to bargain with other mobile nodes or when the mobile node acts alone). According to (5.10) and (5.11), $u_i^d(\{i\})$ is zero. Each mobile node varies the probability from zero to one and selects the value which maximizes the Nash product term of all the payoffs. The optimal solution can be obtained by a search method. Simplex method [93] can be used to optimize the objective function defined in (5.13).

5.5 Formulation of Coalitional Game for Cooperative Packet Delivery

For the cooperative packet delivery scheme described in Section 6.2, we now formulate a coalitional game among rational mobile nodes to improve their individual payoffs.

5.5.1 Rational Coalition Formation

We propose a non-transferable utility (NTU) coalitional game. The players of this game are the mobile nodes. The set of mobile nodes is denoted by $\mathbb{N} = \{1, \ldots, N\}$. A coalition of players is denoted by $\mathcal{S} \subseteq \mathbb{N}$. Each player wants to achieve a low packet delivery delay by participating in a coalition, and at the same time to minimize its cost. Each player is indifferent to the total payoff of the coalition (i.e., $v(\mathcal{S})$). In this NTU game, the payoff of a coalition cannot be arbitrarily divided among the players in a coalition. The payoff $u_i(\mathcal{S})$ of each mobile node (as given in (5.12)) is composed of the cost $C_i(\mathcal{S})$ of helping other mobile nodes to deliver packet(s) and the function of packet delivery delay $R_i(\mathcal{S})$ that the mobile node will experience when it is helped by other mobile nodes. The payoff that each player in a coalition obtains depends on the joint actions selected by players in a coalition. The value of coalition $\mathcal{S}$ is defined as follows:

$$v(\mathcal{S}) = \sum_{i \in \mathcal{S}} u_i(\mathcal{S}), \quad \text{for } v(\emptyset) = 0 \tag{5.14}$$

where $u_i(\mathcal{S})$ is the payoff of each player defined as in (5.12). The strategy of each player is to make a decision on which coalition to form. The solution of the coalitional game is a stable coalitional structure. The coalitional structure is a set of coalitions spanning all the users in $\mathbb{N}$. The coalitional structure is defined as $\Upsilon = \{\mathcal{S}_1, \ldots, \mathcal{S}_l, \ldots, \mathcal{S}_s\}$, where $\mathcal{S}_l \cap \mathcal{S}_l^{'} = \emptyset$ for $l \neq l^{'}$ and s is the total number of coalitions for $1 \leq s \leq N$, and $\bigcup_{l=1}^{s} \mathcal{S}_l^{'} = \mathbb{N}$. The coalition consisting of all mobile nodes is referred to as the grand coalition. There can be $2^N - 1$ distinct non-empty coalitions and D_N different coalitional structures for N players, where D_N is the Nth Bell number given as follows:

$$D_N = \sum_{j=0}^{N-1} \begin{pmatrix} N-1 \\ j \end{pmatrix} D_j, \quad \text{for} \quad N \geq 1 \quad \text{and} \quad D_0 = 1. \tag{5.15}$$

5.5.2 Stable Coalitional Structure

Each player i can decide to leave its current coalition and join another coalition based on the received payoff given that decision. Let $\mathcal{S}^i$ denote a coalition in which mobile node i is a member of. The merge and split rules for the coalition are stated below.

- *Merge Rule*: Given original coalitions $\mathcal{S}_l^i \in \Phi^{\dagger}$, the coalitions can be merged to a new single coalition $\mathcal{S}_{l'}^{i\dagger}$ if all players in all of the original coalitions obtain higher payoffs after merging, i.e.,

$$u_i(\mathcal{S}_{l'}^{i\dagger}) > u_i(\mathcal{S}_l^i), \forall i \in \mathcal{S}_{l'}^{i\dagger}, \quad \text{where } \mathcal{S}_{l'}^{i\dagger} = \bigcup_{\mathcal{S}_l^i \in \Phi^{\dagger}} \mathcal{S}_l^i. \tag{5.16}$$

- *Split Rule*: The players in coalition $\mathcal{S}_l$ can split into multiple new coalitions if the payoffs of all the players are higher than those in the same original coalition, i.e.,

$$u_i(\mathcal{S}_{l'}^{i\ddagger}) > u_i(\mathcal{S}_l^i), \forall i \in \mathcal{S}_l^i \tag{5.17}$$

  where $\mathcal{S}_l^i = \bigcup_{\mathcal{S}_{l'}^{i\ddagger} \in \Phi^{\ddagger}} \mathcal{S}_{l'}^{i\ddagger}$, $\Phi^{\ddagger}$ denotes the set of all new coalitions $\mathcal{S}_{l'}^{i\ddagger}$.

The coalitional structure which has the properties of internal stability and external stability [75] is considered as a stable solution of the proposed coalitional game.

- *Internal Stability:* A coalition $\mathcal{S}$ possesses internal stability if no user can improve its payoff by leaving its coalition and acting alone, i.e., $u_i(\mathcal{S}) \geq u_i(\{i\})$.
- *External Stability:* A coalition $\mathcal{S}$ possesses external stability if merging with another coalition $\mathcal{S}^{'}$ does not improve the payoffs of the players in the coalitions,

i.e., $u_i(\mathcal{S} \cup \mathcal{S}') < u_i(\mathcal{S}')$ for $i \in \mathcal{S}$ and $u_{i'}(\mathcal{S} \cup \mathcal{S}') < u_{i'}(\mathcal{S}')$ for $i' \in \mathcal{S}'$ and $\mathcal{S} \cap \mathcal{S}' = \emptyset$.

5.5.2.1 Distributed Merge-and-Split-Based Algorithm

At time τ, any mobile node in a coalition can decide to leave its current coalition and join a new coalition. For a mobile node, we present a distributed algorithm (**Algorithm 4**) based on the merge-and-split mechanism to find a stable coalitional structure. It is known that any algorithm constructed based on the merge-and-split rules always converges [94].

Algorithm 4 Distributed coalition formation algorithm based on merge-and-split mechanism

Initialize $\tau = 0$ and $\Upsilon(\tau) = \{\mathcal{S}_1(\tau), \ldots, \mathcal{S}_s(\tau)\}$.
loop
  Mobile node i computes its utility $R_i(S_l^i(\tau))$ and cost $C_i(S_l^i(\tau))$ given its current coalition $S_l^i(\tau)$.
  Mobile node i computes its payoff $u_i(S_l^i(\tau))$.
  Randomly select one possible coalitional structure $\Upsilon'(\tau)$ after merging.
  if $u_i(\mathcal{S}_{l'}^{i\dagger}) > u_i(\mathcal{S}_l^i(\tau))$ for $i \in \mathcal{S}_{l'}^{i\dagger}$
    Merge the coalitions: $\mathcal{S}_l^i(\tau+1) = \mathcal{S}_{l'}^{i\dagger}$ for $\mathcal{S}_{l'}^{i\dagger} \in \Phi^\dagger$.
    $\Upsilon(\tau+1) = \Upsilon'(\tau)$
  end
  $\tau = \tau + 1$
  Randomly select one possible coalitional structure $\Upsilon'(\tau)$ after splitting.
  if $u_i(\mathcal{S}_{l'}^{i\ddagger}) > u_i(\mathcal{S}_l^i(\tau))$ for $i \in \mathcal{S}_l^i$
    Split the coalition: $\mathcal{S}_l^i(\tau+1) = \mathcal{S}_{l'}^{i\ddagger}$ for $\mathcal{S}_{l'}^{i\ddagger} \in \Phi^\ddagger$
    $\Upsilon(\tau+1) = \Upsilon'(\tau)$
  end
  $\tau = \tau + 1$
end loop when a stable coalitional structure is obtained.

5.5.2.2 Markov Chain-Based Analysis of the Coalitional Structure

We formulate a discrete-time Markov chain (DTMC) [95] to analyze the stable coalitional structure obtained from the distributed algorithm. The state space of the DTMC can be expressed as follows: $\Omega = \{(\Upsilon_1), \ldots, (\Upsilon_x), \ldots, (\Upsilon_{D_N})\}$, where Υ_x is a coalitional structure, and D_N is the Nth Bell number. The transition probability of this DTMC is denoted by $\rho_{\Upsilon,\Upsilon'}$. Specifically, $\rho_{\Upsilon,\Upsilon'}$ is the probability that the coalitional structure changes from Υ to Υ' during a period of time. Let $\mathcal{B}_{\Upsilon,\Upsilon'}$ denote the set of players who move from its current coalition to the new coalition and the coalitional structure changes from Υ to Υ'. The transition probability from state Υ to Υ' is then found as follows:

$$\rho_{\Upsilon,\Upsilon'} = \begin{cases} \prod_{i \in \mathcal{B}_{\Upsilon,\Upsilon'}} \gamma \varphi_i(\Upsilon' | \Upsilon), & \Upsilon \neq \Upsilon' \\ 1 - \sum_{\Upsilon' \in \Omega, \Upsilon' \neq \Upsilon} \rho_{\Upsilon,\Upsilon'}, & \Upsilon = \Upsilon' \end{cases} \tag{5.18}$$

where γ $(0 < \gamma \leq 1)$ is the probability that a player makes a decision. $\varphi_i(\Upsilon' | \Upsilon)$ is the probability that a player decides to move from its current coalition $\mathcal{S}_l^i$ to a new coalition $\mathcal{S}_{l'}^i$ which changes the coalitional structure from Υ to Υ', i.e.,

$$\varphi_i(\Upsilon' | \Upsilon) = \begin{cases} \varphi, & u_i(\mathcal{S}_{l'}^i) > u_i(\mathcal{S}_l^i) \\ 0, & \text{otherwise} \end{cases} \tag{5.19}$$

where $0 < \varphi \leq 1$, $\mathcal{S}_l^i \in \Upsilon$, and $\mathcal{S}_{l'}^i \in \Upsilon'$. Given the transition matrix $\mathbf{Q}$ whose elements are $\rho_{\Upsilon,\Upsilon'}$, the stationary probability vector $\vec{\boldsymbol{\pi}}$ can be obtained by solving the following equation: $\vec{\boldsymbol{\pi}}^T \mathbf{Q} = \vec{\boldsymbol{\pi}}^T$, where $\vec{\boldsymbol{\pi}}^T \vec{\mathbf{1}} = 1$, and $\vec{\mathbf{1}}$ is a vector of ones, $\vec{\boldsymbol{\pi}} = \begin{bmatrix} \pi_{\Upsilon_1} & \cdots & \pi_{\Upsilon_x} & \cdots & \pi_{\Upsilon_{D_N}} \end{bmatrix}^T$, and π_{Υ_x} is the probability that the coalitional structure Υ_x will be formed.

Observation 1 *If for all coalitions $\mathcal{S} \subseteq \mathbb{N}$, the condition $\sum_{i \in \mathcal{S}} v(\{i\}) < v(\mathcal{S})$ is true, then there is at least one absorbing state which is a stable solution of the coalitional game (Theorem 1 in [95]).*

Proof. This observation states that no player forms a singleton coalition since the player can obtain a better payoff by being a member of any other coalition. Since the payoff of a player will be zero if the player acts alone, from (5.14), we can show that $\sum_{i \in \mathcal{S}} v(\{i\}) = \sum_{i \in \mathcal{S}} u_i(\{i\}) = 0 < v(\mathcal{S})$. Therefore, $v(\mathcal{S})$ will be equal to or higher than zero, and then a stable solution may exist depending on the value of the payoff (i.e., utility and cost functions). Note that the utility and cost functions of the payoff can be adjusted by the weight constants α_i and β_i defined in (5.12). Therefore, the players will act alone if the cost incurred to them is higher than the utility that they obtain from the cooperative packet delivery. ■

The implication of **Observation 1** is that there will be at least one stable solution of the coalitional game which can be analytically obtained from the Markov chain model. This corresponds to the fact that a mobile node will be a member of a non-singleton coalition, since its payoff would be higher than that due to a singleton coalition.

Next, we show the existence of non-empty core of the coalitional game. The core is a solution concept for a coalitional game which is comparable to the Nash equilibrium for a noncooperative game. The core is regarded as a set of payoff allocations such that no player has an incentive to leave the grand coalition (i.e., a set of payoffs of the grand coalition upon which no other coalition can improve). Let $\vec{\mathbf{u}}^{\mathbb{N}} = [u_1(\mathbb{N}), \ldots, u_i(\mathbb{N}), \ldots, u_N(\mathbb{N})]$ and $\vec{\mathbf{u}}^{\mathcal{S}} = [u_1(\mathcal{S}), \ldots, u_i(\mathcal{S}), \ldots, u_N(\mathcal{S})]$ be the payoff vectors of all mobile nodes when they are the members of the grand coalition and any coalition $\mathcal{S}$, respectively. Then, the characteristic function of coalition $\mathcal{S}$ is a set of feasible payoff vector $\vec{\mathbf{x}}^{\mathcal{S}}$ of length $|\mathcal{S}|$ which is defined as follows:

$$V(\mathcal{S}) = \{\vec{\mathbf{x}}^{\mathcal{S}} \in \mathbb{R}^{\mathcal{S}} | \vec{\mathbf{x}}^{\mathcal{S}} \leq \vec{\mathbf{u}}^{\mathcal{S}}\}. \tag{5.20}$$

For an NTU game, the core is defined as follows [95, 96]:

$$\begin{aligned} \mathcal{C} &= \{\vec{\mathbf{u}}^{\mathbb{N}} \in V(\mathbb{N}) | \forall \mathcal{S} \subseteq \mathbb{N}, \nexists \vec{\mathbf{u}}^{\mathcal{S}} \in V(\mathcal{S}) \\ & \quad \text{subject to } \; u_i(\mathcal{S}) \geq u_i(\mathbb{N}), \forall i \in \mathcal{S}\}. \end{aligned} \tag{5.21}$$

For an NTU game, the Bondareva-Shapley theorem [96, 97] states that the core of a game is not empty if and only if the game is balanced.

Definition 1 *Consider an NTU game. For every $\mathcal{S} \subseteq \mathbb{N}$, let $V_{\mathcal{S}} = V(\mathcal{S}) \times \mathbb{R}^{\mathbb{N} \setminus \mathcal{S}}$. The NTU game is balanced if*

$$\bigcap_{\forall \mathcal{S} \subseteq \mathbb{N}} V(\mathcal{S}) \subseteq V(\mathbb{N}). \tag{5.22}$$

Observation 2 *The core of the coalitional game for cooperative packet delivery is not empty if*

(i) $\alpha_i \geq 0$ *and* $\beta_i \geq 0$ *and*

(ii) $\alpha_i R_i(\mathcal{S}) > \beta_i C_i(\mathcal{S})$ *and*

(iii) $\alpha_i R_i(\mathbb{N}) - \beta_i C_i(\mathbb{N}) > \alpha_i R_i(\mathcal{S}) - \beta_i C_i(\mathcal{S})$.

Proof. Since $\alpha_i \geq 0$ and $\beta_i \geq 0$, we can find α_i and β_i such that condition (ii) holds. If condition (ii) does not hold, i.e., $u_i(\mathcal{S}) \leq u_i(i) = 0$, then each mobile node may act alone, and the core is empty. Next, we can express $V(\mathcal{S})$ and $V(\mathbb{N})$ as follows:

$$V(\mathbb{N}) = \{\vec{\mathbf{x}}^{\mathbb{N}} = [\ldots, x_i, \ldots] \in \mathbb{R}^{\mathbb{N}} | x_i \leq \alpha_i R_i(\mathbb{N}) - \beta_i C_i(\mathbb{N}), \forall i \in \mathbb{N}\} \tag{5.23}$$

and

$$V(\mathcal{S}) = \{\vec{\mathbf{x}}^{\mathcal{S}} = [\ldots, x_j, \ldots] \in \mathbb{R}^{\mathcal{S}} | x_j \leq \alpha_j R_j(\mathcal{S}) - \beta_j C_j(\mathcal{S}), \forall j \in \mathcal{S}\}. \tag{5.24}$$

If condition (iii) holds, then $\vec{\mathbf{x}}^{\mathbb{N}} > \vec{\mathbf{x}}^{\mathcal{S}} \times \mathbb{R}^{\mathbb{N}\setminus\mathcal{S}}$ $\forall \mathcal{S} \subseteq \mathbb{N}$ which satisfies the definition of balanced game. Consequently, this game has a non-empty core if the conditions (i), (ii), and (iii) above are satisfied. ■

The implication of **Observation 2** is that the stability of a grand coalition can be verified by checking the above conditions. That is, when the conditions are satisfied, the outcome from the Markov chain and the merge-and-split algorithm (i.e., **Algorithm 4**) will be a stable grand coalition. In many cases, a stable grand coalition is desirable since it ensures that all mobile nodes will be members of the same coalition.

5.5.3 Optimal Social Welfare Solution

The mobile nodes can cooperatively form an optimal coalitional structure, which maximizes their optimal social welfare instead of rational individual payoffs (i.e., The summation of all the mobile nodes' payoffs is maximized), as follows:

$$\Upsilon^* = \{\mathcal{S}_1^*, \ldots, \mathcal{S}_l^*, \ldots, \mathcal{S}_s^*\} = \arg\max_{\mathcal{S}_l^i \in \Upsilon} \sum_{\mathcal{S}_l^i \in \Upsilon} \sum_{i \in \mathcal{S}_l^i} u_i(\mathcal{S}_l^i). \tag{5.25}$$

To obtain this optimal coalitional structure, the Markov chain model presented in Section 6.4.2 can be used. However, the probability p_i that each mobile node will help others to deliver packets needs to be obtained by maximizing the summation of all the mobile nodes' payoffs in the same coalition (instead of maximizing the Nash product term shown in (5.13)) as follows:

$$\begin{aligned} \vec{\mathbf{p}}^* &= \arg\max_{\vec{\mathbf{p}}} \sum_{i \in \mathcal{S}} u_i(\mathcal{S}, \vec{\mathbf{p}}) \\ \text{subject to} \quad & p_i \in \mathcal{P}_i = [0, 1], \ \forall i \in \mathcal{S}. \end{aligned} \tag{5.26}$$

Moreover, the rule that a player decides to move from its current coalition $\mathcal{S}_l^i$ to a new coalition $\mathcal{S}_{l'}^i$, which makes the coalitional structure change from Υ to $\Upsilon^{'}$, as shown in (5.27), becomes

$$\varphi_i(\Upsilon^{'}|\Upsilon) = \begin{cases} \varphi, & \sum_{\mathcal{S}_{l'}^i \in \Upsilon'} v(\mathcal{S}_{l'}^i) > \sum_{\mathcal{S}_l^i \in \Upsilon} v(\mathcal{S}_l^i) \\ 0, & \text{otherwise} \end{cases} \tag{5.27}$$

where $0 < \varphi \leq 1$, $\mathcal{S}_l^i \in \Upsilon$, and $\mathcal{S}_{l'}^i \in \Upsilon^{'}$, and $v(\mathcal{S})$ is defined as in (5.14).

5.6 Performance Evaluation

For performance evaluation of the proposed cooperative packet delivery scheme, we use a vehicle-to-roadside (V2R) communications scenario. In V2R communications, data is transferred through the roadside BSs. That is, the mobile nodes shown in Figure 5.1 are vehicles. Each vehicle is equipped with a Wi-Fi transceiver for downloading data when the vehicle is connected to the BS.

5.6.1 Simulation Parameters

For the simulations, in order to find the encounter information among vehicles and base stations, we use a microscopic road traffic simulation package designed for the large road networks named "SUMO", an acronym for "Simulation of Urban MObility" [99]. Moreover, we use MATLAB to analyze the results obtained from SUMO.

In the simulation, a grid road network with 121 intersections is used. The area of the road network is 2 km × 2 km. A BS is located at an intersection for every 400 m in both horizontal and vertical directions (Figure 5.5). There are 100 vehicles in the area. Each vehicle moves along a shortest path from a random originating position to a random destination position. When the vehicle reaches the destination, a new destination position is selected. Note that each vehicle randomly selects a destination position from its set of specified positions. We perform multiple simulation runs for 833 simulated hours. Unless otherwise specified, the default values of parameters in Table 5.3 are used.

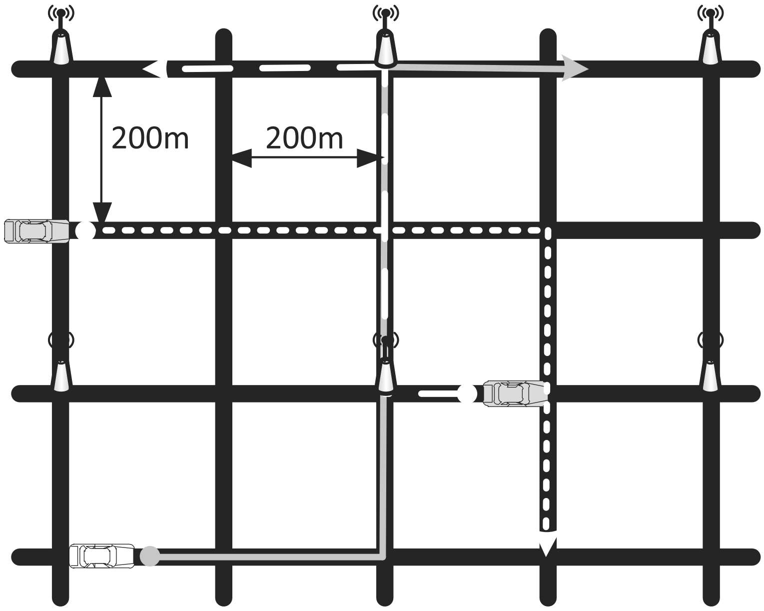


Figure 5.5. *A grid road network used in the simulation.*

To simulate the encounter process for the vehicles, we set the required time and the probability threshold that vehicle j will deliver a packet from the base station to vehicle i within T_i, to be 25s (i.e., $T_i = 25$, $\forall i \in \mathbb{N}$) and 0.07 (i.e., $\omega_i = 0.07$, $\forall i \in \mathbb{N}$), respectively. We also assume that the time-to-live (TTL) value for all packets is 25s. After the simulation is done, we identify and select a group of four vehicles by the SNA-based vehicle grouping approach using the encounter information from the simulation.

For the simulation of coalitional game model, the weight constants of the utility

Table 5.3. *Default values of simulation parameters*

Parameter	Description/value
Road network	The area of the road map is 2 km× 2 km with 121 intersections.
Number of vehicles (M)	100 vehicles
Communication range of base station	Radius of 100 m (i.e., $h_0 = 100$ m)
Communication range of a vehicle	Radius of 50 m (i.e., $h_i = 50$ m)
Maximum speed on roads	50 km/h (31.25 mph)
Vehicle's acceleration and deceleration	0.8 m/s^2 and 4.5 m/s^2, respectively

and cost functions are assumed to be $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 15$ and $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 2$, respectively. If α is set to a large value, the utility of a vehicle, which is a function of the packet delivery delay for the vehicle, will change significantly when the packet delivery delay changes by a small amount. If a vehicle sets β to a small value (e.g., zero), it means that the vehicle does not care about the cost it incurs. That is, the vehicle is more willing to help others. The parameters of the best-reply rule are $\gamma = 0.9$ and $\varphi = 0.99$. Note that φ denotes the probability that a vehicle will change to a new coalition through either the merge or the split process. γ is the probability that the vehicle will make a decision to move at that time. Any values of φ and γ in the range of $(0, 1]$ can be set since the stationary probability will be the same at the end.

5.6.2 Encounter Rate

We verify that the encounters between a pair of vehicles follow a Poisson process (i.e., the time interval between two consecutive encounters is exponentially distributed) as shown in Figure 5.6. The curve of cumulative distribution function of the time interval between two consecutive encounters observed in the simulation is fitted by an exponential distribution curve with encounter rate 0.0145 (i.e., mean = 1/0.0145).

The rates for each vehicle to meet other vehicles and a BS (i.e., r_{ij}) are shown in Table 5.4. We observe that the mean time duration (i.e., $1/r_{ij}$) that all the vehicles will meet the BS and obtain their packets are more than their TTL. The encounter

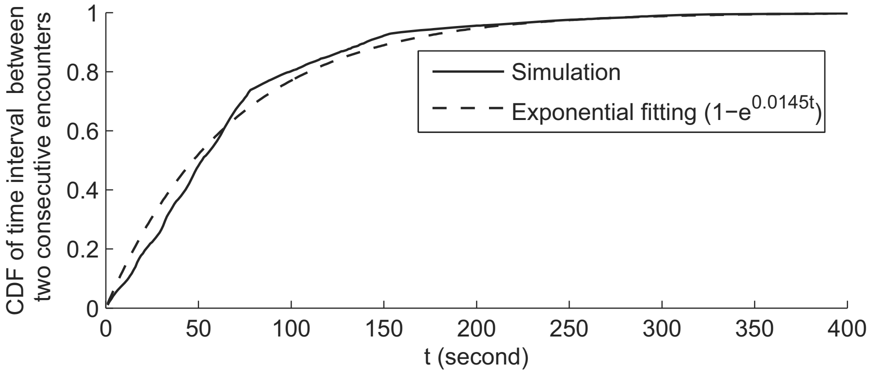


Figure 5.6. *Cumulative distribution function of the time interval between two consecutive encounters of a pair of vehicles.*

Table 5.4. *Rates (r_{ij}) per second that each vehicle meets other vehicles and a base station on a road*

Rate	BS	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Base station	-	0.0339	0.0345	0.0299	0.0308
Vehicle 1	0.0339	-	0.0103	0.0108	0.0104
Vehicle 2	0.0345	0.0103	-	0.0122	0.0145
Vehicle 3	0.0299	0.0108	0.0122	-	0.0247
Vehicle 4	0.0308	0.0104	0.0145	0.0247	-

rate between vehicle 1 and other vehicles from the simulation are shown in Figure 5.7. When the transmission range increases, as expected, the encounter rate increases due to the higher chance to meet other vehicles.

5.6.3 Stable and Optimal Coalitional Structures

We consider the V2R communications scenario as shown in Figure 5.1 with 4 vehicles. As shown in Table 5.5, there are 15 different coalitional structures for 4 vehicles, and there are 15 possible coalitions. In a coalitional structure, the total number of coalitions ranges from 1 to 4.

We compare the solution of optimal social welfare coalition formation (as described in Section 5.5.3) with the stable solution of the rational coalition formation. We set the cost of receiving a packet from and forwarding a packet to other vehicles to be equal (i.e., $c^{\mathrm{f}}_{ij} = c^{\mathrm{r}}_{ij} = c_i$), where c_i is referred to as the cost-coefficient. This cost-coefficient $c_i = 1.5$ and assumed to be the same for all the vehicles.

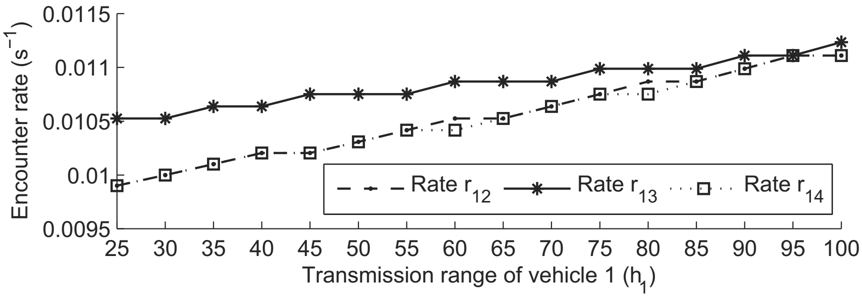


Figure 5.7. *Encounter rate between vehicle 1 and other vehicles when the transmission range of vehicles is varied.*

Table 5.5. *15 different coalitional structures for 4 vehicles*

Coalitional structure					
Υ_1	$\{1\},\{2\},\{3\},\{4\}$	Υ_2	$\{1,2\},\{3\},\{4\}$	Υ_3	$\{1\},\{2\},\{3,4\}$
Υ_4	$\{1,3\},\{2\},\{4\}$	Υ_5	$\{1\},\{3\},\{2,4\}$	Υ_6	$\{1,4\},\{2\},\{3\}$
Υ_7	$\{1\},\{4\},\{2,3\}$	Υ_8	$\{1,2\},\{3,4\}$	Υ_9	$\{1,3\},\{2,4\}$
Υ_{10}	$\{1,4\},\{2,3\}$	Υ_{11}	$\{1,2,3\},\{4\}$	Υ_{12}	$\{1,2,4\},\{3\}$
Υ_{13}	$\{1,3,4\},\{2\}$	Υ_{14}	$\{1\},\{2,3,4\}$	Υ_{15}	$\{1,2,3,4\}$

Figure 5.8 shows the stationary probabilities of the coalitional structures for both stable rational and optimal coalition solutions. There are 4 stable coalitional structures when c_i is 1.5, i.e., $\Upsilon_3 = \{\{1\},\{2\},\{3,4\}\}$, $\Upsilon_8 = \{\{1,2\},\{3,4\}\}$, $\Upsilon_9 = \{\{1,3\},\{2,4\}\}$, and $\Upsilon_{14} = \{\{1\},\{2,3,4\}\}$. With 4 stable coalitional structures, we observe that vehicle 1 should not be in the same coalition that vehicle 4 is a member of, since the encounter rate between these two vehicles is small compared to the encounter rates between vehicle 4 and vehicle 2, and between vehicle 4 and vehicle 3. Moreover, since the encounter rates between vehicle 3 and any BS, and between vehicle 4 and any BS, are small, to reduce the packet delivery delay, both vehicle 3 and vehicle 4 should not act alone. For the optimal solution, since the highest total payoff of the optimal coalitional structure is Υ_3, the probability of the coalitional structure is one.

Figure 5.9 shows the probabilities that each vehicle will help other vehicles to deliver packets. These probabilities are obtained as the solutions of the bargaining game. Given the stable coalitions and the optimal coalition as shown in Figure 5.8, we can determine how much each vehicle is willing to help others. If a vehicle does

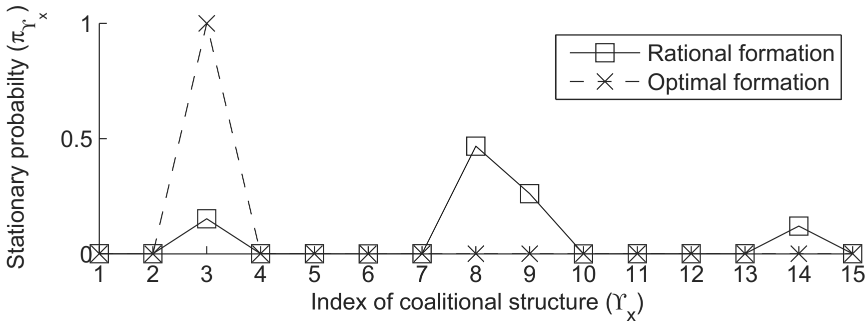


Figure 5.8. *Stationary probability of stable rational and optimal structures.*

not form a coalition, the corresponding helping probability is zero.

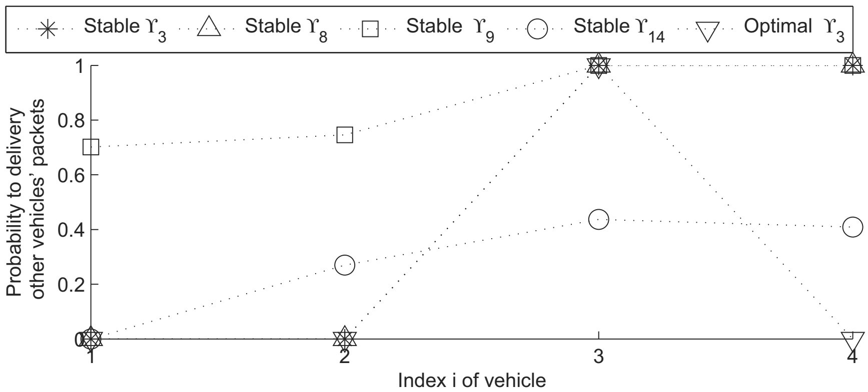


Figure 5.9. *Probability that each vehicle will help deliver other vehicles' packets.*

Figure 5.10 shows the stable coalitional structure obtained from the merge-and-split algorithm when the number of coalitions that can be merged and split at a time is 2. The initial coalitional structure is Υ_1 for each run of the algorithm. When the algorithm runs, we can observe that the coalitional structure changes and then it converges to the stable coalitional structure shown in Figure 5.8. Recall that the algorithm based on merge-and-split rules always converges to the stable solution [94].

5.6.4 Payoff of the Vehicles and Coalition Formation

Assuming that the cost-coefficient c_i is the same for all the vehicles, we vary c_i of all vehicles from 0 to 3. Figure 5.11 shows the total payoff of all the vehicles under

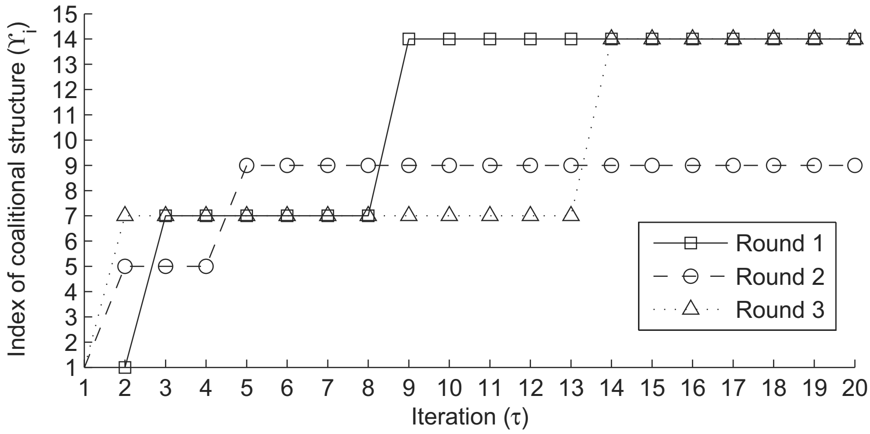


Figure 5.10. *Stable coalitional structure obtained from the merge-and-split algorithm when the number of coalitions that can be merged and split at a time is 2.*

different values of c_i. The expected total payoff of all the vehicles obtained from the bargaining game and the Markov chain-based analysis is given as follows:

$$E[u_{total}] = \sum_{i \in \mathbb{N}} \sum_{x=1}^{D_N} \pi_{\Upsilon_x} u_i(\mathcal{S}_j^i), \quad \text{for} \quad \mathcal{S}_j^i \in \Upsilon_x \tag{5.28}$$

where D_N is the Nth Bell number.

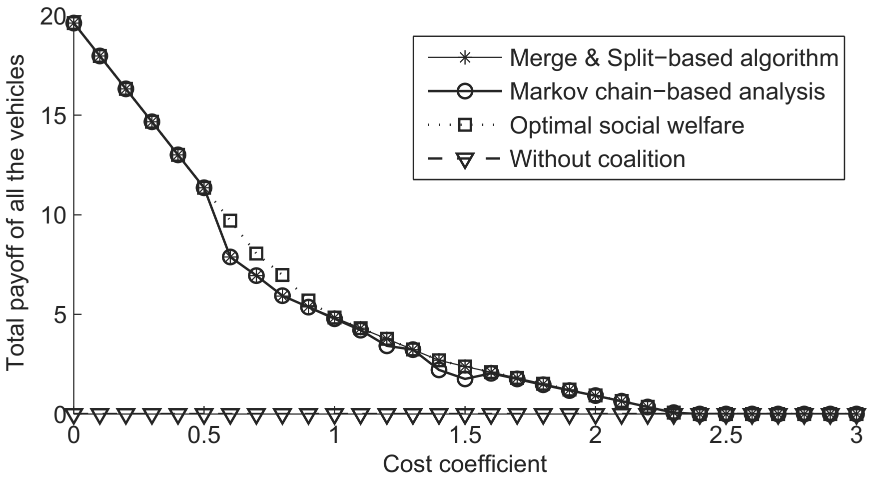


Figure 5.11. *Total payoff of all the vehicles under different cost-coefficient.*

As expected, for a small value of c_i, the total payoff is large when the coalition is formed. However, when the value of c_i increases, the total payoff of all vehicles decreases since a higher cost is incurred to all vehicles involved in cooperative packet delivery. As a result, a vehicle will leave its current coalition if the utility is not higher than the cost incurred from cooperative packet delivery. As shown in Figure 5.11, the total payoff becomes zero when c_i is higher than 2.40. Moreover, the total payoff from the optimal social welfare solution is equal to or higher than the payoffs of the stable solution of the rational coalition formation obtained from the merge-and-split algorithm and the DTMC analysis, and the payoff when all the players act alone.

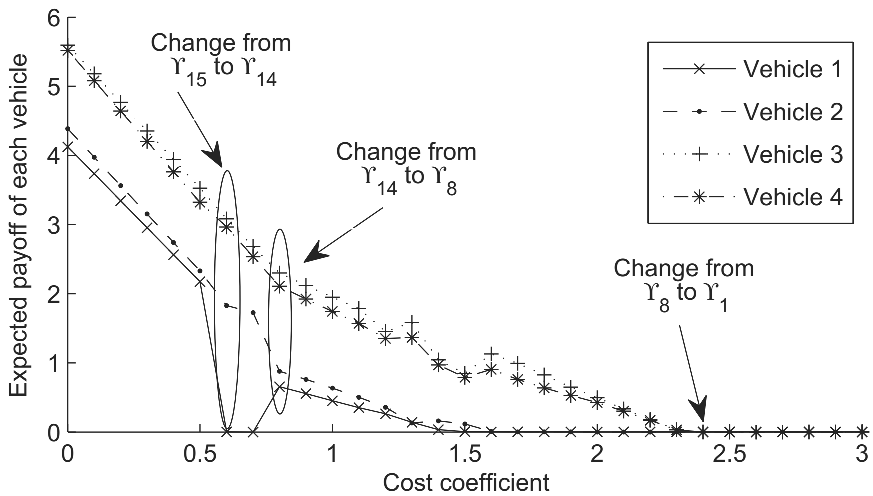


Figure 5.12. *Expected payoff of each vehicle under different values of cost-coefficient. The coalitional structure changes when the cost-coefficient is varied.*

Figure 5.12 shows the expected payoff of each vehicle under different values of c_i calculated as follows:

$$E[u_i] = \sum_{x=1}^{D_N} \pi_{\Upsilon_x} u_i(\mathcal{S}_j^i), \qquad \text{for} \quad \mathcal{S}_j^i \in \Upsilon_x. \tag{5.29}$$

As expected, when c_i is zero, a grand coalition Υ_{15} is formed and becomes stable since all the vehicles will obtain the highest expected payoff (i.e., with the lowest packet delivery delay). When c_i increases, the expected payoff of each vehicle decreases. Also, vehicles in a coalition decide to split into multiple coalitions to reduce their expected cost incurred from cooperative packet delivery. When the cost is too high, no vehicle will form any coalition. As shown in Figure 5.12, when the values of

c_i are 0.6, 0.8, and 2.4, there is a high probability that the stable coalitional structures will change from Υ_{15} to Υ_{14}, from Υ_{14} to Υ_8, and from Υ_8 to Υ_1, respectively. When c_i is higher than 2.4, all the vehicles act alone since any coalition formed will be unstable.

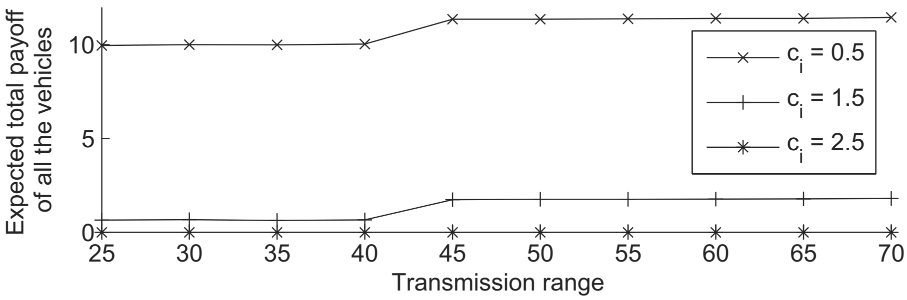


Figure 5.13. *Expected total payoff of all the vehicles under different transmission range of vehicles.*

Figure 5.13 shows the expected total payoff of each vehicle for different transmission ranges (h_i) and different cost-coefficients (c_i). When h_i increases, it might be expected that the payoff will increase since the chance to encounter other vehicles increases (i.e., rate of encounter increases) and then the transmission delay will decrease. However, the vehicles incur more costs due to the increase of rate of encounter with other vehicles. The vehicles can then adjust their probabilities to help others to maintain their optimal utilities. For example, a vehicle will decrease its probability to help others if it knows that the utility to be obtained is not high enough compared to the cost that it will incur. As shown in the figure, the payoff will not always increase as it is expected to be.

5.6.5 Packet Delivery Delay

Figure 5.14 shows variations in the expected delay of each vehicle for different values of c_i, which is calculated as follows:

$$E[d_i] = \sum_{x=1}^{D_N} \pi_{\Upsilon_x} d_i(\mathcal{S}_j^i), \text{ for } \mathcal{S}_j^i \in \Upsilon_x. \tag{5.30}$$

When c_i is zero, a grand coalition Υ_{15} (i.e., all the vehicles are in the same coalition) is formed and it is stable. When the grand coalition is obtained, all the vehicles achieve the lowest packet delivery delay, and in this case, the packet delivery delay requirement is met for all vehicles (i.e., $T_i \leq 25$s). As shown in Figure 5.14, when the cost increases, the packet delivery delay for each vehicle changes due to the change of the coalitional structure. When the cost is too high, all the vehicles act alone. In this case, since there is no help from other vehicles for packet delivery, the packet delivery delay is the highest. Moreover, it is observed that, not only the coalitional structure, but also the cost can affect the packet delivery delay. Considering that the coalitional structure Υ_8 is formed when c_i increases from 0.8 to 2.4, the packet delivery delay changes since each vehicle will recalculate its optimal probability to help to deliver other vehicles' packets.

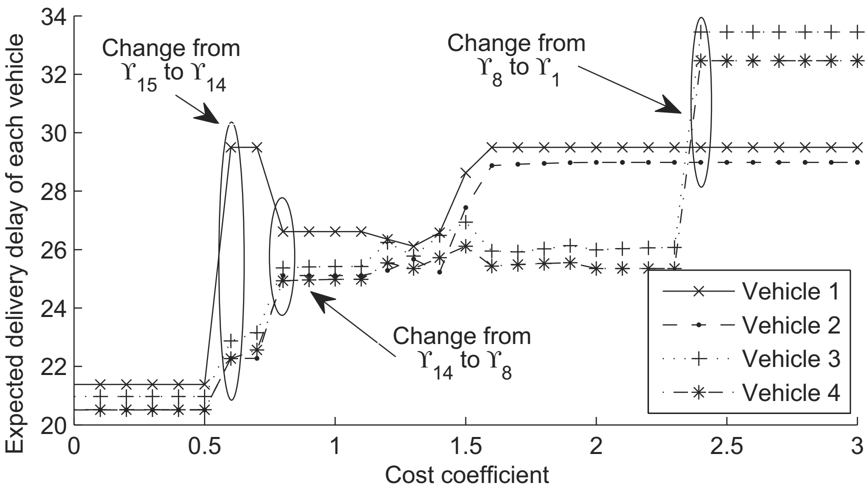


Figure 5.14. *Expected packet delivery delay of each vehicle under different values of cost-coefficient.*

5.7 Related Work

Since the proposed cooperative packet delivery approach is related to the concept of delay-tolerant networks (DTNs), in this section, we review the related work on delay-tolerant and cooperative data transmission in wireless networks. DTNs are characterized by long transmission delay, high error rates, intermittent connectivity, and existence of multiple unreliable links [100]. Vehicular delay tolerant networks (VDTNs) [101] constitute an important class of DTNs.

R. Lu, X. Lin, and X. Shen [101] presented a social-based privacy preserving packet forwarding protocol for VDTNs, called SPRING. The main idea is to deploy roadside BSs at the intersections according to the social centrality information in a VDTN. This social relation-based roadside base station placement approach can improve the packet delivery ratio in store-and-forward-based VDTNs. Q. Li, S. Zhu, and G. Cao [102] considered the social selfishness of mobile nodes in DTN. An optimization model was proposed to achieve the best packet delivery performance given that the nodes will forward packets to the nodes that they have social ties with. The similarity between their scheme [102] and our proposed scheme is the use of social relations and encounter opportunities among mobile nodes to improve routing and packet forwarding in DTNs. However, a key difference between both the schemes is that the formulation of the problem of packet delivery in a DTN. Their scheme formulated the packet delivery as a Multiple Knapsack problem with Assignment Restrictions (MKPAR) [102] but our work formulates it as the game theoretic approach which takes the individual benefits of mobile nodes into account.

P. Hui et al. [103] used a community detection algorithm was proposed based on the mobility traces of the mobile nodes and this algorithm for improved packet delivery performance. D. Niyato and P. Wang [104] studied the performance of a VDTN in terms of throughput and delay, where a vehicle acting as a mobile relay node helps a source node transmit data to a sink node. However, there are multiple source nodes competitively sharing the resources of the vehicle acting as a mobile relay node. The equilibrium solution for the transmission strategies of the source nodes were obtained from a noncooperative game. T. D. C. Little and A. Agarwal [105] proposed a data propagation scheme in the vehicular networks, called Directional Propagation Protocol. The dissemination algorithm was implemented as a routing protocol based on the concepts from mobile ad hoc networks (MANETs) and DTN. Cooperative data transmission schemes based on some other approaches are also worth mentioning. In [73], a vehicle-roadside-vehicle relay communication scheme was presented with the key assumption that vehicles always cooperate with others. H. Su and X. Zhang [74] presented a clustering-based multichannel medium access control protocol for cooperative data dissemination in a clustered vehicular network. O. Brickley et al. [106] introduced a data dissemination strategy for cooperative vehicular systems which considers the application requirements and the quality of the wireless link to determine how the information can be disseminated to the vehicles effectively and efficiently. S. Bai [107] developed a vehicular multi-hop broadcasting protocol for safety message dissemination. The protocol adopts a cooperative forwarding strategy to improve the reliability of broadcasting.

We summarize the related work in Table 5.6. The key assumption in all of the existing cooperative packet delivery schemes is that the mobile nodes (e.g., vehicles) in the same group always help each other for data delivery. However, this assumption may not be always true since there is a tradeoff between performance improvement (i.e., smaller packet delivery delay) and packet transmission/reception cost (i.e., operational cost, energy consumption, bandwidth, and other resources for receiving, carrying, and forwarding a packet). We address this issue in this work using a coalitional game framework. In particular, we use the coalitional game theory to analyze how the mobile nodes can dynamically form coalitions for carry-and-forward-based data delivery in a hybrid wireless network. Moreover, we present an SNA-based node grouping method to reduce the complexity of coalition formation and a bargaining game for efficient cooperative packet delivery.

5.8 Chapter Summary

We have presented a coalitional game framework for carry-and-forward-based cooperative packet delivery to mobile nodes in a hybrid wireless network. The mobile nodes are rational to form coalitions to maximize their individual payoffs. First, a continuous-time Markov chain model has been developed to obtain the packet delivery delay and the expected cost of mobile nodes for cooperative packet delivery. The packet delivery delay and the expected cost depend on the probability that each mobile node will help other mobile nodes in the same coalition. Then, a bargaining game has been formulated to find the optimal helping probabilities for all the mobile nodes. Based on the packet delivery delay and expected cost, a coalitional game has been formulated to model the decision making process of mobile nodes, that is,

Table 5.6. *Summary of Related Work*

Scenario	Solution	Concept used to find the solution	Key assumption/limitation	Reference
Study of packet delivery in vehicle-roadside-vehicle networks	Optimal transmission strategy according to whether it is a direct communication or retransmission	Using multiple frequencies (i.e., separating frequency bands between direct communication and retransmission) to increase packet delivery rate	A vehicle will always relay a packet to other nearby vehicles.	[73]
Study of MAC protocols for data delivery in vehicular ad hoc networks	Optimal transmission strategy	Cluster-based multichannel communications	Vehicles which are located in the same area form a cluster and help each other deliver data.	[74]
Study of packet forwarding protocol in store-and-forward-based VDTNs	Optimal roadside BS placement and packet forwarding protocol	Using social centrality to help deploy roadside BSs	A vehicle will always forward a packet to other nearby vehicles when it has available storage.	[101]
Study of routing algorithm in DTNs	Optimal routing path	Multiple Knapsack problem with assignment restrictions (MKPAR) and social network theory	Nodes are willing to forward packets for nodes with whom they have social ties but not others.	[102]
Study of distributed community detection algorithms in DTNs	Detected social network topology	Algorithms based on graph and social network theories	N/A	[103]
Study of packet delivery from multiple traffic sources to a sink with one relay mobile node in VDTNs	Nash equilibrium solution for the transmission strategies of the source nodes	Noncooperative game	Each source node is rational to compete for transmission to the relay node.	[104]
Study of routing protocol and data propagation in vehicular ad hoc networks	Optimal routing path and data propagation strategy	Cluster-based data propagation protocol	Nearby vehicles have to form a cluster of vehicles in order to disseminate messages.	[105]
Study of data dissemination strategy for cooperative vehicular systems	Optimal dissemination strategy to achieve the highest throughput	A simple policy based dissemination management function	Only infrastructure-to-vehicle communications are considered	[106]
Study of safety message dissemination protocol in vehicular ad hoc networks	Optimal data propagation strategy	Algorithm based on optimization of packet forwarding delay	Forwarder candidates (i.e., relay vehicles) are selected to help others based on their forwarding delay and location constraints. No cost of cooperative packet forwarding is considered.	[107]

whether they will cooperatively deliver packets to other mobile nodes or not. A stable coalitional structure (i.e., set of coalitions) has been considered as the solution of this coalitional game. Using the coalitional game model, the performance of cooperative packet delivery has been analyzed in terms of average packet delivery delay. As an extension of the work, the problem of mechanism design can be addressed to enforce truthful packet delivery and prevent the misbehavior of the mobiles nodes under the proposed coalitional game framework.

Chapter 6

Distributed Cooperative Channel Access Under Uncertainty: A Dynamic Bayesian Coalitional Game

6.1 Introduction

Mobility of the nodes can be exploited for data dissemination in wireless mobile networks with intermittent connectivity and very low link reliability such as the wireless mobile delay-tolerant networks (DTNs) [100]. A few works in the literature proposed cooperative communications models with relay-based mechanisms in DTNs and mobile ad hoc networks to decrease the delay of data delivery (e.g., the research papers of T. Yamada et al. [72] and V. N. G. J. Soares et al. [108]). The key assumption in all of the existing schemes is that the mobile nodes which are located near each other always help for data delivery. However, due to the tradeoff between performance improvement (i.e., smaller packet delivery delay) and transmission cost (i.e., bandwidth usage and energy consumption), the rational mobile nodes may not always want to help the same other mobile nodes. Consequently, cooperation among the nodes in a group would be dynamic, and the dynamics of the formation of groups among cooperative nodes (or coalitions) needs to be analyzed. In this proposed work, we use the theory of coalitional games [75, 109] to analyze how the coalitions are formed among mobile nodes for cooperative packet delivery.

As an example, Figure 6.1 shows a downlink data communications scenario based on coalition formation where carry-and-forward-based cooperative packet delivery is used to send packets from the base station to mobile nodes. Mobile nodes in the same coalition help each other to deliver packets sent from the base station to the destinations. Here, each rational mobile node makes a decision to leave its current coalition and join another coalition based on its individual preference over coalitions. When the number of mobile nodes in a coalition increases, the packet delivery delay decreases (i.e., due to the fact that there are more mobile nodes to carry and forward the packet) [110].

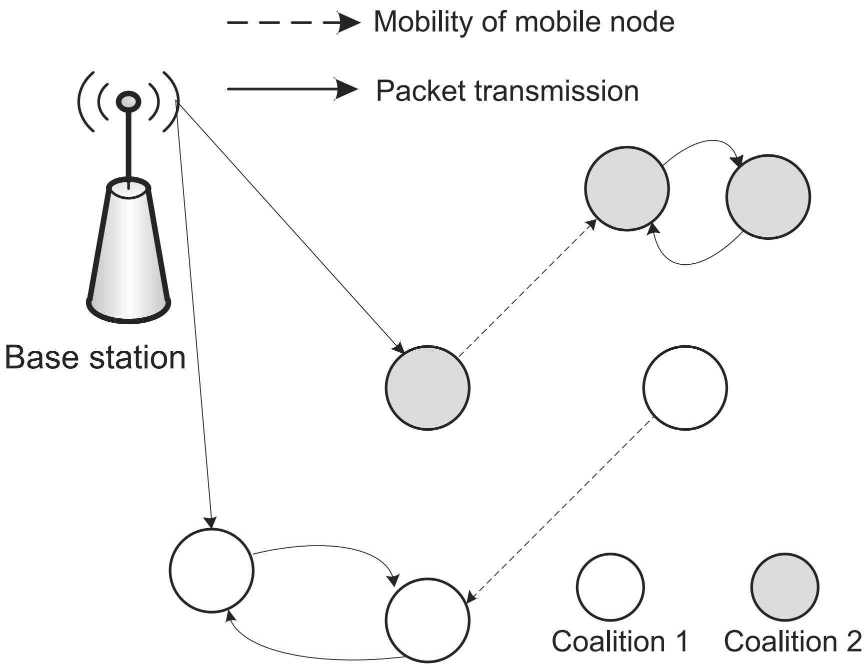


Figure 6.1. *In a wireless network, mobile nodes can form coalitions to help forward data from a base station to other mobile nodes which are out of the transmission range of the base station.*

After the coalitions of mobile nodes are formed, the rational mobile nodes, which are the members of a coalition, will agree to always help each other for packet delivery as studied in Chapter 5. However, some misbehaving mobile nodes may break the agreement and may not help other nodes (e.g., to reduce their transmission costs [86] and improve their own benefits). As a result, a fully cooperative scenario may not exist. Also, whether a mobile node is well-behaved or misbehaving cannot be perfectly known to the other mobile nodes. That is, a mobile node cannot observe whether other mobile nodes will forward packets to third-person or destination mobile nodes or not. Nevertheless, a mobile node can gradually learn other mobile nodes' behaviors. Since each of the mobile nodes will encounter the other mobile nodes in the same coalition, it can estimate the *type* of a particular node whether it is *well-behaved* or *misbehaving* by maintaining its own belief based on its experience of interactions with that node.

To model the dynamics of coalition formation under the uncertainty of node behaviors (which is referred to as the *types* of mobile nodes), we propose a Bayesian coalitional game for coalition-based cooperative packet delivery. In this model, the mobile nodes' observations are used to update their beliefs about other mobile nodes' *types* and used when the next coalition formation game is played. Therefore, this can be considered as a dynamic Bayesian coalitional game.

The major contributions of this work can be summarized as follows:

- formulation of a Bayesian coalitional game to model the uncertainty in node behavior for cooperative packet delivery in wireless mobile networks,
- analysis of two solution concepts, namely, *Nash-stable equilibrum* and *Bayesian core*, for the proposed Bayesian coalitional game,
- extension of the static Bayesian coalitional game to a multi-stage dynamic coalitional game and proposal of a belief update mechanism for the dynamic Bayesian coalitional game, and
- a comprehensive performance evaluation of the proposed game model.

The rest of this chapter is organized as follows. Section II describes the system model and assumptions. The Bayesian coalitional game model and the coalition formation algorithm under uncertainty in node behavior are presented in Section III. Section IV presents the analysis of the Bayesian coalition formation process. In particular, two solution concepts, namely, the Nash-stable coalitional structure and Bayesian core are analyzed. The dynamic Bayesian coalitional game is presented in Section V. Section VI presents the performance evaluation results for the proposed Bayesian coalitional game framework. Section VII presents the related work and

Section VIII concludes the chapter. Note that the list of symbols used in this chapter is shown in Table 6.1 and Table 6.2.

6.2 System Model and Assumptions

6.2.1 Network and Communication Model

We consider a scenario with M rational mobile nodes which can form coalitions among them for cooperative packet delivery to/from the base stations. We assume that each mobile node will carry-and-forward packets to other mobile nodes in the same coalition when they meet each other. In this scenario, we assume that, over a period of time, the patterns of mobility and inter-encounter time of each mobile node can be predicted (e.g., by using the technique proposed by Nelson S. C. Nelson, M. Bakht, and R. Kravets [81]). The inter-encounter interval between nodes is assumed to be exponentially distributed [85][1]. Let mobile node i meet another mobile node j with rate $r_{ij} = r_{ji}$ per unit of time. Let r_{i0} and r_{0i} denote the rates that mobile node i meets the base station and vice versa. Note that "0" is used as the index for a base station. Since the end-to-end connectivity among mobile nodes does not always exist, statistical data about the encounter rates among the mobile nodes are used for estimation of mobility patterns of the nodes [82, 86]. We assume that there is a coordinator at the central application server to collect information about the mobile nodes (e.g., mobility and encounter-rate information).

Any mobile node i receives packets from the base station or from another mobile node j in the same coalition at the cost of c^{r}_{ij} per packet[2]. Mobile node i then forwards the packets to their destination or to another mobile node j' in the same coalition which does not have these packets. For mobile node i, the cost of this transmission is $c^{\mathrm{f}}_{ij'}$ per packet. The cost of receiving its own packets by a mobile node, and the cost of packet transmission by a base station are assumed to be zero. Let d_i denote the packet delivery delay which is the duration from when a packet is originally transmitted from

[1]We verify this assumption the previous chapter

[2]This cost can be defined based on the application as well as the physical transmission parameters. For example, in the research paper of L. M. Feeney and M. Nilsson [111], for packet forwarding in an ad hoc network, the cost was defined in terms of the energy-consumption.

Table 6.1. *List of symbols used in Chapter 6*

Symbol	Definition
"0"	The index of any base station
A_Ω	The set of cooperative and noncooperative acknowledgements
A_ω	The set of observations of cooperative and noncooperative acknowledgements
$\mathcal{B}_{\Upsilon,\Upsilon'}$	The set of players who move from its current coalition to the new coalition and the coalitional structure changes from Υ to Υ'
$\mathcal{C}$	The core of the coalitional game
C_i	The total cost of mobile node i for packet delivery to any mobile node j in the same coalition
c_{ij}^{r}	The cost incurred to mobile node i for receiving packet(s) from a BS or from other mobile node j in the same coalition
$c_{ij'}^{\mathrm{f}}$	The cost incurred to mobile node i for forwarding packet(s) to its destination or to another mobile node j' in the same coalition
D_M	The number of different coalitional structures for N players
d_i	The packet delivery delay from when the packet is originally transmitted from the base station to when the packet is received by mobile node i
$d_i(\mathcal{S})$	The packet delivery delay for mobile node $i \in \mathcal{S}$
d_i^{TTL}	The time-to-live (TTL) value for a packet
G	The proposed Bayesian coalitional game
i	The index of each mobile node
M	The number of mobile nodes
$\mathbb{M}$	The set of all mobile nodes
$\mathcal{P}$	The common a priori probability over the type in $\mathbb{T}$
$P_j^i(t_j)$	The mobile node i's belief probability about mobile node j's type t_j
$p_i^{'}(\vec{\mathbf{t}}^i_{\mathcal{S}\setminus\{i\}})$	The joint belief probability of mobile node i about other mobile nodes in the same coalition $\mathcal{S}$
p_e	The probability that a false positive observation error occurs
p_s	The probability that a false negative observation error occurs
$\mathbf{Q}$	The transition probability matrix of the DTMC for the coalition formation analysis
R_i	The utility of mobile node i
r_{ij}	The encounter rate between mobile node i and mobile node j during a period of time
r_{i0}	The encounter rate between mobile node i and base station during a period of time
$\mathcal{S}$	A coalition of players (i.e., mobile nodes)
$\mathcal{S}_l^i$	Any coalition $\mathcal{S}_l$ which mobile node i is a member of
$\mathbb{T}$	The type space of all the mobile nodes' types
$\mathbb{T}_i$	The mobile node i 's possible type set
T_w	The well-behaved type
T_m	The misbehaving type
t_i	The mobile node i's type
t_0	the type of a base station
$\vec{\mathbf{t}}^i_{\mathcal{S}}$	The vector of beliefs of mobile node i about the types of all mobile nodes in $\mathcal{S}$
t_j^i	The belief of mobile node i about the type of mobile node j
$\bar{u}_i$	The expected payoff of player or mobile node i
$V(\mathcal{S})$	The characteristic function of coalition $\mathcal{S}$
α_i	The positive weight constant of the utility of delivering a packet to other mobile nodes in the same coalition
β_i	The positive weight constant of the cost of delivering a packet to other mobile nodes in the same coalition
χ_{ij}	The event that mobile node i observes an acknowledgement from mobile node j
Ω	The state space or set of all possible coalitional structures
Ω_c	The cooperative acknowledgement
Ω_n	The noncooperative acknowledgement
ω_c	The observation of cooperative acknowledgement
ω_n	The observation of noncooperative acknowledgement

Table 6.2. *List of symbols used in Chapter 6 (continued)*

Symbol	Definition
Ψ	The state space of the CTMC for the cooperative packet delivery scheme
$\vec{\boldsymbol{\pi}}$	The stationary probability vector of all stable coalitional structures
π_{Υ_x}	The probability that the coalitional structure Υ_x will be formed
$\rho_{\Upsilon,\Upsilon'}$	The probability that the coalitional structure changes from coalitional structure Υ to coalitional structure Υ'
ϕ	The index of time iterattion
τ_{ij}	The τ_{ij}-th time of observation of mobile node i on an acknowledgement of mobile node j
Υ	The coalitional structure
$\varphi_i(\Upsilon'\|\Upsilon)$	The probability that a player decides to move from its current coalition $\mathcal{S}_l^i$ to a new coalition
ς_i	The probability that misbehaving node i may refuse to deliver a packet of other nodes in the same coalition
$\succeq_i$	Player i's preference

the base station to when the packet is received by its destination. Given the benefit of smaller delay due to cooperative packet delivery at the cost of relaying packets to the other mobile nodes in the same coalition, a coalitional game-theoretic approach is applied to analyze the coalition formation process among mobile nodes.

6.2.2 Uncertainty in Node Behavior for Cooperative Packet Delivery

We assume that there are two *types* of mobile nodes, i.e., *well-behaved* node and *misbehaving node*.

- A *well-behaved node* always helps to deliver packets to the other nodes in the same coalition.
- A *misbehaving node* does not always help to deliver packets to other nodes.

In particular, a misbehaving node i may refuse to deliver a packet of other nodes in the same coalition with probability ς_i. In other words, the probability that a *well-behaved node* and a *misbehaving node* will forward the packets of other nodes is 1 and $1 - \varsigma_i$, respectively. We assume that a mobile node does not know the *types* of other mobile nodes. Due to the absence of a monitoring mechanism such as the one in the research paper of W. Yu and K. J. R. Liu [112], a mobile node cannot observe whether a packet sent to the next mobile node will be forwarded to other mobile nodes or not.

We define a set of cooperative and noncooperative acknowledgements as $A_\Omega = \{\Omega_c, \Omega_n\}$ and a set of observations of cooperative and noncooperative acknowledgements as $A_\omega = \{\omega_c, \omega_n\}$. In particular, cooperative acknowledgement (i.e., Ω_c) and noncooperative acknowledgement (i.e., Ω_n) mean that a mobile node accepts and refuses, respectively, to help deliver a packet. In other words, when the mobile node sends a packet (i.e., a data packet that will be forwarded) to another mobile node, it implies that a cooperative acknowledgement is done by the mobile node who is a sender. If the mobile node does not send any new packet to another mobile node, it implies that a noncooperative acknowledgement is done by the sending node. Next, we consider two observation errors that can cause imperfect observations in the network.

- *False positive observation error*, which occurs with probability p_e, means that a cooperative acknowledgement Ω_c from one mobile node is observed by another mobile node as a noncooperative acknowledgement ω_n due to, for example, link breakage, transmission error, or no new packet to transmit.
- *False negative observation error*, which occurs with probability p_s, means that a noncooperative acknowledgement Ω_n corresponding to one mobile node is observed by another mobile node as a cooperative acknowledgement ω_c which is caused by the malicious behavior of a misbehaving node.

When a pair of mobile nodes (e.g., mobile nodes 1 and 2) encounter each other, a connection is initialized and packet transmission starts. Mobile node 2 requests a packet from mobile node 1 and mobile node 2 observes the behavior of mobile node 1. If mobile node 2 receives a packet from mobile node 1, mobile node 2 perfectly knows that mobile node 1 helps to forward packets at this time (i.e., mobile node 2 observes $\omega_c = \Omega_c$). If no packet is received by mobile node 2, a noncooperative acknowledgement ω_n is observed. Moreover, if mobile node 1 has a new packet but it does not transmit the packet (i.e., mobile node 1 does a noncooperative acknowledgement Ω_n), mobile node 2 will definitely not receive any packet and thus observe a noncooperative acknowledgement ω_n.

Since mobile node 2 itself directly experiences the packet forwarding from mobile 1, a false negative observation error (i.e., the event that mobile node 1 does a noncooperative acknowledgement Ω_n but mobile node 2 observes a cooperative acknowledgement ω_c) cannot occur in our model. In other words, mobile node 2 itself directly experiences only a noncooperative acknowledgement ω_n[3]. However, observation of a noncooperative acknowledgement ω_n may be caused by the event of packet forwarding refusal if mobile node 1 is misbehaving or by the event of false positive observation error if mobile node 1 is well-behaved. Then, mobile node 2 cannot conclude whether mobile node 1 is a well-behaved or a misbehaving node. Note that mobile node 2 may not need to actually carry the packet after it is received if mobile node 2 is also a misbehaving mobile node.

6.2.3 Cooperative Packet Delivery Protocol

The observations on the other mobile nodes' behaviors are used to estimate the *types* of other mobile nodes. Then, given the uncertainty of *types* of other mobile nodes, we obtain the expected payoff function for mobile nodes. The expected payoff is a function of the average cost of communication and the average packet delivery delay. The expected payoffs of all the mobile nodes are used to determine whether the current coalitional structure is stable or not. If it is unstable, a new coalitional structure will be formed, and then the new expected payoff is calculated. Moreover, while mobile nodes are traveling and participating in the cooperative packet delivery with others in the same coalition, they observe other mobile nodes' behavior in cooperative packet delivery. Then, the mobile nodes update their beliefs, i.e., the probabilities of *types* of other mobile nodes, by using a belief update mechanism. This process is repeated until a stable solution is reached.

The cooperative packet delivery protocol for the mobile nodes to achieve a stable coalition-based solution works as follows:

(i) Mobile node i has to be registered to a coordinator at the central application server.

(ii) Mobile node i submits its information (i.e., rate of encounter r_{ij} with other mobile nodes) to the coordinator.

(iii) Mobile node i can ask for the information about the other mobile nodes from the coordinator.

[3]False negative observation error will not be used later in the analysis.

(iv) The mobile nodes play a coalitional game to obtain a stable coalitional structure (i.e., stable groups of mobile nodes participating in cooperative packet delivery).

(v) Each mobile node carries and forwards packets to others within the same coalition.

(vi) Each mobile node observes others' behaviors of packet delivery and updates its beliefs about other mobile nodes' *types* based on the observations.

(vii) The mobile nodes repeatedly play the coalitional game.

6.3 Formulation of the Bayesian Coalitional Game Model

We formulate a Bayesian coalitional game model to capture the uncertainty in players' *types* in coalition formation in an incomplete information environment. This Bayesian coalitional game is similar to a Bayesian noncooperative game [113]-[115].

6.3.1 Bayesian Coalitional Game with Non-Transferable Utility

Definition 2 *A Bayesian coalitional game with non-transferable utility is defined as*

$$G = \langle \mathbb{M}, \mathbb{T}, \mathcal{P}, (\bar{u}_i)_{i \in \mathbb{M}}, (\succeq_i)_{i \in \mathbb{M}} \rangle. \tag{6.1}$$

The formulation of this game is as follows:

- *Players*: The set of players consists of M rational mobile nodes and is denoted by $\mathbb{M} = \{1, \ldots, M\}$.
- *Type*: The type space is denoted by $\mathbb{T} = \mathbb{T}_1 \times \cdots \times \mathbb{T}_M$, where $\mathbb{T}_i = \{T_w, T_m\}$ denotes player $i \in \mathbb{M}$'s possible type set – *type* T_w is for well-behaved nodes and *type* T_m is for misbehaving nodes. Each player i has a *type* $t_i \in \mathbb{T}_i$. Each mobile node can observe its own *type* completely but not the *type*s of other mobile nodes. Each well-behaved mobile node always acts cooperatively with others. That is, it always tries to send or receive packets to or from others when

it encounters any other mobile node in the same coalition (i.e., a cooperative acknowledgement Ω_c occurs with probability 1). However, a misbehaving mobile node does not always cooperate with others. That is, a misbehaving node refuses to deliver a packet with probability ς_i (i.e., a cooperative acknowledgement Ω_c and a noncooperative acknowledgement Ω_n occur with probabilities $1-\varsigma_i$ and ς_i, respectively). Also, the probability ς_i for mobile node i is unknown to the other mobile nodes. t_0 is the *type* of a base station which is always T_w and is perfectly known to all the mobile nodes. Note that a player cannot have both the *type*s at the same time and its *type* is assumed not to change for a sufficiently long period of time[4].

- *Probability Distribution:* $\mathcal{P}$ is a common *a priori* probability over the *type* in $\mathbb{T}$. Let $P_j^i(t_j = T_w) = p_{ij}$ and $P_j^i(t_j = T_m) = 1 - p_{ij}$ denote mobile node i's belief probabilities about mobile node j over types T_w and T_m, respectively.
- *Payoff*: $\bar{u}_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})$, is defined as the expected payoff of mobile node i which is the difference between the average utility and the average cost given the beliefs of node i about the *types* of all players in the coalition $\mathcal{S}$. The vector of *types* of all players is denoted as $\vec{\mathbf{t}}^i_{\mathcal{S}} = [\ldots, t^i_j, \ldots]^T, j \in \mathcal{S}$, where t^i_j is the belief of node i about the *type* of mobile node j, which is a member of coalition $\mathcal{S}$.

  With a discrete *type* space, the expected payoff of node i can be defined as follows [1]:

$$\begin{aligned}\bar{u}_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) &= E[\alpha_i R_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) - \beta_i C_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})] \\ &= \sum_{k=1}^{2^{|\mathcal{S}|-1}} p_i^{'k}(\vec{\mathbf{t}}^i_{\mathcal{S}\setminus\{i\}})(\alpha_i R_i^k(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) - \beta_i C_i^k(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})) \qquad (6.2)\end{aligned}$$

  where α_i and β_i denote, respectively, the non-negative weight constants of the average utility and the average cost of delivering a packet to other mobile nodes in the same coalition. Since the *type* t_i of mobile node i is completely known to itself, for node i, $p_i^{'k}(\vec{\mathbf{t}}^i_{\mathcal{S}\setminus\{i\}})$ is its joint belief probability about other mobile

[4]If the *type* of a node changes frequently, during coalition formation, it may not be possible to learn what the *type* of this node is.

nodes in the same coalition $\mathcal{S}$ corresponding to the index k, and $\vec{\mathbf{t}}^i_{\mathcal{S}\backslash\{i\}}$ is the belief vector of mobile node i about the *types* of other mobile nodes. For a particular index k, the joint belief probability can be expressed as follows:

$$p_i^{'}(\vec{\mathbf{t}}^i_{\mathcal{S}\backslash\{i\}}) = \prod_{j\in\mathcal{S}\backslash\{i\}} P_j^i(t_j = t_j^i) \tag{6.3}$$

where t_j^i is the *type* of mobile node j believed by mobile node i.
The utility of mobile node i is defined as a function $R_i(\mathcal{S})$ as follows:

$$R_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) = \begin{cases} \max\left(0, 1 - \frac{d_i(\mathcal{S})}{\min(\hat{d}_i, d_i^{TTL})}\right), & |\mathcal{S}| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{6.4}$$

where $d_i(\mathcal{S})$ is the packet delivery delay for mobile node $i \in \mathcal{S}$, $\hat{d}_i = d_i(\{i\})$ is the packet delivery delay when mobile node i acts alone, and d_i^{TTL} is the time-to-live (TTL) value for a packet.
The average cost of mobile node i for delivering a packet to any mobile node j in the same coalition can be expressed as follows:

$$C_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) = \begin{cases} \sum_{j\in\mathcal{S}, j\neq i} c_{ij}(\mathcal{S}), & |\mathcal{S}| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{6.5}$$

where $c_{ij}(\mathcal{S})$ is the average cost that mobile node i incurs for delivering a packet destined to mobile node j in the same coalition $\mathcal{S}$ and $|\mathcal{S}|$ is the number of mobile nodes in coalition $\mathcal{S}$. In **Appendix B.1**, we formulate a Markov chain model to find the utility and the average cost (and hence the expected payoff) of each mobile node under uncertainty about other mobile nodes' *type*s.

- *Preference*: $\succeq_i$ describes player i's preference. For example, $\mathcal{S}_1 \succeq_i \mathcal{S}_2$ means that player i prefers to be a member of coalition $\mathcal{S}_2$ at most as much as $\mathcal{S}_1$.
- *Action*: The action of each player is to make a decision on which coalition to form (i.e., to join or leave a coalition) based on its own payoff and the payoffs of other players in the current coalition as well as the new coalition.

Each of the well-behaved mobile nodes always helps others by sending cooperative acknowledgements and doing cooperation. However, due to a false positive observation error which occurs with probability $0 < p_e < 1$, a mobile node imperfectly observes other mobile nodes' behaviors. Note that a false negative observation error occurs with probability $p_s = 0$.

In this work, we consider a non-transferable utility (NTU) coalitional game since the individual payoff of each mobile node (i.e., utility as a function of packet delivery delay minus cost of helping other nodes to deliver packets) cannot be given or transferred arbitrarily to other mobile nodes. The solution of the coalitional game is a stable coalitional structure.

6.3.2 Coalition Formation

Definition 3 *A coalitional structure is a set of coalitions spanning all the users in* $\mathbb{M}$ *which is defined as* $\Upsilon = \{\mathcal{S}_1, \ldots, \mathcal{S}_l, \ldots, \mathcal{S}_S\}$, *where* $\mathcal{S}_l \cap \mathcal{S}_l^{'} = \emptyset$ *for* $l \neq l^{'}$ *and* S *is the total number of coalitions for* $1 \leq S \leq M$, *and* $\bigcup_{l=1}^{s} \mathcal{S}_l = \mathbb{M}$. *The coalition consisting of all the mobile nodes is referred to as a grand coalition. There can be* $2^M - 1$ *distinct non-empty coalitions and* D_M *different coalitional structures for* M *players, where* D_M *is the* M*th Bell number given as follows:*

$$D_M = \sum_{j=0}^{M-1} \binom{M-1}{j} D_j, \quad \textit{for} \quad M \geq 1 \quad \textit{and} \quad D_0 = 1. \tag{6.6}$$

Let $\mathcal{S}_l^i$ denote any coalition $\mathcal{S}_l$ for $i \in \mathcal{S}_l$. In a coalitional game, a player's action is to choose a coalition that the player prefers to be a member of according to its expected payoff. Therefore, the concept of *preference* has to be defined.

Definition 4 *The preference of any mobile node* i *is denoted by* $(\succeq_i)_{i \in \mathcal{S} \subseteq \mathbb{M}}$. $\mathcal{S}_l^i \succeq_i \mathcal{S}_{l'}^i$ *denotes that mobile node* i *weakly prefers to be a member of* $\mathcal{S}_l^i$, $i \in \mathcal{S}_l \subseteq \mathbb{M}$ *over* $\mathcal{S}_{l'}^i$, $i \in \mathcal{S}_{l'} \subseteq \mathbb{M}$ *or at least, mobile node* i *prefers to be a member of both the coalitions.* $\mathcal{S}_l^i \succ_i \mathcal{S}_{l'}^i$ *denotes that mobile node* i *strictly prefers to be a member of* $\mathcal{S}_l^i$ *over* $\mathcal{S}_{l'}^i$.

Since a player is rational and the expected payoff of a player in a coalition depends only on the members of the coalition and can be predicted, this game can be considered a *hedonic game* which is a special case of NTU game [116]. From the definition of hedonic game, the preference of a node can be defined as follows.

- $\mathcal{S}_l^i \succ_i \mathcal{S}_{l'}^i$ is valid if two following conditions are true. First, all the other mobile nodes j in $\mathcal{S}_l^i$ believe that they are not worse off when mobile node i is a member of $\mathcal{S}_l^i$ (i.e., $\bar{u}_j(\mathcal{S}_l^i, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i}) \geq \bar{u}_j(\mathcal{S}_l^i \setminus \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i \setminus \{i\}}), \forall j \in \mathcal{S}_l^i \setminus \{i\}$). Second, mobile node i believes that its payoff, when this node is a member of $\mathcal{S}_l^i$, is greater than that when this node is a member of $\mathcal{S}_{l'}^i$ (i.e., $\bar{u}_i(\mathcal{S}_l^i, \vec{\mathbf{t}}^i_{\mathcal{S}_l^i}) > \bar{u}_i(\mathcal{S}_{l'}^i, \vec{\mathbf{t}}^i_{\mathcal{S}_{l'}^i})$).
- $\mathcal{S}_l^i \succeq_i \mathcal{S}_{l'}^i$ is valid if two following conditions are true. First, all the other mobile nodes j in $\mathcal{S}_l^i$ believe that they are not worse off when mobile node i is a member of $\mathcal{S}_l^i$ (i.e., $\bar{u}_j(\mathcal{S}_l^i, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i}) \geq \bar{u}_j(\mathcal{S}_l^i \setminus \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i \setminus \{i\}}), \forall j \in \mathcal{S}_l^i \setminus \{i\}$). Second, mobile node i believes that its payoff, when this node is a member of $\mathcal{S}_l^i$, is not less than that when this node is a member of $\mathcal{S}_{l'}^i$ (i.e., $\bar{u}_i(\mathcal{S}_l^i, \vec{\mathbf{t}}^i_{\mathcal{S}_l^i}) \geq \bar{u}_i(\mathcal{S}_{l'}^i, \vec{\mathbf{t}}^i_{\mathcal{S}_{l'}^i})$), **or**
- $\mathcal{S}_l^i \succeq_i \mathcal{S}_{l'}^i$ is valid if the following condition is true. At least one of the other mobile nodes j in $\mathcal{S}_{l'}^i$ believes that it is worse off when mobile node i is a member of $\mathcal{S}_{l'}^i$ and no mobile node j in $\mathcal{S}_l^i$ believes that it is worse off when mobile node i is a member of $\mathcal{S}_l^i$, or at least one of the other mobile nodes j in both $\mathcal{S}_l^i$ and $\mathcal{S}_{l'}^i$ believes that it is worse off when mobile node i is a member of $\mathcal{S}_l^i$ (i.e., $\bar{u}_j(\mathcal{S}_{l'}^i, \vec{\mathbf{t}}^j_{\mathcal{S}_{l'}^i}) < \bar{u}_j(\mathcal{S}_{l'}^i \setminus \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_{l'}^i \setminus \{i\}}), \exists j \in \mathcal{S}_{l'}^i \setminus \{i\}$ and $\bar{u}_j(\mathcal{S}_l^i, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i}) < \bar{u}_j(\mathcal{S}_l^i \setminus \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_l^i \setminus \{i\}}), \nexists j$ or $\exists j \in \mathcal{S}_l^i \setminus \{i\}$).

6.3.3 Coalition Formation Algorithm

At any time ϕ, any single mobile node in a coalition can decide to leave its current coalition and/or join a new coalition (i.e., make an individual decision). We present a distributed algorithm (**Algorithm 5**) based on mobile nodes' strict preferences as presented in **Definition 4** to achieve a solution of the game.

Algorithm 5 works as follows. First, the time ϕ is initialized to be zero, and also the coalitional structure is initialized. The algorithm repeats the following steps. Any mobile node i makes a decision to leave or to join the new coalition. To do so, the mobile node has to compute its expected payoff. Given the calculated expected payoff, the mobile node randomly selects a coalition to join. After joining, the mobile node recalculates its expected payoff. If the new expected payoff is higher, the mobile node requests to join the new coalition by sending request message to the coordinator. Upon receiving the request message, the mobile nodes in the target coalition evaluate the expected payoffs in the case that mobile node i joins their coalition. If the expected payoff is higher, the new coalition will be formed. Otherwise, there is no change of the coalitional structure.

Next, we consider whether any coalitional structure obtained from **Algorithm 5** is Nash-stable. The definition of a Nash-stable coalitional structure is given as follows:

Definition 5 *A coalitional structure* $\Upsilon = \{\mathcal{S}_1, \ldots, \mathcal{S}_l, \ldots, \mathcal{S}_s\}$ *is Nash-stable if* $\forall i \in \mathbb{M}, \mathcal{S}_l^i \succeq_i \mathcal{S}_k \cup \{i\}$ *for all* $\mathcal{S}_k \in \Upsilon \setminus \mathcal{S}_l^i \cup \{\emptyset\}$ *[116].*

From the definition, if a coalitional structure (i.e., a set of coalitions) is stable, then

- No player i has an incentive to leave its current coalition $\mathcal{S}_l^i$ and act alone (i.e., $\mathcal{S}_l^i \succeq_i \{i\}$). This implies that no player believes that she will be better off (in terms of expected payoff) by acting alone, i.e., $\bar{u}_i(\mathcal{S}_l, \vec{\mathbf{t}}^i_{\mathcal{S}_l}) \geq u_i(\{i\}, t_i)$.
- Given a player's beliefs about the other players, no player i will have an incentive to move from its current coalition $\mathcal{S}_l^i$ to any other coalition (assuming that the other coalitions do not change) that makes the coalitional structure to change (i.e., $\mathcal{S}_l^i \succeq_i \mathcal{S}_{l'} \cup \{i\}, \mathcal{S}_{l'} \in \Upsilon \setminus \mathcal{S}_l^i$, $i \in \mathbb{M}$ and $\mathcal{S}_{l'} \succ_j \mathcal{S}_{l'} \cup \{i\}$, $\forall\, j \in \mathcal{S}_{l'}$). This implies no player believes that she will be better off by joining the new coalition $\mathcal{S}_{l'}$ without making all the players in the coalition $\mathcal{S}_{l'}$ believe that they will be worse off, i.e., $\bar{u}_i(\mathcal{S}_l^i, \vec{\mathbf{t}}^i_{\mathcal{S}_l^i}) \geq \bar{u}_i(\mathcal{S}_{l'} \cup \{i\}, \vec{\mathbf{t}}^i_{\mathcal{S}_{l'} \cup \{i\}})$, $i \in \mathbb{M}$ and $\bar{u}_j(\mathcal{S}_{l'}, \vec{\mathbf{t}}^j_{\mathcal{S}_{l'}}) > \bar{u}_j(\mathcal{S}_{l'} \cup \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_{l'} \cup \{i\}})\ \forall\, j \in \mathcal{S}_{l'}$.

In the next section, we analyze the stability of the Bayesian coalitional game.

6.4 Analysis of the Bayesian Coalitional Game

The concepts of *Nash-stability* and *core* [20, 96] are used to analyze the stability of the Bayesian coalition formation game. Also, a discrete-time Markov chain model is developed to analyze the coalition formation algorithm. Note that since the preferences of players are based on their expected payoffs given their beliefs about other players' *types*, the Nash-stability may be described as the Bayesian Nash-stability

Algorithm 5 Distributed coalition formation algorithm based on individual preferences for cooperative packet delivery

```
Initialize $\phi = 0$ and $\Upsilon(\phi) = \{\mathcal{S}_1(\phi), \ldots, \mathcal{S}_s(\phi)\}$
loop
  At time $\phi$, mobile node $i$ is randomly selected to make a decision to leave $\mathcal{S}_l^i(\phi)$ and join any coalition $\mathcal{S}_k \in \Upsilon(\phi) \setminus \mathcal{S}_l^i(\phi) \cup \{\emptyset\}$.
  Mobile node $i$ computes its expected payoff $\bar{u}_i(S_l^i(\phi), \vec{\mathbf{t}}^i_{S_l^i(\phi)})$.
  Mobile node $i$ randomly selects one of coalitions, i.e., $\mathcal{S}_k$, to join.
  Mobile node $i$ computes its expected payoff $\bar{u}_i(\mathcal{S}_k(\phi) \cup \{i\}, \vec{\mathbf{t}}^i_{\mathcal{S}_k(\phi)\cup\{i\}})$.
  if $\bar{u}_i(\mathcal{S}_k(\phi) \cup \{i\}, \vec{\mathbf{t}}^i_{\mathcal{S}_k(\phi)\cup\{i\}}) > \bar{u}_i(S_l^i(\phi), \vec{\mathbf{t}}^i_{S_l^i(\phi)})$
    Mobile node $i$ sends its request to the central coordinator to join $\mathcal{S}_k(\tau)$.
    Mobile node $j \in \mathcal{S}_k(\phi)$ computes and sends its expected payoff $\bar{u}_j(\mathcal{S}_k(\phi) \cup \{i\}, \vec{\mathbf{t}}^j_{\mathcal{S}_k(\phi)\cup\{j\}})$ to the central coordinator.
    Note that if there is no change of information (e.g., beliefs about the *types* of other mobile nodes, and delivery costs) that causes any payoff to change, no new calculation or update is required.
    if $\mathcal{S}_k(\phi) \cup \{i\} \succ_i \mathcal{S}_l^i(\phi)$ is true
      Mobile node $i$ joins $\mathcal{S}_k(\phi)$.
      $\Upsilon(\phi+1) = (\Upsilon(\phi) \setminus \{\mathcal{S}_l^i(\phi), \mathcal{S}_k(\phi)\}) \cup \{\mathcal{S}_k(\phi) \cup \{i\}\} \cup \{\mathcal{S}_l^i(\phi) \setminus \{i\}\}$
    else
      $\Upsilon(\phi+1) = \Upsilon(\phi)$
    end
  else
    $\Upsilon(\phi+1) = \Upsilon(\phi)$
  end
  $\phi = \phi + 1$
end loop when a Nash-stable coalitional structure $\Upsilon^*$ is obtained (i.e., no mobile node prefers to move to another coalition).
```

which is comparable to the Bayesian Nash equilibrium of a noncooperative game with incomplete information.

6.4.1 Bayesian Nash-Stability

Theorem 1 ***Algorithm 5*** *will converge to a Nash-stable coalitional structure* Υ^*.

Proof. From **Definition 4**, any mobile node will be able to move to another coalition only when none of the mobile nodes in that coalition is worse off (i.e., the mobile nodes believe that they will not be worse off in terms of expected payoff after the new node joins). Starting with any coalitional structure Υ, if any mobile node i still prefer to move to a new coalition based on **Definition 4** (i.e., $\mathcal{S}_k \cup \{i\} \succ_i \mathcal{S}_l^i$, $\mathcal{S}_k \in \Upsilon \setminus \mathcal{S}_l^i \cup \{\emptyset\}$), then the current coalitional structure is not Nash-stable. Consequently, the current coalitional structure changes to a new coalitional structure after mobile node i joins a new coalition (i.e., lines 10–12 of **Algorithm 5**). Since there can be $2^M - 1$ distinct non-empty coalitions and D_M different coalitional structures as given in (6.6), this implies that there are maximum 2^{M-1} coalitions including an empty coalition for each mobile node i to possibly join. The worst case is that if mobile node i cannot find any non-empty coalition (i.e., the number of members of the coalition is greater than zero, $|\mathcal{S}_k| > 0$) to join, mobile node i then forms its singleton coalition.

Note that mobile node i moving to the empty coalition from its current singleton coalition (i.e., currently it is not a member of any other coalition) is considered to have no incentive to deviate from the current coalition because there would be no change in the coalition structure (i.e., it is still the same singleton coalition). Since the number of coalitions that each mobile node i can be a member of is finite, the algorithm will converge to a Nash-stable coalitional structure Υ^*. ■

From [116], a Nash-stable coalitional structure is also an *individually stable* coalitional structure (i.e., Nash-stability is a subset of individual stability).

Definition 6 *A coalitional structure* $\Upsilon = \{\mathcal{S}_1, \ldots, \mathcal{S}_l, \ldots, \mathcal{S}_s\}$ *is individually stable if* $\nexists i \in \mathbb{M}, \nexists \mathcal{S}_k \in \Upsilon \setminus \mathcal{S}_l^i \cup \{\emptyset\}$ *such that* $\mathcal{S}_k \cup \{i\} \succ_i \mathcal{S}_l^i$ *and* $\forall j \in \mathcal{S}_k, \mathcal{S}_k \cup \{i\} \succeq_j \mathcal{S}_k$.

This definition means that no player can move to another coalition, which it prefers to join, without making some members of that coalition worse off. Moreover, we can observe a more specific example of the condition of existence of an individually stable and also Nash-stable coalitional structure which does not consist of any singleton coalition. In particular, no player will leave its current coalition and join an empty coalition (i.e., no singleton coalition will be formed) if the following proposition is true.

Proposition 2 *If for all coalitions $\mathcal{S} \subseteq \mathbb{M}$, the condition $\forall i \in \mathcal{S}, \mathcal{S} \succ_i \{i\}$ is true, then there exists at least one a Nash-stable and also individual stable coalition structure in which all coalitions in the coalition structure are not singleton coalitions.*

Proof. This observation states that no player forms a singleton coalition since each player believes that a better expected payoff can be obtained by being a member of a coalition. Since the payoff of a player will be zero if the player acts alone, from (6.2), we can show that $u_i(\{i\}, t_i) = 0 < \bar{u}_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})$ (i.e., $\mathcal{S} \succ_i \{i\}$), $\forall i \in \mathcal{S}$. According to **Algorithm 5**, we can obtain a Nash-stable and individual stable coalitional structure at the end. ■

Since there can be multiple Nash-stable coalition structures, we formulate a discrete-time Markov chain (DTMC) to analyze the Nash-stable coalitional structure [95] resulting from the distributed algorithm.

6.4.2 Discrete-Time Markov Chain-Based Analysis of Coalition Formation

The DTMC follows **Algorithm 5** when the state (i.e., coalitional structure) changes based on individual preferences of the players. As an example, with three players, the state transition diagram of the DTMC for coalition formation is shown in Figure 6.2.

The state space of the DTMC can be expressed as follows:

$$\Theta = \{(\Upsilon_1), \ldots, (\Upsilon_x), \ldots, (\Upsilon_{D_M})\} \tag{6.7}$$

where Υ_x is a coalitional structure and D_M is the Mth Bell number. The transition probability of this DTMC is denoted by $\xi_{\Upsilon,\Upsilon'}$. In particular, $\xi_{\Upsilon,\Upsilon'}$ is the probability that the coalitional structure changes from Υ to Υ'. Let $\mathcal{B}_{\Upsilon,\Upsilon'}$ denote the set of players

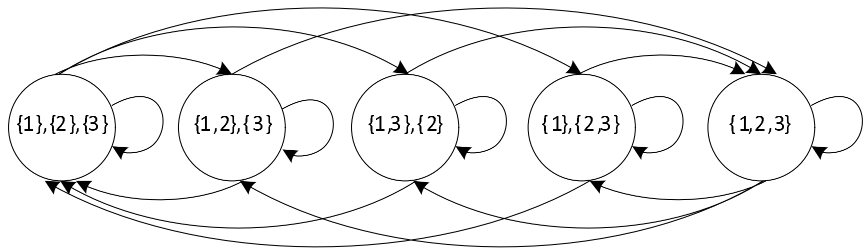


Figure 6.2. *State transition diagram of the discrete-time Markov chain (DTMC) for coalition formation among 3 players.*

involved in the change of coalitional structure from Υ to the coalitional structure $\Upsilon^{'}$. For example, players 1 and 2 are involved in the change of the coalitional structure from $\Upsilon = \{\{1\}, \{2\}, \{3\}\}$ to $\Upsilon^{'} = \{\{1, 2\}, \{3\}\}$. The transition probability from state Υ to $\Upsilon^{'}$ is then found as follows:

$$\xi_{\Upsilon,\Upsilon'} = \begin{cases} \sum_{i\in\mathcal{B}_{\Upsilon,\Upsilon'}} \frac{1}{M}\frac{1}{|\Upsilon\setminus\mathcal{S}_l^i\cup\{\emptyset\}|}\varphi_i(\Upsilon^{'}|\Upsilon), & \Upsilon\neq\Upsilon^{'} \ \& \ \Upsilon^{'} = (\Upsilon\setminus\{\mathcal{S}_l^i,\mathcal{S}_k\})\cup\{\mathcal{S}_k\cup\{i\}\} \\ & \cup\{\mathcal{S}_l^i\setminus\{i\}\} \\ 0, & \Upsilon\neq\Upsilon^{'} \ \& \ \Upsilon^{'} \neq (\Upsilon\setminus\{\mathcal{S}_l^i,\mathcal{S}_k\})\cup\{\mathcal{S}_k\cup\{i\}\} \\ & \cup\{\mathcal{S}_l^i\setminus\{i\}\} \\ 1-\sum_{\Upsilon''\in\Theta,\Upsilon''\neq\Upsilon}\xi_{\Upsilon,\Upsilon''}, & \Upsilon=\Upsilon^{'} \end{cases} \tag{6.8}$$

where $\mathcal{S}_k \in \Upsilon \setminus \mathcal{S}_l^i \cup \{\emptyset\}$, $\frac{1}{M}$ is the probability that player i is selected to make her individual decision, $\frac{1}{|\Upsilon\setminus\mathcal{S}_l^i\cup\{\emptyset\}|}$ is the probability that player i selects one possible coalition $\mathcal{S}_k \in \Upsilon\setminus\mathcal{S}_l^i\cup\{\emptyset\}$ to join. $\varphi_i(\Upsilon^{'}|\Upsilon)$ is the probability that a player decides to move from its current coalition $\mathcal{S}_l^i$ to a new coalition $\mathcal{S}_{l'}^i$ which makes the coalitional structure to change from Υ to $\Upsilon^{'}$, i.e.,

$$\varphi_i(\Upsilon^{'}|\Upsilon) = \begin{cases} 1, & \mathcal{S}_{l'}^i \succ_i \mathcal{S}_l^i \\ 0, & \text{otherwise} \end{cases} \tag{6.9}$$

where $\mathcal{S}_l^i \in \Upsilon$ and $\mathcal{S}_{l'}^i \in \Upsilon^{'}$.

Given the transition matrix $\mathbf{Q}$, whose elements are $\xi_{\Upsilon,\Upsilon'}$, the stationary probability vector $\vec{\boldsymbol{\pi}}$ can be obtained by solving the following equation: $\vec{\boldsymbol{\pi}}^T\mathbf{Q} = \vec{\boldsymbol{\pi}}^T$, where $\vec{\boldsymbol{\pi}}^T\vec{\mathbf{1}} = 1$, and $\vec{\mathbf{1}}$ is a vector of ones. $\vec{\boldsymbol{\pi}} = \begin{bmatrix}\pi_{\Upsilon_1} & \cdots & \pi_{\Upsilon_x} & \cdots & \pi_{\Upsilon_{D_M}}\end{bmatrix}^T$, where π_{Υ_x} is the probability that the coalitional structure Υ_x will be formed.

6.4.3 Bayesian Core

In this solution concept, the *core* is regarded as a set of payoffs corresponding to a grand coalition upon which no other coalition can improve, and therefore, no player has an incentive to leave the grand coalition. The grand coalition refers to a coalition of all the M players, i.e., all mobile nodes participating in the game. We study the conditions to achieve the core of the Bayesian coalitional game (i.e., Bayesian core).

Let $\vec{\mathbf{u}}^{\mathbb{M}} = [\bar{u}_1(\mathbb{M}, \vec{\mathbf{t}}^1_{\mathbb{M}}), \ldots, \bar{u}_i(\mathbb{M}, \vec{\mathbf{t}}^i_{\mathbb{M}}), \ldots, \bar{u}_M(\mathbb{M}, \vec{\mathbf{t}}^M_{\mathbb{M}})]$ and $\vec{\mathbf{u}}^{\mathcal{S}} = [\ldots, \bar{u}_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}), \ldots]$ denote the expected payoff vectors of all the mobile nodes when they are members in the grand coalition and the expected payoff vectors of the mobile nodes in any coalition $\mathcal{S} \subseteq \mathbb{M}$ calculated from (6.2), respectively.

Definition 7 *The characteristic function of coalition $\mathcal{S}$, which is a set of feasible payoff vector $\vec{\mathbf{x}}^{\mathcal{S}}$ of length $|\mathcal{S}|$, is defined as follows:*

$$V(\mathcal{S}) = \{\vec{\mathbf{x}}^{\mathcal{S}} \in \mathbb{R}^{\mathcal{S}} | \vec{\mathbf{x}}^{\mathcal{S}} \leq \vec{\mathbf{u}}^{\mathcal{S}}\}. \tag{6.10}$$

We can use the concepts of *core* and *Bayesian core* in the non-transferable utility game [20, 96] and the transferable utility game [113]-[115], respectively, to define the Bayesian core in NTU game in **Definition 8** and **Definition 9**.

Definition 8 *For an NTU Bayesian coalitional game, the* weak Bayesian core *is defined as follows:*

$$\mathcal{C} \;=\; \{\vec{\mathbf{u}}^{\mathbb{M}} \in V(\mathbb{M}) | \forall \mathcal{S} \subseteq \mathbb{M}, \nexists \vec{\mathbf{u}}^{\mathcal{S}} \in V(\mathcal{S}) \ s.t.\ \mathcal{S} \succeq_i \mathbb{M}, \forall i \in \mathcal{S}\}. \tag{6.11}$$

This definition indicates that there exist payoffs from the grand coalition upon which no other coalition can improve so that no member in the grand coalition believes that she is better off by deviating from the grand coalition (i.e., no other coalition blocks the grand coalition and its payoffs).

Remark 1 *Clearly, in our game model, the coalitional structure composed of only the grand coalition can be a Nash-stable coalitional structure but its expected payoffs may* *not be the Bayesian core (i.e., the grand coalition can be blocked by other coalitions). On the other hand, if the Bayesian core is not empty, then the coalitional structure composed of only the grand coalition exists and is Nash-stable.*

Next, we consider another stability concept called *strong Bayesian core*. Let $\bar{u}^i_j(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})$ and $\succeq^i_j$ be the expected payoff vector of mobile node j and the preference of mobile node j believed by mobile node i, respectively, when they are members in any coalition $\mathcal{S}$. Note that, $\bar{u}^i_i = \bar{u}_i$, as shown in (6.2), and $\bar{u}^i_j$, for $j \neq i$, can be calculated based on the *types* of other mobile nodes believed by mobile node i as follows:

$$\bar{u}^i_j(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) = E[\alpha_j R_j(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) - \beta_j C_j(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}})]. \tag{6.12}$$

Then, the preference of mobile node j believed by mobile node i can be found by following **Definition 4** and using (6.12) to find the expected payoffs.

Definition 9 *For an NTU Bayesian coalitional game, the* strong Bayesian core *is defined as follows:*

$$\begin{aligned} \mathcal{C} &= \{\vec{\mathbf{u}}^{\mathbb{M}} \in V(\mathbb{M}) | \forall \mathcal{S} \subseteq \mathbb{M}, \nexists \vec{\mathbf{u}}^{\mathcal{S}} \in V(\mathcal{S}) \\ & \quad \textit{s.t. } \mathcal{S} \succeq_i \mathbb{M}, \forall i \in \mathcal{S} \textit{ and } \mathcal{S} \succeq^i_j \mathbb{M}, \forall i \in \mathcal{S}, \forall j \in \mathcal{S}, j \neq i\}. \end{aligned} \tag{6.13}$$

The definition states that there exist payoffs from the grand coalition such that, no member in the coalition believes that she is better off by leaving the grand coalition, and each member, who uses her own view of expected payoffs of others members, believes that no other member is better off if she leaves the grand coalition. The strong Bayesian core is a subset of the weak Bayesian core. Therefore, if the weak Bayesian core exists, it may or may not be the strong Bayesian core. In our NTU game, the strong Bayesian core cannot be considered if all the needed information about the other mobile nodes (i.e., weight constants and costs of packet delivery) except their actual *type*s are not known to each player. Moreover, the *core* is a special case of the weak Bayesian core when there is no *type* uncertainty (i.e., all the players perfectly know each other's actual *type*). Since a Bayesian coalitional game generalizes a coalitional game, the Bayesian core may be empty [113].

For an NTU game, the Bondareva-Shapley theorem [96, 97] states that the *core* of a game is not empty if and only if the game is balanced.

Definition 10 *Consider an NTU game. For every* $\mathcal{S} \subseteq \mathbb{M}$*, let* $V_{\mathcal{S}} = V(\mathcal{S}) \times \mathbb{R}^{\mathbb{M}\backslash\mathcal{S}}$*. The NTU game is balanced if*

$$\bigcap_{\forall \mathcal{S} \subseteq \mathbb{M}} V(\mathcal{S}) \subseteq V(\mathbb{M}). \tag{6.14}$$

Observation 3 *The weak Bayesian core of the coalitional game for cooperative packet delivery is not empty if*

$$\alpha_i R_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) > \beta_i C_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}), \quad \textit{and} \tag{6.15}$$

$$\alpha_i R_i(\mathbb{M}, \vec{\mathbf{t}}^i_{\mathbb{M}}) - \beta_i C_i(\mathbb{M}, \vec{\mathbf{t}}^i_{\mathbb{M}}) > \alpha_i R_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) - \beta_i C_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}). \tag{6.16}$$

Proof. Since $\alpha_i \geq 0$ and $\beta_i \geq 0$, we can find α_i and β_i such that constraint in (6.15) holds. If the constraint in (6.15) does not hold, i.e., $u_i(\mathcal{S}, \vec{\mathbf{t}}^i_{\mathcal{S}}) < u_i(\{i\}, t_i) = 0$, then each mobile node will act alone, and the core is empty. Next, we can express $V(\mathcal{S})$ and $V(\mathbb{M})$ as follows:

$$V(\mathbb{M}) = \{\vec{\mathbf{x}}^{\mathbb{M}} = [\ldots, x_i, \ldots] \in \mathbb{R}^{\mathbb{M}} | x_i \leq \alpha_i R_i(\mathbb{M}, \vec{\mathbf{t}}^i_{\mathbb{M}}) - \beta_i C_i(\mathbb{M}, \vec{\mathbf{t}}^i_{\mathbb{M}}), \forall i \in \mathbb{M}\} \quad \text{and} \tag{6.17}$$

$$V(\mathcal{S}) = \{\vec{\mathbf{x}}^{\mathcal{S}} = [\ldots, x_{i'}, \ldots] \in \mathbb{R}^{\mathcal{S}} | x_{i'} \leq \alpha_{i'} R_{i'}(\mathcal{S}, \vec{\mathbf{t}}^{i'}_{\mathcal{S}}) - \beta_{i'} C_{i'}(\mathcal{S}, \vec{\mathbf{t}}^{i'}_{\mathcal{S}}), \forall i' \in \mathcal{S}\}. \tag{6.18}$$

If the constraint in (6.16) holds, then $\vec{\mathbf{x}}^{\mathbb{M}} > \vec{\mathbf{x}}^{\mathcal{S}} \times \mathbb{R}^{\mathbb{M}\backslash\mathcal{S}}$, $\forall \mathcal{S} \subseteq \mathbb{M}$, which satisfies the definition of a balanced game. Consequently, the Bayesian core is not empty if the constraints in (6.15) and (6.16) above are satisfied.

For example, if $\alpha_i = 0$, $\forall i \in \mathbb{M}$, then each mobile node in any coalition has no cost for packet delivery. Intuitively, the expected payoffs of all the mobile nodes will be the highest (i.e., the lowest delivery delay for all the mobile nodes). Then, we can obtain $\mathbb{M} \succ_i \mathcal{S}$, $\forall i \in \mathbb{M}$ and $\forall\ \mathcal{S} \subseteq \mathbb{M}$. Moreover, the obtained coalitional structure, which contains only the grand coalition, i.e., $\Upsilon = \{\mathbb{M}\}$, is also Nash-stable and individually stable since there is no mobile node i that has an incentive to leave the grand coalition and act alone (i.e., $\mathbb{M} \succ_i \{i\}$). ■

Remark 2 *From **Observation 2**, there can be multiple Nash-stable coalitional struc-*

Table 6.3. *Solution concepts and the corresponding conditions for the proposed cooperative packet delivery game*

Solution concept	**Condition**
Nash stability	1) No player has an incentive to leave its current coalition and act alone. 2) No player will have an incentive to move from its current coalition to any other coalition (assuming that the other coalitions do not change) that makes the coalitional structure to change.
Individual stability	No player can move to another coalition, which it prefers to join, without making some members of that coalition worse off.
Weak Bayesian core	There exist payoffs from the grand coalition upon which no other coalition can improve so that no member in the grand coalition believes that she is better off by deviating from the grand coalition (i.e., no other coalition blocks the grand coalition and its payoffs).
Strong Bayesian core	There exist the payoffs and the grand coalition that based on each player's beliefs, no player in the coalition believes that she is better off from the grand coalition. Moreover, each player who uses her own view of expected payoffs of other players believes that no other player is better off if he or she deviates from the grand coalition.

*tures which are the solutions of the game and one of them can be the grand coalition. The grand coalition for which the set of associated expected payoffs may or may not be the Bayesian core, may not be reached by the proposed algorithm since the algorithm will terminate when any Nash-stable coalitional structure is achieved. Hence, if the Nash-stable coalitional structure composed of only the grand coalition needs to be obtained, the initial coalitional structure in **Algorithm 5** has to be set to the grand coalition. Then, if the grand coalitional structure is not Nash-stable, any other coalitional structure, which is Nash-stable, will be obtained.*

The different solution concepts described above for the proposed cooperative packet delivery game are summarized in Table 6.3.

6.5 Dynamic Bayesian Coalitional Game

In this section, we extend the static Bayesian coalitional game to a multi-stage dynamic Bayesian coalitional game and propose a distributed algorithm for this game. In this game, a player can update her beliefs (i.e., probabilities) about the *types* of other players as the game evolves. The update is made based on each player's observations about others' behaviors. When the coalitional game with belief update mechanism is repeatedly played, it will converge to a solution which is the same as the solution that could be obtained when all the information are known (i.e., players' *types* are known).

6.5.1 Belief Update Mechanism

Each player (i.e., mobile node) can update her beliefs about the *type*s of other players according to *Bayes'theorem* [117]. As in Section 6.2.2, let us consider the situation that mobile node i requests a packet from node j. In this case, mobile node i can observe whether node j sends the packet or not. Two cases can happen in this scenario, which we define as $\chi_{ij}(\omega_c = \Omega_c)$ and $\chi_{ij}(\omega_n)$. Here $\chi_{ij}(\omega_c = \Omega_c)$ denotes the event that mobile node i observes a cooperative acknowledgement ω_c implying that it receives the packet from mobile node j successfully. $\chi_{ij}(\omega_n)$ denotes the event that mobile node i observes a noncooperative acknowledgement ω_n implying that it has not received any packet from mobile node j. Given an observation $\chi_{ij}(\omega_c = \Omega_c)$ or $\chi_{ij}(\omega_n)$ at the τ_{ij}-th time of observation, where $\tau_{ij} \geq 0$, mobile node i can update its belief probability about mobile node j's well-behaved *type* according to Bayes' theorem as shown in (6.19) and (6.20).

$$p_{ij}^{\tau_{ij}+1}(\chi_{ij}(\omega_c = \Omega_c)) = \frac{p_{ij}^{\tau_{ij}}(1-p_e)}{p_{ij}^{\tau_{ij}}(1-p_e) + (1-p_{ij}^{\tau_{ij}})(1-\varsigma_{ij}^{\tau_{ij}+1})(1-p_e)}. \tag{6.19}$$

$$p_{ij}^{\tau_{ij}+1}(\chi_{ij}(\omega_n)) = \frac{p_{ij}^{\tau_{ij}}p_e}{p_{ij}^{\tau_{ij}}p_e + (1-p_{ij}^{\tau_{ij}})(\varsigma_{ij}^{\tau_{ij}+1} + (1-\varsigma_{ij}^{\tau_{ij}+1})p_e)}. \tag{6.20}$$

If mobile node j is misbehaving, the probability that the mobile node will refuse to deliver packets is ς_i. At the time instant $\tau_{ij}+1$, the belief probability of mobile node i that mobile node j refuses to deliver a packet, when mobile node j is misbehaving, is denoted by $\varsigma_{ij}^{\tau_{ij}+1}$, and can be found by using (6.21) and (6.22). Let $|\chi_{ij}(\omega_c = \Omega_c)|$, $|\chi_{ij}(\omega_n)|$, and $|\chi_{ij}|$ denote, respectively, the number of observations of cooperative acknowledgement ω_c, noncooperative acknowledgement ω_n, and total observations of acknowledgement. In (6.21), the probability that mobile node i will observe a cooperative acknowledgement ω_c can be expressed as the ratio between $|\chi_{ij}(\omega_c = \Omega_c)|$ and $|\chi_{ij}|$. In (6.22), the probability that mobile node i will observe a noncooperative acknowledgement ω_c can be expressed as the ratio between $|\chi_{ij}(\omega_n)|$ and $|\chi_{ij}|$. Note that the expression on the left hand side of the equation is the theoretical probability but the expression on the right hand side is the probability computed from the actual observations.

$$p_{ij}(1-p_e)+(1-p_{ij})(1-\varsigma_{ij})(1-p_e)=\frac{|\chi_{ij}(\omega_c=\Omega_c)|}{|\chi_{ij}|}. \tag{6.21}$$

$$p_{ij}p_e+(1-p_{ij})(\varsigma_{ij}+(1-\varsigma_{ij})p_e)=\frac{|\chi_{ij}(\omega_n)|}{|\chi_{ij}|}. \tag{6.22}$$

Then, given mobile node i's belief probability $p_{ij}^{\tau_{ij}}$ about mobile node j's well-behaved *type* and the number of observations $|\chi_{ij}|^{\tau_{ij}+1}$, $|\chi_{ij}(\omega_n)|^{\tau_{ij}+1}$, and $|\chi_{ij}(\omega_c = \Omega_c)|^{\tau_{ij}+1}$ at the $\tau_{ij}+1$-th time of observation, mobile node i can estimate its $\varsigma_{ij}^{\tau_{ij}+1}$ as shown in (6.23) and (6.24), where $|\chi_{ij}|^{\tau_{ij}+1}=\tau_{ij}+1$.

$$\varsigma_{ij}^{\tau_{ij}+1\dagger}=\begin{cases}\left(\dfrac{(1-p_e)-\frac{|\chi_{ij}(\omega_c=\Omega_c)|^{\tau_{ij}+1}}{|\chi_{ij}|^{\tau_{ij}+1}}}{(1-p_{ij}^{\tau_{ij}})(1-p_e)}\right), & |\chi_{ij}(\omega_c=\Omega_c)|^{\tau_{ij}+1}>0\\[2ex] \left(\dfrac{\frac{|\chi_{ij}(\omega_n)|^{\tau_{ij}+1}}{|\chi_{ij}|^{\tau_{ij}+1}}-p_e}{(1-p_{ij}^{\tau_{ij}})(1-p_e)}\right), & |\chi_{ij}(\omega_n)|^{\tau_{ij}+1}>0.\end{cases} \tag{6.23}$$

For mobile node i, we obtain the new belief probability that mobile node j will refuse to deliver packet at the $\tau_{ij}+1$-th time of observation, i.e., $\varsigma_{ij}^{\tau_{ij}+1\dagger}$, in (6.23). Note that in (6.23), when both the number of observations of cooperative acknowledgement (i.e., $|\chi_{ij}(\omega_c=\Omega_c)|^{\tau_{ij}+1}$) and the number of observations of noncooperative acknowledgement (i.e., $|\chi_{ij}(\omega_n)|^{\tau_{ij}+1}$) are greater than zero, using either the first equation or the second equation will give the same result. Since the probability obtained at each time of observation is independently calculated using the statistical data (i.e., $|\chi_{ij}|^{\tau_{ij}+1}$, $|\chi_{ij}(\omega_n)|^{\tau_{ij}+1}$, and $|\chi_{ij}(\omega_c=\Omega_c)|^{\tau_{ij}+1}$), each mobile node can update its belief probability $\varsigma_{ij}^{\tau_{ij}+1}$ as the weighted sum of the previous value $\varsigma_{ij}^{\tau_{ij}}$ and the new value $\varsigma_{ij}^{\tau_{ij}+1\dagger}$ as shown in (6.24) below:

$$\varsigma_{ij}^{\tau_{ij}+1}=w_1\varsigma_{ij}^{\tau_{ij}+1\dagger}+w_2\varsigma_{ij}^{\tau_{ij}} \tag{6.24}$$

where w_1 and w_2 are adjustable weight constants such that $0<w_1<1$, $0<w_1\le 1$,

and $w_1 + w_2 = 1$. Note that the linear combination in (6.24) is based on the concept of exponential moving average (EMA) which is a standard method of estimating an unknown parameter [118]. It is used to estimate the belief $\varsigma_{ij}^{\tau_{ij}+1}$ at step $\tau_{ij} + 1$ when the instantaneous belief $\varsigma_{ij}^{\tau_{ij}+1\dagger}$ in (6.23) is given.

We can compare the solution of the dynamic Bayesian coalitional game with a dynamic Bayesian noncooperative game. In a dynamic Bayesian noncooperative game [1], a combination of strategies and beliefs is a perfect Bayesian equilibrium if

- the beliefs of each information set are updated by Bayes' theorem whenever applicable, and
- the strategy of each player at each information set is optimal or it maximizes her expected payoff with respect to her beliefs given the strategies of all the other players (i.e., this is called sequential rationality).

Then, when the coalitional game is repeatedly played (i.e., in a multi-stage game), the players' beliefs are updated according to Bayes' theorem and the players make their decisions to leave and join any coalition optimally based on their preferences (i.e., optimal actions with respect to their beliefs given the strategies of all the others) until a (Bayesian) Nash-stable coalitional structure is achieved. Hence, the solution of each subgame, which is Nash-stable coalitional structure, can be compared to the perfect Bayesian equilibrium for a dynamic Bayesian noncooperative game.

6.5.2 Distributed Algorithm

We present an algorithm for dynamically playing a coalitional game with belief update mechanism based on (6.19)–(6.24) in **Algorithm 6**. First, mobile node i initializes the counter for time of observation, and its belief. Then, the coalitional game is played and a Nash-stable coalitional structure is obtained according to **Algorithm 5**. Each mobile node then updates its beliefs about other mobile nodes' *type*s while it is helping others in packet delivery. When a period of time to do cooperative packet delivery ends, the mobile nodes repeatedly play the coalitional game given their updated beliefs. In this case, if any player is *misbehaving*, the belief probabilities for other players about this player's *well-behaved type* will decrease or that of *misbehaved type* will increase due to the belief update mechanism. When the mobile nodes repeatedly play the coalitional game given their updated beliefs, the algorithm converges to the Nash-stable coalitional structure which is the same as the solution that could be obtained when all the players' types are known.

Algorithm 6 Distributed algorithm for dynamic Bayesian coalitional game with belief update mechanism

1: Mobile node i initializes the counter τ_{ij}, $\forall\ j \in \mathbb{M}$ and $j \neq i$. τ_{ij} is the τ_{ij}-th time of observation of helping behavior of mobile node j observed by mobile node i (i.e., $\tau_{ij} = 0, \forall j$).
2: Mobile node i initializes its beliefs $P^i_j(t_j = T_m) = p^{\tau_{ij}}_{ij}$ and $P^i_j(t_j = T_w) = 1 - p^{\tau_{ij}}_{ij}$ $\forall\ j \in \mathbb{M}$ and $j \neq i$, where $0 < p^{\tau_{ij}}_{ij} < 1$.
3: The coalition formation algorithm (**Algorithm 5**) is run (i.e., a Nash-stable coalitional structure based on mobile node's preferences with respect to their beliefs).
4: **loop**
5: Mobile node i in $\mathcal{S}^i_l \in \Upsilon$ helps others to deliver packet according to the current stable coalitional structure Υ.
6: Mobile node i observes the helping behavior $\chi^{\tau_{ij}}_{ij}$ of mobile node j.
7: Mobile node i updates its the belief probability of packet delivery to be refused by other mobile node j, if mobile node j is a misbehaving node, i.e., $\varsigma^{\tau_{ij}+1}_{ij}(\chi^{\tau_{ij}}_{ij}(\omega_n))$, according to (6.23)-(6.24).
8: Mobile node i updates its probabilistic belief about another mobile node j's type $p^{\tau_{ij}+1}_{ij}(\chi^{\tau_{ij}}_{ij})$ according to (6.19)–(6.20).
9: **end loop** until packet delivery is done or network state changes
10: Go to Step 3.

6.6 Performance Evaluation

We apply the proposed cooperative packet delivery framework in a vehicle-to-roadside (V2R) communications scenario (i.e., the mobile nodes shown in Figure 6.1 are vehicles). In such a scenario, data is transferred through the roadside base stations (RBSs) or wireless access points. Each vehicle is equipped with a Wi-Fi transceiver for downloading data when the vehicle is connected to the RBS.

Table 6.4. *Default values of parameters*

Parameter	Description/value
Communication range of base station	Radius of 100 m
Communication range of vehicle	Radius of 50 m
Maximum speed on roads	50 km/h (31.25 mph)
Vehicle's acceleration	0.8 m/s^2
Vehicle's deceleration	4.5 m/s^2

Table 6.5. *Rates (r_{ij}) per second that each vehicle meets other vehicles and an RSB on a road*

Rate	RBS	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
RSB	-	0.0339	0.0345	0.0299	0.0308
Vehicle 1	0.0339	-	0.0103	0.0108	0.0104
Vehicle 2	0.0345	0.0103	-	0.0122	0.0145
Vehicle 3	0.0299	0.0108	0.0122	-	0.0247
Vehicle 4	0.0308	0.0104	0.0145	0.0247	-

6.6.1 Simulation Parameters and Assumptions

To obtain the parameters on rate of encounters among the vehicles, we use a microscopic road traffic simulation package named "SUMO", an acronym for "Simulation of Urban MObility" [99] and then use MATLAB to analyze the results obtained from the SUMO simulator. The rates for each vehicle to meet other vehicles and an RBS (i.e., r_{ij}) are shown in Table 6.5. The rates are obtained using the parameters in Table 6.4. The area of the road map is of size 2 km$\times$2 km with 121 intersections. An RBS is located at an intersection for every 400 m in both horizontal and vertical directions, and they are connected by a wired infrastructure. There are 100 vehicles in the area among which 4 vehicles, namely, vehicles 1 to 4, are selected to show the performance evaluation results. Each vehicle moves along the shortest path from a random originating position to a random destination position.

We assume that the *type* of each of vehicle 1, vehicle 2, and vehicle 3 is *misbehaving* with $\varsigma_1 = 0.90$, $\varsigma_2 = 0.70$, and $\varsigma_3 = 0.50$, respectively. Vehicle 4's *type* is *well-behaved* (i.e., $\varsigma_4 = 0$). Vehicle i initially believes that the *type*s of the other vehicles j are *well-behaved* with probability $p_{ij} = 0.99$ and *misbehaving* with probability $1 - p_{ij} = 0.01$. The false positive observation error occurs with $p_e = 0.1$. Also, each vehicle i initially believes that if another vehicle j is misbehaving, it will refuse to deliver a packet with the same probability $\varsigma_{ij} = 0.1$. The weight constants of the utility function

Table 6.6. *15 different coalitional structures for 4 vehicles*

Coalitional structure					
Υ_1	$\{1\},\{2\},\{3\},\{4\}$	Υ_2	$\{1,2\},\{3\},\{4\}$	Υ_3	$\{1\},\{2\},\{3,4\}$
Υ_4	$\{1,3\},\{2\},\{4\}$	Υ_5	$\{1\},\{3\},\{2,4\}$	Υ_6	$\{1,4\},\{2\},\{3\}$
Υ_7	$\{1\},\{4\},\{2,3\}$	Υ_8	$\{1,2\},\{3,4\}$	Υ_9	$\{1,3\},\{2,4\}$
Υ_{10}	$\{1,4\},\{2,3\}$	Υ_{11}	$\{1,2,3\},\{4\}$	Υ_{12}	$\{1,2,4\},\{3\}$
Υ_{13}	$\{1,3,4\},\{2\}$	Υ_{14}	$\{1\},\{2,3,4\}$	Υ_{15}	$\{1,2,3,4\}$

are assumed to be $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 15$. A large value of α means that the utility of a vehicle will change significantly when the packet delivery delay changes by a small amount. The weight constants of the cost function are assumed to be $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 1.5$. A small value of β (e.g., zero) means that the vehicle does not care about the cost it incurs. We assume that w_1 and w_2 (i.e., the weight constants for updating ς_i) are 0.9 and 0.1, respectively. Since there are 4 vehicles, there are 15 possible coalitions. The Time-To-Live (TTL) value for all packets is assumed to be $d_i^{TTL} = 35$ s. We set the cost of receiving a packet from and forwarding a packet to other vehicles to be equal (i.e., $c_{ij}^{\mathrm{f}} = c_{ij}^{\mathrm{r}} = c_i$), where c_i is referred to as the cost-coefficient. This cost-coefficient is $c_i = 1.0$ and assumed to be the same for all the vehicles.

We compare the stable solution from the proposed rational coalition formation game with incomplete information with the solution from optimal coalition formation, and the solution from rational coalition formation with complete information. In the optimal coalition formation, vehicles will form coalitions to maximize the total payoff of all the vehicles given that all the information are completely known. In the case of rational coalition formation with complete information, the coalitions are formed by the vehicles to maximize their individual payoff given that all the vehicles' *type*s are completely known.

6.6.2 Numerical Results

6.6.2.1 Nash-stable Coalitional Structure

Figure 6.3 shows the stationary probabilities of the Nash-stable rational coalition solutions with incomplete information, with complete information, and optimal coali-

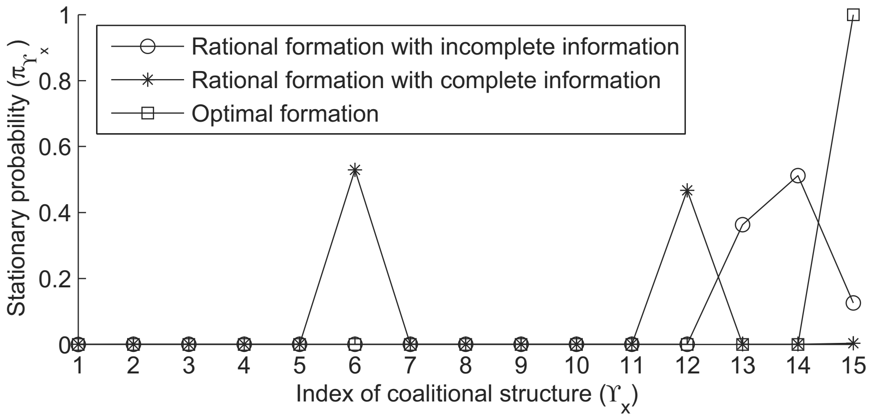


Figure 6.3. *Stationary probability of the Nash-stable rational coalitional structures with incomplete and complete information and optimal coalitional structure.*

tion solution. For the Nash-stable rational coalition formation with incomplete information, there are 3 Nash-stable coalitional structures, i.e., $\Upsilon^*_{13} = \{\{1,3,4\},\{2\}\}$, $\Upsilon^*_{14} = \{\{1\},\{2,3,4\}\}$, and $\Upsilon^*_{15} = \{\{1,2,3,4\}\}$. For the Nash-stable rational coalition formation with complete information, there are 2 Nash-stable coalitional structures, i.e., $\Upsilon^*_{6} = \{\{1,4\},\{2,3\}\}$ and $\Upsilon^*_{12} = \{\{1,2,4\},\{3\}\}$. For the optimal solution, since the highest total payoff of the optimal coalitional structure is Υ^*_{15}, the probability of this coalitional structure is one.

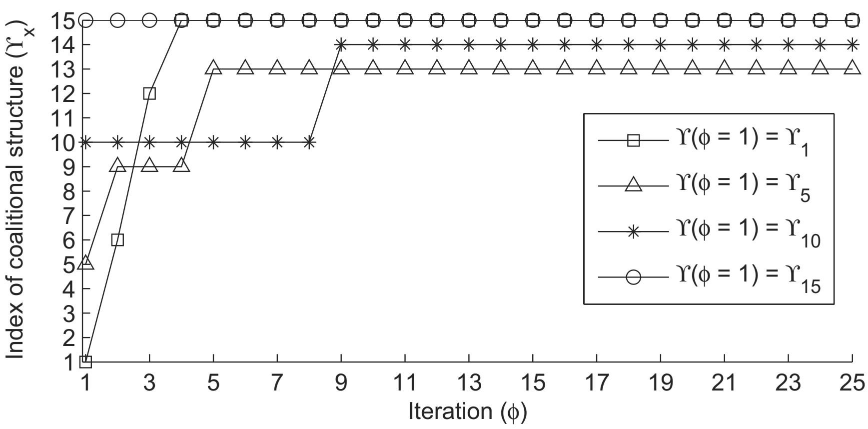
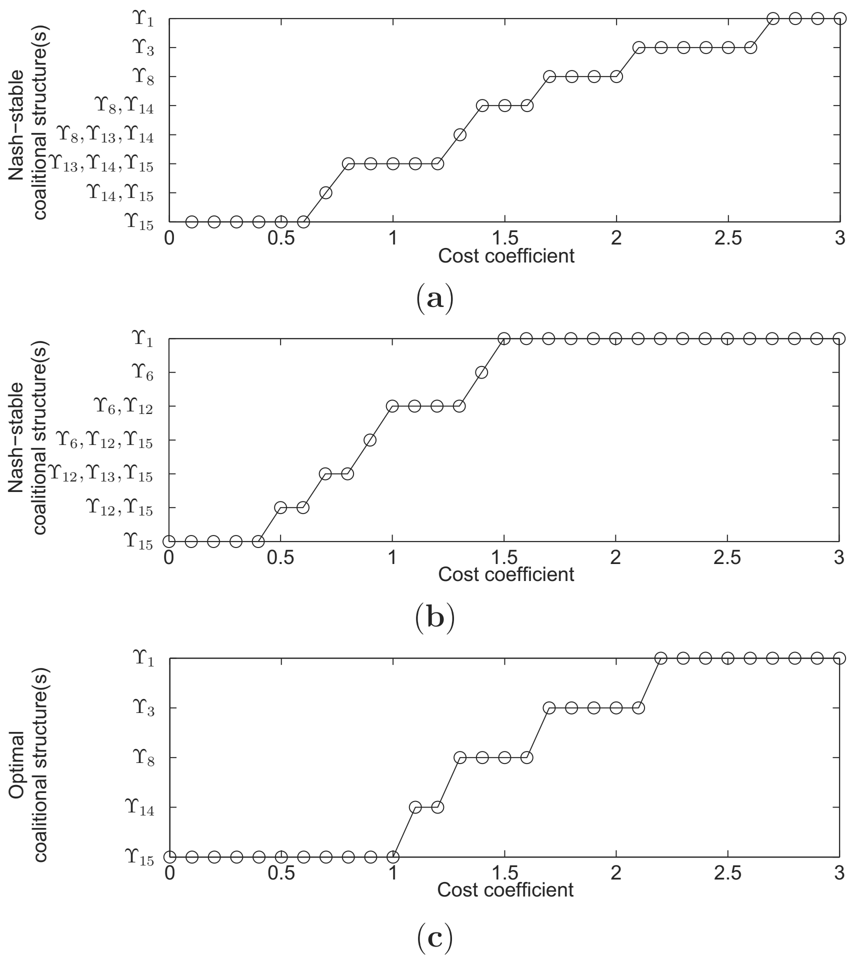


Figure 6.4. *Nash-stable coalitional structure obtained from the individual preference-based algorithm.*

Figure 6.4 shows the Nash-stable coalitional structure with incomplete information obtained from the individual preference-based algorithm (i.e., **Algorithm 5**). The initial coalitional structure for each run of the algorithm is set to Υ_1, Υ_5, Υ_{10}, and Υ_{15}. When the algorithm runs, we can observe that the coalitional structure changes and then it converges to the Nash-stable coalitional structure, i.e., coalitional structure $\Upsilon^*_{13}, \Upsilon^*_{14}$, or Υ^*_{15} as shown in Figure 6.3.



(**a**)

(**b**)

(**c**)

Figure 6.5. *(a) Nash-stable coalitional structures with incomplete information, (b) Nash-stable coalitional structures with complete information, and (c) optimal coalitional structures under different values of cost-coefficient.*

Assuming that the cost-coefficient c_i is the same for all the vehicles, we vary the cost-coefficient c_i of all vehicles from 0 to 3. Figures 6.5(a), (b), and (c) show, respectively, the Nash-stable coalitional structures with incomplete information, with complete information, and the optimal coalitional structure under different values

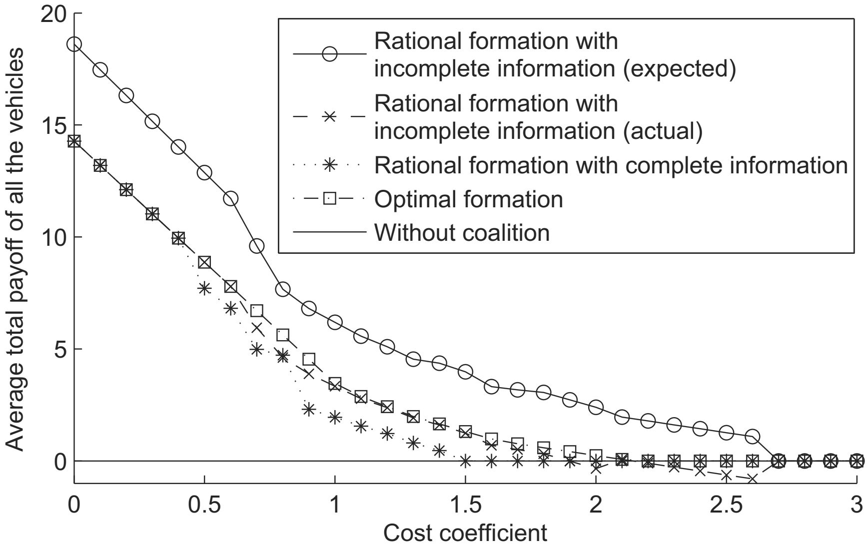


Figure 6.6. *Total payoff of all the vehicles under different values of cost-coefficient.*

of the cost-coefficient. As shown in Figure 6.5, all the vehicles will act alone (i.e., Υ_1^* is formed) and the total payoff becomes zero when the cost-coefficient is greater than 2, 1.4, or 2.1 in the cases of incomplete information, complete information or optimal solution, respectively. Moreover, as shown in Figure 6.5(a), with incomplete information, the grand coalition and the Bayesian core (i.e., the payoffs of the grand coalition) exist when the cost-coefficient is between 0 and 0.6 since there is only one Nash-stable coalitional structure Υ_{15}^*. When the cost-coefficient lies between 0.7 and 1.2, the grand coalition may not be formed since it can be blocked by other Nash-stable coalitional structures (e.g., there are two other Nash-stable coalitional structures Υ_{13}^* and Υ_{14}^*). Also, as shown in Figure 6.5(b), with complete information, the grand coalition is Nash-stable when the cost-coefficient lies between 0 and 0.4. When the cost-coefficient is between 0.5 and 1.9, the grand coalition may not be formed since other Nash-stable coalitional structures (e.g., Υ_6^*, Υ_{12}^*, and Υ_{13}^*) can also be formed.

6.6.2.2 Payoffs of the Nodes

Given all the possible Nash-stable coalitional structures as shown in Figure 6.5, Figure 6.6 shows the average total payoff of all the vehicles under different values of the cost-coefficient. The average total payoff of all the vehicles is obtained as follows:

$$E[u_{total}] = \sum_{i \in \mathbb{M}} \sum_{x=1}^{D_M} \pi_{\Upsilon_x} u_i(\mathcal{S}_l^i), \qquad \text{for} \qquad \mathcal{S}_l^i \in \Upsilon_x \tag{6.25}$$

where D_M is the Mth Bell number and $u_i(\mathcal{S}_l^i)$ is the payoff of vehicle i when it is a member of coalition $\mathcal{S}_l^i$.

As expected, for small value of cost-coefficient, the average total payoff is high when the coalition is formed. However, when the value of cost-coefficient increases, the average total payoff of all vehicles decreases since a higher cost is incurred to all vehicles involved in the cooperative packet delivery. As a result, a vehicle will leave its current coalition if the utility is not higher than the cost incurred from cooperative packet delivery. Moreover, the average total payoff from the optimal solution is equal to or higher than the average total payoffs of the Nash-stable solutions of the rational coalition formations with incomplete and complete information and the payoff when all the players act alone. Note that the Nash-stable solutions of the rational coalition formations with incomplete and complete information are different. Hence, the average payoff of the Nash-stable solution of the rational coalition formation with incomplete information may or may not be higher than that with complete information.

Observation 4 *Given a coalitional structure obtained from **Algorithm 5**, without any belief update, the expected payoff of each vehicle computed under incomplete information is not necessarily lower than the payoff when the vehicle acts alone. However, the payoff of each vehicle actually obtained may be lower than the payoff when the vehicle acts alone.*

Discussion: A coalitional structure obtained from **Algorithm 5** is guaranteed to be Nash-stable. Consequently, each vehicle believes that its expected payoff is greater than or equal to the payoff when it acts alone. However, the coalitional structure may not be a Nash-stable when the complete information scenario is considered. Hence, the vehicle's actual payoff (i.e., the payoff computed based on the actual *type*s of the vehicles after the coalitional structure is formed based on the vehicles' beliefs) may be lower than the payoff when the vehicle acts alone as shown in Figure 6.7. ■

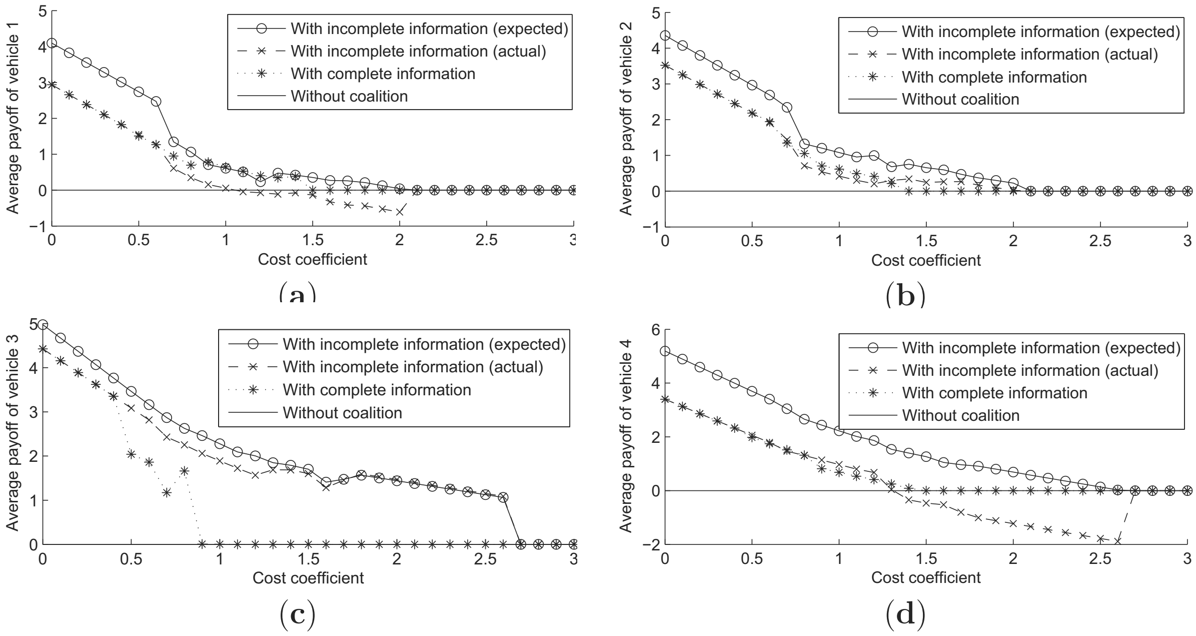
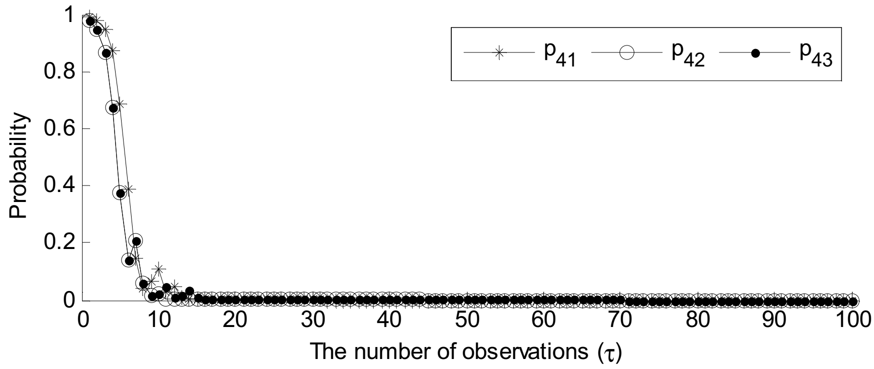


Figure 6.7. *Average payoffs obtained from the proposed coalitional game with incomplete information (i.e., both expected and actual payoffs), with complete information, and without coalition: (a) for vehicle 1, (b) for vehicle 2, (c) for vehicle 3, and (d) for vehicle 4.*

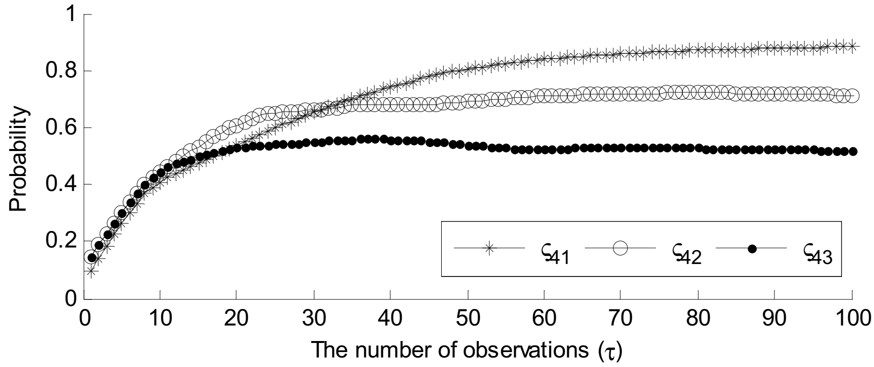
Figures 6.7(a), (b), (c), and (d) show the average payoffs of vehicles 1, 2, 3, and 4, respectively. We can see that the average payoffs of all vehicles obtained from the proposed game model with incomplete information and with complete information are not lower than zero. In particular, the expected payoff of vehicles at the Nash-stable coalition is not lower than that when they act alone. However, with incomplete information, in some cases, the actual payoff can be lower than zero due to lack of true information about other vehicles' types.

Observation 5 *Given a Nash-stable coalitional structure, with the belief update mechanism, each vehicle will obtain the expected payoff close to the actual payoff. Moreover, finally, the actual payoff obtained from the dynamic Bayesian coalitional game can be similar to that from the coalitional game with complete information or at least the actual payoff when the vehicle acts alone.*

Discussion: When the Bayes' theorem is used to update the beliefs about the other vehicles in the same coalition, the probabilistic beliefs of the vehicles will converge



(a)



(b)

Figure 6.8. *(a) Vehicle 4's belief probabilities that vehicles 1, 2, and 3 are well-behaved (i.e., p_{41}, p_{42}, p_{43}), and (b) vehicle 4's belief probabilities that vehicles 1, 2, and 3 will refuse to deliver a packet (i.e., ς_{41}, ς_{42}, ς_{43}).*

to the actual values. Then, the expected payoff of each vehicle will converge to its actual payoff. The updated expected payoff may change the Nash-stable coalitional structure. If all of the vehicles' beliefs converge to the actual values, the actual payoffs from the dynamic Bayesian coalitional game will converge to the same values of payoff obtained from the coalitional game with complete information. The results are shown in Figures 6.8-6.9. However, if a vehicle has no chance to update its beliefs, its actual payoff may not converge to the payoff obtained from the coalitional game with complete information. In the worst case, the vehicle acts alone after the vehicle can learn some other vehicles' actual *type*s. Hence, the actual payoff is not lower than the payoff when the vehicle acts alone. ■

6.6.2.3 Dynamic Bayesian coalitional game

Given that the grand coalition is formed when the cost-coefficient is 1.0, Figures 6.8(a) and (b) show the probabilistic beliefs of vehicle 4 when vehicles 1, 2, and 3 are well-behaved and the probabilistic beliefs of vehicle 4 when vehicles 1, 2, and 3 refuse to deliver a packet, respectively. After vehicle 4 observes the behaviors of vehicles 1, 2, and 3, it updates its beliefs about the other vehicles' *type*s accordingly. Vehicle 4's belief probabilities that vehicles 1, 2, and 3 are well-behaved converge to zero. Also, vehicle 4's belief probabilities that vehicles 1, 2, and 3 will refuse to deliver a packet are close to the actual probabilities (i.e., 0.9, 0.7, and 0.5, respectively).

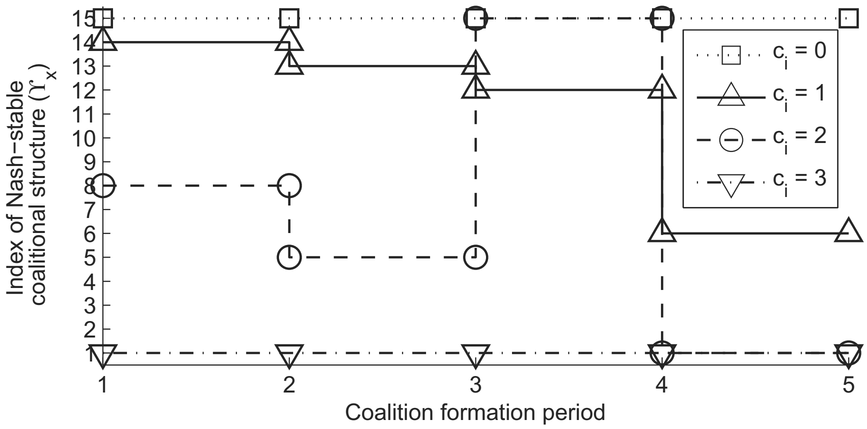


Figure 6.9. *Nash-stable coalitional structure during each period of coalition formation.*

Figure 6.9 shows the Nash-stable coalitional structure formed during each period of coalition formation according to **Algorithm 6**. Given the initial beliefs of all the vehicles and after the first period of coalition formation, with the cost-coefficient 0, 1, 2, and 3, the Nash-stable coalitional structures are Υ^*_{15}, Υ^*_{14}, Υ^*_{8}, and Υ^*_{1}, respectively. Each vehicle in the same coalition updates its beliefs during the period of each round of coalition formation. After that, the coalition formation starts its next round. Given that the cost-coefficient is 1, the Nash-stable coalitional structure changes from Υ^*_{14} to Υ^*_{13}, from Υ^*_{13} to Υ^*_{12}, and from Υ^*_{12} to $\Upsilon 6^*$ at the end of the coalition formation periods 1, 2, 3, and 4, respectively. Given that the cost-coefficient is 2, the Nash-stable coalitional structure changes from Υ^*_{8} to Υ^*_{5}, from Υ^*_{5} to Υ^*_{15}, and from Υ^*_{15} to Υ^*_{1}, at the end of coalition formation periods 1, 2, 3, and 4, respectively. When the cost-coefficient is 0 and 3, the Nash-stable coalitional structure does not change. When the cost-coefficient is 0, all the vehicles will always form the grand coalition regardless of the *type*s of all the vehicles. When the cost-coefficient is 3, Υ_1^* is firstly formed, and no vehicle has a chance to update its beliefs. However, with the complete information, the same Nash-stable coalitional structure is reached.

Comparing the results shown in Figure 6.5 and Figure 6.9, we observe that, the Nash-stable coalitional structure obtained from the dynamic Bayesian coalitional game with incomplete information and the belief update mechanism converges to the same Nash-stable coalitional structure obtained from the coalitional game with complete information. Hence, the actual payoff from the dynamic Bayesian coalitional game is similar to the payoff obtained from the coalitional game with complete information. Moreover, there is a case that a vehicle has no chance to join any coalition with others. For example, with incomplete information of the vehicles' types and given the vehicles' beliefs, the Nash-stable coalitional structure in which all the coalitions are singleton coalitions, i.e., Υ_1^* is firstly formed. Then, a vehicle will not have a chance to update its beliefs about the other vehicles' *type*s. With complete information, if the obtained Nash-stable coalitional structure is not the same as that with incomplete information (i.e., it is not Υ_1^*), it is not possible that the actual payoff from the Bayesian coalitional game will converge to the payoff obtained from the coalitional game with complete information. However, if a vehicle cannot update all its beliefs, its actual payoff will not be lower than the payoff when it acts alone.

6.7 Related Work

There are a very few work using the dynamic Bayesian game theory to solve the resource allocation problem in wireless and mobile communications systems. For example, Y. Yan et al. [119, 120] modeled a multi-slot coopeartive spectrum sharing mechanism as a dynamic Bayesian bargaining game. A primary user (PU) offers its licensed spectrum to a secondary user (SU) while the secondary user will relay the primary user's data. However, the information about SU's energy cost is unknown by the PU. A perfect Bayesian equilibrium or sequential equilibrium, which is a refinement of perfect Bayesian equilibrium, can be obtained as the solution of the game.

In our cooperative packet delivery model, we have used a dynamic Bayesian coalitional game. The key idea of the coalitional game theory is to study the formation of coalition among players in a game. In wireless networks, coalitional games have been used to model and analyze the resource allocation problem, where coalitions of mobile nodes are formed so that the mobile nodes achieve higher utilities compared to when they do not form coalitions. Z. Han and H.V. Poor [109] used a coalitional game model to solve the problem of packet-forwarding among boundary nodes and backbone nodes in wireless networks. As the result, the boundary nodes can transmit their packets effectively. W. Saad et al. [76] proposed a coalitional game for cooperative data service among the base stations in vehicular networks. Through coalitions, the revenue of any cooperative group of base stations can be improved by exploiting the underlying vehicle-to-vehicle content-sharing network. D. Niyato and P. Wang [75] proposed a coalitional game for cooperative bandwidth sharing among mobile nodes (i.e., vehicles) in vehicle-to-roadside communications scenarios. When mobile nodes form coalitions, the mobile nodes can reduce the cost of bandwidth reservation while meeting their quality-of-service (QoS) requirements; hence, higher utilities can be achieved.

In reality, it is not guaranteed that the rational mobile nodes, which are the members of the coalition, will agree to always help each other in the same coalition since some of them may misbehave. For packet forwarding in mobile ad hoc networks (MANETs), some reputation-based and game theory-based cooperation enforcement mechanisms were proposed [121]-[123] to prevent nodes from misbehaving. However, most of the existing schemes assume that, to detect the misbehaving nodes, perfect observations of mobile nodes' behaviors (e.g., through monitoring systems) are available. There are only a very few work which consider that the nodes' behaviors cannot be perfectly observed. For example, Z. Ji, W. Yu, and K. J. R. Liu [123] presented a noncooperative repeated game with belief-based cooperative enforcement mechanism for packet forwarding in mobile ad hoc networks under imperfect observation.

In order to study the problems of cooperation under uncertainty or imperfect observation of mobile nodes' behaviors or types, coalitional game was generalized to Bayesian coalitional game [113]-[115]. In the research paper of G. Chalkiadakis and C. Boutilier [113] and the research paper of S. Ieong and Y. Shoham [115], the *Bayesian core*, which is a solution concept of the Bayesian coalitional game, was studied. With this concept, no group of players would prefer to leave a grand coalition and form a new coalition. G. Chalkiadakis and C. Boutilier [113] proposed the notion of Bayesian core in a transferable-utility Bayesian coalitional game based on how the payoffs can make a grand coalition stable given the beliefs about players' *type*s. S. Ieong and Y. Shoham [115] proposed the notion of *ex-interim blocking* to achieve the Bayesian core. Ex-interim blocking means that given the beliefs of the players, a grand *contract* is blocked by a coalition (i.e., a set of expected payoffs in the coalition, which the authors call a *contract*).

6.8 Chapter Summary

We have presented a dynamic Bayesian coalitional game for coalition-based cooperative packet delivery among mobile nodes in a mobile network under uncertainty in node behavior (i.e., selfishness of nodes). The mobile nodes are rational to form coalitions to maximize their individual payoffs. Based on the individual preferences, which are related to the expected payoffs of the nodes, a Bayesian coalitional game has been formulated to model the decision making process of mobile nodes (e.g., to cooperatively deliver the packets of other mobile nodes or not). A Nash-stable coalitional structure, which is the solution of this coalitional game, can be obtained by using the individual preference-based algorithm. Moreover, a belief update mechanism based on Bayes' theorem has been proposed. With this mechanism, each mobile node can update its beliefs about the other mobile nodes' *type*s (i.e., *well-behaved* or *misbehaving*) under the proposed Bayesian coalitional game. A comprehensive performance evaluation has been carried out for the proposed Bayesian coalitional game.

Chapter 7

Discussions and Summary

In recent years, wireless access services have become increasingly widespread to support anytime-anywhere communications among users. Due to resource constraints and multiple mobile nodes (i.e., users) in a wireless communication network, the transmitting nodes share the limited radio resources (e.g., wireless channels and transmission power). Therefore, one critical issue is how the nodes share these resources to transmit data so that the optimal network performance can be achieved. In a multiple access scheme, nodes can either cooperate or compete to achieve their objectives. Consequently, the theory of both noncooperative and cooperative games has become a very efficient tool to model and analyze multiple access schemes in wireless networks, and to obtain solutions for resource allocation. Built on the game theory, this thesis presents a set of game models to solve the aforementioned problems for multiple access and resource allocation in wireless networks. Our results show that the proposed game-theoretic models can bring optimal and equilibrium solutions for both the noncooperative and cooperative scenarios.

While the game-theoretic approach is effective, it may not scale well in some cases, e.g., coalition formation when the number of players is high. Then, we discuss about the complexity and scalability of the proposed algorithms and other issues in Section 7.1. After that we conclude by summarizing the contributions of this thesis in Section 7.2 and later point out interesting avenues for future research in Section 7.3.

7.1 Discussions

In this section, we discuss the complexity and scalability of the proposed distributed algorithms. Moreover, we discuss about the core solution of coalitional game

7.1.1 Complexity and Scalability of the Proposed Algorithms

The proposed best response-based algorithms, i.e., **Algorithm 1** and **Algorithm 2**, which rely on an iterative strategy update, scale with the number of mobile nodes. The number of mobile nodes will depend on the type of application. For example, with a vehicle-to-roadside (V2R) communications scenario, the typical number of vehicles (i.e., mobile nodes) at a roadside base station (RSB) can be, for example, 10 (due to the limited space at the bus stop). We have used the system model in Chapter 4 conducted new simulations considering 10 vehicles as shown in **Appendix C.1**. From the new result, we observe that **Algorithm 2** can converge to the solution within about 12 bidding rounds as shown in Fig. C.1. However, to maintain the consistency throughout the numerical study in Chapter 4, we present the results only for three vehicles in the chapter (i.e., Figures. 4.3, 4.4, 4.5, and 4.6 are for 3-vehicle case). The new result shows that **Algorithm 2** can achieve the scalability. Moreover, the result also implies that **Algorithm 1** can achieve the scalability as well since both the algorithms are based on the same concept of best-response update.

In Chapter 5 and Chapter 6, for an N-player coalitional game, the number of coalitional structures is given by the Nth Bell number (defined in (6.6)) and the number of possible non-empty coalitions is $2^N - 1$. As the number of mobile nodes increases, the number of coalitional structures and the number of coalitions increase exponentially. To obtain a Nash-stable coalitional structure, let us consider the merge-and-split algorithm. Since there are 2^{N-1} coalitions which each node can join as a coalition's member, the total number of payoff computation of all mobile nodes is $O(N2^{N-1})$. In each time step (τ), each mobile node compares its current payoff with the payoff when it is a member of a new coalition if the coalitional structure changes. Since there are D_N coalitional structures, the number of comparisons used to obtain the stable solution is $O(ND_N)$. The complexity incurred is at the analysis, but not at the implementation of the coalition formation. In particular, as the number of mobile nodes increases, the state space of Markov chain model will increase. However, the mobile nodes can use the distributed algorithms to reach the solution. Regarding **Algorithm 6**, taking the belief update mechanism does not incur significant complexity, since each mobile node updates its beliefs about the other mobile nodes types when they encounter each other by using Bayes rule. Moreover, the algorithms (**Algorithms 4–6**) are scalable since they do not need the global information about the network and about all nodes all the time. When a mobile node would like to move to another coalition, the mobile node needs some information (e.g., information of payoffs of the mobile nodes in the new coalition) is needed.

Using the SNA-based mobile node grouping as **Algorithm 3** in Chapter 5, we can filter mobile nodes which have not have the opportunity to help others. As a result of the reduction of the number of mobile nodes in the game, the complexity of finding the solution of the game model will reduce dramatically. The objective of the SNA-based mobile node grouping, i.e., **Algorithm 3**, is to reduce the complexity of coalition formation which increases exponentially when the number of nodes increases [20, 87]. In the social network analysis-based mobile node grouping, the complexity of building the graph of relationship among M mobile nodes is $M(M-1)/2 = O(M^2)$. The complexity of listing all groups of M mobile nodes (i.e., maximal cliques in the M-vertex relationship graph) is at most of $O(3^{M/3})$ [98]. All maximal cliques in the graph may be generated in time $O(M|\mathcal{E}|)$ per clique, where $|\mathcal{E}|$ is the number of edges in the graph [88]. The complexity and computational time increase when the number of mobile nodes increases. However, the mobile node grouping algorithm can be performed offline to update the mobile nodes' relationships (i.e., no real-time update is needed.). The statistical data (i.e., encounter rates and the number of encounters) sent from mobile node is collected by the central coordinator at the application server periodically) and then relationship among mobile nodes is analyzed and updated according to **Algorithm 3**.

7.1.2 Core Solution in Coalitional Games

In Chapter 5 and Chapter 6, the grand coalition (i.e., coalition with all mobile nodes) will be stable, if the core is non-empty. Therefore, in each proposed game, one of the cores can be obtained if all the conditions (i.e., **Observation 2** in Chapter 5

Table 7.1. *Approaches to find the existence of the core and the payoffs that lie in the core of a coalitional game [20]*

Game theoretical and mathematical approaches
1. A graphical approach can be used for finding the core of TU games with up to 3 players. 2. Using duality theory, a necessary and sufficient condition for the non-emptiness of the core exists through the Bondareva-Shapley theorem (Theorem 1) for TU and NTU. 3. A class of canonical games, known as convex coalitional games always has a non-empty core. 4. A necessary and sufficient condition for a non-empty core exists for a class of canonical games known as simple games, i.e., games where $v(S) \in \{0, 1\}, \forall S \subseteq N$ and $v(N) = 1$.
Application-specific approaches
5. In several applications, it suffices to find whether payoff distributions that are of interest in a given game, e.g., fair distributions, lie in the core. 6. In many games, exploiting game-specific features such as the mathematical definition or the underlying nature and properties of the game model, helps finding the imputations that lie in the core.

or **Observation 3** in Chapter 6) are satisfied which are based on the Bondareva-Shapley theorem. In [20], the approaches to find the existence of the core and the payoffs that lie in the core of a coalitional game (without finding the complete set of the core solution) are given. These approaches are summarized in Table 7.1 of this response. However, the core could be a set, and it is not easy to obtain the complete set of the core solution especially with the non-transferable utility (NTU) coalitional games. The problem of obtaining the complete set of the core solutions is an open research problem in coalitional game theory.

7.2 Summary of Contributions

The contribution of *Chapter 2* is a comprehensive survey on the applications of game theory used to model, analyze and solve the multiple access and resource allocation problem in wireless networks.

The contribution of *Chapter 3* is the proposed auction mechanism for distributed bandwidth sharing among multiple mobile nodes. In this auction game, a group of mobile nodes competes with other groups by offering bid prices to the wireless access point to obtain its required amount of the bandwidth (i.e., a scenario of single-hop transmission when each mobile node can be directly connected to the access point) and maximize the group payoff. The wireless access point then allocates portions of bandwidth to all the group by using a fair allocation strategy. The allocated bandwidth to the group is further divided among the nodes based on the maximization of the group payoff. Each mobile node in the same group will pay the same cost per unit of bandwidth. We have presented a distributed iterative auction mechanism to obtain a solution of the game which is Nash equilibrium. The distributed algorithm is based on the best response update that can converge to the solution within a few bidding iterations.

The contribution of *Chapter 4* is the proposed distributed noncooperative game model for resource allocation under uncertainty. We have presented an auction mechanism to solve the problem of bandwidth allocation among rational mobile nodes in a wireless network as same as in Chapter 3. However, we also consider the problem under incomplete information. We have developed a queueing model to analyze the required amount of bandwidth for all the mobile nodes. Given the mobility and application parameters, the required amount of bandwidth (i.e., transmission rate) is obtained such that the buffer underrun probability is below the target threshold. In this study, we have considered a case when the mobility of a mobile node is unknown by other nodes. We have formulated a Bayesian noncooperative game to model the decision making process of mobile nodes for bandwidth auction. A distributed mechanism has been proposed for the bidding process which achieves the solution of the bandwidth auction game, namely, the Bayesian Nash equilibrium. Also, we have analyzed the uniqueness of the Bayesian Nash equilibrium of the proposed game. We have used the proposed auction game model for bandwidth allocation in vehicle-to-roadside communications as an example.

The contribution of *Chapter 5* is the proposed distributed cooperative channel access method for carry-and-forward-based packet delivery. Differently from Chapter 3 and Chapter 4, in this chapter, we have considered a scenario of the multi-hop cooperative transmission among mobile nodes. In particular, a coalitional game framework has been proposed to deal with packet delivery among mobile nodes in a downlink transmission scenario. The rational mobile nodes form coalitions to increase their individual payoffs. We have first used a social network analysis to group mobile nodes such that each mobile node has enough capability to help others in the same group. Next, we have developed a continuous-time Markov chain model to obtain the packet delivery delay and the expected cost that each mobile node will incur when it participates in the cooperative packet delivery process. Both the packet delivery delay and the expected cost depend on how mobile nodes in the same coalition are willing to help each other. We have then proposed a bargaining game to find the optimal helping probabilities for all the mobile nodes. Next, we have formulated a nontransferable payoff coalitional game to analyze the decision making process of mobile nodes whether to be members in any coalitions or not. Their decisions to cooperatively deliver packets to other mobile nodes are based on their packet delivery delays and expected costs. The solution of this coalitional game is a stable coalitional structure. We have proposed a distributed merge and split algorithm to obtain the solution. The improvement of packet delivery delay using the proposed coalitional game model for cooperative packet delivery has been illustrated through numerical results.

The contribution of *Chapter 6* is the proposed distributed cooperative channel access method for carry-and-forward-based packet delivery under uncertainty. We have relax the cooperative concept in Chapter 5 that mobile nodes in the same coalition always help each other according to the cooperative agreement. In particular, a coalitional game framework has been proposed to deal with packet delivery among mobile nodes in a downlink transmission scenario. Each mobile node can be well-behaved or misbehaving in the cooperative delivery. A well-behaved node always helps to deliver packets to the other nodes in the same coalition but a misbehaving node may refuse to deliver a packet of other nodes in the same coalition. Each mobile node's behavior or type is not completely known by other nodes. Then, we have first formulated a Bayesian coalitional game to analyze the decision making process of mobile nodes whether to be members in any coalitions or not based on the mobile node's beliefs about other mobile nodes' types. The solution of this coalitional game is a stable coalitional structure under the incomplete information of mobile nodes' types. Moreover, Bayesian core which is another solution concept has been analyzed. We have proposed a distributed merge and split algorithm to obtain the solution. We have then extended the static coalitional game to a dynamic Bayesian a multi-stage dynamic. In this game, according to Bayes' theorem, a mobile node can update its beliefs about the types of other mobile nodes as the game evolves. The mobile nodes repeatedly play the coalitional game. Finally, it will converge to a solution which is the same as the solution that could be obtained when all the information are known. We have proposed an algorithm for dynamically playing a coalitional game with belief update mechanism. The improvement of packet delivery delay using the proposed static coalitional game model for cooperative packet delivery and the performance of the proposed dynamic Bayesian coalitional game have been presented through the numerical results.

7.3 Open Problems and Future Directions

We have studied the problem of multiple access at a single base station as a noncooperative game in Chapter 4. The main objective of each mobile node is to obtain an optimal and equilibrium individual throughput. However, we did not consider a scenario that mobile nodes cooperatively access a channel when they are connected to a base station. Given a cooperative group, each mobile node shares its channel access information with other mobiles in the group. Then, the mobile nodes try to not send access the channel at the same time. Hence, the cooperative channel access among mobile nodes can increase the overall network throughput since the number of transmission collisions decreases. However, the cooperative channel access may not be useful if the cost of cooperative operations (e.g., signaling overhead for exchanging personal information among mobile nodes) is higher than the benefit obtained from the cooperation. Moreover, the mobile nodes can travel in a service area where multiple base stations are deployed. The mobile nodes may be connected to different base stations or same base stations at a time. Combining both the mobility and cooperative channel access in a unified framework is an interesting avenue for future research. The key question is when and how cooperative groups of mobile nodes should be formed to achieve the network objectives such as maximization of overall throughput while ensuring fair channel access among mobile nodes.

In Chapter 5 and Chapter 6, we have considered the coalition-based cooperative channel access method for carry-and-forward based packet delivery. Mobile nodes which are in the same cooperative group or coalition help each other to carry and forward packets in order to decrease the packet transmission delay and increase the network throughput. One of the limitations of the proposed work is that a mobile node in a coalition will not carry and forward packets to other mobile nodes which are in different coalitions even if they can occasionally encounter each other. We can extend the work by considering cooperative packet delivery among coalitions. In particular, we can an extend the proposed work to a game-based hierarchical framework consisting of coalitional and bargaining games. The first game is a coalitional game similar to the one proposed in this thesis and the second one is a bargaining game. Each coalition formed by using the first coalitional game acts as a player in this bargaining game. Each coalition (i.e., mobile nodes in the coalition) helps other coalitions to deliver packets across the coalitions according to a bargaining game model (i.e., two or more players prefer to reach an agreement regarding how much each player will help others). In this case, not all mobile nodes but at least one mobile node in each coalition needs to have encounter relationships with other mobile nodes in the different coalitions. Then, the benefit obtained by each coalition from the bargaining game may be fairly distributed to all the members according to how much each mobile node in the coalition helps deliver packet to other coalitions.

Finally, the multiple access methods based on game theory need to consider the resource constraints as well as application requirements [124]. For example, a multiple access (MAC) protocol for vehicular wireless networks needs to consider high mobility of the nodes that causes the topology of the network to vary rapidly, limited radio bandwidth, as well as vehicle density. Transmission delay (i.e., emergency messaging delay) is one of the main performance measures for such a MAC protocol. For a game theoretic multiple access scheme, the utility functions for the players should take the related parameters into account. Again, since users' quality of experience (QoE) depends on the performance of the transport level protocol (e.g., TCP, UDP), performance of the developed MAC schemes needs to be investigated from transport layer's point of view. Accordingly, cross layer optimizations can be performed. In our future work, we will also focus on application-centric and transport-level evaluation of game theoretic models and cross-layer optimization issues.

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Appendix A

A.1 Proof of the Uniqueness of Bayesian Nash equilibrium

Theorem 3 *The noncooperative game in Section 4.5 of Chapter 3 has a unique Bayesian Nash equilibrium.*

Proof.

Since the strategy space b_i of each player i is convex, compact, and nonempty, the expected payoff function $E[P_i(\cdot)]$ is continuous in both b_i and $\vec{b_{-i}}$, and $E[P_i(\cdot)]$ is concave for any $\vec{b_{-i}}$. Therefore, it is guaranteed that at least one Bayesian Nash equilibrium (or Nash equilibrium) exists (please see reference [125]).

Let us consider equation (3) of the revised manuscript. The Karush-Kuhn-Tucker (KKT) conditions yield the necessary and sufficient conditions for BNE in this game. In other words, $\vec{\mathbf{b}}^* = (\vec{\mathbf{p}})^*$ is a BNE if and only if the following conditions hold:

$$\sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i} \leq 0, \text{if} \quad b_i^* = p^{min} \tag{A.1}$$

$$\sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i} = 0, \text{if} \quad p^{min} < b_i^* < p_i^{max} = \min\{\rho_i^{max}, p_i(g_i = q_i)\} \tag{A.2}$$

$$\sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i, \vec{\mathbf{b}}_{-i}, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i} \geq 0, \text{if} \quad b_i^* = p_i^{max} = \min\{\rho_i^{max}, p_i(g_i = q_i)\} \tag{A.3}$$

where p^{min} is the minimum bid price defined by the wireless access point, ρ_i^{max} is the maximum bid price that mobile node i affordably pays, and $p_i(g_i = q_i)$ is the bid price such that with $g_i \geq q_i$, mobile node i cannot gain higher utility even if mobile node i offers a higher bid price (i.e., the payoff will decrease when $p_i > p_i(g_i = q_i)$ and hence, mobile node i will not offer a bid price higher than $p_i(g_i = q_i)$). Then, p_i^{max} is the maximum bid price that mobile node will pay, which is the minimum value between ρ_i^{max} and $p_i(g_i = q_i)$.

Now we prove the uniqueness of the BNE of the game by using contradiction. Suppose that $\vec{b}^{*1}$ and $\vec{b}^{*2}$ are two different BNEs. We consider the following cases:

(i) $g_i^1 = g_i^2$, where $g_i^1 = g_i(\vec{b}^{*1})$ and $g_i^2 = g_i(\vec{b}^{*2})$

(ii) $g_i^1 \neq g_i^2$.

We show that both the cases lead to a contradiction if the BNE is not unique.

(i) When $g_i^1 = g_i^2$:
Since $g_i(\vec{\mathbf{b}} = \vec{\mathbf{p}}) = \frac{p_i t_i}{\sum_{\forall i'}\left(p_{i'} t_{i'}\right) + \epsilon} C$, if $b_i^1 < b_i^2$ (i.e., $p_i^1 < p_i^2$), we get

$$\sum_{\forall i'} \left(p_{i'}^1 t_{i'}\right) + \epsilon < \sum_{\forall i'} \left(p_{i'}^2 t_{i'}\right) + \epsilon \tag{A.4}$$

and if $b_i^1 > b_i^2$ (i.e., $p_i^1 > p_i^2$), we have

$$\sum_{\forall i'} \left(p_{i'}^1 t_{i'}\right) + \epsilon > \sum_{\forall i'} \left(p_{i'}^2 t_{i'}\right) + \epsilon. \tag{A.5}$$

Suppose $b_i^1 < b_i^2$. Then, we get $b_i^1 < p_i^{max}$ and $b_i^2 > p^{min}$. Hence, from the KKT conditions, we have

$$\begin{aligned} \sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i^1, \vec{\mathbf{b}}_{-i}^1, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i^1} &\leq 0 \\ \Longrightarrow \sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \{t_i \alpha_i \frac{1}{\ln(10)(1+\gamma_i g_i^1)} \frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right) + \epsilon}(C - g_i^1) - & \\ \delta_i t_i (\frac{g_i^1}{C}(C - g_i^1) + g_i^1)\} &\leq 0 \end{aligned} \tag{A.6}$$

and

$$
\begin{aligned}
\sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i^2, \vec{\mathbf{b}}_{-i}^2, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i^2} &\geq 0 \\
\Longrightarrow \sum_j f_T'^j(\vec{\mathbf{t}}_{-i})\{t_i\alpha_i \frac{1}{\ln(10)(1+\gamma_i g_i^2)} \frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon}(C-g_i^2)- & \\
\delta_i t_i(\frac{g_i^2}{C}(C-g_i^2)+g_i^2)\} &\geq 0.
\end{aligned}
\tag{A.7}
$$

However, since we assume that $g_i^1 = g_i^2$ and $b_i^1 < b_i^2$ (i.e., $p_1^1 < p_i^2$), using (A.4), the term $\frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon}$ in (A.6) is greater than the term $\frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon}$ in (A.7). Therefore, the left hand side of (A.6) has to be greater than the left hand side of (A.7). This leads to a contradiction. Also, if we assume that $b_i^1 > b_i^2$ (i.e., $p_1^1 > p_i^2$), we will arrive at a contradiction. Hence, it is proved that $\vec{\mathbf{b}}^{*1} = \vec{\mathbf{b}}^{*2}$.

(ii) When $g_i^1 \neq g_i^2$:
Let us consider two subcases, which are $\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon \geq \sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon$ and $\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon < \sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon$.

- (Subcase 1) $\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon \geq \sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon$:
  Since $g_i^1 \neq g_i^2$, there exists a player i such that $g_i^1 > g_i^2$. Then, we obtain that $b_i^1 > b_i^2$ (i.e., $p_1^1 > p_i^2$). Also, we obtain $b_i^1 > p^{min}$ and $b_i^2 < p_i^{max}$. Hence, from the KKT conditions, we have

$$
\begin{aligned}
\sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \frac{\mathrm{d}P_i^j(b_i^1, \vec{\mathbf{b}}_{-i}^1, t_i, \vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i^1} &\geq 0 \\
\Longrightarrow \sum_j f_T'^j(\vec{\mathbf{t}}_{-i})\{t_i\alpha_i \frac{1}{\ln(10)(1+\gamma_i g_i^1)} \frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon}(C-g_i^1)- & \\
\delta_i t_i(\frac{g_i^1}{C}(C-g_i^1)+g_i^1)\} &\geq 0 \\
\Longrightarrow \sum_j f_T'^j(\vec{\mathbf{t}}_{-i}) \left\{ t_i\alpha_i \frac{1}{\ln(10)(1+\gamma_i g_i^1)} \frac{t_i(C-g_i^1)(\gamma_i - \delta_i p_i^1 t_i)}{\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon} - \delta_i t_i g_i^1 \right\} &\geq 0
\end{aligned}
\tag{A.8}
$$

and

$$\begin{aligned}
\sum_j f_T^{\prime j}(\vec{\mathbf{t}}_{-i})\frac{\mathrm{d}P_i^j(b_i^2,\vec{\mathbf{b}}_{-i}^2,t_i,\vec{\mathbf{t}}_{-i})}{\mathrm{d}b_i^2} &\leq 0 \\
\Longrightarrow \sum_j f_T^{\prime j}(\vec{\mathbf{t}}_{-i})\{t_i\alpha_i\frac{1}{\ln(10)(1+\gamma_i g_i^2)}\frac{\gamma_i t_i}{\sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon}(C-g_i^2)- \\
\delta_i t_i(\frac{g_i^2}{C}(C-g_i^2)+g_i^2)\} &\leq 0 \\
\Longrightarrow \sum_j f_T^{\prime j}(\vec{\mathbf{t}}_{-i})\left\{t_i\alpha_i\frac{1}{\ln(10)(1+\gamma_i g_i^2)}\frac{t_i(C-g_i^2)(\gamma_i-\delta_i p_i^2 t_i)}{\sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon}-\delta_i t_i g_i^2\right\} &\leq 0.
\end{aligned} \tag{A.9}$$

Since $g_i \leq C$ and we have assumed that $g_i^1 > g_i^2$, from (A.8) and (A.9), we obtain $\frac{1}{\ln(10)(1+\gamma_i g_i^1)} < \frac{1}{\ln(10)(1+\gamma_i g_i^2)}$, $-\delta_i t_i g_i^1 < -\delta_i t_i g_i^2$, and $(C-g_i^1) < (C-g_i^2)$. Now, from (A.8) and (A.9), we have

$$\frac{(\gamma_i-\delta_i p_i^1 t_i)}{\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon} > \frac{(\gamma_i-\delta_i p_i^2 t_i)}{\sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon}. \tag{A.10}$$

Since we have assumed that $\sum_{\forall i'}\left(p_{i'}^1 t_{i'}\right)+\epsilon \geq \sum_{\forall i'}\left(p_{i'}^2 t_{i'}\right)+\epsilon$, from (A.10), we get

$$(\gamma_i-\delta_i p_i^1 t_i) > (\gamma_i-\delta_i p_i^2 t_i). \tag{A.11}$$

However, $p_i^1 > p_i^2$; hence, this leads to a contradiction.

- (**Subcase 2**) $\sum_{\forall j}\left(p_j^1 t_j\right)+\epsilon < \sum_{\forall j}\left(p_j^2 t_j\right)+\epsilon$:
Since $g_i^1 \neq g_i^2$, there exists a player i such that $g_i^1 < g_i^2$. Then, we obtain that $b_i^1 < b_i^2$ (i.e., $p_1^1 < p_i^2$). Also, we obtain $b_i^1 < p_i^{max}$ and $b_i^2 > p^{min}$. Next, we use the KKT conditions and follow the similar procedure as in the previous subcase to arrive at a contradiction.
From the proofs of both the subcases, we conclude that $\vec{\mathbf{b}}^{*1} = \vec{\mathbf{b}}^{*2}$.

■

Appendix B

B.1 Markov Chain Model for Cooperative Packet Delivery

We focus only on a particular coalition $\mathcal{S} \subseteq \mathbb{M} = \{1, \ldots, M\}$ of mobile nodes. A continuous-time Markov chain (CTMC) with absorbing states can be formulated for the scenario in which one mobile node in the coalition is considered as the destination of a packet transmitted from the base station, and the rest of the mobile nodes in the coalition help the base station to deliver the packet to the final destination. Specifically, the CTMC is used to obtain the average packet delivery delay (d_i) of a mobile node which is the final destination of the packet originally transmitted from the base station. Also, the CTMC is used to obtain the average cost of other mobile nodes (c_{ij}) in the same coalition in delivering the packet to the final destination. Subsequently, the expected payoff of a mobile node can be calculated.

B.1.1 Formulation of the CTMC

Let $K \in \mathcal{S}$ be the mobile node which is the final destination for a packet transmitted from the base station. The state space of the Markov chain model for the cooperative packet delivery scheme can be expressed as follows:

$$\Psi = \{(\mathcal{X}); \mathcal{X} \subseteq \mathcal{S}, \mathcal{S} \subseteq \mathbb{M}\} \tag{B.1}$$

where $\mathcal{X}$ is the set of mobile nodes which already have the packet destined to node K in the same coalition $\mathcal{S}$. $\mathbb{M}$ is the set of all mobile nodes. The state space Ψ can be partitioned into Ψ_A (absorbing states) and Ψ_T (transient states), i.e., $\Psi = \Psi_A \cup \Psi_T$. State $\mathcal{X} \in \Psi$ is an absorbing state if mobile node K is a member of $\mathcal{X}$. Otherwise, it is a transient state.

Let $\mathcal{Y} = \mathcal{X} \cup \{0\}$ and $\mathcal{Z} = \mathcal{X} \cap \mathcal{X}'$, where $\mathcal{X}'$ is another state. The total state transition rate from $\mathcal{X}$, which is a transient state, to another state $\mathcal{X}'$ is defined as follows:

$$q_{\mathcal{X},\mathcal{X}'} = \begin{cases} \sum_{i' \in \mathcal{Y}, i'' \in \mathcal{Z}} r_{i'i''}, & (|\mathcal{Z}| = 1)\ \&\ (|\mathcal{X}'| - |\mathcal{X}| = 1)\ \&\ (K \notin \mathcal{X}) \\ 0, & \text{otherwise} \end{cases} \tag{B.2}$$

where $|\mathcal{X}|$ and $|\mathcal{X}'|$ are the cardinalities of sets $\mathcal{X}$ and $\mathcal{X}'$, respectively, and & denotes the logical AND operator. Recall that $r_{i'i''}$ denotes the rate that mobile node i' meets mobile node i'' for $i' \neq i''$ and $r_{i'0} = r_{0i'}$ is the rate that mobile node i' meets the base station. Hence, the state transition rate $q_{\mathcal{X},\mathcal{X}'}$ is the rate that any mobile node in $\mathcal{X}$, or the base station (i.e., any member of set $\mathcal{Y}$) will meet another mobile node which does not have the packet destined to mobile node K. Then, the state changes from $\mathcal{X}$ to $\mathcal{X}'$.

Given the state transition rate of the Markov chain model, the corresponding discrete-time Markov chain (DTMC), which is called the embedded Markov chain [32], can be obtained. As an example, Figure. B.1 shows the DTMC for a packet delivery scenario when there are 3 mobile nodes in the same coalition. Mobile nodes 1 and 2 help the base station to deliver a packet to mobile node 3. The shaded states are the absorbing states.

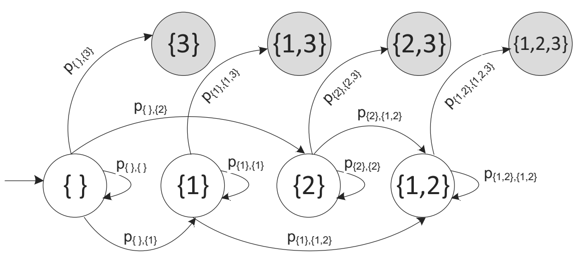

Figure B.1. *DTMC for cooperative packet delivery from a base station to the destination mobile nodes.*

Let $\rho^{i}_{i'i''}$ denote the belief probability of mobile node i that a packet is successfully sent by mobile node i' to another mobile node i'' according to the *type*s $t_{i'}$ and $t_{i''}$ of mobile node i' and i'', respectively. This probability is defined regardless of whether mobile node i' observes that mobile node i'' completely receives the packet or not. This belief probability is given in (B.3), where $|$ is the logical OR operator and $\varsigma_{ii'}$ and $\varsigma_{ii''}$ are mobile node i's belief probabilities that mobile node i' and mobile node i'' refuse to deliver a packet. Note that if mobile node i' is the destination (i.e., $i' = K$), mobile node i' will not drop the packet.

$$\rho^i_{i'i''} = \begin{cases} (1-p_e), & t_{i'} = T_w \quad \& \\ & (t_{i''} = T_w \quad | \quad (t_{i''} = T_m \quad \& \quad i'' = K)) \\ (1-p_e)(1-\varsigma_{ii''}), & t_{i'} = T_w \quad \& \quad (t_{i''} = T_m \quad \& \quad i'' \neq K) \\ (1-\varsigma_{ii'})(1-p_e), & t_{i'} = T_m \quad \& \quad t_{i''} = T_w \\ (1-\varsigma_{ii'})(1-p_e)(1-\varsigma_{ii'}), & t_{i'} = T_m \quad \& \quad (t_{i''} = T_m \quad \& \quad i'' \neq K). \end{cases} \tag{B.3}$$

Let $q_{\mathcal{X}} = \sum_{\mathcal{X}' \in \Psi} q_{\mathcal{X},\mathcal{X}'}$ be the summation of state transition rates from state $\mathcal{X}$ to any state $\mathcal{X}'$. Then, the probability of state transition can be obtained from (B.4).

$$p_{\mathcal{X},\mathcal{X}'} = \begin{cases} \sum_{i' \in \mathcal{Y}, i'' \in \mathcal{Z}} \frac{\rho^i_{i'i''} r_{i'i''}}{q_{\mathcal{X}}}, & (q_{\mathcal{X}} \neq 0) \quad \& \quad (|\mathcal{Z}| = 1) \quad \& \\ & (|\mathcal{X}'| - |\mathcal{X}| = 1) \quad \& \quad (K \notin \mathcal{X}) \\ 1 - \sum_{\mathcal{X}'' \in \Psi, \mathcal{X}'' \neq \mathcal{X}} p_{\mathcal{X},\mathcal{X}''}, & (q_{\mathcal{X}} \neq 0) \quad \& \quad (\mathcal{X} = \mathcal{X}') \\ 1, & (q_{\mathcal{X}} = 0) \quad \& \quad (\mathcal{X} = \mathcal{X}') \\ 0, & \text{otherwise.} \end{cases} \tag{B.4}$$

The transition probability matrix of the absorbing DTMC can be partitioned [33] as follows:

$$\mathbf{P} = \left[\begin{array}{c|c} \mathbf{T} & \mathbf{F} \\ \hline \mathbf{0} & \mathbf{I} \end{array} \right] \tag{B.5}$$

where $\mathbf{T}$ is the transition probability matrix corresponding to the transitions among the transient states, $\mathbf{I}$ is an identity matrix, $\mathbf{0}$ is a zero matrix, and $\mathbf{F}$ is the transition probability matrix corresponding to transitions from the transient state to the absorbing state.

For an absorbing DTMC with transition probability matrix $\mathbf{P}$, the matrix $\mathbf{M} =$

$(\mathbf{I}-\mathbf{T})^{-1}$ is called the fundamental matrix. The entry $m_{\mathcal{X},\mathcal{X}'}$ of $\mathbf{M}$ gives the expected amount of times that the process is in transient state $\mathcal{X}'$ if it starts in transient state $\mathcal{X}$ before the Markov chain reaches any absorbing state. The transition probability matrix $\mathbf{P}$ and the element of fundamental matrix (i.e., $m_{\mathcal{X},\mathcal{X}'}$ of $\mathbf{M}$) depend on the *type*s of all the mobile nodes in the coalition $\mathcal{S}$ believed by mobile node i or $\vec{\mathbf{t}}^i_{\mathcal{S}}$ and the destination of packet (i.e., mobile node K). Therefore, we denote $m_{\mathcal{X},\mathcal{X}'}(\vec{\mathbf{t}}^i_{\mathcal{S}}, K)$ as the element $m_{\mathcal{X},\mathcal{X}'}$ of $\mathbf{M}$.

B.1.2 Average Utility

Let mobile node i with *type* t_i be the destination of the packet (i.e., $i = K$). Given $\vec{\mathbf{t}}^i_{\mathcal{S}}$, which is the belief vector of node i about the *type*s of all the mobile nodes in the coalition $\mathcal{S}$, we can obtain the packet delivery delay from the base station to the destination mobile node i by using the DTMC described above. Let state $\mathcal{X} = \emptyset$ be the initial transient state (i.e., the state that none of the mobile nodes in coalition $\mathcal{S}$ obtains the packet destined to mobile node K). Then, the average packet delivery delay to the final destination (i.e., mobile node K) is defined as follows:

$$d_{i=K} = \sum_{\mathcal{X}' \in \Psi_T} \varrho_{\mathcal{X}'} m_{\mathcal{X}=\emptyset,\mathcal{X}'}(\vec{\mathbf{t}}^i_{\mathcal{S}}, i = K) \tag{B.6}$$

where $\varrho_{\mathcal{X}'}$ is the mean sojourn time in state $\mathcal{X}'$ (i.e., the amount of time spent in state $\mathcal{X}'$ before the process leaves state $\mathcal{X}'$) given as follows:

$$\varrho_{\mathcal{X}'} = \frac{1}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}'\mathcal{X}''}}, \quad \text{where } \mathcal{X}'' \in \Psi. \tag{B.7}$$

Then the utility of a mobile node as defined in Section III-A of Chapter 6 can be calculated.

B.1.3 Average Cost

We can obtain the average cost (c_{ij}) that mobile node $i(\neq K)$ incurs for delivering the packet destined to mobile node $j(=K)$, which is defined as follows [91]:

$$c_{ij} = \begin{cases} \sum_{\mathcal{X}' \in \Psi_T} c_{ij}^{\mathcal{X}'} m_{\mathcal{X}=\emptyset,\mathcal{X}'}(\vec{\mathbf{t}}_{\mathcal{S}}^{i}, j = K), & (i \neq j) \quad \& \quad (j = K) \\ 0, & i = j \end{cases} \tag{B.8}$$

where $c_{ij}^{\mathcal{X}'}$ is the average cost that mobile node i incurs for delivering the packet to mobile node $j(=K)$ in state $\mathcal{X}'$. If mobile node i is in set $\mathcal{X}'$, where $\mathcal{X}'$ is the set of mobile nodes which already have the packet for mobile node K, there will be a cost incurred to mobile i for packet forwarding. If mobile node i is not in set $\mathcal{X}'$, there will be only an average cost of receiving the packet from the base station or from other mobile nodes, i.e.,

$$c_{ij}^{\mathcal{X}'} = \begin{cases} \sum_{i' \in \mathcal{S} \cap \mathcal{X}'} \frac{\rho_{ii'} r_{ii'}}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}',\mathcal{X}''}} c_{ii'}^{\mathrm{f}}, & i \in \mathcal{X}' \\ \sum_{i' \in \mathcal{X}' \cup \{0\}} \frac{\rho_{i'i} r_{i'i}}{\sum_{\mathcal{X}'' \in \Psi} q_{\mathcal{X}',\mathcal{X}''}} c_{ii'}^{\mathrm{r}}, & i \notin \mathcal{X}'. \end{cases} \tag{B.9}$$

Then the average cost of a mobile node as defined in Section III-A in Chapter 6 can be calculated.

Appendix C

C.1 Result of Running Algorithm 2 with Ten Vehicles

We have used the system model in Chapter 4 conducted new simulations considering 10 vehicles which are labeled as V1-V10. The parameter setting for this simulation is shown in Table C.1. Given the ten vehicles and the parameter setting, we have run **Algorithm 2** and found that the bid price and corresponding allocated amount of bandwidth of each vehicle converge to the Nash equilibrium solution within 12 rounds.

Table C.1. *Parameter Setting*

Parameter	Values for vehicles (V1 to V10, respectively)
Connection time (seconds)	30, 20, 25, 20, 20, 25, 30, 30, 25, and 35
Disconnection time (seconds)	60, 60, 70, 70, 65, 70, 70, 60, 60, and 70
Target buffer underrun probability	0.25, 0.20, 0.40, 0.30, 0.35, 0.25, 0.40, 0.30, 0.25, and 0.40
Transmission modes	5, 4, 6, 5, 6, 4, 4, 5, 5, and 6
Speed of vehicles $N(\text{mean}, \text{variance})$ (km/h)	$N(70, 21)$, $N(90, 27)$, $N(90, 27)$, $N(70, 21)$, $N(80, 24)$, $N(80, 24)$, $N(70, 21)$, $N(80, 24)$, $N(90, 27)$, and $N(70, 21)$
Data transfer rate (packets/second)	20, 15, 25, 25, 25, 20, 30, 20, 20, and 30

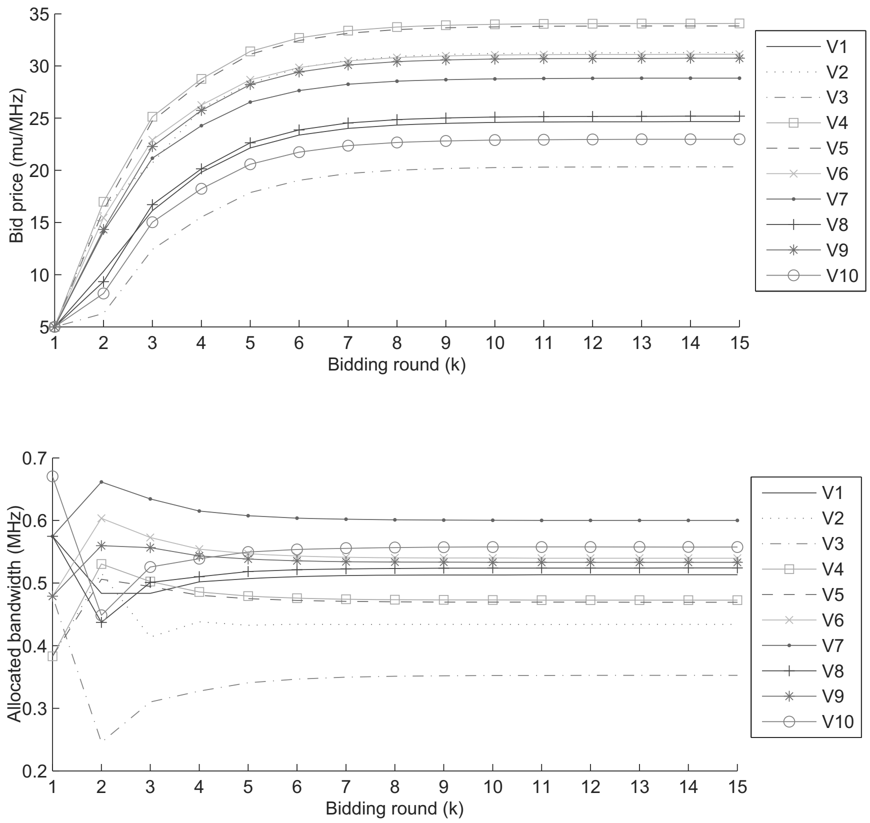

Figure C.1. *Bid price and amount of bandwidth for ten vehicles at each bidding round.*

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Publications

1. **K. Akkarajitsakul**, E. Hossain, and D. Niyato, "Cooperative packet delivery in hybrid wireless mobile networks: A coalitional game approach," *IEEE Transactions on Mobile Computing*, to appear.
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