Coexistence of unlicensed band wireless networks in a non-cooperative environment

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Coexistence of Unlicensed Band Wireless Networks in a Non-Cooperative Environment

by
Joo Ghee Lim

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List of Publications

- **Chapter 3**: Joo Ghee Lim, Chun Tung Chou, and Sanjay Jha. Non-Cooperative Coexistence of Co-located Independent Wireless Mesh Networks. In *IEEE Conference on Mobile Adhoc and Sensor Systems (MASS '07)*, Pisa, Italy, October 2007.
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- †Chun Tung Chou, Junaid Qadir, Joo Ghee Lim, and Archan Misra. Advances and Challenges with Data Broadcasting in Wireless Mesh Networks. *IEEE Communications Magazine*, 45(11):78–85, November 2007.
- †Junaid Qadir, Chun Tung Chou, Archan Misra, and Joo Ghee Lim. Localized Minimum-Latency Broadcasting in Multi-rate Wireless Mesh Networks. In *IEEE Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM '07)*, Helsinki, Finland, June 2007.

†These papers were published during the period of the author's Ph.D. candidature, but are not related to this thesis.

Abstract

There has been an exponential increase in the deployment of wireless networks that operate in the unlicensed band, such as the IEEE 802.11 Wireless Local Area Networks (WLANs) and the Wireless Mesh Networks (WMNs). These networks do not require any additional regulatory approval before deployment and co-located networks often belong to different managing entities. Due to their use of the unlicensed band, no single network can claim exclusive use of a channel. Interference may subsequently arise, leading to suboptimal performance. Besides Medium Access Control (MAC) protocols, radio resource control schemes like channel allocation, power control and link adaptation have been proposed to reduce this interference. In this thesis, we are interested in the coexistence issues of such independent unlicensed band networks. Due to the autonomous nature of these networks, they may not cooperate or even use the same MAC protocol. We investigate the use of radio resource control schemes to improve the performance of such co-located networks. Our proposed schemes make use of utility-based techniques that are derived from game theory and optimization theory.

We first model the interactions as a non-cooperative game and study the characteristics of the resultant game. We develop channel selection schemes for respectively, independent multihop WMNs and single-hop WLANs that are located together. We show that our proposed schemes improve the performance of non-cooperative WMNs by as much as 36%. In WLANs, our schemes show as high as 30% increase in aggregate throughput when evaluated against two existing channel selection schemes. Subsequently, we investigate how non-cooperation affects the solution of a cross-layer resource allocation algorithm designed for multi-radio, multi-channel, multihop wireless networks. We show that in the presence of non-cooperative networks, there exists efficiency loss due to the incomplete information of the contention environment. As a result, we propose an adaptation to the algorithm that is shown to improve performance by up to 3.2 times for a general physical/link layer model and 21% for a more realistic CSMA model.

Dedicated to the loving memory of my father, Lim Chai Kim
1938 – 2010

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Chapter 1

Introduction

Wireless communication has become an indispensable part of modern life. In the past decade, mobile phones utilizing the cellular technologies (e.g. AMPS, GSM, UMTS), along with laptops and smartphones connected to Wi-Fi networks, have enabled individuals to stay connected wherever they are. While cellular networks have been widely deployed, the initial setup phase is usually laborious and involves high cost. Firstly, the operating spectrum has to be allocated or *licensed* to the network operator, usually by the governing body. Often, these precious spectrum resources are auctioned to interested parties at hefty prices. Secondly, expensive infrastructure like basestations and servers have to be deployed, but not before conducting extensive site surveys to ensure adequate network coverage. Clearance also needs to be sought before the installation of the basestations and cell towers. The leasing of these sites where the basestations are placed leads to further costs.

Apart from licensing the operating frequencies to network operators, an alternative approach in wireless communication is to pre-allocate a fixed band of frequencies, but not license them to any particular operator. These bands of frequencies are free to be utilized by any communication device manufacturers and users, provided they comply with some requirements set out by the governing body, e.g. maximum transmit power and average power density. These frequencies are commonly known as the *unlicensed band*[1].

[1] Note that "unlicensed" does not mean unregulated, as the specifications for operating in these frequencies are still to be adhered to. In addition, many regulatory bodies require the devices to be certified or approved before they can be sold.

1.1 Unlicensed Band Networks

In many countries, certain frequency bands have been reserved for unlicensed use. For instance, in the United States and some parts of the world, the Industrial, Scientific and Medical bands (commonly known as the ISM bands) were initially set aside for use for industrial, scientific and medical purposes. These consist of a range of non-continuous frequency bands, including the popular 2.4 GHz band. Apart from their use in the above fields, other communication devices are allowed to utilize the channel, provided they do not interfere with the ISM users. It is interesting to note that products as diverse as the cordless phone system, remote control toys, as well as the microwave oven all make use of the 2.4 GHz band.

An *unlicensed band network* consists of devices that are able to communicate with one another over the unlicensed band. The most well known of such networks has to be the IEEE 802.11 Wireless Local Area Network (WLAN) [54]. Its utilization of the unlicensed band means that once the authorities have certified a new WLAN device to be adhering to the necessary regulatory requirements, no further approval is needed for it to be used. Anyone can install a WLAN access point (AP) or use a WLAN client card.

The ease of deployment of WLANs has greatly increased the adoption of such networks. With the economies of scale, the production cost of the hardware has been reduced, leading to more inexpensive chipsets and wireless cards. These cards can now be found in many mobile devices, such as laptops, PDAs and smartphones. This has further expanded their popularity among users for connecting to the Internet [63]. As a further proof of the attributes of unlicensed band networks, the United States Federal Communications Commission (FCC) has been allocating more frequency bands for this purpose [41]. Consequently, the FCC is also exploring the adoption of white spaces within the currently allocated licensed bands for unlicensed use [124].

We now briefly introduce two types of unlicensed band networks. The first type of networks has been widely deployed for wireless connection. The second type of networks has been attracting much research interests in recent years for its ability to extend network coverage without expensive wired infrastructure.

1.1.1 IEEE 802.11 Wireless LANs

As mentioned earlier, the 802.11 WLAN is one of the success stories of the unlicensed band networks. The IEEE 802.11 standards were created by the IEEE 802 working group for the purpose of standardizing the WLAN. The base 802.11 specification comprises of the Medium Access Control (MAC) layer and the Physical (PHY) layer. The MAC layer deals primarily with allowing different 802.11 devices to share the wireless medium, with mechanisms to perform collision avoidance, contention resolution, etc. On the other hand, the PHY layer focuses on how the data is actually transmitted over the wireless channel. It encompasses permitted operating frequencies, modulation schemes, error correction and other mechanisms that try to ensure that the transmission is as robust as possible.

The most popular versions of the IEEE 802.11 standards implemented and used in wireless hardware today are the IEEE 802.11b [9], IEEE 802.11g [11] and IEEE 802.11a [8] versions. The “b” and “g” versions operate in the 2.4 GHz ISM unlicensed band, while the “a” version operates in the 5 GHz Unlicensed National Information Infrastructure (U-NII) band. Recently, there have been more versions of the standards, serving as amendments to the existing versions. For example, the 802.11e amendment [10] addresses the Quality of Service (QoS) issues in the standards. The 802.11n amendment [13] seeks to extend the throughput performance by among other things, using Multiple-Input Multiple-Output (MIMO) technology and wider channel bands at the PHY layer, and frame aggregation at the MAC layer. In this thesis, we will focus mainly on the basic a/b/g versions, as they are still the most commonly deployed versions of the 802.11 standards.

1.1.2 Wireless Mesh Networks

In a typical 802.11 WLAN configuration, the AP is connected to the Internet via a wired connection (e.g. a Cat-5 cable or telephone line). Therefore, any client communicating with the AP is 1 wireless hop away from the physical wired network. This is commonly known as a “single-hop” network. In such a network, only clients that are within the communication range of the AP is able to access the resources in the wired network, such as the Internet.

In recent years, work has been done to extend the access of the clients beyond the

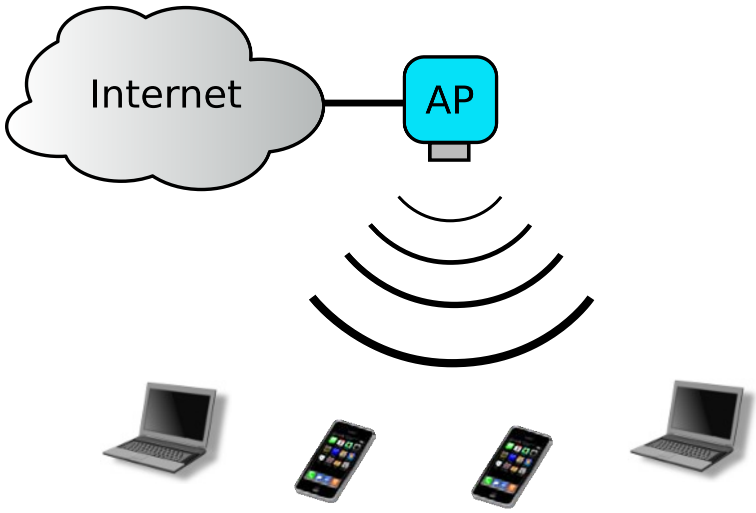
1 hop limitation. The idea is to deploy intermediate nodes that can wirelessly relay the traffic between the node that is connected to the wired network, to a client several hops away. This type of “multihop” network is known as a Wireless Mesh Network (WMN) [21]. The relay nodes, typically high performance devices with no power constraints, are called mesh routers. The nodes that are connected to the physical network are known as mesh gateways. In addition, there are mesh access points that provide wireless connection to mobile clients. In some cases, a single device may serve more than one of the above functions. Figure 1.1 shows the difference between a single-hop WLAN and a multihop WMN. We can view a typical WMN as consisting of infrastructure backbone links (formed by the mesh gateways and mesh routers) and access links (formed by the mesh access points and mobile clients).

As mentioned, one of the attributes of the WMN is that it allows clients located further away (several hops) from a gateway node to have access to the wired network, e.g. the Internet. In addition, deploying of the mesh routers reduces the need for wired networking cables. This will in turn reduce the setup costs of the network, which include the cost of the cables, the cost of leasing the land needed for their laying, as well as labor cost. For this reason, as well as the fact that the devices can be easily built using commodity hardware components that operate in the unlicensed band, WMN has generated great interest not just within the research community [21, 31], but also on the commercial front. There are currently many developments of mesh products and systems [1, 3, 6], as well as practical wide-area deployments [52, 137].

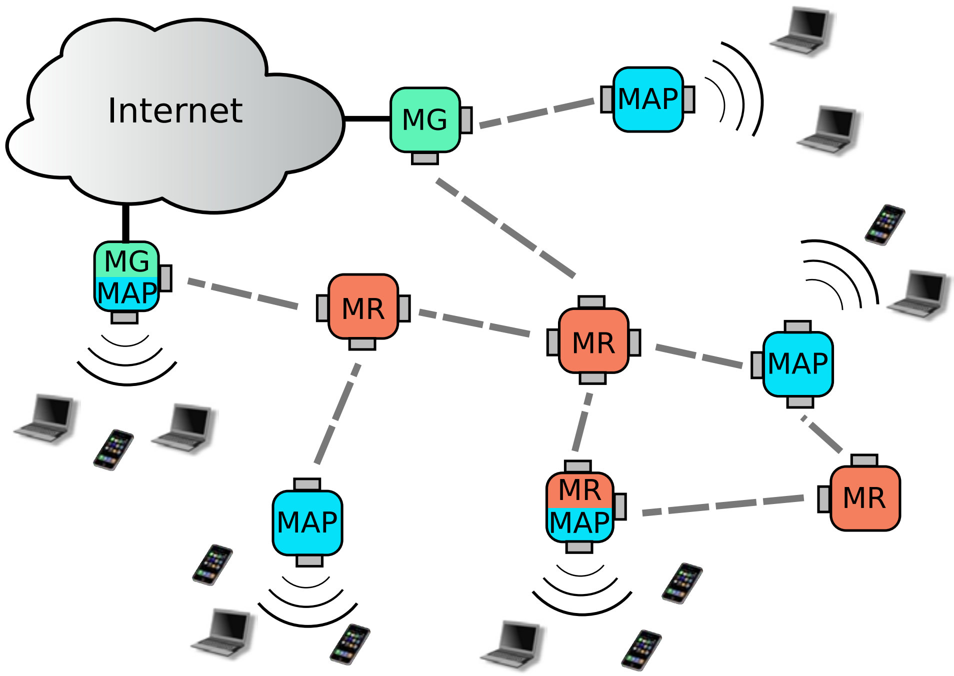
There have been some efforts in trying to standardize the WMN architecture, led by the IEEE 802.11 working group under the 802.11s Mesh Networking Task Group [32]. In spite of this, we believe that many of the WMN implementations are likely to be proprietary, especially at the core backbone. In addition, due to the advantages as highlighted above, we believe that a significant number of WMN deployments will be utilizing the unlicensed band. In this thesis, we will be focusing on these types of WMNs.

1.2 Interference and Coexistence Issues

The wireless communication channel is essentially a broadcast medium. When a packet is sent by a transmitter, the signal is received not only by the intended receiver,



(a)



(b)

Figure 1.1: (a) A typical WLAN with an access point (AP) and clients. (b) A typical WMN with mesh gateways (MGs), mesh routers (MRs), mesh access points (MAPs) and clients.

but also by other devices in the vicinity. If a receiver nearby happens to be receiving a packet from a another transmitter, collision can occur and both packets will be lost. This is one of the causes of interference in wireless networks. A major challenge in the deployment of wireless networks, especially in networks that use the unlicensed band, is how to mitigate this intereference.

1.2.1 Coexistence Issues

Because unlicensed band networks do not have exclusive use of the frequency bands, the coexistence of these networks becomes a critical issue. Coexistence is needed on two fronts:

Inter-technologies There are currently multiple technologies developed that operate in the unlicensed band. Take for example, the 2.4 GHz band: It is used by Wi-Fi (IEEE 802.11b/g), Bluetooth (IEEE 802.15.1) [30] and Zigbee (IEEE 802.15.4) [57] networks. Coexistence among these technologies [26, 60, 67, 130] is required to ensure that all the networks can operate with acceptable performance when they are co-located together. A key challenge in maintaining coexistence in this situation is the absence of explicit control messages among these networks. The reason is that each technology's protocols use different schemes, even though they may be occupying the same spectrum band. For instance, the above technologies that operate in the 2.4 GHz band use different modulation and coding schemes, which can only be decoded by devices implementing the particular technology. In addition, even if it can be successfully decoded, a control message like an Request-To-Send (RTS) frame sent by a Wi-Fi station would be useless to a Bluetooth device since RTS/CTS is not part of the Bluetooth standards.

Intra-technologies Even within the same network, there is a need to ensure coexistence. As we will discuss in Chapter 4, different links may experience different performance due to their differing views of the channel condition. In addition, even when two co-located networks are using the same technology, they often belong to different operating entities. This is especially true in the context of 802.11 WLAN. Its popularity has resulted in tremendous growth in the deployment of APs. In any given location, such as a residential area or business district, one would have no problem finding countless APs and clients [20, 44, 73, 104].

A characteristic of these APs is that they are usually operated by different owners, e.g. individual residents or companies. For each of these owners, the main interest is to get the best performance possible. There is no incentive for them to cooperate and coexist. In this thesis, we term these networks as *independent* or *autonomous* networks.

1.2.2 Why MAC is not Enough

Typically, the MAC protocol is used to reduce the interference and collision occurrence among wireless communication links. However, when dealing with potential interference among autonomous networks of the same technology, as well as networks belonging to different technologies, the inherent MAC protocol or protocols may not be sufficient. Below are some reasons why additional mechanisms are required:

- Among independent networks using the same technology, it has been shown that due to different views of the channel condition, co-located networks can experience drastically varying performance [53]. This is despite the fact that they are using the same MAC protocol (e.g. 802.11 Distributed Coordination Function or DCF MAC). For instance, in a typical information asymmetry scenario as described in [53], a transmitter may not be aware of the transmissions of a second link nearby, as the second transmitter is out of its carrier sensing range. Its transmissions will collide with the packets arriving at the second receiver, even though its own receiver can successfully receive its packets, as the second link is out of its interference range. The persistent collisions will result in a much lower throughput for the second link.
- Across different technologies, there is seldom any mechanism for the different MAC protocols to communicate in order to resolve contention issues. For example, when an 802.11 WLAN uses the RTS/CTS mechanism to better coordinate transmissions, these control frames may not even be decoded by another system in the interference range. This is because the contending system may be using an entirely different PHY layer modulation scheme [2].
- When the interference is caused by links beyond the transmission range, using

[2]While the different versions of 802.11 have gone to great lengths to ensure some forms of coordination at the PHY layer, e.g. a common preamble for 802.11b and 802.11g, the same cannot be said about entirely different technologies.

control frames to resolve contention does not work, as these frames cannot be decoded.

- MAC protocol development and standardization is often a complicated and time-consuming process. It involves many parties with different agendas, seeking to identify and address the various problems that may arise when sharing the communication channel. One has to look no further than the 802.11 MAC protocol to understand the intricate mechanisms that work together to allow the WLANs to access the wireless medium efficiently. It is therefore a complex, if not impossible task to design a MAC that can meet all the requirements of every single network.

Naturally, additional mechanisms beyond the MAC protocols may be introduced to improve the interference situation among multiple networks. There is actually a set of mechanisms that is not specifically defined in most MAC protocols, which we could use to achieve this purpose. We term them *Radio Resource Control* mechanisms and will formally introduce and describe them in the next section.

1.3 Radio Resource Control

In this thesis, we define Radio Resource Control as mechanisms, generally not defined in any particular MAC or PHY layer, that allow a wireless device to more efficiently make use of the radio resource.

As an example, again consider the 802.11 standards. In 802.11 systems, the operating frequencies, maximum transmit power and modulation schemes are either defined in the standards or required by the regulatory authorities. In terms of operating frequencies, the frequency spectrum that is allocated is further divided into sub-bands (known as channels). For example, 802.11b/g operates on the 2.4 GHz band and can have up to 14 channels (depending on the regulation where the device is deployed). Channel 1 has the center operating frequency of 2.412 GHz, channel 2's center operating frequency is 2.417 GHz, and so on. As for maximum transmit power, the United States FCC sets a limit of 1W, although most device manufacturers never reach that high. Modulation schemes in 802.11b/g result in PHY transmission rates of 1 Mbps, 2 Mbps, 5.5 Mbps, 6 Mbps, 9 Mbps, 11 Mbps, 12 Mbps, 18 Mbps, 24 Mbps, 36 Mbps, 48 Mbps and 54 Mbps.

Even though the above parameters have been defined, there are no specific guidelines on how they should be used. Hence, manufacturers have been given the freedom to adopt their own channel selection, transmit power control as well as rate adaptation schemes. These schemes constitute the radio resource control mechansims as defined in this thesis, as they determine a network's usage of the wireless channel. Similarly, new schemes could be designed with the purpose of improving the channel efficiencies of co-located unlicensed band networks, without making any changes to the standards. As part of this thesis, we will be developing channel selection/assignment schemes, for both single-hop as well as multihop networks, to achieve this objective.

1.4 Problem Statement

Given the increasing widespread deployment of unlicensed band networks, and the fact that the wireless channel is interference-prone; ensuring that these networks can operate effectively when they are located near each other is of paramount importance. This thesis investigates the coexistence issue of multiple co-located, autonomous wireless networks operating in the unlicensed band. We shall call this the *Coexistence Problem*. We seek to design channel selection schemes that will allow multiple unlicensed band networks to operate in the same spatial region, without adversely affecting each other's performance.

1.5 Contributions

Interference in wireless networks has been extensively studied. However, most works either assume interference from nodes and links belonging to a single network, e.g. [75, 145], or that external interference arises from simple sources that do not themselves adapt [60, 120]. In the former, cooperation and communication are often possible, and the nodes work together to achieve the common objective of improving system performance. In the latter, the network adapts to the interference that does not respond to the adaptation. Other works on non-cooperative networks often involve just competitive single-hop links, for instance in wireless ad-hoc networks [45, 97] or cognitive radio networks [46, 111]. The main contribution of this thesis is that it constitutes one of the first attempts of analyzing interference among non-cooperative networks, each consisting of more than one link. For a network, interference arises not just within itself, but also from external networks that could themselves adapt in response to the actions of the first network.

In addition, this thesis makes the following contributions:

1. Using game theory, we motivate and model the coexistence of independent wireless networks that are co-located in a non-cooperative environment as a non-cooperative game. Each independent network constitutes a player in the game, with the radio resource controls represented as actions or strategies. The utility each player receives as a result of every player choosing its own particular action denotes the outcome of the strategies played by the players. This is found in Chapter 3.

2. Also in Chapter 3, we apply the game theoretic model to independent WMNs co-located in a single collision domain[3]. Using the model, we investigate the use of channel assignment among the links of the WMNs to enable coexistence. We are able to characterize the conditions required to achieve Nash Equilibrium (NE); i.e., where no network has any benefit from deviating from the strategy (channels) played (chosen). We apply game theoretic learning to develop a set of channel assignment schemes and show that they do arrive at the NE outcomes.

3. In Chapter 4, we apply the game theoretic model to independent 802.11 WLANs that are co-located across multiple collision domains. From the model, we develop a set of channel selection schemes based on game theoretic learning. These channel selection schemes allow a WLAN to operate in a manner that takes into account the performance of other contending independent WLANs found within its collision domain, giving it a *socially conscious* characteristic. We are able to achieve this without violating the limitation of non-cooperation, where the networks do not communicate using explicit control messages. This is done using a novel way of detecting contention experienced by *other* networks, estimating the level of contention and including this value in the channel selection algorithm. Simulations show a marked improvement over existing channel selection schemes.

4. We investigate the effects of cross-layer channel assignment schemes on multiple independent multihop networks that span across multiple collision domains,

[3] A collision domain is defined as the set of links which if transmissions are active at the same time, will result in collisions.

where a subset of links interferes with one another. We show that even though such schemes are able to achieve a maximal capacity region when performed in a single network, the same result cannot be guaranteed when multiple networks apply these schemes non-cooperatively. We propose a simple solution to improve the performance of such cross-layer schemes among independent co-located wireless multiple networks. This is found in Chapter 5.

1.6 Non-Cooperative Game Theory

Game theory [49] is a branch of applied mathematics that describes and studies the interactions of decision processes. It has been used in diverse fields like economics, psychology, biology, etc. More recently, game theory has been applied to network interactions [58] and in particular, wireless multihop networks [131].

In classical game theory, a game consists of a set of players, a set of actions (or strategies) and utilities or payoffs related to the actions chosen by every player in the game. In non-cooperative game, the key assumption is that all players choose the strategies independent of one another, even though each player may be influenced by the other players indirectly through the eventual payoff. In Chapters 3 and 4, we will study the coexistence problem by modelling it as a non-cooperative game. In addition, we will be applying game theoretic learning algorithms to develop practical channel selection schemes that will allow multiple independent networks to be deployed together without adverse performance degradation. Additional background information of non-cooperative game theory and game theoretic learning will be described in those chapters.

1.7 Cross-Layer Network Optimization

Traditionally, network protocols are organized into different layers, with each layer independently implemented to optimize its performance. In their seminal work, Kelly et al. [81] show how to optimize a network using a utility maximization framework. In their framework, utilities are defined as functions of the flow rates in the network, and the problem is to maximize these utilities subject to constraints imposed by the physical network. This approach has since been adapted widely to develop cross-layer network optimization algorithms, both in the wired and wireless networks.

It has been shown that it is possible to develop cross-layer resource allocation algorithms that optimize the throughput capacity available to a wireless network and at the same time, guarantee fairness across the traffic flows within the network [95]. In Chapter 5, we investigate how the performance of such cross-layer algorithms can be affected in the presence of multiple non-cooperative networks. This is done by looking at a particular cross-layer scheme that has been proposed for multi-radio, multi-channel, multihop wireless networks. We are particularly interested in whether coexistence can be achieved if such a scheme is operated independently within each network.

1.8 Thesis Organization

This section provides the outline for the entire thesis. More details of the organization of each chapter will be provided in the Chapter Outline section within the individual chapter.

Chapter 2 contains a literature review of the related works in the areas of non-cooperative wireless environment, channel selection schemes that are applied to single-hop as well as multihop wireless networks, and the application of game theory and cross-layer network optimization to wireless networks.

In Chapter 3, we describe our work in formulating the coexistence of independent wireless unlicensed band networks as a non-cooperative game. We apply the framework to study the interaction of independent multihop WMNs that are co-located in a single collision domain. These networks have nodes that are equipped with multiple radio interfaces to operate on multiple channels, and we model their channel assignment strategies as a game. From the analysis, we design a set of channel assignment algorithms that helps the WMNs to arrive at Nash Equilibrium outcomes.

The same game theoretic framework is applied to the coexistence of independent 802.11-based WLANs in Chapter 4. The WLANs are co-located across multiple collision domains, where the 802.11 DCF MAC interactions among the networks could result in undesirable fairness issues. We design a set of socially conscious channel selection schemes that does not require any explicit communication among the independent WLANs, making them suitable for application to the independent, non-cooperative scenario.

We return to multihop wireless networks in Chapter 5, where we extend our treatment of these networks to their interaction in multiple collision domains. Specifically, we investigate the effects these non-cooperative networks have on the performance of a joint congestion control, routing and channel allocation algorithm that has been designed based on a cross-layer resource allocation framework. We show that there is a drop in overall system performance due to the non-cooperative nature of the independent networks. In addition, we propose a simple solution to improve the performance of such algorithms when applied to autonomous networks.

Finally, we conclude the thesis in Chapter 6.

Figure 1.2 shows a pictorial representation of the thesis outline. In the network domain, we look at interactions of both multiple single-hop as well as multiple multihop wireless networks that are autonomous and uncooperative in their operations. These networks operate in the unlicensed band and so have the potential of interfering with one another. In the solution domain, we first make use of a game theoretic framework to study the interactions of these networks. Next, we make use of the network utility maximization model to study the interactions of multihop networks. These can be broadly classified as utility-based network optimization techniques. From these models, we propose solutions that are able improve system performance. These solutions have the characteristics of online operation and require no explicit communication among the independent networks.

While this thesis focuses on the coexistence issues of non-cooperative wireless networks, the author has also proposed a MAC protocol for multi-channel, multi-radio wireless mesh network. This standalone piece of work has been produced during the course of the author's Ph.D. candidature. Therefore, it is included in this thesis as an appendix in Appendix A. This work can be related back to some of the key themes in this thesis from the perspective of how the MAC can improve the performance of a multi-channel, multi-radio wireless network in a interference-limited environment.

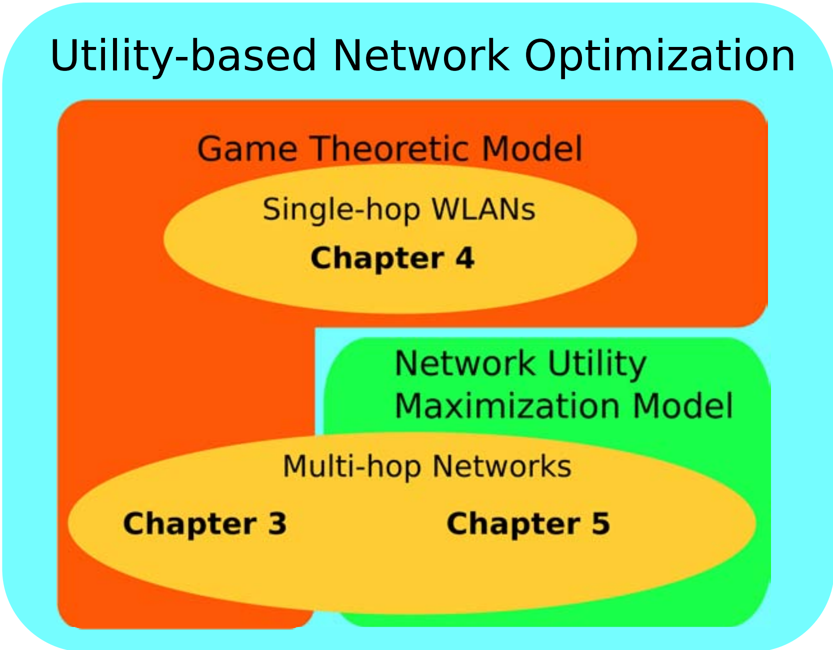


Figure 1.2: A pictorial representation of the thesis outline.

Chapter 2

Literature Review

2.1 Introduction

In this chapter, we provide a comprehensive review of the existing works related to this thesis. There is an extensive list of related work examining the issue of effective operation of networks in an interference-limited environment. Essentially, most MAC protocols need to address this issue. As this thesis investigates the option of building radio resource control on top of pre-existing MAC protocols, we will focus on works that make use of these controls to improve network performance. In particular, we review channel selection schemes, as this is the main technique applied in this thesis to achieve the radio resource control. We will also cover significant attempts in applying game theory and cross-layer network optimization in wireless networks, especially in the area of resource allocation.

2.1.1 Chapter Outline

In Section 2.2, we first discuss works that motivate and explore the issue of coexistence in a non-cooperative environment that is similar to that of the unlicensed band. Following that, Section 2.3 reviews channel selection schemes for both the single-hop and multihop networks. Application of game theory to wireless networks, in particular resource allocation is discussed in Section 2.4. Finally, we review the application of cross-layer network optimization to wireless networks in Section 2.5

2.2 The Interference-limited Wireless Environment

This section lists works that motivate the need for coexistence in a wireless environment that is similar to that found in the unlicensed band networks.

In their seminal work, Gupta and Kumar [61] analyze the capacity of a network in a wireless environment, where the nodes could interfere with one another. They show that for a network containing n numbers of randomly distributed transmitting nodes, the capacity bound of each node is of the order of $1/\sqrt{n \log n}$. Even with optimal node placement and traffic, the bound is of the order $1/\sqrt{n}$. Essentially, increasing the number of transmitting nodes reduces the capacity available, due to the interference among the nodes. While their analysis shows the worst-case asymptotic bounds, it nevertheless highlights the issue of interference in wireless communications.

Similarly, Jain et al. [75] discuss the issue of interference on a multihop wireless network that spans multiple collision domains. Using the notion of conflict graphs to model the collision domain, they formulate a multi-commodity flow problem. They show that the problem is NP hard and present approaches to compute the upper and lower bounds of the optimal throughput for any given network and traffic. Their results show that in general, performance of the network is related to the traffic load and number of nodes. At low traffic load, increasing the number of nodes can improve performance, as the additional nodes provide alternative paths for the flows to reach their destinations. However, at high traffic load, the channel is often saturated and having more nodes actually results in higher interference and correspondingly lower performance.

In addition to the general wireless networks described by Gupta and Kumar [61] and Jain et al. [75], there has been a stream of papers that investigate how 802.11 performs in networks deployed across multiple collision domains. [34, 51, 53, 143, 144] are a representation of the works in this area. Of these, [53] stands out in its analysis of the interaction among interfering links belonging to different collision domains. The authors develop a model that is able to compute the flow throughput in 802.11 networks. They also explain situations when starvation occurs — which they attribute to information asymmetry (IA) and flow-in-the-middle (FIM) scenarios. However, their throughput computation requires a centralized, iterated process that can take a long time to arrive at an accurate solution.

The above references highlight the general issues of interference in wireless networks. In the next two sections, we discuss the works related to the interference and coexistence of networks belonging to different operating entities — first among networks using different technologies and then, for networks employing the same technology.

2.2.1 Coexistence across Different Technologies

The issue of coexistence among different devices using the same frequency band was brought into focus after the United States FCC released the Unlicensed Personal Communication Services (UPCS) band for short-range wireless communication use. In [132], Steer outlines the rules needed to ensure wireless "etiquette" when using this frequency band. These rules include listen before send, restricting the maximum transmit power and having a limit on the transmission duration. The author acknowledges the opportunities the unlicensed band can provide for manufacturers and operators, but also motivates the coexistence problem that can potentially arise.

More generally, Satapathy and Peha [128] highlight the advantages of spectrum sharing by networks operating in an unlicensed band. In addition, they discuss a few challenges that need to be overcome in order to make efficient use of the unlicensed band. One of the problems is that with free use of the channel, designers of the communication devices have no incentive to share the radio resources efficiently. Everyone may take the greedy approach of utilizing as much as possible, leading to a classical Tragedy of the Commons [65] situation. In addition to regulatory requirements, they note that there is a need for designing hardware as well as protocols that ensure efficient spectrum sharing.

Similarly, Raychaudhuri and Jing point out the challenge of effective and efficient sharing of the unlicensed spectrum. In [123], they explain that due to the varied requirements of the different wireless networking systems (e.g. throughput and delay demands of multimedia applications), the traditional "Listen-Before-Talk" (LBT) etiquette is no longer sufficient. In addition, as some of these systems overlap only partially in the frequency or time domain, the LBT etiquette can lead to suboptimal efficiency. In response, they propose the need for a more advanced etiquette protocol that spans the different PHY/MAC standards using the unlicensed band. Their solution involves a narrow-band channel, known as common spectrum coordination channel (CSCC), that devices from different systems or technologies can use to coordinate their spectrum usage. However, we believe that such a cross-technology solution may not be feasible, as it requires existing legacy standards to be updated in order to conform to the solution. This will pose a big challenge for the devices that have already being deployed and used.

More recently, Gummadi et al. [60] report on experiments that have been conducted to investigate the effects of interference on 802.11 WLANs by devices sharing the ISM unlicensed band, e.g. Zigbee and cordless phones. They show that even weak and narrow band signals from these interferers can adversly affect the performance of 802.11 devices, and identify a few causes of this performance degradation. More importantly, the authors show that modifying the 802.11 parameters like carrier sensing threshold and transmission rate does not improve the situation. They note that a viable option is to perform channel hopping in the presence of interference. Another interesting observation made in the paper is that versions of 802.11 that support higher transmission rates (e.g. 802.11g and 802.11n) are still susceptible to these types of interference.

Thus far, the works presented here highlight the challenges of inter-technologies coexistence from a more general perspective. The following are some works that look at the coexistence of specific pairs of technologies sharing the unlicensed band.

WLAN (802.11) and Bluetooth (802.15.1)

Coexistence among Bluetooth devices and 802.11b/g WLANs is a critical issue, as Bluetooth performs frequency hopping in the 2.4 GHz unlicensed band, which is also being used by the 802.11b/g WLANs. Because of this, a single Bluetooth device could potentially interfere with multiple WLANs when it hops into their channels during its transmission. This issue has warranted the IEEE 802 Working Group to come up with a Recommended Practice document that addresses the coexistence issue of Bluetooth with WLANs, in [14]. The document lists both collaborative as well as non-collaborative coexistence mechanisms.

The Recommended Practice document in [14] has proposed an adaptive frequency hopping (AFH) mechanism and a Bluetooth interference aware scheduling (BIAS) mechanism, to improve coexistence among Bluetooth devices and 802.11 WLANs.

In [130], Song et al. essentially combine these two mechanisms. Their interference-aware adaptive frequency hopping (IAFH) mechanism defers transmission during rapidly varying interference levels and performs AFH if the interference lasts for a longer duration.

Nallanathan et al. [26] develop a model to analyze the interference between a Bluetooth system and a 802.11b WLAN system. Their model takes into account the PHY aspects of the systems (e.g. coding, modulation, propagation) as well as the MAC elements (e.g. packet size adjustment in a Bluetooth piconet). Using the model, they investigate several parameters of both the Bluetooth and 802.11b systems that affect the performance of the 802.11b system. For example, they discover that using a 5-slot packet size in the Bluetooth piconet reduces its frequency hopping rate, which in turn decreases the chance of it hopping into the 802.11b channel. This has the effect of improving the packet transmission success probability of the 802.11b WLAN.

WLAN (802.11) and Zigbee (802.15.4)

Howitt and Gutierrez investigate the impact of Zigbee personal area networks on a 802.11b station in [71]. Using a stochastic model, they evaluate the collision probability of the 802.11b station given the aggregate transmission activity of the nodes within the Zigbee network. They show that unless the station is situated near a Zigbee network with high transmission activity, the impact on the 802.11b station is minimal. Since most Zigbee networks consist of low bit-rate applications, they argue that this conclusion holds true in general. However, the paper does not evaluate the impact of the 802.11b network on the Zigbee network.

More recently, Hauer et al. [67] study the effects of 802.11 WLANs on body area networks (BANs) that use Zigbee as the communication platform. Using a pair of Tmote Sky sensors worn by a person, they measure the packet losses experienced in both a controlled WLAN environment as well as an uncontrolled urban city area. They report that packet losses in these devices are largely due to the external interference from 802.11 WLANs, as their experiments show a strong correlation between the packet failure rate and the 802.11 channel activity.

The above reviewed literature points to the fact that interference among networks and devices belonging to different technologies, yet sharing the same frequency bands, needs to be properly managed in order for them to exist together. We next look at the need for coexistence among networks using the same technology.

2.2.2 Coexistence within the Same Technology

Akella et al. [20] investigate the issue of the deployment of 802.11 WLANs that are uncoordinated and self-managed. Using data collected from a few US cities, they show that the situation where a WLAN is in close proximity to a large number of neighboring autonomous WLANs is a common phenomenon. Their data includes a case where a particular WLAN has as many as 85 neighbors. They also found that the distribution of the channels used is not uniform, with Channel 6 being the most occupied. They coin the term “chaotic” wireless deployment to describe this phenomenon. By running simulations using position information from one of the data sets, they show that performance could degrade under such an environment.

In [44], Ergin et al. provide experimental and simulation results of similar unplanned WLAN deployments. They show that the efficiency of an 802.11 network is more affected by the number of interfering autonomous 802.11 networks than the clients within the network. From their investigations, the authors propose a contention window adaption scheme, using the number of active APs a particular AP can detect. However, their study assumes a single collision domain for all the WLANs and therefore do not address the unfairness that arises when these networks are deployed across multiple collision domains.

The fairness issue that arises due to these chaotic, unplanned and uncoordinated 802.11 networks is brought up by Mishra et al. in [104]. Due to the autonomous nature of the WLANs, they point out that load-balancing (i.e., by redistributing clients across the APs) to improve fairness is not a possible solution. Commonly used methods like AP placements from site surveys are also not practical since these APs are deployed in a decentralized and ad hoc manner by individual users. As a result, the authors propose a channel hopping algorithm (MAXchop) that seeks to maintain fairness among the non-cooperative WLANs. In addition, they contend that fairness should be defined by comparing the aggregated throughput of all the clients in each AP, rather than individual flow or client traffic.

So far in this section, we have described works addressing the coexistence issue of 802.11 single-hop networks. Wu and Hsieh [142] motivate that the same problem also arises in co-located 802.11 multihop WMNs belonging to different management authorities. By using a linear programming formulation, they explore the performance of multiple WMNs that may be partially or fully overlapping in their coverage areas. Their simulation results show that without coordination among the WMNs, performance degradation as well as unfairness appears.

2.3 Channel Selection

As mentioned in Section 1.3, while most wireless standards provide for multiple operating frequencies to allow co-location of more than one network, the actual channel selection schemes are left as a design freedom. This section reviews the existing work on channel selection and assignment in single-hop and multihop networks respectively.

2.3.1 Channel Selection in Single Hop Networks

In most adaptive channel selection schemes, a WLAN makes the decision of the operating channel based on some feedback from its environment. The differentiating features in many of these schemes are essentially the metric to be measured within each channel, how the channel condition (otherwise known as *utility* here) is computed and how the channel switching decision is made.

Least Congested Channel Search (LCCS) [15] is a simple channel selection scheme where an AP scans its channels to find the one with the fewest number of neighboring APs. This scheme is currently implemented in some APs. It is not difficult to see that LCCS provides only basic information for an AP to make its channel selection decision.

In [101], Mishra et al. propose a Hminmax distributed algorithm that formulates a weighted graph coloring problem, where an edge is defined for every WLAN that is within the communication range of a particular WLAN, say i. For every edge, they define the number of i's clients that will be affected by the interference of the WLAN sharing that edge (if they share the same channel) as W. Along with the channel separation[1] I between the WLANs sharing the edge, they compute the weight of each edge as $I \times W$. Hminmax is performed periodically and ensures that network i selects

[1] Since the scheme makes use of partially-overlapping channels, the channel separation indicates how much two channels overlap in their frequencies.

the channel that minimizes the $I \times W$ value of its maximum weighted edge. Hminmax has been shown to outperform LCCS, although it requires the clients to also scan the available channels and provide feedback to the AP. This increases the complexity and communication overheads of the scheme.

In both LCCS and Hminmax, a WLAN scans a channel by listening for frames from neighboring WLANs in order to compute the channel's utility. However, they are unable to detect the interference that comes from WLANs lying outside the communication range, where frames cannot be correctly received. LCCS and Hminmax also do not take into account the traffic load of the networks in each channel. A number of works have highlighted these deficiencies and have proposed solutions that compute channel utilities using more detailed metrics. We highlight these works below.

In [88], Leith et al. propose a simple learning algorithm, making use of frame error rate as the metric (although they state that other metrics could be used as well). In the algorithm, known as Communication-Free Learning (CFL), if a channel yields no interference, it will be used again during the next iteration. On the other hand, if interference is experienced, the probability of using that channel will be reduced. The authors' motivating premise, as in this thesis, is that interference could come from beyond the transmission range. Therefore, channel selection schemes that do not require explicit information exchange between the APs are needed. However, the algorithm only receives as inputs the presence or absence of interference, but is not able to take into account the degree of interference.

Chen et al. [35] introduce a few measurement-based frequency allocation algorithms that capture degrees of channel interference. One of the algorithms uses a number of metrics, namely, the client's measurement of the channel interference I_c; the received signal power R_c of the AP, as received by the client; and the traffic volume Y_c between the AP and client, to compute the channel utility. The resulting utility is computed by summing up $(\frac{Y_c}{S_c} \cdot I_c)$ for all the clients of the AP. This utility is used in the No-Coord User (No-U) algorithm, where each AP performs periodic scanning and independently chooses the channel with the lowest utility. Because it takes into account the clients' view of the channel as well as the degree of interference, No-U shows improved performance when compared to CFL [88].

802.11k [12] is the amendments to the 802.11 standards that allow measurements of radio resource parameters, so that a 802.11 WLAN can better manage these resources.

Two works [42, 147] propose to use the parameters defined in the standards as metrics to perform channel selection. In [42], the authors describe a Dynamic Channel Allocation Mechanism (DCAM) that makes use of the channel load information and the noise histogram parameters. Briefly, when the channel load value goes below a threshold, it triggers the AP to choose a new channel with the lowest noise histogram value. Like the CFL algorithm in [88] and No-U scheme in [35], DCAM does not assume communication exists among APs. However, it requires clients to perform the measurements and update their own AP of these 802.11k parameters.

Similarly, Yoo and Kim [147] utilize the 802.11k parameters to perform channel selection. In addition, their algorithm also performs load balancing. By computing the channel busy time resulting from internal traffic (intra-load), as well as from both internal and external traffic (channel load), an AP can decide whether to perform channel switching or load balancing. When the channel load is high but the intra-load is low, the AP will perform channel switching by selecting a different channel. If both channel load and intra-load are high, the AP will perform load balancing by directing a client to associate with another AP. Although this channel assignment plus load balancing (CA+LB) scheme is decentralized in operation, the authors assume clients can associate with more than one AP.

As mentioned previously, Mishra et al. in [104] propose a channel hopping algorithm that is specifically designed to target the uncoordinated, non-cooperative WLAN environment. Each AP executing this MAXchop algorithm computes a hopping sequence that seeks to divide the interference equally among the networks that interferes with it. It does this using the information of the hopping sequences that are used by the interfering networks. This is acquired by scanning the networks within its communication range. Thus, similar to LCCS and Hminmax, MAXchop do not account for interference that comes from WLANs that lie outside the communication range of a network.

Channel selection in the non-coordinated WLAN environment is also being investigated by Ihmig and Steenkiste in [73]. Like Akella et al. in [20], the authors first motivate the problem of chaotic WLAN deployment using real-world data. The data was acquired from measurements made around the Carnegie Mellon campus in Fall 2005, to show the high density of AP deployment. They propose a Distributed Dynamic Channel Selection (DDCS) scheme that periodically compares the channel quality of the current channel with a threshold value. A channel switch is triggered if the channel quality falls below this threshold. To evaluate the channel quality, they compare 3 different metrics — the channel busy time, the AP transmit queue length and the packet delay at the MAC layer.

The channel selection schemes that we have described so far are distributed and non-cooperative in nature. Each AP essentially makes its own decision with respect to which is the best channel, as it receives feedback from the surroundings and in some cases, its associated clients. As a result, these schemes are well-suited for use in the non-cooperative environment described in this thesis. There are other channel selection schemes, which are either centralized in nature or require explicit communication among the APs. These schemes are not suitable for our scenario but are briefly described here for completeness sake.

Mishra et al. describe a centralized algorithm that assigns channels to WLANs in such a way as to maximize the number of conflict-free clients in [102]. The algorithm is known as CFAssign-Rac. Specifically, it involves a central entity solving a global optimization problem using a conflict set coloring model. At the same time, it is able to achieve load-balancing in terms of the number of clients associated with each AP. Rozner et al. [127] propose centralized schemes that also incorporate traffic-awareness. Both approaches are centralized in nature, and they assume that all the WLANs belong to a single managing entity. In [140], even though the authors do not assume a single managing entity and the channel selection scheme (known as PACA) is decentralized, they assume explicit communication (hence cooperation) among the WLANs. Similarly, in [101], a second algorithm that is proposed along with Hmin-max, known as Hsum, requires cooperation among the APs. Information needs to be exchanged among the APs to achieve a minimization of the $I \times W$ value of each AP's maximum weighted edge and the aggregate $I \times W$ values of the APs in each AP's neighborhood. Such schemes do not offer a suitable solution to our problem.

This section provides an extensive overview of the current channel selection schemes in 802.11 single hop networks. Table 2.1 organizes these schemes into the general algorithms used (e.g. centralized or distributed, periodic or threshold-triggered) and the types of channel information required. As highlighted, channel selection schemes suitable for deployment in uncoordinated, non-cooperative environment are required to be distributed in nature. In addition, channel information that extends beyond just the number of networks that can be scanned within the communication range will also provide more accurate metrics for the channel selection process.

As can be seen from Table 2.1, there are a few schemes that fulfill the distributed and channel information requirements needed in coexisting independent WLANs. However, by virtue of their distributed and non-cooperative operation, these schemes are "selfish" in nature — seeking to improve the channel metric at all cost. We show in Chapter 4 that this can result in fairness issues, due primarily to the 802.11 DCF MAC protocol. We investigate this aspect of the channel selection schemes in the chapter. The schemes that we propose there, while meeting the necessary requirements, will improve system fairness by incorporating a *social conscious* element in their operations.

2.3.2 Channel Assignment in Multihop Networks

In a multihop wireless network like WMN, each node could potentially be attached with more than one radio. The challenge is to assign the available channels to the radios so as to reduce interference, increase capacity and prevent network partitioning. In this section, we will only focus on the channel assignment schemes that are specific to networks with nodes that are equipped with multiple radios[2]. In such networks, the channel assignment strategy can be either fixed or dynamic. In *fixed channel assignment*, there is usually an algorithm that computes the best channel assignment offline or at the start of the network's operation, given certain constraints. Once assigned, the radios will not switch channels for a sufficiently long period of time. On the other hand, in *dynamic channel assignment*, the radios switch among the available channels as they sense the channel conditions. For instance, high interference in the form of increased packet loss rate may trigger the radio to switch to another channel.

Das et al. [43] outline the fixed channel assignment problem for multi-radio WMNs as a problem of optimizing the number of communicating links that can be active concurrently. They propose two integer linear programming models to solve the problem. They analyze the time complexities of their methods when applied to grid topology, which seem to grow very high for some combinations of number of radios to number of channels. It remains to be seen how a practical algorithm can be designed from the

[2] The reader is directed to [43] for a comprehensive review of the channel assignment problem in a single-radio, multihop network with multiple available channels.

			Channel Information			
			No. of Neighbors		**Other Channel Conditions (+Load-aware)**	
			AP	**AP+Clients**	**AP**	**AP+Clients**
Algorithms	**Centralized and/or Cooperative**	**Best Response – Periodic**		Hsum [101], CFAssign-Rac [102]		
		Best Response – Threshold Triggered				PACA [140], Traffic-Aware Channel Assignment [127]
	Distributed	**Best Response – Periodic**	LCCS [15]	Hminmax [101]		Measurement-based Frequency Allocation (incl. No-U) [35]
		Best Response – Threshold Triggered			DDCS [73], DCAM [42]	CA+LB[147]
		Others		MAXchop [104]	CFL [88]	
					Our Game Theoretic Learning Schemes (Chapter 4)	

Table 2.1: Overview of channel selection schemes grouped into channel information required and types of algorithm.

methods, and how it performs in non-grid topologies.

In [24], Alicherry et al. formulate a joint channel assignment, routing, and link scheduling problem that takes into account both the interference as well as fairness constraints. They propose an algorithm that solves the problem and provides a provably worst case performance bound. However, their algorithm requires the problem to be solved in a centralized manner. In addition, they assume that the network and traffic conditions do not change in the short term.

Also taking the optimization approach, Rad and Wong present a series of work in the area of WMN channel assignment by formulating the problem as a constrained optimization problem. In [115], they present a joint channel assignment and congestion control solution using decentralized constrained utility maximization, taking into account the neighboring interference as constraints. A key attribute of their solution is that it is able to make use of partially overlapping channels. Subsequently, in [116] and [117], they extend their work to incorporate interface assignment and link-layer flow control, by using a non-linear mixed-integer optimization approach.

In general, fixed channel assignment schemes tend to be derived from some theoretical formulation. The advantage of such an approach is that optimality and convergence can often be proven. However, since the channel allocations are fixed, they also assume that the channel conditions and the network traffic profile remain unchanged. Dynamic channel assignment schemes are more suitable in situations where environmental and/or traffic conditions do change with time. We review some dynamic channel assignments schemes below. Owing to their adaptive nature, these schemes are often heuristic in nature.

As discussed above, dynamic channel assignments allow nodes to change the channel their radios are operating on, often in response to changes in the network environment. The advantages of such channel assignment schemes are obviously their flexibility and adaptability. However, these schemes are often more complex and care must be taken to prevent network partitioning from occurring. This can happen for example, when a pair of nodes providing the only link between two parts of a network switch their radios to operate on entirely different channels. Kyasanur et al. [85] highlight some of the issues involved in multi-channel WMNs (e.g. maintaining connectivity) and propose a hybrid scheme where a node always has at least one radio operating on a fixed and known channel. In addition, each node will have one or more switchable radios that can be allowed to operate on any of the channels. Pre-assigning of a channel to the fixed radio allows the WMN to remain connected, while the switchable radios allow all the channels to be utilized.

In [122], Raniwala et al. propose a multi-radio multi-channel WMN architecture that can be implemented using commodity 802.11 hardware. It includes a dynamic channel assignment scheme that works in a centralized manner. The channel assignment scheme takes into account the traffic load between every pair of nodes in the WMN. By doing so, the scheme is able to perform load balancing as well as adapt to changes in traffic condition. Through simulation, the authors show that by adding an additional radio to each node, the average aggregate throughput of the WMN improves by up to a factor of 8. Subsequently in [121], the same authors present distributed versions of their channel assignment scheme and report an improvement of factors of 6 to 7, when compared to using a single radio and channel.

Subramanian et al. [134] study the problem of channel assignment in a WMN where the number of radio per node is less than the number of available channels, with the goal of reducing the overall network interference. They acknowledge the problem to be NP hard and develop two channel assignment algorithms. In order to evaluate their proposed algorithms, they formulate their problem using linear programming and semidefinite programming to obtain the network interference lower bounds. Comparing with these bounds, they show that their algorithms perform close to them.

All the works described above address channel assignment in the presence of interference from links within the same network. Ramachandran et al. [120] provide a new perspective to the channel assignment problem by including the interference that can arise from radios belonging to external networks. Like this thesis, they argue that WMNs will normally have to exist side-by-side with other wireless networks operating in the same frequencies. Hence, besides minimizing interference from within the network, the channel assignment algorithm must be able to minimize the interference that comes from other co-located, external networks. Their idea involves using a Multi-radio Conflict Graph (MCG) to model interference between nodes with multiple radios and incorporate the effects of external interfering radios. However, their scheme assumes that IEEE 802.11-based nodes can decode the frames from interfering radios. It thus fails to address the problem caused by interference from radios that are out of the transmission range, as well as those belonging to other technologies, e.g. Bluetooth.

The majority of the works on channel assignment in multihop networks tend to only take into account interference that arises from nodes and links belonging to the same network. As a result, the solutions developed either involve a centralized manner of resolving these interferences (e.g. [24, 122, 134]), or assume that control messages are exchanged among the nodes so that a distributed algorithm becomes possible (e.g. [85, 115, 121]). The only exception is Ramachandran et al. [120], where they take into account possible interference from external networks in their channel assignment scheme. However, even there the interference is understood to be arising from external links that do not form a network among themselves. In Chapters 3 and 5 of this thesis, the focus of our investigation is on the interference relationship among links belonging to 2 or more co-located independent WMNs. We assume that the individual WMNs are all able to perform channel assignment and study the possible outcomes.

2.4 Game Theory in Wireless Networks

Game theory has been widely applied to networking problems in recent years. It would be impossible to include all the references in this review. Instead, this section provides an overview of the application of game theory to wireless networks and in particular, will focus on works that are related to the topics discussed in this thesis.

In [98], MacKenzie and DaSilva provide a number of fundamental results in non-cooperative game theory and discuss their application to wireless communications and networkings. The book provides a bottom-up approach by covering the basics in non-cooperative game theory before moving to different game models. In addition, it also includes discussions and references on how these models have been applied to the wireless domain. Challenges and limitations on direct game theoretic applications are also discussed. Subsequently, the authors (along with other members of their research group) offer a similar but shorter treatment of the topic that is specifically directed at wireless ad hoc networks in [131].

2.4.1 Modeling Channel Assignment as a Game

Félegyházi et al. [46] provide a game theoretic perspective of channel allocation in non-cooperative wireless networks. In their networks, each device can operate on multiple channels by being equipped with more than 1 radio. Their analysis provides understanding on the possible Nash Equilibrium (NE) channel allocation outcomes when the devices operate within a single collision domain. Although non-cooperative in nature, their solution is more directed towards cognitive radio systems. Our game theoretic analysis in this thesis, on the other hand, includes both networks that lie within a single as well as across multiple collision domains. In addition, their network is static while our solution for single hop WLANs in Chapter 4 is applicable to dynamic network changes.

In [141], Wu et al. highlight that the NE solution of [46] is not an ideal solution as the assumption is that all players will keep at their equilibrium strategies. Additionally, NE outcomes are not always socially efficient, in the sense that the aggregate system performance is not optimized. Using the same network model as [46], they propose a payment scheme where each player (link) pays an assumed system administrator a price for using a channel. Their proposed scheme allows the players to compute the globally optimal channel assignment, defined as an assignment where no link is starved and there is social efficiency. They show that the globally optimal channel assignment thus gotten results in a stronger Strongly Dominant Strategy Equilibrium (SDSE) solution concept.

A similar system model is considered by Chen and Zhong in [37], where each device is assumed to have access to multiple radio interfaces, but only interactions among pairs of nodes are investigated. As in [46] and [141], all the links are assumed to lie within the same collision domain. The authors seek to achieve a Nash Equilibrium solution that ensures perfect fairness with respect to the throughput of the links. Specifically, perfect fairness occurs when the utilities and the aggregate throughputs of the links are equal. This is again accomplished by incorporating a payment into the utility function, where the payment is the price each player needs to give an assumed system administrator for using the channel. Although the works of both [141] and [37] assume the networks to be non-cooperative, the presence of the centralized entity to enforce the payment scheme will limit their applications.

Nie and Comaniciu [111] also apply game theory to study the channel assignment of networks, specifically with cognitive radios. They look at both the case of cooperative networks as well as non-cooperative, selfish networks. In cooperative networks, they use a potential game formulation [106] that is shown to arrive at a NE channel allocation outcome. In the non-cooperative case (of greater interest to us in this thesis), they use no-regret learning algorithms to solve the problem. Although the use of game theoretic learning to solve the problem is similar to our approach in parts of this thesis, the problem they study in their work is confined to only single-hop links within a single collision domain. On the other hand, we investigate the more complex issue of multihop networks (in Chapter 3), as well as single-hop networks located across multiple collision domains (in Chapter 4).

Halldórsson et al. provide a different game theoretic analysis of the channel assignment of multiple networks in [62]. Their problem assumes the presence multiple network service providers that each sets up a number of APs over a period of time. The main constraint is that if a new AP lies within the interference range of one or more existing APs (either from the same service provider or other providers), the AP would have to be assigned a non-interfering channel. Under certain conditions, service providers may enter into different bargaining processes to change their pre-assigned channels. Their formulation makes use of a graph coloring game model and they use it to investigate the *price of anarchy* under different conditions and bargaining strategies. The price of anarchy, defined by Koutsoupias and Papadimitriou in [83], relates how far the performance of a (typically non-cooperative) strategy profile departs from that of the socially-optimal (typically cooperative) strategy profile. Although their work provides interesting results on the issue of non-cooperation and bargaining in wireless networks, Halldórsson et al. do not include cases where networks may potentially share a single channel, something that we have done in this thesis.

2.4.2 Game Theoretic Learning

As part of this thesis makes use of a number of game theoretic learning algorithms, this section provides an overview of the relevant works in this area, including how this type of learning has been applied to some network resource allocation problems.

In [112], Blum and Mansour contribute an excellent chapter (Chapter 4) on learning in games, where the actions of other players are not known. In it, they cover the general framework, state-of-the-art and current directions in this area of research. A few different learning algorithms are introduced and some significant results (e.g. equilibrium and complexity analysis) are also discussed. Included in the chapter is the class of regret minimization (or no-regret) learning algorithms which are being used in this thesis. The authors also discuss how learning can be done when even the utilities of some of a player's actions are not perfectly known.

Greenwald, Friedman and Shenker apply game theoretic learning to networking in their work in [58]. They give an extensive treatment of how the particular characteristics of general networks make them unsuitable to be studied using traditional game theoretic methods. For example, players in the network game (which could mean anything from individual networks, links to end-users, depending on the context and model definition) often do not have all the information of the game, such as actions of other players, their payoffs, etc. In addition, some properties of the game, e.g. payoff functions and player population may change over time. These characteristics, along with others discussed in the paper, make applying traditional methods challenging. As a result, they explore the use of learning in games that arise in the networking context. Using numerical simulations, they apply a number of learning algorithms that have been developed in the game theoretic community to the network context, in order to study their performance in the long run. The work also explores issues like the effects of limited information, asynchronous play and speed of the payoff updates.

In this thesis, we apply a number of no regret or regret-minimization learning algorithms to the channel assignment of coexisting independent networks. The attributes of these types of learning algorithms that make them suitable for our problem are, namely, they generally involve simple online computation, they do not require perfect information of the game, and as [58] have shown, variants of the algorithms that incorporate limited information and asynchronicity can be developed. In the next few references, we will review the works that these algorithms are most commonly attributed to. However, our description here will not include the specific workings of the algorithms — this will be left to the relevant sections in the thesis.

In [48], Freund and Schapire describe a learning algorithm that updates the weights of playing strategies using a simple multiplicative rule. They show that using this algorithm, the average difference between a player's utility and that of the best mixed strategy, can be made arbitrarily small. This property has been described as "no-external" regret in common literature [58, 74][112, Chp 4]. In the paper, this result is also used to prove the von Neumann's Minmax Theorem, a well-known theorem in Game Theory. In addition, they show that the algorithm can be used to approximately solve a 2-player zero-sum game. Although the paper relates primarily to such 2-player games, subsequent works have applied the algorithm to games with more than 2 players [59, 74].

Foster and Vohra [47] study a similar *online decision problem*, where a decision maker chooses an action at discrete points in time. The utility obtained by the decision maker depends on the choice of the action, as well as the state of the world at that time. To make meaningful comparisons of different decision schemes, the authors define the notion of "regret". In the paper, the authors also describe an internal regret minimization learning algorithm, that they prove to be able to approach zero regret almost surely when the algorithm is repeated for infinite number of times. The algorithm is applied to a number of different problems — 2-player repeated game, sequence predictions, statistics and finance.

In [66], Hart and Mas-Colell essentially describe a similar algorithm as Foster and Vohra but with emphasis on N-player games. The main result in the paper shows that in a game where all the players use the learning algorithm, the empirical distribution of play will almost surely converge to the set of correlated equilibrium distributions, if the game is played repeatedly for infinite number of times. A *correlated equilibrium*, briefly, is a strategy profile where players choose actions based on a publicly observed signal and where no player will benefit from deviating from that strategy[3]. The authors also discuss the modification of the algorithm to cases where only the payoffs of the actions actually played in the history of the game are available.

There has been some effort in applying learning to the wireless network context. Besides Nie and Comaniciu [111] discussed previously, Han et al. [64] have also applied the no-internal regret algorithm to the cognitive radio problem, where secondary users try to choose the appropriate rates and channel in the presence of other interfering secondary users. Our work in Chapters 3 and 4 represents one of the first attempts at applying these learning algorithms to independent unlicensed band networks like WLANs and WMNs.

[3]A more detailed discussion of correlated equilibrium is outside the scope of this thesis and will therefore not be attempted here.

2.5 Cross-Layer Optimization of Multihop Networks

A key distinction in the performance of wired versus wireless networks lie in the presence of interference among the links in the wireless networks due to the radio frequency (RF) medium. There is a large body of works on improving wireless network performance in the presence of interference. Some of these are based purely on heuristics and others have some theoretical basis behind the solutions. Some of these solutions are applied over a single protocol layer, while others offer a cross-layered approach. In this section, we review a particular group of works that makes use of the theoretical foundation of utility-based optimization, commonly known as Network Utility Maximization. We will place particular emphasis on their applications to multihop wireless networks.

The majority of the works in Network Utility Maximization have their origins in the work by Kelly, Maulloo and Tan in [81]. In this famous paper, the authors show that congestion control algorithms like TCP in the Internet can be viewed as a primal-dual algorithm that solves a maximization problem. The problem consists of the sum of the utilities of the source flow rates, which should be maximized subject to the constraints of the capacities of the links the flows will traverse through. Thus given these constraints, it is possible to optimize the utilization of the network by using feedback mechanisms to signal their violations. Mo and Walrand [105] subsequently show that by defining different utility functions, different types of fairness (e.g. proportional, max-min, etc.) can be enforced.

The work of Kelly, Maulloo and Tan has since been extended in numerous ways, no less than in the wireless domain. For example, in [145], Xue et al. adapt the model to the wireless context by defining the constrained capacity regions of the wireless links using a graph-theoretic model. Specifically, they define constrains on the link capacities using maximal cliques of the contention graph formed by the interfering wireless links. Based on how each link rate affects the other links in the maximal cliques it belongs to, their model provides a natural pricing mechanism that regulates the rates of the end-to-end flows. In addition, they propose a two-tier distributed algorithm that allows the network to essentially allocate the flow rates at the source based on the prices each flow will incur on the way to the destination. It should be noted that though their scheme is distributed, control messages need to be exchanged within the network, e.g. price information to the source nodes.

Tassiulas and Ephremides, in their widely-cited paper [135], study the scheduling of links within a multi-hop wireless network. They develop a scheduling algorithm that always attempts to send packets on links that have the maximum difference between the output and input queues of the sender and receiver respectively. In the paper, they show that this algorithm, commonly known as Maximum-Weight scheduling, is able to support the maximum set of arrival rates of a network without the packet queues becoming unbounded. Such a algorithm is said to be able to support the "maximum capacity region" or to be "throughput optimal".

It was not long before researchers started to combine the congestion control algorithm with maximum weight scheduling, in order that a network can optimally control both the rates of flows entering into the network as well as how the traffic is sent on each link. In [95], Lin and Shroff analyze the joint problem of congestion control and link scheduling. They use an optimization model much like that of Kelly, Maulloo and Tan. The way they define the capacity region (constraints) allows the whole problem to be elegantly decomposed into a number of sub-problems, when it is solved using the commonly-used primal-dual technique. The congestion control is solved as a sub-problem with pricing signals from the network, in the form of either control packets or the queue buffer sizes. An optimal scheduling involves the Maximum-Weight algorithm similar to that proposed by Tassiulas and Ephremides. The algorithm is shown to be able to fully utilize the capacity of the network as well as achieve flow-level fairness.

It turns out that the main challenge in such cross-layer optimization problems is the scheduling component. While the congestion control can be performed in a distributed manner in every flow source, to solve the scheduling optimally requires a global centralized algorithm. In addition, the problem has been proven to be NP-complete. As a result, there is motivation to find suboptimal (and possibly distributed) approximating algorithms that perform with acceptable efficiency losses. Thus, in [96], Lin and Shroff extend their work in [95] by looking at how such suboptimal (or imperfect) scheduling affects the performance of these cross-layer algorithms. They show that even a suboptimal cross-layer algorithm still outperforms a layered approach, where congestion control and scheduling are designed independently. Additionally, they propose a fully distributed joint congestion control and scheduling algorithm for the more restrictive node-exclusive model.

Radunović et al. [118] present a practical implementation that makes use of the theoretical foundation developed by Lin and Shroff. Their work provides an insight to how such cross-layer algorithms can be realized in a practical system. Their system, known as Horizon, allows packets to be routed over multiple paths in an 802.11 wireless mesh network. By implementing Horizon as a layer between the data link layer and network layer, they are able to leave the 802.11 MAC, as well as the TCP/IP layer unmodified. Using an actual testbed, they show that the system is able to route packets around bottlenecks and improve flow fairness by performing load-balancing.

Other variants of cross-layer network optimization have also been developed. For example, congestion control, routing and scheduling [36], routing and power control [109], congestion control and power control [38], congestion control and link rate control [138], among others. More details and examples can be found in the excellent tutorial and overview papers of [39], [55] and [96]. In this thesis, we are interested in cross-layer algorithms involving nodes equipped with multiple radio interfaces, operating on multiple channels. We review 2 significant related work in the following.

Lin, working with Rasool, investigates the issue of joint channel assignment, scheduling and routing in multihop networks with multiple radio interfaces and channels in [93]. They show that direct application of imperfect scheduling algorithms like Greedy Maximal Scheduling and Maximal Scheduling either has too high complexity or has very high efficiency loss. As a result, they develop a 2-step algorithm that first assigns packets to be sent on "good" channels, before performing the scheduling algorithm. Their algorithm is able to achieve a bounded efficiency loss when compared to a hypothetical centralized maximum weight scheduling algorithm. While their work represents one of the first attempts at analyzing cross-layer optimization algorithm for networks with multiple radio interfaces/channels, it does not include the congestion control component. They assume that packets are injected into the network by users at fixed rates that do not change over time.

Last but not least, Merlin, Vaidya and Zorzi [100] propose a joint congestion control, channel assignment, routing and scheduling algorithm for multi-radio, multi-channel wireless multihop networks. Their model is similar to Lin and Rasool, consisting of queues that hold incoming packets which are subsequently assigned to different outgoing channel queues depending on the quality of the channel. Unlike Lin and Rasool, who use explicit information from neighboring nodes to compute channel quality, the authors use the differential backlog between the incoming and outgoing queues to gauge the channel quality. This has the effect of reducing the number of control messages exchanged among the nodes. In addition, they include the congestion control component in their algorithm.

Both of the above works on cross-layer optimization in multi-radio multi-channel networks assume that only one autonomous network is in operation. In Chapter 5, we apply a similar cross-layer algorithm to multiple independent networks and study the effects of non-cooperation on the performance of such an optimization algorithm.

Chapter 3

Channel Assignment for WMNs in a Non-Cooperative Environment

This chapter[1] looks at the coexistence of independent multihop Wireless Mesh Networks (WMNs). We argue that cooperation is difficult in such scenarios. Using non-cooperative game theory, we define a coexistence game model and apply it to study channel assignment in co-located WMNs. In addition, we propose using no-regret learning algorithms that allow WMNs to iteratively arrive at Nash Equilibrium outcomes. Simulation results show that the informed no-regret learning algorithms we have tested converge to a set of Nash Equilibrium strategy profiles. We also show that network information is not critical for games with large number of players.

3.1 Introduction

As described in Section 1.1.2, Wireless Mesh Networks (WMNs) represent a class of multihop wireless networks consisting of multiple wireless routers forwarding data packets to and from a small set of gateways. Each gateway is usually connected via a physical wired interface to the Internet. Wireless clients, e.g. laptops and PDAs, could potentially communicate with each other and the Internet over multiple hops via this infrastructure.

The merits of WMNs as a means of extending coverage and improving performance

[1]Part of the work in this chapter has been presented in the IEEE MASS 2008 [92].

over existing single-hop Wireless LAN (WLAN) access points (APs) have prompted much activity in the research, standardization and business communities. Community wireless mesh networks are being set up in neighborhoods where residents pool together wireless networking resources to enable connectivity to one another, as well as the Internet [25]. Municipal and city councils have also shown interest in setting up city-wide wireless mesh deployments that can serve both the government agencies and residents [56, 137]. In the home, individual users will soon be able to connect up their wireless devices to form a mesh network by using the IEEE 802.11s standard [32].

Despite the advances made in WMNs, several key technical challenges still remain. One such challenge relates to the broadcast nature of the wireless medium. This creates the potential of interference among communicating nodes that reside within the same collision domain. Briefly, if more than a pair of communicating nodes are present in a collision domain, coordination is required to prevent both links from being active at the same time. Otherwise, packet collisions occur. As a result, much efforts have gone into addressing the interference experienced within a single multi-hop network. These include equipping the nodes with multiple interfaces to operate on multiple channels [24, 43, 117, 121, 122], flow rate control using resource allocation [50, 114, 145], link layer solutions [19, 28], even a combination of cross-layer approaches.

In many of the above solutions, only one network is assumed and the concern is regarding interference that arises from nodes within the network. We call this the *intra-network* interference problem. Under such circumstances, nodes can cooperate to achieve the overall optimal performance. This is rightly so, since the nodes engaged in the optimization process (i.e. to get the optimum network performance) are under the same management control. For example, in a municipal mesh network, all the mesh routers are under the control of the city council or contracted company. Even when the routers belong to different users, as in the case of community wireless networks, there is generally an acceptable ethos that all must abide by in order to be part of that community.

In this chapter, we postulate that with the popularity of WMNs, more than one WMN can be deployed within the same locality. Hence, the interference among WMNs under different management control will increasingly become a critical problem. This *inter-network* interference is different from the interference found among nodes belonging to the same network. Since interfering nodes may belong to different WMNs, there is often no mechanism or incentive for them to cooperate. It essentially becomes a competitive environment where networks try to utilize the available resources in a selfish manner, leading to a sub-optimal performance. We term these non-cooperative networks *Independent WMNs*.

Although the intra-network interference problem has been and still is being extensively studied, there are few works looking at the issue of inter-network interference, especially in multihop networks. In this chapter, we are interested in looking at the coexistence issue related to independent WMNs that experience this type of inter-network interference.

Following are the primary contributions of the work presented in this chapter:

- Using non-cooperative game theory, we develop a framework to analyze the coexistence of independent wireless networks that are co-located together. We believe our framework is suitable to be used to model many kinds of interactions, especially in the domain of autonomous networks that have to share the unlicensed band.
- We apply the coexistence game model to a restricted interaction of independent WMNs in a single collision domain and characterize the Nash Equilibrium stability points of the interactions, where all WMNs have no incentive to deviate from their respective strategies.
- Applying no-regret learning, we show how independent WMNs can arrive at NE outcomes without explicit exchange of information among the networks.

3.1.1 Chapter Outline

In the next section, we will take a closer look at the coexistence problem present among independent WMNs. Following that, we provide some background information of non-cooperative game theory in Section 3.3 and highlight the usefulness of game theoretic tools in analyzing and solving this problem. In Section 3.4, we present a generic coexistence game framework that we use to analyze the problem. Using this model, we will apply it to study single collision domain problems. Section 3.5 contains results of simulations conducted to investigate the interaction of WMNs that use game theoretic learning to solve the coexistence problem. Finally, we conclude in Section 3.6.

3.2 Motivation of the Coexistence Problem

In this section, we motivate the need to look at coexistence issues among co-located independent WMNs.

3.2.1 Interference among Independent WMNs

Due to the broadcast nature of the wireless medium, multiple communication links located within interference range of one another will experience degradation of performance if there is no mechanism to coordinate and manage the communication [76]. In single-hop networks, e.g. IEEE 802.11 WLANs, the access point (AP) of the Basic Service Set (BSS) can coordinate the communications among the different links with the stations using mechanisms like RTS/CTS, and Point Coordination Function (PCF). In [20], the authors highlight the increasing problem of multiple WLAN deployments located in the same area. Using actual data of hotspot deployments in major cities, they argue that the presence of multiple independently-managed APs may lead to a "chaotic" environment, where networks experience sub-optimal performance. This has been corroborated by subsequent researchers like Mishra et al. in [103] and Ihmig and Steenkiste in [73].

We believe that as communities of residential users cooperate by linking up their APs, and as Wireless Broadband Providers, city councils and even individuals set up their own WMNs, there may exist more than one WMN in a particular geographic area. Like the WLAN hotspots, these WMNs are independently operated and so have limited mechanisms and few incentives to cooperate. However, the multihop nature of WMNs makes it a different problem to that found in single-hop WLANs. Some of the differences are highlighted below:

Coverage A single WMN consists of multiple mesh routers and wireless clients that covers over an extensive area, compared to a WLAN hotspot. In an area with

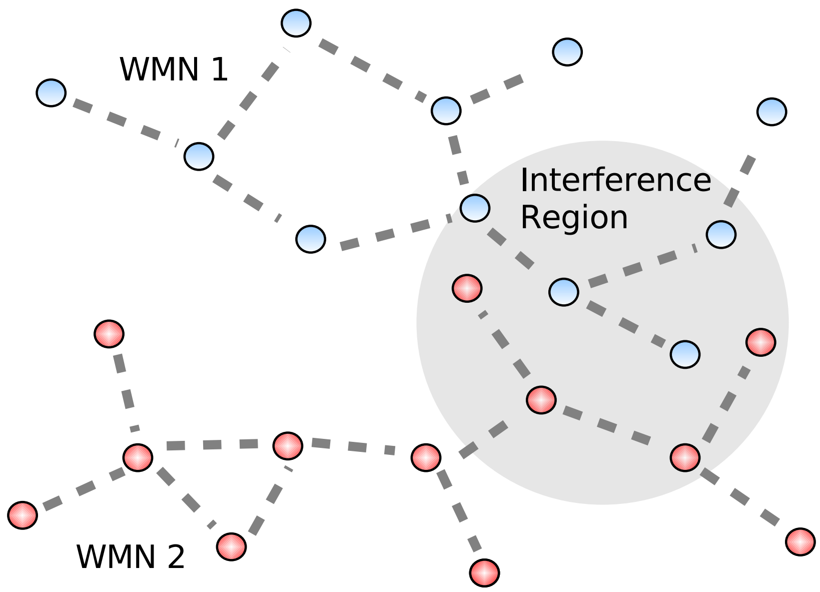


Figure 3.1: Example showing the interference region covering parts of two co-located, independent WMNs.

more than one independent WMN, only a subset of the links of a WMN may interfere with another part of a second WMN. For example, in Figure 3.1, which can represent a city-wide deployment of two independent WMNs, only a subset of the links are within the interference range of one another.

Link Dependency Under normal circumstances, reducing the interference experienced by a link between an AP and station in a WLAN will increase the bandwidth available to the flow traversing that link. In WMN, where a flow may travel over multiple links to reach its destination, reducing the interference on a link may not increase the bandwidth available to the flow. This is illustrated in the example of Figure 3.2. In the example, even though the interference experienced by link 1c is removed when it uses a different channel from link 2b, the bandwidth available to flow f1 in WMN 1 is still constrained by the interference between bottleneck links of 1b and 2a, as they are on the same channel.

In wireless multihop networks, the bandwidth available to a flow is a function of not just the interference between independent flows on different links (inter-flow interference), but also the interference of the same flow with itself on subsequent

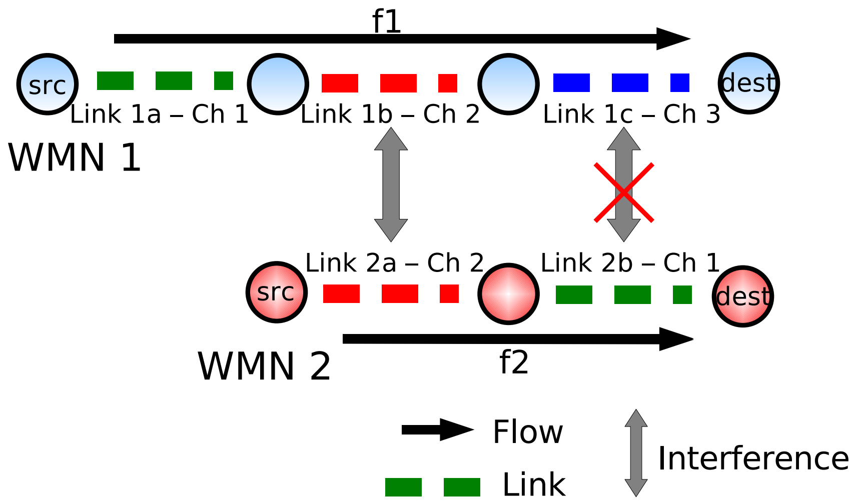


Figure 3.2: Reducing interference by using channel assignment. Flows $f1$ and $f2$ are limited by the bottleneck links of $1b$ and $2a$ respectively.

paths along its route (intra-flow interference). This phenomenon has been studied in [79] and [145]. In co-located WMNs, we assert that the inter-flow interference can be subdivided into two categories — *internal* inter-flow interference and *external* inter-flow interference.

While internal inter-flow interference occurs among independent flows on different links within a *single* WMN, external inter-flow interference relates to the interference experienced by flows from links belonging to *different* WMNs. A distinction between them is needed because the solution needed is very different. The former interference can be managed *cooperatively* using schemes implemented within a network, e.g. rate control, channel assignment and routing. One the other hand, high level cooperation is not available in the case of external inter-flow interference, as the links belong to different independent WMNs. In reality, networks may adopt a selfish approach of trying to get as much resource (e.g. bandwidth) as possible, thereby creating a competitive environment. In addition, the cooperative schemes used to optimize network resources in the presence of internal interferences assume a certain degree of network information available, e.g. size, topology and traffic patterns. A WMN would have less information about other co-located WMNs. For instance, a WMN often do not know the size, topology or even number of co-located WMNs.

We have thus far motivated the need to study the coexistence problem among independent WMNs. We have also illustrated why it is a different and more challenging problem than interference among single-hop networks, or within a single multihop network. We propose game theory as a suitable tool for studying and managing the coexistence problem. We will next present a brief description of game theory.

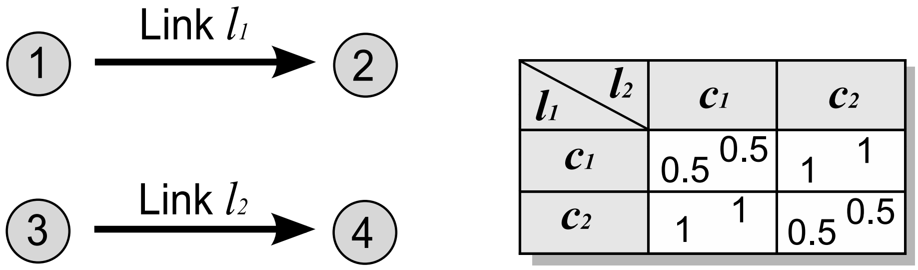
3.3 Non-Cooperative Game Theory

As introduced in Section 1.6, game theory relates to the interactions of decision processes that affect eventual outcomes. Although the vast array of research in this area include among others, non-cooperative and cooperative game theory, we will restrict our description here to the former, as it directly relates to the topic of this thesis.

Before formally describing the classical game model, we will illustrate the basic idea of a non-cooperative game by way of a simple example. Consider a pair of links l_1 and l_2 that are within interference range of each other, as shown in Figure 3.3a. Each link has the option of using either channel c_1 or c_2, where c_1 and c_2 are orthogonal channels. The channel choices correspond to the actions that each link can adopt. Let us assume the links are the players in the game. For each action, there is an outcome or payoff that is associated with the actions chosen by both players. This is the likely benefit that the link will experience if it chooses a particular action, given that the other link independently chooses some action. Figure 3.3b shows the payoff matrix for the corresponding actions. In this case, the payoffs represent the normalized capacities that the links can attain.

From Figure 3.3b, we can see that choosing different channels will allow both links to have higher payoffs, as opposed to operating on the same channel. When choosing different channels, the links do not interfere with each other and so are able to get the full channel capacity, as reflected by the higher payoffs. On the other hand, if both links choose the same channel, they have to share the channel, resulting in lower payoffs.

We now formally describe the non-cooperative game model — otherwise known as the normal form game model — which we will be using in this chapter and the next.



(a) (b)

Figure 3.3: A game example involving (a) two links (l_1 and l_2) belong to the same collision domain and (b) the corresponding payoff matrix of the game. Note that the payoffs of links l_1 and l_2 are in the bottom-left and top-right corners of each cell respectively.

3.3.1 Normal Form Game Model

A normal form game is defined by $\Gamma = \langle \mathcal{N}, \mathcal{S}, \{U_i\}_{i\in\mathcal{N}} \rangle$, where $\mathcal{N}$ is a finite set of players, and $\mathcal{S}$ is the Cartesian product of the set of strategies available to each player in $\mathcal{N}$. That is, $\mathcal{S} = \times_{i\in\mathcal{N}} \mathcal{S}_i$ where $\mathcal{S}_i$ is the set of strategies available to player i. Further, let $N = |\mathcal{N}|$. We denote $S = [s_1, s_2, \ldots, s_N] \in \mathcal{S}$ as a strategy profile consisting of strategies of all the players. $U_i : \mathcal{S} \to \mathbb{R}$ is defined as a utility function of player i that can represent the value player i attaches to the outcome from a strategy profile of S. For a particular strategy profile S, if the strategy used by player i is $s_i \in \mathcal{S}_i$, we collectively term the strategies of the other players as s_{-i}. Hence, $S = [s_i, s_{-i}], i \in \mathcal{N}$. Table 3.1 provides a summary of the symbol definitions.

We will now describe some of the key concepts in game theory that will arise in the course of this chapter.

3.3.2 Nash Equilibrium

A Nash Equilibrium (NE) is a strategy profile where no player has any incentive to unilaterally use a different strategy s_i'. Mathematically, a strategy profile $S = [s_i, s_{-i}]$ is a pure strategy NE if and only if $U_i(s_i, s_{-i}) \geq U_i(s_i', s_{-i}), \forall i \in \mathcal{N}, s_i' \in \mathcal{S}_i$. It should be noted that a NE may involve mixed strategies. Essentially, a NE is an equilibrium point when we assume all players are rational, as no player will see any need to change strategy. In reality, there may exist multiple or no pure strategy NEs in a game. From the 2-link example in Figure 3.3a, channel choices of (c_1, c_2) and (c_2, c_1) are the two NE outcomes of the game.

Symbols:	
Γ	Game
$\mathcal{N}$	Set of players in the game
$N = \lvert\mathcal{N}\rvert$	No. of players in the game
$\mathcal{S}_i$	Set of strategies available to player $i \in \mathcal{N}$
$s_i \in \mathcal{S}_i$	Strategy (or action) chosen by player i
s_{-i}	Collective strategies chosen by players other than i
$S = \left[s_i, s_{-i}\right]$	A strategy profile where all the players each chooses a strategy
$\mathcal{S} = \times_{i\in\mathcal{N}}\mathcal{S}_i$	Set of all possible strategy profiles in the game
$U_i\left(s_i, s_{-i}\right)$	Utility of player i
$q_i(s_i)$	Probability assigned to strategy s_i in a mixed strategy
$Q = \left[q_1, \ldots, q_N\right]$	A mixed strategy profile where all the players each chooses a mixed strategy

Table 3.1: Summary of symbol definitions used in Chapter 3.

For a finite game, it has been proven that even if a pure strategy NE does not exist, a mixed strategy NE can be found. We denote $q_i(s_i)$ as the probability assigned to strategy $s_i \in \mathcal{S}_i$, where $\sum_{s_i\in\mathcal{S}_i} q_i(s_i) = 1$. A mixed strategy profile can thus be denoted as $Q = [q_1, q_2, \ldots, q_N]$. The expected utility of a player i, given a mixed strategy profile of Q, is given by

$$U_i(Q) = \sum_{S=(s_1,\ldots,s_N)\in\mathcal{S}} \left[\prod_{j=1}^{N} q_j(s_j)\right] U_i(S).$$

3.3.3 Pareto Efficiency

A NE outcome, even though it is an equilibrium point, may not be efficient or even desirable. Also, in the situation where there are more than one unique NE outcomes, a way to compare among these outcomes is needed. Pareto Efficiency (PE) or Pareto Optimality is sometimes used as a measure of the efficiency of an outcome. We say that a strategy profile is PE when a player cannot further increase its utility without decreasing the utility of another player. Therefore, the strategy profile S is PE if and only if there exists no other strategy profile S' where $U_i(S') > U_i(S)$, for some $i \in \mathcal{N}$ when $U_j(S') \geq U_j(S), \forall j \in \mathcal{N}, j \neq i$.

Extending from this definition, we further define that a strategy profile is more *efficient* than another, if the utility of at least one of the player is higher while the utilities of the rest of the players are not worse off; i.e., S is more efficient than S' if $U_i(S) > U_i(S')$, for some $i \in \mathcal{N}$ when $U_j(S) \geq U_j(S'), \forall j \in \mathcal{N}, j \neq i$.

3.3.4 Applying Game Theory to the Coexistence Problem

We shall now illustrate how the coexistence problem can be modeled as a game. In the interactions of co-located, non-cooperative networks, each network can be seen as independently making decisions from a set of controls available. The aim of each network is to optimize its performance, such as total network capacity, individual flow bandwidth, etc., with these action choices. Clearly, the performance experienced by each network is affected by the collective actions taken by all the networks within a region. We can therefore model this interaction as a non-cooperative game, where each network[2] constitutes a player, the available controls represent the action set, and the resulting performance mapped to the utility. This fits ideally with the non-cooperative game model that we have just described. In Section 3.4, we will formally define a model of this General Coexistence Game. We will also provide an example of how this model can be used to study the interaction of two WMNs in an interference-limited environment.

However, even though classical non-cooperative game theory concepts can help to provide invaluable insights about the interactions among co-located networks, the assumptions inherent within classical game theory limit how well it can be applied towards the development of practical solutions. For instance, classical game theory assumes common knowledge of the set of players and strategies involved. This is highly unlikely given the distributed nature of independent networks. For example, an independent WLAN would not be aware of all the WLANs that could affect its performance (like the networks that are located beyond its communication range, but are still within the carrier-sensing range). In addition, the utility function and the players in the game change as new WLANs are deployed and old ones are taken down over time. These challenges have also been attested by Greenwald et al. in [58], where they study the application of game theory in the networking environment.

In the next section, we introduce the concept of learning in game theory that can

[2] Alternatively, there could be more than one decision entity within each network.

provide practical channel selection solutions to the independent networks.

3.3.5 No-Regret Learning

Learning in game [112, Ch. 4] allows initially uninformed players to acquire information about the state of the world they are in, as the game is repeatedly played. It can be seen as a relaxation of the tight assumptions of common knowledge in classical game theory. Learning has been applied to networking context in [58], where the authors study what strategies players will play in the long run as they learn more about their environment. The main attribute of game theoretic learning is that information like the number and identity of players in the game and their utility functions is not required by a player for it to play efficient strategies in the long run.

In game theoretic learning, time dependency is introduced in the form of t, where U_i^t denotes the utility of player i at time t. $S^t = (s_1^t, s_2^t, \ldots, s_N^t), \forall s_i^t \in \mathcal{S}_i$ denotes the strategy profile of the players at time t. Note that the strategy s_i^t that is played by player i may not be a pure action. It may arise from a probability distribution q_i^t which denotes the probability of playing each pure strategy $s_i \in \mathcal{S}_i$. Over time, the probability distribution q_i^t will evolve with more favorable strategies taking higher values, as determined by the learning algorithm. In each period, player $i \in \mathcal{N}$, chooses a strategy $s_i^t \in \mathcal{S}_i$ in accordance to q_i^t. Thus, q_i^t is analogous to a mixed strategy of player i at time t. The parameter q_i^t can also be interpreted as a function $q_i^t(s_i)$, returning the probability of playing strategy $s_i \in \mathcal{S}_i$ at time t, which is done in this thesis.

We now describe a class of learning, known as *No-Regret Learning*, which we will be using to solve the coexistence problem in this chapter.

No-regret learning allows a player to play its strategies with certain probabilities. The concept of *regret* involves the benefits a player feels after playing a particular strategy, compared to its other strategies. Those strategies that produce lower regrets will be updated with higher probabilities in the long run. Ultimately, strategies that are more successful will be played more often. There are different algorithms relating to different regret measures and updating methods. We will first describe two such algorithms, attributed to Freund and Schapire [48] and Foster and Vohra [47] respectively. In Section 3.5, we will simulate how WMNs can make use of these two algorithms to solve the coexistence problem.

Freund and Schapire

This algorithm makes use of the cumulative utility obtained by player i over time t if it plays s_i, given that the other players had played s^t_{-i}, for every $s_i \in \mathcal{S}_i$. We denote this as $U^t_i(s_i) = \sum_{x=1}^{t} U_i(s_i, s^x_{-i})$. The weights updating algorithm is such that at time $t+1$, the probability of playing strategy s_i is updated using:

$$q^{t+1}_i(s_i) = \frac{(1+\alpha)^{U^t_i(s_i)}}{\sum_{s'_i \in \mathcal{S}_i} (1+\alpha)^{U^t_i(s'_i)}}$$

for some $\alpha > 0$. At the end of any time t, the algorithm will update the probability distribution (or weights) for $t+1$ accordingly, and proceed to choose the strategy s^{t+1}_i to be played in the next time $t+1$ according to it[3].

This algorithm, which we will call Freund and Schapire (FS), essentially compares the cumulative utility of playing strategy s_i with all other strategies $s'_i \neq s_i$ when other players are playing their own strategies at each time t. We can see that for any strategy that has been performing better up till time t, it will result in a higher probability of playing that strategy in the next time instant $t+1$. Thus, it places higher probabilities on those strategies that give better utilities over time.

In [48], the authors prove that when using this algorithm, the average difference of the utility of a player, when compared with the best mixed strategy can be made arbitrarily small. Hence, one can say that there is no "regret" in using the strategies dictated by this algorithm.

Foster and Vohra

In this next algorithm, we denote the regret r^t_i that player i feels at time t for playing strategy s^t_i rather than s_i, as the difference in the utilities obtained from playing the strategies, given that the other players play the strategy profile, s^t_{-i} ; i.e.,

$$r^t_i(s_i, s^t_i \mid s^t_{-i}) = U_i(s_i, s^t_{-i}) - U_i(s^t_i, s^t_{-i})$$

[3]If the probability distribution q^t_i does not change over time, it is easy to see that the algorithm ensures that the player will choose a mixed strategy as determined by the distribution.

This algorithm, which we will call Foster and Vohra (FV)[4], makes use of the cumulative regret felt by a player i over time t, given by $R_i^t(s_i) = \sum_{x=1}^{t} r_i^x(s_i, s_i^x \mid s_{-i}^x)$ for playing s_i^x rather than s_i. In this case, the probability of playing strategy s_i is updated using:

$$q_i^{t+1}(s_i) = \frac{[R_i^t(s_i)]^+}{\sum_{s_i' \in \mathcal{S}_i} [R_i^t(s_i')]^+}$$

where $[R]^+ = \max(\{R, 0\})$.

While the FS algorithm attributes a strategy resulting in a consistently higher utilities, over time, with a higher associated probability, the FV algorithm compares the difference of this utility with utilities obtained if other strategies have instead been played. Similar to the FS algorithm, the strategy to be used in time $t+1$ will be chosen according to this probability distribution.

Informed vs. Naïve No-Regret

The above learning algorithms are known as informed algorithms. This is because they assume that a player i is able to evaluate how s_{-i}^t, the strategies played by the other players at time t, could affect the utilities of all its strategies, $s_i \in \mathcal{S}_i$, even those that are not being played at that time. When the player is only able to know the utility of the strategy that it has played, a modification to the learning algorithms is needed.

In [58], the authors provide a way to convert an informed algorithm to a naïve one. It involves converting the utility function, U_i to $\widehat{U}_i$, where

$$\widehat{U}_i(s_i, s_{-i}^t) = \begin{cases} \frac{U_i(s_i, s_{-i}^t)}{\hat{q}_i^t(s_i)}, & \text{if } s_i^t = s_i; \\ 0, & \text{otherwise.} \end{cases}$$

The same algorithms could then be used with $\widehat{U}_i$ replacing U_i, and modifying the resulting probabilities q_i^t with $\hat{q}_i^t = (1-\epsilon)q_i^t + \frac{\epsilon}{|\mathcal{S}_i|}$, for some $\epsilon > 0$.

[4]Although strictly speaking, this is a simplified algorithm subsequently proposed by Hart and Mas-Colell [66].

3.4 The Coexistence Game

In this section, we will define a general model of the Coexistence Game. The model is made as general as possible here in order to encompass the different interactions of co-located independent WMNs. It could easily be adapted to more specific interaction scenarios. Subsequently, we will describe a channel assignment coexistence game using this model to study and solve a specific coexistence problem.

3.4.1 The General Coexistence Game

We believe many of the schemes proposed to minimize internal and external interferences can be studied as a game. We define the general Coexistence Game as Γ_g.

In Γ_g, the set of players $\mathcal{N}$ represents the *decision makers* in the independent WMNs. Each WMN consists of a set of nodes or links whose collective actions affect network performance. There are two possibilities of defining $\mathcal{N}$, depending on the entities taking part in the decision making process. In the first case, each WMN has a centralized decision making process, where a single entity within each WMN collects information (e.g. network conditions) from the nodes/links, makes the decisions and directs the nodes/links to act on them. In this case, we represent each WMN as a player. Alternatively, the decision making can be distributed; i.e., the nodes/links within each WMN make decentralized decisions that collectively (as a coalition) seek to optimize the performance of their respective network. In this case, we represent each WMN as a coalition of players where each player is a node/link from the WMN. In this chapter, we will use the centralized process to explain the concepts. Henceforth, the terms network and player will be used interchangeably.

Each player has at its disposal a set of strategies $\mathcal{S}_i$, which may be different for different schemes. For example, when routing is used to direct traffic flows to paths with low interference(as in [133]), $\mathcal{S}_i$ represents the set of routes available. If transmit power control is used to limit the interference of the links, $\mathcal{S}_i$ consists of the power levels a player can assign to each of its links. In this chapter, we use channel assignment as the strategies available, where a strategy s_i represents of the channels associated to player i's links.

The utility function U_i denotes the value player i places on the outcome of a strategy profile S. Player i can be seen as trying to optimize U_i through its choice of s_i in the light of s_{-i} that are played by the other players. One possible way is to express the utility of a WMN as the sum of the utilities of all its individual flows. For instance, let us assume a WMN has flows with rates $r_1, \ldots, r_k$. The utility of this WMN can be expressed as $\sum_{i=1}^{k} u_i(r_i)$, where u_i is some concave function. Note that this type of utility definition is commonly used in network utility maximization [113, 145].

3.4.2 Channel Assignment Coexistence Game

In this section, we apply the general coexistence game, Γ_g to a more specific scenario — channel assignment. We define this as a channel assignment coexistence game, Γ_{ca}. In Γ_{ca}, the player set $\mathcal{N}$ contains the independent WMNs. We define $\mathcal{C}$ as the set of channels available, with $c = |\mathcal{C}|$.

In Γ_{ca}, we will consider multi-radio WMNs, where each node may be equipped with multiple radio interfaces. We focus on channel assignment in this game. In order to simplify the explanation and analysis, we assume that each link within a WMN is bound to a pair of dedicated interfaces, giving us a fixed topology of nodes and links per WMN[5]. This can be accomplished by schemes found in multi-radio WMN architectures like [121]. These links are represented by $\mathcal{L}_i = \{1, 2, \ldots, l_i\}$ for a player i. A strategy s_i of player i assigns a channel $j \in \mathcal{C}$ to each of the link $k \in \mathcal{L}_i$. For now, we assume that the links are unidirectional, i.e., each link has a predetermined transmitter and receiver.

Let $\mathcal{F}_i$ represent the set of flows in player i, where $f_{i,k} \in \mathcal{F}_i$ is the flow originating on link k. In other words, the source of flow $f_{i,k}$ is the transmitter of link k. We restrict each source to one unicast flow. For convenience, we will identify each flow $f_{i,k}$ with its flow rate. Let $x_{i,k}$ be the aggregate flow rate of all the flows that pass through link k, i.e., $x_{i,k} = \sum f_{i,r}$, where $f_{i,r}$ is every flow that has to go through link k to reach its destination.

We now represent the set of links $\mathcal{L}_i$ as the vertices of a contention graph, with an edge drawn between a pair of vertices if the links they represent interfere with each other when they are on the same channel. Each collision domain is represented by a *maximal clique*[6] in the contention graph [76, 145]. Let $\mathcal{D}$ denote the set of maximal

[5]Including processes like interface-link bonding, routing into the analysis involves redefining the strategy space. This is possible although it may increase the complexity of the game and its analysis.

[6]In graph theory, a *clique* is a complete subgraph; i.e., every vertex is connected to every other

cliques, where $d \in \mathcal{D}$ represents the set of links in a game that are in the same collision domain. For a strategy profile S that allocates every link in a game to a channel $j \in \mathcal{C}$, we define $d_j \subseteq d$ where $\bigcup_{j \in C} d_j = d$. In other words, S can be seen as breaking up each maximal clique d, into smaller maximal cliques $d_j, \forall j \in \mathcal{C}$. We will use the term collision domain and maximal clique interchangeably in this chapter.

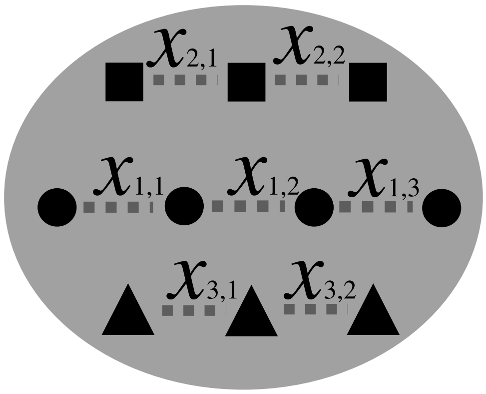
Finally, we assume all the nodes use a common MAC protocol that allocates the rates to the links in each channel collision domain $d_j, j \in \mathcal{C}$, in a max-min fair manner (like e.g. [72]). We also assume there is a transport layer or flow control protocol [145] in each WMN that ensures each link does not transmit more than the aggregate end-to-end flow rates.

Example 1. *To illustrate the notations and concepts described so far, consider 3 WMNs within a single collision domain as shown in Figure 3.4a. $\mathcal{N} = \{1, 2, 3\}$ and the collision domain d contains the links of all the players. There are 3 channels available, $\mathcal{C} = \{A, B, C\}$. Except for the first and last node, each node has two interfaces, one for each link. Suppose flows $f_{1,1}$, $f_{1,2}$ and $f_{1,3}$ flow through all of player 1's, 2's and 3's links respectively. We have $x_{1,1} = x_{1,2} = x_{1,3} = f_{1,1}$, $x_{2,1} = x_{2,2} = f_{2,1}$ and $x_{3,1} = x_{3,2} = f_{3,1}$.*

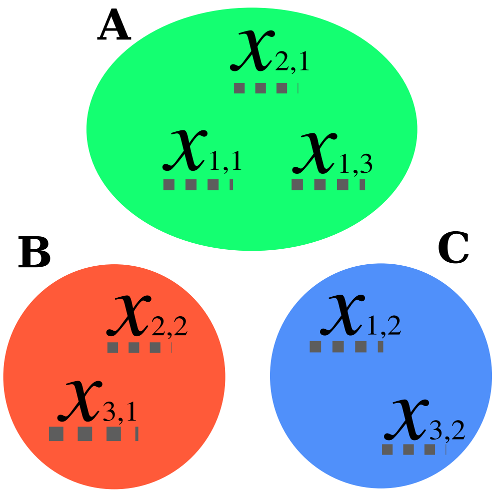
If a strategy profile involves player 1 assigning its links 1 and 3 to channel A, and link 2 to channel C, player 2 assigning its link 1 to channel A and link 2 to channel B, and player 3 assigning link 1 to channel B and link 2 to channel C, d would be broken up into d_A, d_B and d_C, as shown in Figure 3.4b. The rates of flows $f_{1,1}$ and $f_{2,1}$ are $\frac{1}{3}$ each, since $x_{1,1}+x_{1,3}+x_{2,1} = 1$ in d_A. Even though links $x_{1,2}$ and $x_{2,2}$ can use $\frac{1}{2}$ of the bandwidth in channels C and B respectively, a flow control protocol limits them to $\frac{1}{3}$, as the flows $f_{1,1}$ and $f_{2,1}$ are limited by the links in channel A to that rate. A max-min fair MAC allows $x_{3,1}$ and $x_{3,2}$ to get the remaining $\frac{2}{3}$ of the bandwidth. Hence, $f_{3,1} = \frac{2}{3}$. We shall call channel A the constrained channel of players 1 and 2, since it is the channel that limits the rates of their flow. Both channels B and C are player 3's constrained channel.

From Example 1, we can see that the channel assignment choices of the players affect each other's flow rates. If a player's objective is to maximize the rate of its flows, the utility can be defined as $U_i = \sum_k f_{i,k}$. Hence, $U_1 = U_2 = \frac{1}{3}$ and $U_3 = \frac{2}{3}$ in the example. Note that different players in the same game can have different utility functions, depending on objective of each player.

vertex. A maximal clique is a clique that is not contained in any other cliques.



(a)



(b)

Figure 3.4: Example 1 showing three WMNs in a collision domain. (a) Network topology. (b) The 3 channel collision domains after channel assignment.

In the next section, we will use this model to analyze a restricted case of our channel assignment coexistence game. In particular, we want to know what it can tell us about the strategies players should play as well as what they will play, from the perspectives of Nash Equilibrium and Pareto Efficiency.

3.4.3 Single Collision Domain

In this game, we assume that the WMNs have links that are all within a single collision domain, i.e., $|\mathcal{D}| = 1$. Each player i has $l_i + 1$ mesh nodes with each node containing 2 interfaces. There is a single unicast flow ($\left|\mathcal{F}_i\right| = 1$) from a source node to a destination, going through l_i links. The flow is always saturated, i.e., the source tries to send as much traffic as possible. Note that Example 1 described above can be classified as such a game. We call this 2 interface per node, single collision domain, 1 flow per WMN game, $\Gamma_{ca\text{-}2\text{i-}1\text{d-}1\text{f}}$. By starting with this simple scenario, we hope to gain insights into the usefulness of such a model. A future work is to extend this to more realistic and complex scenarios.

Since f_i flows through each of the l_i links, $x_{i,k} = f_i$, $\forall k \in \mathcal{L}_i$. Consider a channel assignment that allows link k to have h_k of the channel capacity. Since $f_i = x_k \leq h_k, \forall k \in \mathcal{L}_i$, it follows that $f_i = \min_{k \in \mathcal{L}_i} h_k$. In other words, the rate of flow f_i is constrained by the channel with the minimum share of the capacity, normalized to 1. We define this as the utility of player, U_i.

Since all the links belong to the same collision domain, each link of player i is indistinguishable from another. A strategy s_i can be simplified to $[l_{i1}, l_{i2}, \ldots, l_{ic}]$ where l_{ij} is the number of links player i has on channel $j, \forall j \in \mathcal{C}$. Hence, $\sum_j l_{ij} = l_i$. Let $L_j = \sum_i l_{ij}$ denote the total number of links on channel j. The total number of links in the game is $L = \sum_j L_j = \sum_i l_i$. We will look at the non-trivial case when $L > c$ and $c > 1$.

We define $\mathcal{C}_{max} = \{j \in \mathcal{C} : L_j = \max_j L_j\}$. In other words, $\mathcal{C}_{max}$ contains the set of channels with the maximum number of links among all the channels. Moreover, we define $\mathcal{N}_{max} \subseteq \mathcal{N}$, where $i \in \mathcal{N}_{max}$ iff $l_{ij} \neq 0$ for some $j \in \mathcal{C}_{max}$. That is, $\mathcal{N}_{max}$ contains the set of players with at least one link in any channel belonging to $\mathcal{C}_{max}$.

Recall that we define the utility of a player i to be $U_i = f_i$, the rate of its flow. As f_i flows through all of player i's links, this also happens to be the minimum share of the bandwidth a player can get from any of its links across all the channels. Obviously, if $i \in \mathcal{N}_{max}$, $U_i = \frac{1}{L_j}$, where $j \in \mathcal{C}_{max}$.

As an example, consider Figure 3.5, where we assume a flow in each player (network) going through all the links; $\mathcal{C} = \{\text{A,B,C}\}$ and $\mathcal{N} = \{1,2,3\}$. Figure 3.6b represents a particular strategy profile where the letter below each column represents a channel and the number in each box represents a link belonging to the player. For players 1 and 2, their utilities are 0.25 each, since they have been constrained by the channel C, where $\mathcal{C}_{max} = \{\text{C}\}$. On the other hand, player 3 is constrained by its two links in the channel A. Since player 1's link in channel A cannot go above 0.25, and we assume a max-min scheduler present, player 3 can make use of all the left-over capacity not used by player 1, resulting in a utility of $(1 - 0.25)/2 = 0.375$.

Nash Equilibrium

We will now look at what constitutes a pure strategy Nash Equilibrium (NE) in the game $\Gamma_{ca\text{-2i-1d-1f}}$.

Proposition 1. *In the single collision domain channel assignment game, $\Gamma_{ca\text{-2i-1d-1f}}$, a strategy profile that results in every channel having either r or $(r-1)$ links, where $r = \left\lceil \frac{L}{c} \right\rceil$ is a pure strategy Nash Equilibrium.*

Example 2. *Consider the networks shown in Figure 3.5, where $L = 4 + 4 + 2 = 10$ and $\mathcal{C} = \{A,B,C\}$ (i.e., $c = 3$). In addition to $\mathcal{C}_{max}$, we define $\mathcal{C}_{min} = \{j \in \mathcal{C} : L_j = \min_j L_j\}$, and $\mathcal{N}_{min} \subseteq \mathcal{N}$ where $i \in \mathcal{N}_{min}$ iff $l_{ij} = 0$, $\forall\, j \in \mathcal{C}_{max}$. That is, $\mathcal{C}_{min}$ is the set of channels with the minimum number of links among all the channels, and $\mathcal{N}_{min}$ is the set of all players with no link in the channels in $\mathcal{C}_{max}$.*

With the strategy profiles shown in Figures 3.6a and 3.6b, the number of links in $\mathcal{C}_{max} = \{C\}$ is $r = \left\lceil \frac{10}{3} \right\rceil = 4$ and the number of links in $\mathcal{C}_{min} = \{A,B\}$ is $r - 1 = 3$. Therefore, these two strategy profiles meet the condition in Proposition 1. Clearly, if the condition in Proposition 1 holds, $i \in \mathcal{N}_{max}$ or $i \in \mathcal{N}_{min}$, $\forall i \in \mathcal{N}$. As we can see from the way the links are distributed in Figures 3.6a and 3.6b, this also results in all the links in the game being spread evenly across the channels. We will call this type of strategy profile a global spreading of links.

We note here that if $i \in \mathcal{N}_{max}$, player i's utility $U_i = \frac{1}{r}$, since it is restricted by its links

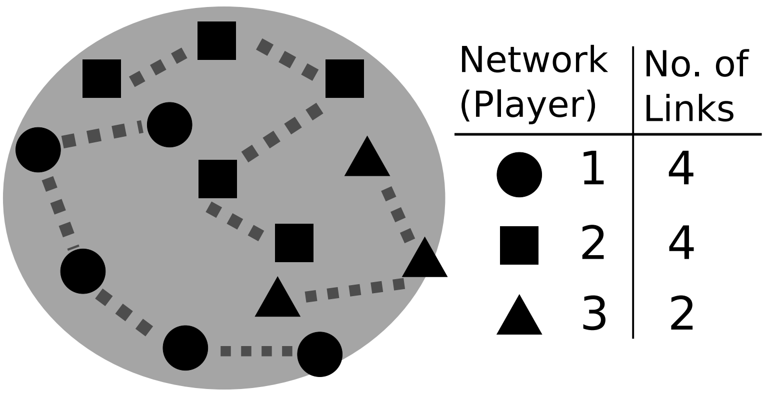


Figure 3.5: Example 2: Three WMNs in a single collision domain.

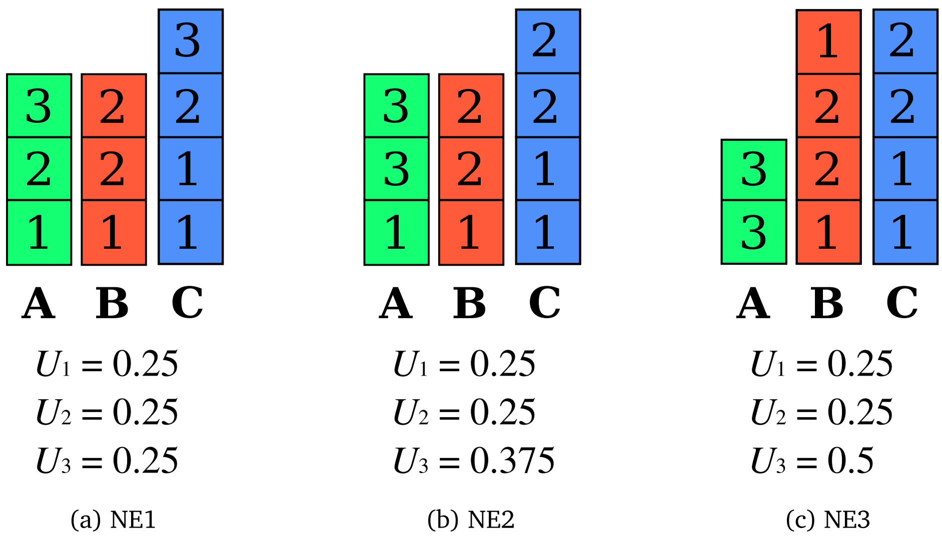


Figure 3.6: Different possible NE channel assignments for networks in Example 2. The letters represent the channels, each box represents a link and the number in the box represents the player the link belongs to.

in some channel in $\mathcal{C}_{max}$. However, if $i \in \mathcal{N}_{min}$, player i's utility $U_i \geq \frac{1}{r-1}$. This is because if all the links in the channels with player i's links belong to players in $\mathcal{N}_{min}$, it can get a utility of $\frac{1}{r-1}$. If in all the channels with player i's links, there exist links belonging to players in $\mathcal{N}_{max}$, player i can get additional bandwidth not used by those players and its utility becomes larger than $\frac{1}{r-1}$.

To prove Proposition 1, we will show that for all $i \in \mathcal{N}$, moving player i's links to another channel will not improve its utility.

Proof. The proof is divided into 2 cases — Case 1: player i belongs to $\mathcal{N}_{max}$; and Case 2: player i belongs to $\mathcal{N}_{min}$.

In Case 1, player i's current utility is $U_i = \frac{1}{r}$. If it moves any of its link from a channel $j \in \mathcal{C}$ to a different channel, it can choose to move this link to a channel $j' \in \mathcal{C}_{max}$ or $j' \in \mathcal{C}_{min}$, where $j' \neq j$. If it moves the link to channel $j' \in \mathcal{C}_{max}$, its new utility will be $U_i' = \frac{1}{r+1}$ which is less than the original U_i. If it moves the link to $j' \in \mathcal{C}_{min}$, its utility becomes $U_i' = \frac{1}{(r-1)+1} = \frac{1}{r}$, which is the same as the original. Either way, player i has no incentive to move its links.

For Case 2, player i's current utility is $U_i \geq \frac{1}{r-1}$. It can choose to move its link in channel $j \in \mathcal{C}_{min}$ to a channel $j' \in \mathcal{C}_{max}$ or $j' \in \mathcal{C}_{min} \setminus \{j\}$. If it chooses channel $j' \in \mathcal{C}_{max}$, its new utility will be $U_i' = \frac{1}{r+1}$. If it chooses $j' \in \mathcal{C}_{min} \setminus \{j\}$, its new utility becomes $U_i' = \frac{1}{r}$. Both are less than its current utility. Therefore, player i has no incentive to move its links.

Since player i does not benefit from changing its strategy, this is a pure strategy NE. □

Proposition 1 is a sufficient condition for the existence of NE. There may exist other NE outcomes that are not global spreading. To describe a necessary condition for the existence of NE, we state the following lemma:

Lemma 1. *For the game $\Gamma_{\textit{ca-2i-1d-1f}}$ with L links and c channels, if there exists a channel j with more than r links, where $r = \left\lceil \frac{L}{c} \right\rceil$, then there always exists a channel $j' \neq j$ such that $L_j - L_{j'} > 1$.*

Proof. We will proof Lemma 1 by contradiction.

The condition in Lemma 1 means that the total number of links, $L = (r-1)c + k$ where $0 < k \leq c$. Hence, $(r-1)c < L \leq rc$. Assuming the lemma does not hold. Then, there exists a channel $j \in \mathcal{C}_{max}$ where $L_j \geq r+1$; and for all other channel $j' \neq j$, $L_j - L_{j'} \leq 1$; i.e., $L_{j'} \geq r$. Summing up the links in all the channels, $L_j + \sum_{j' \neq j} L_{j'} \geq (r+1) + (c-1)r = rc + 1$. Since this is greater than the maximum possible L, it is a contradiction. Therefore, Lemma 1 is true. □

We now state the following necessary condition for the existence of pure strategy NE:

Proposition 2. *In the channel assignment game $\Gamma_{ca\text{-}2i\text{-}1d\text{-}1f}$, a strategy profile that results in at least one channel with more than r links, where $r = \left\lceil \frac{L}{c} \right\rceil$, is not a pure strategy NE.*

In other words, a necessary condition for a NE outcome is that all the channels can have *at most* r links. We can see that the NE outcome of Proposition 1 satisfies this condition. To prove this proposition, we will show that when a strategy profile results in a channel having more than r links, at least one player can increase its utility by changing its strategy.

Proof. Suppose a strategy profile results in $\mathcal{C}_{max}$ channels such that $L_j > r, \forall j \in \mathcal{C}_{max}$. We consider an arbitrary player i with at least a link in any channel in $\mathcal{C}_{max}$. We will refer to those channels in $\mathcal{C}_{max}$ that player i has a link in as $j_1, j_2, \ldots, j_x$. Let us consider the channel j_1. We know from Lemma 1 that there always exists a channel $j' \neq j_1$ such that $L_{j_1} - L_{j'} > 1$, we move a link of player i from channel j_1 to channel j'. If $x = 1$, then the utility of player i has increased by this operation. If $x > 1$, we can repeat the above operation by another $(x-1)$ times. This is possible because Lemma 1 guarantees the existence of a channel which has at least 2 links fewer than those in $\mathcal{C}_{max}$.

Therefore, player i is able to increase its utility, which means that this cannot be a NE strategy profile. □

Hence, we have shown that the necessary condition for a NE outcome is that all the channels can contain at most r links, where $r = \left\lceil \frac{L}{c} \right\rceil$.

Pareto Efficiency

We note that depending on where a player's links are found, a more efficient NE may be possible.

Consider Example 2 shown in Figure 3.5 with possible channel assignments shown in Figure 3.6. Figure 3.6a shows a possible strategy profile (NE1) that results in global spreading, and hence a NE. Each player has a utility of 0.25 since they all have links in the $\mathcal{C}_{max} = \{\mathrm{C}\}$ channel. A different NE strategy profile (NE2) allows player 3 to get a utility of 0.375, as shown in Figure 3.6b. We say that NE2 is more efficient than NE1 as it allows player 3 to get a higher utility without lowering the other players' utilities. Incidentally, Figure 3.6c shows an even more efficient NE outcome that is not global spreading. It can be easily verified that NE3 is also a NE since no player can improve its utility by deviating. Notice that NE3 satisfies the necessary condition in Proposition 2.

From studying this single collision domain example as a game, we find that a way to achieve an equilibrium point is for a network to monitor all the channels to ensure that its channel assignment does not cause any channel to contain more than $\left\lceil \frac{L}{c} \right\rceil$ links. Ensuring that there is a global spreading of the links across all channels will also guarantee a NE. Short of using explicit communication, trying to do so is extremely difficult. In Section 3.5, we describe simulations done to explore the possibility of co-located WMNs arriving at NE outcomes without explicit communication, by using no-regret learning algorithms.

In addition, we learn that there may exist more efficient NE outcomes and it is desirable for networks to reach such outcomes. Again, this is not easy to achieve without explicit communication. We also find that at times, a game can have a social optimal outcome that is not a NE. Briefly, a *social optimal* outcome is one that maximizes the total utility of *all* the players in the game. Consider the game $\Gamma_{ca\text{-2i-1d-1f}}$ with 2 players and 3 channels $\{\mathrm{A}, \mathrm{B}, \mathrm{C}\}$. Player 1 has 3 links and player 2 has 2 links. If the utility of a player is given by its flow rate, it can be shown that a social optimal outcome is realized by player 1 putting all its links in channel A and player 2 putting one link in each of channels B and C. However, this channel allocation is not a NE, because it does not satisfy the condition in Proposition 2. In Chapter 4 we investigate the issue of social optimality in single-hop independent WLANs and propose channel selection schemes that seek to achieve a more social optimal outcome.

3.5 Simulation

From Section 3.4.3, we know that there exist NE outcomes in a single collision domain channel assignment game. In this section, we look at whether players can arrive at these equilibrium outcomes by using learning.

We implement the Freund and Schapire algorithm [48], for both the informed (FSI) and naïve (FSN) cases, and the Foster and Vohra informed algorithm (FVI) [47], described in Section 3.3.5. At every iteration, each player evaluates its utility gained during the previous iteration and uses the algorithms to update the weights associated to its strategies. We compare the two different no-regret learning algorithms (FSI and FVI) to evaluate their respective merits and drawbacks. We also compare an informed version of the algorithm (FSI) with its naïve counterpart (FSN). In addition, we compare how these no-regret learning algorithms compare against a purely random strategy, where each player simply chooses a strategy randomly at each iteration.

In all our simulations, we have chosen appropriate values of $\alpha = 0.2$ in FSI and FSN, and $\epsilon = 0.1$ in FSN. We do not aim to evaluate the performance of different values of α and ϵ here. Essentially, α and ϵ determine how much and how fast an algorithm reduces the probability of playing a strategy when it results in a bad utility. A high α and low ϵ causes larger and faster reduction. As we shall observe from the simulation results, this may mean faster convergence but it also increases the chance of players dropping those strategies that could have formed an efficient strategy profile.

3.5.1 Simulation Results

In this simulation, we have $n = |\mathcal{N}|$ number of players in a single collision domain. Each player has $l_i = 3$ links and there are $c = 4$ available channels. At each iteration, as a player updates its weights, we also record the mean utility that the player has acquired so far. This is done by normalizing the total utility the player has acquired since the start of the simulation with the number of iterations that has gone by.

Figure 3.7 shows a typical simulation run with $n = 2$ players. We present the total mean utility acquired by both players over 6000 iterations. We observe that all the algorithms are able to converge to a fix mean utility. Though not shown, we have also collected the mean utilities for individual players and note that each player is able to get a fair share of the total utility over time.

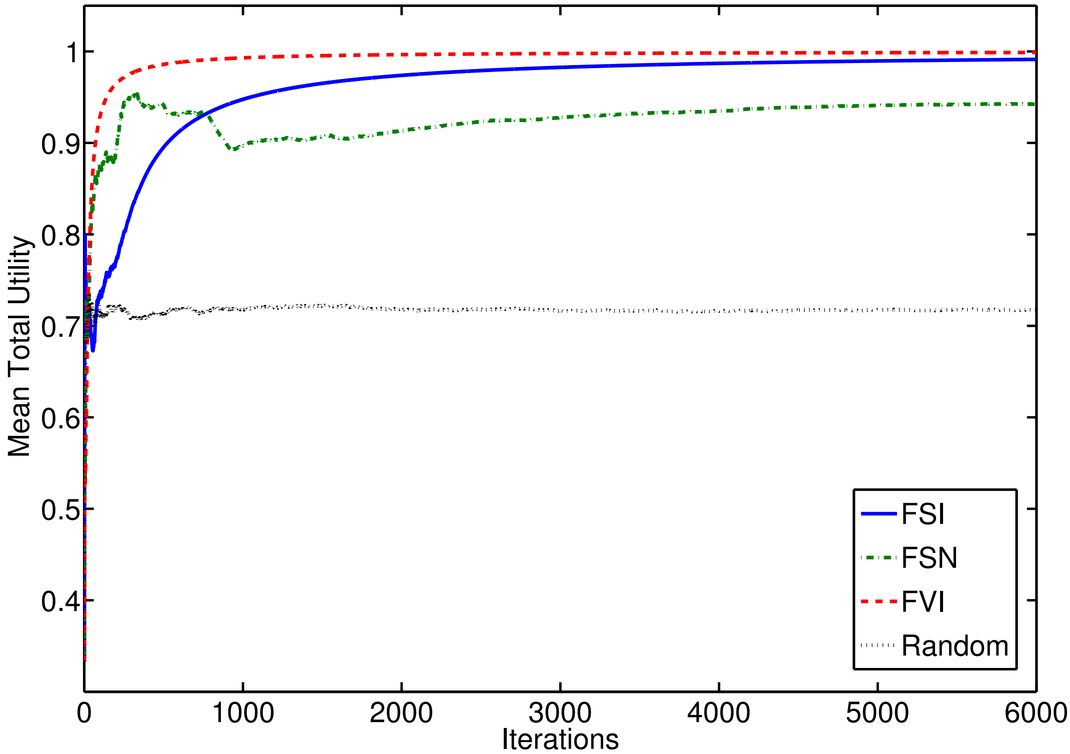
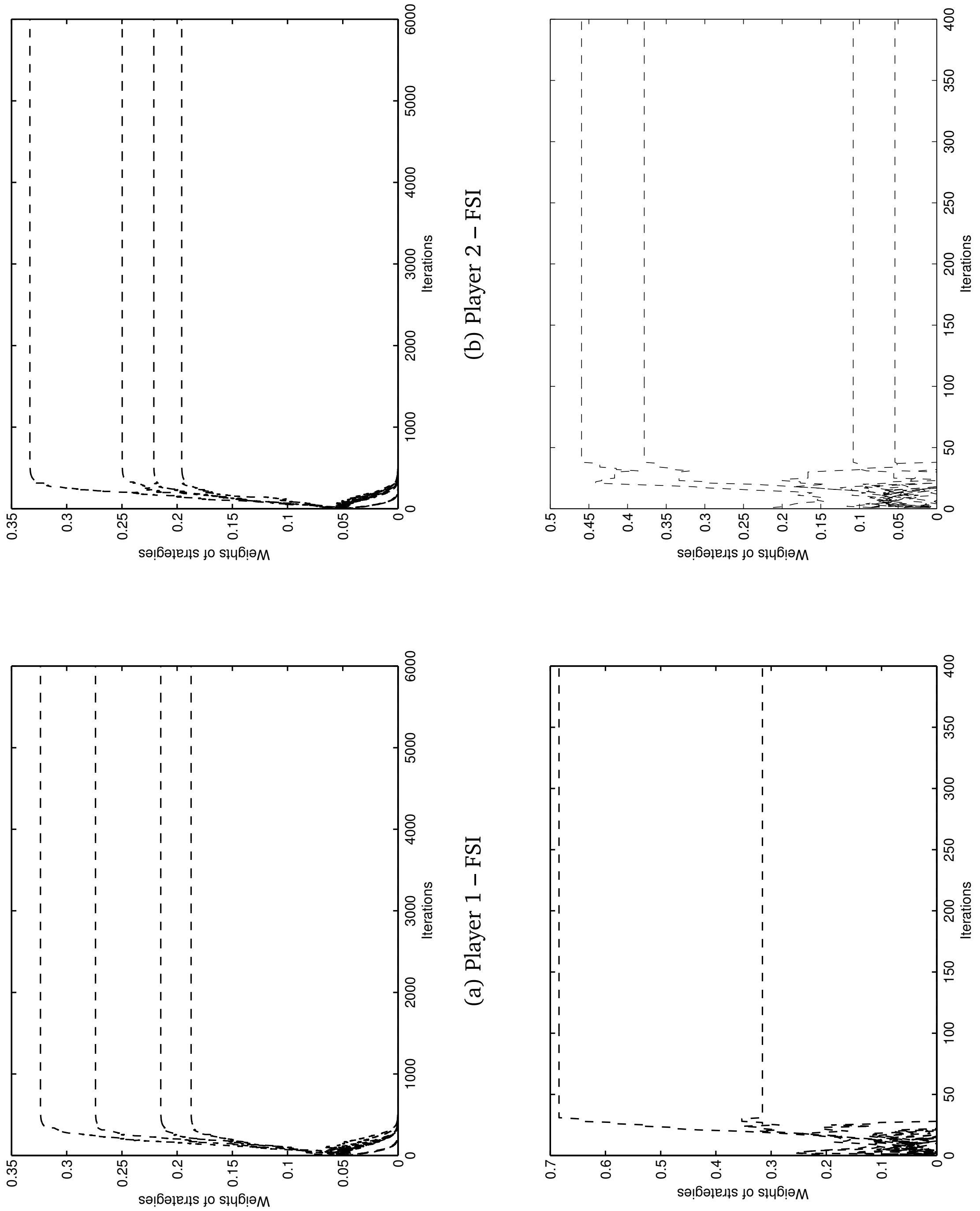


Figure 3.7: Total mean utilities acquired by two players during a typical simulation run.

Comparing FSI and FVI, the two informed no-regret learning algorithms, we see that the players are able to get similar utilities in the long run. FVI tends to converge faster, i.e., seemingly unsuccessful strategies are dropped faster in FVI, resulting in stable, long-term utilities. This is confirmed by Figure 3.8, which shows how the weights associated with each of the player's strategies evolve over time. We observe that in FSI (Figures 3.8a and 3.8b), both players converge to playing a fix set of strategies after about 500 iterations. When using FVI, the players' choice of strategies converges within 50 iterations (Figures 3.8c and 3.8d).

Figure 3.9 shows the proportion of time the NE outcomes occur during the duration of the simulation, computed by normalizing the number of times NE outcomes have occurred with the number of iterations so far. We notice that both the informed algorithms are able to learn to play NE outcomes over time. In all the simulations for multiple players, we find that the set of strategies that each player plays in the long run results in a global spreading of the links across the channels, a NE outcome as described by Proposition 1. With FSN, the players generally are not able to converge to a fix set of strategies to play, resulting in NE strategies only played a certain proportion of the time. Nonetheless, FSN learns to eliminate the strategies that gives low utility for one player whatever strategies the other player play (known as dominated strategies in game theory). In all cases, learning outperforms random choosing of channel assignments in terms of utilities and NE outcomes.

Figure 3.10 shows the total mean utilities of all the players in the game, at the end of 6000 iterations, averaged over 100 independent simulation runs. We investigate the results for $n = 2$ to 5 players. We first note that in the presence of perfect scheduling, where all the players are able to make use of the channel without any collisions or overheads, the total share of the bandwidth (utility) for 2 or more players in a game is $\frac{|\mathcal{C}|}{L} \times |\mathcal{N}| = \frac{3}{|\mathcal{N}| \times 4} \times |\mathcal{N}| = 1.33$. This forms the upper bound on the total utility. We see that the total mean utilities acquired through FSI and FVI are almost similar, especially when the size of the players is small. When there are 5 players in the game, FVI performs better, but with a larger standard deviation. This is because FVI eliminates seemingly inefficient strategies faster. While it decreases convergence time, efficient strategy profiles may also be missed, leading to lower total utility. A player's utility does not just depend on its strategy, but also the corresponding strategies used by other players. The role of learning is to find efficient strategy profiles. If a strategy is dropped before it has a chance to be played against many other strategies, the



(a) Player 1 – FSI

(b) Player 2 – FSI

(c) Player 1 – FVI

(d) Player 2 – FVI

Figure 3.8: Weights associated to strategies over time for two players in a collision domain.

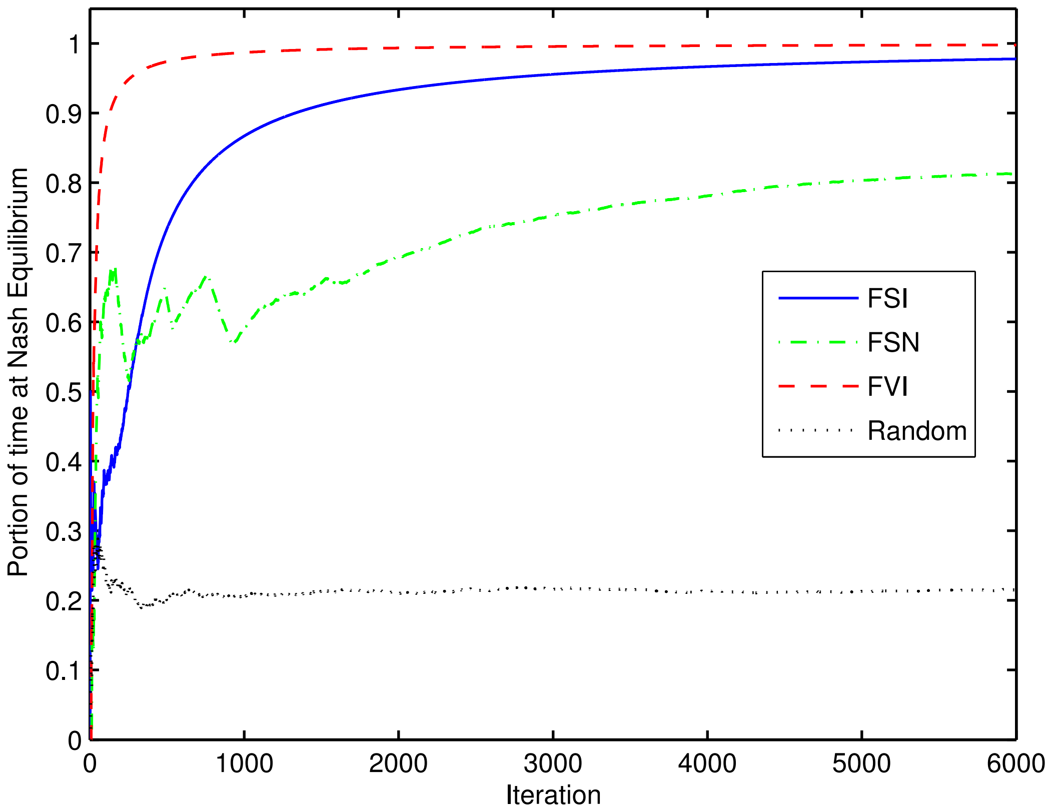


Figure 3.9: Proportion of time a NE strategy profile is played during a typical simulation with two players.

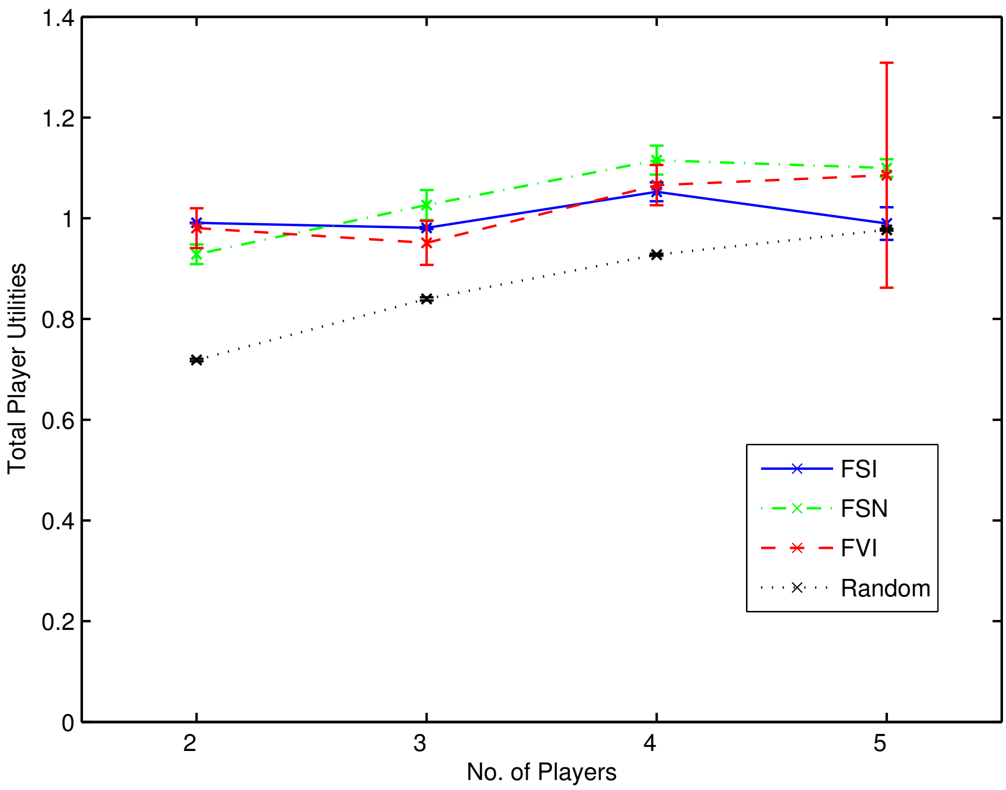


Figure 3.10: Total mean utilities acquired by the players at the end of 6000 iterations, for different number of players.

chance of finding efficient strategy profiles is reduced. Of course, when FVI happens to get a highly efficient strategy profile, it will be played consistently, leading to much higher utility. This accounts for the higher standard deviation.

In comparing FSI with FSN, we notice that as we increase the number of players in the game, the naïve scheme actually performs better. This counter-intuitive observation can be attributed to the fact that in the informed algorithms, the players' strategies converge to a small set of strategies, as demonstrated by the results in Figure 3.8. In FSN, the set of strategies played do not generally converge, though the most inefficient ones (dominated strategies) are eliminated. Therefore, certain players are able to get much higher utilities that are not NE outcomes in some iterations. This accounts for the slightly higher utility in cases where there are larger number of players.

3.5.2 Discussion

We make the following observations based on our simulation results:

1. No-regret learning algorithms allow players in our channel assignment coexistence game to learn to play NE outcomes. Hence, there is a potential for using them to solve the Coexistence Problem.

2. A learning algorithm that converges faster to playing NE strategies is useful in dynamic scenarios, e.g. when the traffic patterns of the networks changes constantly. However, the fast convergence may cause the networks to miss out on some optimal (Pareto efficient) outcomes.

3. A naïve learning algorithm performs worse than informed learning when the set of players is small, as the players do not have enough information to converge to efficient strategies. However, this lack of information may be advantageous when the size of the player set is large.

4. Our simulation assumes that all the players update their weights at the same time. This is unlikely in practical scenario. We will look into the effects of asynchronicity in updates as part of our future work.

5. The game we have studied in this chapter relates to channel assignment with one decision maker within each WMN. Practically, this can introduce delays into the learning and decision process. We plan to investigate the effects of such delays and look into the possibility of a distributed approach, where each link learns and makes the decision.

3.6 Conclusion

In this chapter, we motivate the need to study and manage the coexistence of co-located independent WMNs. Reducing the interference caused by links from other WMNs requires non-cooperative approaches. We propose a non-cooperative game theoretic approach to solve this Coexistence Problem, consisting of a general framework. As an example, we have used the framework to describe a channel assignment game and study a special case of multiple WMNs in a single collision domain. We apply no-regret learning algorithms as a practical means to solve the problem. Simulation results show that no-regret learning allows multiple networks to learn to play strategies that arrive to Nash Equilibrium outcomes.

This work represents just the first step in our look at the Coexistence Problem in WMNs. As such, some of the assumptions and scenarios described in this chapter may seem too idealized. In Chapter 5, we will look at a more realistic interaction of independent multi-radio, multi-channel multihop wireless network where many of these assumptions have been removed.

3.7 Acknowledgement

The work presented in this chapter is supported by the Cooperative Research Centre for Smart Internet Technology.

Chapter 4

Socially Conscious Channel Selection of 802.11 WLANs

In Chapter 3, we modeled the channel assignments of autonomous multi-radio multi-channel WMNs as a game. The chapter also included a framework that models the interactions of co-located, non-cooperative wireless networks belonging to different operating entities. In this chapter[1], we apply the framework to the study of independent uncoordinated 802.11 WLANs. Specifically, we model the channel selection of these WLANs as a non-cooperative game in a learning setting. Using a novel method of acquiring a disruption factor value, we propose a class of socially conscious channel selection schemes based on game-theoretic learning. These schemes are distributed, adaptive and are able to improve fairness without explicit communication among the networks. These features allow the independent WLANs to coexist in an interference-limited but non-cooperative environment. These schemes also have the advantage of not requiring any modification to the existing 802.11 standards. Through simulation, we evaluate our schemes against two existing channel selection schemes.

4.1 Introduction

IEEE 802.11 has become the predominant technology to enable devices like laptops, PDAs and smartphones to access the Internet. As a result, it is not uncommon to have

[1]Part of the work in this chapter has been presented in the ACM MSWiM 2009 [92]

multiple Wireless Local Area Networks (WLANs) deployed in a single locality. This increasingly widespread deployment can potentially lead to degradation of network performances. This is mainly due to the CSMA/CA (Carrier Sensing Multiple Access/Collision Avoidance) mechanism that is used by 802.11-based WLANs to share the wireless medium [53].

One way of improving the performance of multiple WLANs in an interference-limited environment involves making use of the different channels available in the standards. In IEEE 802.11b/g, for example, there are up to 14 channels, with at most 4 non-overlapping channels possible at any given time. IEEE 802.11a has at least 12 non-overlapping channels. Each WLAN could be configured to operate on a different non-overlapping channel. Nevertheless, with the increase in the number of co-located WLANs, the number of channels may not be enough to solve this problem. As a result, some networks need to share the same channel. Given the limited number of channels and the large number of WLANs with varying traffic load, a lot of research has been devoted to developing effective and efficient channel selection schemes. An extensive review of these schemes has been provided in Section 2.3.1.

Apart from locations like a university campus or a corporate office, most WLANs can be characterized as a single Access Point (AP) providing Internet connectivity to one or more clients. These individual WLANs are known as Basic Service Sets (BSSs) in the standards terminology. They are often set up by individuals (e.g. residential occupants, small businesses) and are therefore owned and managed by separate entities. We term these networks *Independent WLANs*. The terms independent WLAN and network will be used interchangeably in this chapter.

These networks generally have the following characteristics:

Uncoordinated They have variable and uncoordinated operating times. Over a longer timescale, new APs may be installed and old ones removed in the same irregular manner. This uncoordinated deployment also leads to uneven density, with more APs located in highly concentrated residential and business areas.

Non-cooperative Unlike enterprise or campus WLANs, these networks do not have any network management software to ensure efficient use of the radio resources, for example, by coordinating channel usage or power control in a centralized or cooperative manner.

With the widespread availability of inexpensive APs, these types of WLANs have seen exponential growth in recent years [20, 63]. Due to their uncoordinated and non-cooperative nature, independent WLANs require channel selection schemes that are *distributed* and *adaptive* in operation, with no explicit control messages exchanged among them.

Another issue with 802.11-based WLANs is the fairness when the networks are deployed over an area spanning multiple cells or collision domains. As described in the previous chapters, in wireless networks, a collision domain is the region where links located within it interfere with one another. In [53], the authors show that, due to the inherent MAC protocol, IEEE 802.11 can exhibit unfairness in such situations. Depending on their locations, some links or even networks can experience much lower throughput performances compared to others. In this chapter, we define them as *starved* links or networks.

Even with an adaptive channel selection scheme, a starved network may not always be able to improve its throughput by unilaterally switching to a different channel. In this chapter, we will show that fairness among independent WLANs can be improved when the other WLANs that are causing the starvation are able to detect this unfairness and take steps to alleviate it. We term these networks as *socially conscious* networks, since they proactively improve the "welfare" of disadvantaged networks.

In this chapter, we propose a class of channel selection schemes that is distributed and adaptive, as well as socially conscious, with the aim of increasing overall throughput performance and inter-network fairness among independent WLANs.

Following are the primary contributions of the work presented in this chapter:

- We propose a class of channel selection schemes based on game theoretic learning, which is practical to be implemented in existing 802.11 networks. Our schemes require no modification to existing standards and hence can interoperate with existing networks.

- We present a *disruption factor* value for each independent WLAN that seeks to inform it of the unfairness it is causing to the surrounding networks. We describe a novel approach to acquire this value that requires no explicit message exchange among the networks. This is essential for independent deployments.

We incorporate the disruption factor into our channel selection schemes to create socially conscious WLANs.

- Through extensive simulations, we show that our schemes achieve higher overall throughput (as high as 30%) as well as better fairness (as high as 17%) when compared to two existing channel selection schemes that are also suitable for independent WLAN deployment.

4.1.1 Chapter Outline

The chapter is organized as follows: In the next section, we briefly discuss the issue of unfairness in 802.11-based WLANs. This is followed by an introduction to a class of learning algorithms based on non-cooperative game theory. These algorithms are used to develop socially conscious channel selection schemes. In Section 4.4, our channel selection schemes are described in detail. We present results of simulations conducted to evaluate and compare our schemes in Section 4.5. Finally, we conclude the chapter with Section 4.6.

4.2 Unfairness in IEEE 802.11

Like all wireless access technologies, transmission of data in 802.11-based WLANs is broadcast in nature. At any given time, if multiple devices within a certain range transmit in the same frequency band, data could be lost as a result of collisions. Therefore, a Medium Access Control (MAC) protocol is needed to manage the access of the channel among these co-located devices. In 802.11, the default and most commonly implemented MAC is the Distributed Coordination Function (DCF) MAC. We will describe briefly the components of the 802.11 DCF MAC that are relevant to this thesis. The interested reader is directed to the actual standards document [7] for a more comprehensive description.

4.2.1 Carrier Sense Multiple Access (CSMA)

CSMA works on the basic principle of "listen before send". Specifically, a device would only transmit on the channel if it is sensed to be not busy. There are two ways that a device can determine if the channel is busy — physical carrier sensing and virtual carrier sensing. In physical carrier sensing, if the radio frequency (RF) energy level that a device has sensed from the channel is above a threshold value, the channel will be deemed as busy. This occurs irrespective of whether the device can decode the actual MAC frame. As a result, another transmitter that lies beyond the communication range of a device (where the frame can be decoded) may still contend with it. The transmitter is said to be within the carrier sensing range of the device. In virtual carrier sensing, upon decoding the MAC frame, the device will be informed that the channel is reserved for the duration of time set in the frame's "duration" field, known as the Network Allocation Vector (NAV). The duration of the NAV usually ensures that an atomic operation of frame exchanges[2] takes place without interruption.

4.2.2 Interframe Spacing

The interframe spacing determines how long a transmitter will wait after the channel has become free, before sending an intended frame onto that channel. In 802.11 DCF MAC, there are 3 different types of interframe space duration:

Short Interframe Space (SIFS) The SIFS allows frames to be sent at the highest priority since it is of the shortest duration. It precedes response frames like data frames after a RTS/CTS exchange, CTS frames and acknowledgment (Ack) frames. As these frames will access the channel faster than other types of frames, it allows the full atomic message transaction to take place with minimal disruption, such as corruption of the response frames as a result collisions.

DCF Interframe Space (DIFS) The DIFS is the typical duration a transmitter waits before sending a frame that starts a new message transaction, e.g. RTS frame or data frame without RTS/CTS turned on. This is longer than the SIFS duration, to ensure, that the new transmission will not disrupt any existing message transaction that is taking place. The transmitter will also wait for the duration of a DIFS before it starts or resumes a backoff countdown (see section on Collision Avoidance below).

Extended Interframe Space (EIFS) Whenever a transmitter experiences error in frame transmission or reception, it replaces the DIFS duration with EIFS. This happens for example, when a frame is received with error caused by interference from

[2]An atomic frame exchange operation is a series of messages that completes the communication process, e.g. RTS-CTS-Data-Ack or Data-Ack.

other stations. The EIFS duration is much longer than the other interframe space durations.

4.2.3 Collision Avoidance (CA)

CA is achieved primarily by the deferring of transmission. Even after a busy channel becomes free, a device that is intending to transmit will not immediately access the channel. Instead, it will wait for a duration of time, using a backoff counter. This duration (calculated in slots) is chosen randomly from a "contention window size" parameter. This simple mechanism serves to reduce the chance of a situation where multiple transmitters try to simultaneously access a channel that has just become free. In the presence of many competing transmitters performing countdown, it is clear that the transmitter that has the smallest backoff counter will get to transmit first.

To further lower the probability of collision, the standards also mandate that for every failed transmission, the contention window size will be doubled before a retransmission is attempted. This is done until it reaches a maximum contention window size value. For instance, in 802.11b, the initial contention window size is 31 slots and it can be increased (doubling in size each time) to a maximum of 1023 slots. Once the maximum contention window size is reached, it will be used either until the frame is successfully transmitted, or when the maximum retransmission threshold is reached. If the retransmission threshold is reached, the frame will be dropped and the contention window reset to its initial value. This mechanism is commonly known as *Exponential Backoff*. This means that in a congested channel, where the chance of frame loss is high, the devices will reduce their channel accessing attempts.

It should also be noted that when the channel becomes busy during the transmission deference phase, the device will stop the countdown of the backoff counter until the channel becomes free again. Once the channel has become free for a DIFS duration, the countdown continues. As we shall see in Section 1.2, this has a significant effect on the unfairness and starvation issues that arise in 802.11-based networks.

4.2.4 Sources of Unfairness

While DCF seeks to ensure some level of fairness within a single collision domain, it has been shown to result in significant unfairness when the stations span over multiple collision domains. This is true regardless of whether they belong to the same BSS, or are associated with different APs. In [53], through detailed modeling and analysis, the authors show that this unfairness is primarily caused by the difference in the channel conditions perceived by the stations. In particular, they highlighted two sources of unfairness:

Information Asymmetry (IA) IA occurs when the transmitters of two links are not in the sensing range of each other, but the receiver of the first link is within the sensing range of the transmitter of the second. This case is shown in Figure 4.1a.

Here, transmitter T2 may transmit even though T1 is transmitting, leading to collision at R1. The situation is further exacerbated by the exponential backoff mechanism in DCF that causes T1 to increase its contention window during retransmission. On the other hand, R2 receives the frame from T2 successfully and there is no increase in the contention window. The end result is that the traffic on Link 1 becomes starved while that on Link 2 remains high.

Flow-in-the-Middle (FIM) FIM occurs when a transmitter is in the sensing range of two or more transmitters that cannot sense one another, as shown in Figure 4.1b.

In this situation, transmitter T2 freezes its backoff counter whenever T1 or T3 is transmitting. T1 (T3 respectively), on the other hand, can keep decreasing its backoff counter when T3 (T1 respectively) is transmitting. In fact, both T1 and T3 can potentially be transmitting at the same time. This results in a much limited transmission opportunity for T2 compared to T1 and T3. Subsequently, traffic on Link 2 becomes starved while those on Links 1 and 3 remain high.

From the examples in Figure 4.1, it is clear that the issue of unfairness in 802.11-based networks is related to the location of the links relative to one another. In the case of independent WLANs, the location of each network is often constrained by the location of the user. E.g. a resident could only set up an AP within the confines of his/her home, or a cafe owner could only set up an AP within the business premises. If a network happens to be situated in a location between two other WLANs that cannot

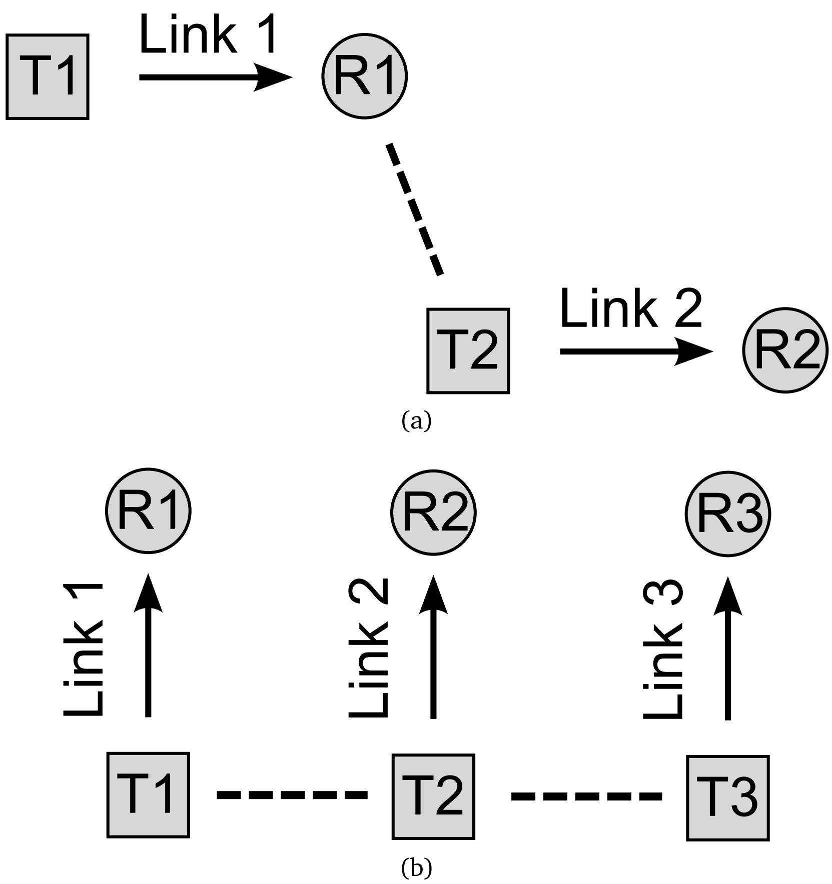


Figure 4.1: (a) IA example: T2 is within the sensing range of R1 (and vice versa) but not T1. (b) FIM example: T2 is within the sensing range of T1 and T3 but T1 and T3 are out of each other's sensing range.

sense each other (a classic FIM case), it is unduly penalized for no fault of its own. In addition, since the source of the unfairness is due to the CSMA/CA mechanism, we believe this phenomenon is likely to appear regardless of the 802.11 PHY layer versions, whether 802.11a/b/g or the more recent 802.11n.

In 802.11 DCF MAC, individual WLANs transmit data in a "selfish" manner, sending as much traffic as is allowed by the rules set about in the standards. One could modify the existing MAC or design an entirely new MAC to achieve fairness, e.g. in [69] and [78]. However, this may result in interoperability issues with existing networks that use the legacy DCF MAC. In this chapter, to ensure interoperability with existing WLANs, we assume that the fundamental 802.11 MAC protocol is unlikely to be changed in the short term. Instead, we will utilize channel selection, a form of radio resource control, to improve the fairness among the WLANs. The existing DCF MAC remains unchanged, since channel selection schemes are not defined within the standards.

4.3 Game Theoretic Learning

In Chapter 3, we assert that non-cooperative game theory is suitable to model the interactions of independent wireless networks, where each network constitutes a *player* and the actions available to the network, e.g. operating channels, transmit power, represent the *strategies* available. We also show that game theoretic learning can be applied to independent wireless mesh networks, to develop practical schemes that are able to achieve better coexistence of these networks. In this chapter, we extend our application of game theoretic learning to channel selection schemes in independent WLANs operating across multiple collision domains.

We will present two different learning algorithms — best response learning and internal regret minimization learning — in the subsequent sections. Unless expressed specifically, the notations here follow closely those in Chapter 3.

4.3.1 Best Response Learning

In best response (BR) learning, the probability distribution of player i's strategies q_i^t is updated in the following manner (assuming no tie among utilities):

$$q_i^{t+1}(j) = \begin{cases} 1, & \text{if } j = \arg\max_{s_i \in \mathcal{S}_i} U_i^t(s_i); \\ 0, & \text{otherwise.} \end{cases} \tag{4.1}$$

Essentially, BR learning (as the name suggests) *always* uses the strategy that yields the highest utility during the last period when the game is played. Many existing channel selection schemes are in fact using some form of best response strategy; i.e., a network periodically chooses the channel that gives the highest utility. Examples of utilities are minimum number of AP peers, lowest network activity and signal-to-noise ratio.

4.3.2 Internal Regret Minimization Learning

While BR learning uses the immediate past period to determine its strategy choice, internal regret minimization (IRM) learning can be viewed as using a history of periods to make the decision. Before describing the IRM learning algorithm, the notion of *internal regret* must first be defined.

At time t, we denote the internal regret R_i^t, that player i feels for playing strategy s_i^t rather than $s_i \neq s_i^t$ as

$$R_i^t(s_i^t, s_i) = \left[D_i^t(s_i^t, s_i)\right]^+ \tag{4.2}$$

where $[\cdot]^+ = \max\{\cdot, 0\}$ and

$$D_i^t(s_i^t, s_i) = \frac{1}{t} \sum_{\tau \le t; s_i^\tau = s_i^t} \left[U_i(s_i, s_{-i}^\tau) - U_i(s_i^t, s_{-i}^\tau)\right] \tag{4.3}$$

The value $D_i^t(s_i^t, s_i)$ can be interpreted as the average difference in utilities a player would have obtained if for every time he had played s_i^t in the past, he had instead played $s_i \neq s_i^t$. In [66], Hart and Mas-Colell introduce an IRM learning algorithm using the following q_i^t updating scheme:

$$q_i^{t+1}(j) = \begin{cases} \frac{1}{\mu} R_i^t(s_i^t, j), & \text{for all } j \neq s_i^t, \\ 1 - \sum_{j \in \mathcal{S}_i; k \neq j} q_i^{t+1}(k), & \text{otherwise.} \end{cases} \tag{4.4}$$

where $\mu > 0$ is a sufficiently large value[3].

Briefly, the IRM learning algorithm of Hart and Mas-Colell updates the probability that a player would switch strategy as a linear function of the average regret. The IRM learning algorithm ensures that as $t \to \infty$, the expected internal regret over the probability distribution q_i^t almost surely becomes zero [66].

One can see that unlike BR learning, a better utility of another strategy in the previous period does not trigger an immediate strategy change in IRM learning. This is because it uses a probability distribution, as well as a regret value that is computed over the history of play.

4.4 Socially Conscious Channel Selection Learning

In this section, we describe how we incorporate the learning algorithms in the previous section into practical channel selection schemes. We also introduce a novel way of detecting unfairness in the network environment that requires no explicit message exchange among the independent WLANs. By adding this capability into our channel selection schemes, we are able to come up with schemes that are socially conscious.

4.4.1 WLANs Channel Selection Game

We first define the WLANs Channel Selection Game. The game is played by a set of players $\mathcal{N}$, where each player $i \in \mathcal{N}$ is an independent WLAN deployed within a predefined area. We assume each WLAN consists of an Access Point connected to the Internet via a wired connection, and a collection of one or more wireless clients. Henceforth, the terms player and WLAN will be used interchangeably in this chapter.

Each WLAN i is able to switch between $|\mathcal{S}_i|$ numbers of channels, where $\mathcal{S}_i$ is the set of channels available. We assume that each WLAN can only be on one channel at any given time. The channel $s_i \in \mathcal{S}_i$ that WLAN i chooses to operate on thus constitutes the strategy chosen by player i from the available strategy set of $\mathcal{S}_i$. Henceforth, the terms strategy and operating channel will be used interchangeably. As mentioned before, the classical way of computing U_i as a known function of the strategy profile

[3] In most cases, it suffices for μ to be $\left|\mathcal{S}_i\right| - 1$, which is the value used in our simulations.

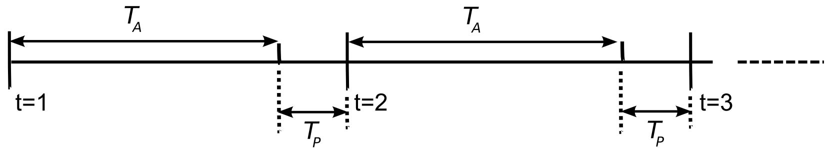


Figure 4.2: Timing diagram of the channel selection game, where each iteration contains an active period of T_A duration and (passive) scanning period of T_P duration.

of all the players in the game is not possible here. Instead, U_i is computed by player i through some measurement process.

This game is played repeatedly through time: $t = 1, 2, \ldots$, where after every $T_A \in \mathbb{R}^+$ period of normal operation, each player i will perform some process for $T_P \in \mathbb{R}^+$ duration, which will determine U_i^t and choose a channel s_i^{t+1} for the next T_A period (shown in Figure 4.2). The operation performed during the T_P period differs for the different learning schemes. Note that we do not assume that the time when the players perform the channel switching operation is synchronized.

4.4.2 Channel Selection using BR Learning (CSBRL)

In the CSBRL scheme, during each T_P period, a player i performs a passive scanning operation of all channels in $\mathcal{S}_i$ where each channel is scanned for t_s time units. In each t_s scanning duration, player i measures ${t_b}_i^t(s_i)$, which is the total time the channel s_i is sensed busy at time period t. Practically, this is the time the clear channel assessment (CCA) function, as defined in the standards, is set to busy within the t_s period.

For each channel scanned, we compute the utility of the channel as:

$$U_i^t(s_i) = 1 - \frac{{t_b}_i^t(s_i)}{t_s}, \forall s_i \in \mathcal{S}_i \tag{4.5}$$

The utility can be seen as an estimation of the fraction of the channel non-busy time. A higher U_i^t suggests that player i could have more opportunity to transmit data on that channel.

With the utilities acquired for each channel, the player updates q_i^{t+1} using (4.1), which is essentially choosing the channel with the lowest channel utilization.

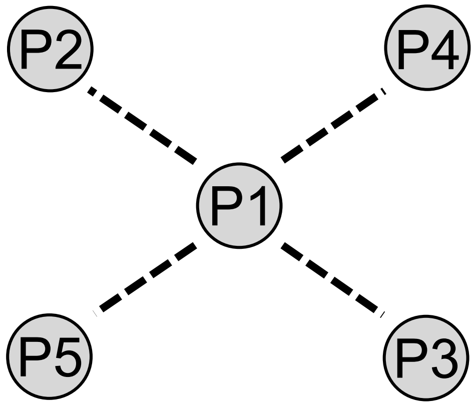


Figure 4.3: Channel Selection Game with $\mathcal{N} = \{\text{P1}, \text{P2}, \ldots, \text{P5}\}$ and $\mathcal{S}_i = \{\text{C1,C2}\}$. Dotted lines denote interference if players are on the same channel.

4.4.3 Channel Selection using IRM Learning (CSIRML)

In the CSIRML scheme, we apply IRM learning to the channel selection process. The scanning process and utility remains as described in (4.5) for the CSBRL scheme. The difference is in the updating of the probability distribution, where (4.2), (4.3) and (4.4) is used instead. At the end of the updating process, the new channel will be chosen over the probability distribution q_i^{t+1}.

4.4.4 Disruption Factor

While most channel selection schemes, including the ones proposed in this chapter so far, allow a starved player to switch to a channel with a higher utility (i.e., lower utilization). The player is unlikely to see any improvement in its situation if no such channel exists. Figure 4.3 provides an example of this case, consisting of 5 players using 2 channels.

One can see that if both channels are occupied by exactly 2 outer players, Player P1 would not be able to get a better utility, whichever channel it chooses. This is because P1 is in a FIM situation in both channels. However, if any of the outer players can detect that P1 is unfairly starved, and switches to the other channel, then P1 could potentially share this channel with the remaining player. In fact, one can do even better. If both outer players switch channel such that only P1 remains in that channel, all players will get maximum performance, since there is now no interference.

The main challenge is to allow a player to detect that it is causing unfairness to some players without exchanging any explicit control messages. That is because in independent WLANs, the players are not likely to cooperate through direct communication. In addition, interference often extends beyond the communication range of a network. Therefore, two interfering networks may not be able to exchange any control messages because they lie outside each other's communication range.

We will now describe a novel way for a player to make this detection, by computing a disruption factor value δ without requiring any explicit interaction among the players. To compute δ, we make use of the fact that during the operation of our channel selection schemes, there is both an active phase, and a passive phase. The active phase occurs when a player is sending data over the channel it has chosen, with duration of T_A. The passive phase occurs when the player is scanning the channel set, with duration of T_P, which is $(|\mathcal{S}_i| \times t_s)$ plus the processing and channel switching times.

During the active phase, a player i can compute the utility when it is actively transmitting on the channel s_i^t using

$$\bar{U}_i^t(s_i^t) = 1 - \frac{T_{b_i}^{\ t}(s_i^t)}{T_A - T_{d_i}^{\ t}(s_i^t)} \tag{4.6}$$

where $T_{b_i}^{\ t}$ is the total time in the duration T_A that the channel is sensed busy by player i and $T_{d_i}^{\ t}$ is the time that player i spent in transmission mode.

For the period t, let

$$\delta^t(i) = \left[\bar{U}_i^t(s_i^t) - U_i^t(s_i^t)\right]^+ \tag{4.7}$$

The value δ thus gives a sense of the difference between the state of the channel activity when player i is participating actively in the medium, compared to when it is not. A high δ value would mean that there is more channel activity when player i is passive compared to when it is active (i.e., a lower U_i^t compared to $\bar{U}_i^t$). This gives an indication that player i may be unfairly causing starvation to one or more other players, due to different perceptions of the channel conditions (e.g. in the FIM case). In Section 4.5.1, we show that δ is able to detect starvation in a FIM setting.

4.4.5 Incorporating Social Consciousness

As defined earlier, a channel selection scheme is *socially conscious* if it enables a player to detect unfairness and to take actions to improve it. Using the disruption factor acquired as described in the previous section, we show how social consciousness can be incorporated into our channel selection schemes.

To enable social consciousness in our schemes, we define a new utility function, $V_i^t(s_i^t)$ which is computed according to Algorithm 1.

Algorithm 1 Compute SC Utility V_i^t

1: **for** $t = 1, 2, 3, \ldots$ **do**
2:   Compute $U_i^t(s_i)$ using (4.5)
3:   Compute $\bar{U}_i^t(s_i^t)$ using (4.6)
4:   Compute $\delta^t(i)$ using (4.7)
5:   **if** $t = 1$ or $s_i^{t-1} \neq s_i^t$ **then**
6:     cumDel$\leftarrow 0$
7:   **end if**
8:   cumDel$\leftarrow$ cumDel $+\delta^t(i)$
9:   **for** every $s_i \in \mathcal{S}_i$ **do**
10:     **if** $s_i = s_i^t$ **then**
11:       $V_i^t(s_i) \leftarrow U_i^t(s_i) - \alpha$ cumDel, where $\alpha \in \mathbb{R}^+$
12:     **else**
13:       $V_i^t(s_i) \leftarrow U_i^t(s_i)$
14:     **end if**
15:   **end for**
16: **end for**

Algorithm 1 can be understood as follows: For every time period, the values $U_i^t, \bar{U}_i^t$ and the disruption factor δ are computed. As long as a player continues using a channel consecutively, each δ is added to a cumDel value (line 8). The cumDel value can be viewed as the cumulative effect of a player's disruption factor and it gets larger the longer this player stays on a particular channel. This counter is reset to 0 when a player chooses to switch channel (line 6).

The utility of the current channel is discounted by a factor α of this cumDel value, while those of the other channels remain unchanged. The effect of this is to penalize a player for continuing to use a channel that it is causing disruption to (i.e., consistently having a high δ). U_i^t will be substituted with V_i^t in either (4.1) or (4.3) to compute the probability distribution for BR Learning or IRM Learning respectively. We will term the socially conscious schemes Channel Selection using BR Learning with Social Consciousness (CSBRL-SC) and Channel Selection using Internal Regret Minimization Learning with Social Consciousness (CSIRML-SC) respectively.

Note that the value α determines how much a player is conscious about its disruption to other networks. When $\alpha = 0$, CSBRL-SC is essentially CSBRL and CSIRML-SC is CSIRML. We investigate the effect of this SC factor α in Section 4.5.2.

4.4.6 Discussion

This section discusses a number of issues related to the learning algorithms and channel selection schemes described in this chapter.

Implementation Issues The channel selection schemes can be implemented by updating the firmware of the AP. Compared to some client-based channel selection schemes, our schemes do not require modification at the client end. In addition, the DCF MAC remains unchanged. Our schemes therefore can easily interoperate with legacy 802.11 system.

The channel switching time of WLAN hardware has dropped consistently with every generation of chipsets (e.g. $25\mu s$ in [99]). This has resulted in the lowering of the channel switching cost. Additional delays due to the re-association of clients to the AP at the new channel can be reduced by using the Channel Switch Announcement management frames defined in the standards.

Comparison with NUM Our schemes bear some similarities with the Network Utility Maximization (NUM) approach of managing network resources [39]. In NUM, every decision maker seeks to optimize some objective function based on feedbacks received from the system in the form of shadow prices. These feedbacks usually involve some explicit communication among the decision makers. This communication cannot be assumed in the setting of independent WLANs. In our socially conscious (SC) schemes, feedback takes the form of the disruption factor. Explicit communication is absent and a player tries to infer the system condition by passive monitoring. An interesting extension to this work would be to compare quantitatively the performance of NUM with our SC schemes. This is left as future work.

Enforcing Social Consciousness It remains unanswered what would motivate a WLAN to implement a SC scheme, especially if the higher system fairness comes at the cost of a lower personal throughput. The answer to this question may appear to border on the philosophical side, akin to asking why a rich person would be motivated to be generous. In fact, it may be possible to design a system where independent WLANs have incentives to be socially conscious. This falls into the area of *mechanism design* in game theory and is beyond the scope of this thesis. It suffices to point out here that in independent WLANs, a network often has no control over whether it is in a position of starvation or not. It makes sense to be socially conscious and hope that other networks do likewise. In addition, our simulation results show that besides improving fairness, our SC schemes perform better than their non-SC counterparts in terms of the aggregate network throughput.

Informed vs. Naïve Learning As a result of scanning all the channels in each iteration, the IRM Learning algorithms in this chapter provide a player with an idea of what utilities it could have gotten if it had played the other strategies during that period. The difference in these utilities is used in the regret computation. This is known as *informed* learning, as defined by Greenwald et al. in [58]. As we have done in Chapter 3, the algorithms can be modified into *naïve* learning, where the player has no knowledge of the utilities of its other strategies in that given period. This will reduce overheads as no scanning of other channels is needed, but may degrade performance as the information available becomes less accurate. Comparisons between informed and naïve IRM Learning, as well as the partially-informed version (where a player only scans a subset of channels) will be part of our future work.

4.5 Performance Evaluation

In this section, we present results of simulations conducted to evaluate the performance of our channel selection schemes. All the simulations have been conducted on the Qualnet simulator [129], allowing us to evaluate the performance using realistic channel conditions. In addition, the 802.11 DCF MAC and PHY layers have been realistically implemented in the simulator. We build our channel selection schemes on top of these layers to illustrate their backward compatibility with existing WLANs. Since as highlighted in Section 4.2, unfairness results from the MAC protocol, we use

802.11b PHY without loss of generality.

In evaluating the channel selection schemes, we run a total of 20 random topologies for each simulation set. Unless stated otherwise, the following parameters apply to all the simulations. In each topology, 10 WLANs are deployed with each WLAN consisting of an AP and 4 clients. There are 3 channels available for selection. Each WLAN appears randomly in time at the beginning of the simulation and begins the channel selection process. Since most clients currently attached to APs are mobile devices, the predominant traffic are downlink flows originating from the Internet [107]. Therefore, application data packets of size 1460B flow from every AP to each of its clients, with each flow lasting 2000s.

To evaluate the performance, we look at 3 different metrics:

Fairness To investigate overall system fairness, we compute Jain's fairness index [77], given as $\left(\sum x_i\right)^2 / \left(n \sum x_i^2\right)$, where x_i is the application throughput of each flow i of the n flows in the system. A number that is closer to 1 signifies that the WLANs are able to achieve a better fairness.

Aggregate Network Throughput The total application throughput of all the networks in each simulation run tells us how well the various schemes utilize the channel resources.

Minimum Flow Throughput As we are interested in the performance of the starved networks, the minimum flow throughput captures the performance of the worst-performing link in the simulation.

4.5.1 Evaluation of Disruption Factor δ

We first evaluate the effectiveness of the disruption factor δ to detect the unfairness in the network region through passive scanning. We deploy 3 links in the configuration of Figure 4.1b. At the beginning of the simulation, only links 1 and 2 are active, transmitting saturated traffic. During this time, both links should experience similar throughput as they share the channel equally. After about 1000s, link 3 starts transmitting saturated traffic, resulting in link 2 being starved. At the end of each interval ($T_A = 60$s) of actively sending traffic, the links will passively scan the channel for t_s, after which δ will be computed. We vary t_s to investigate the effect of passive scan time on δ.

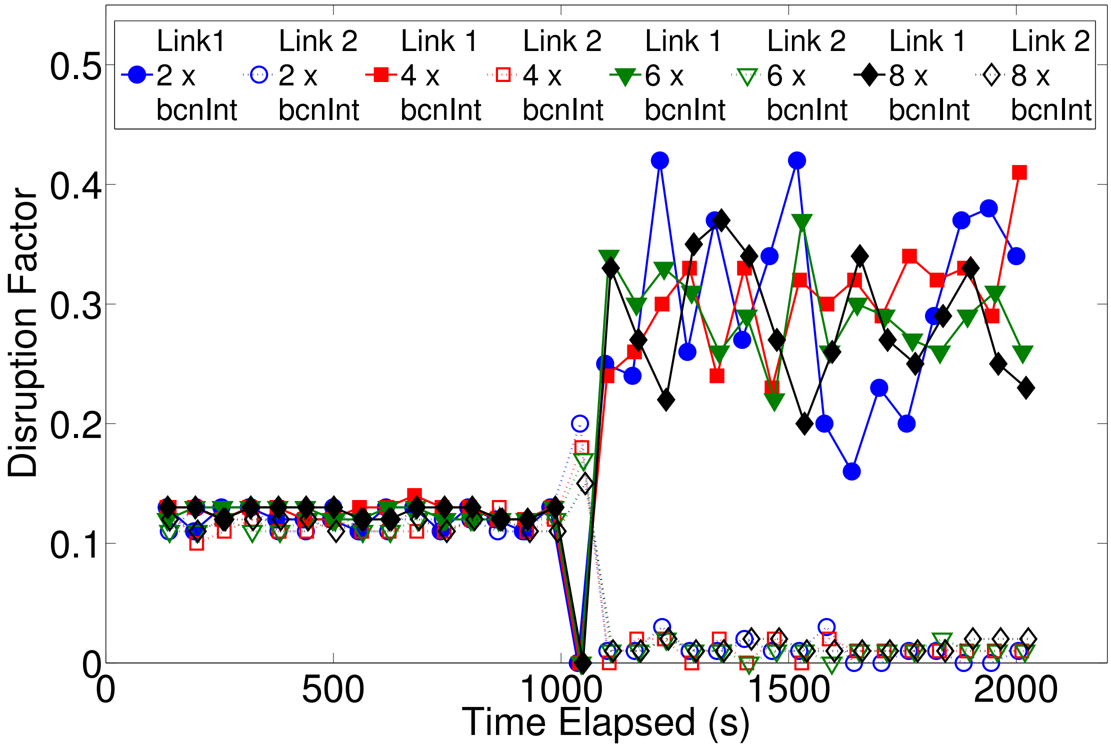


Figure 4.4: The change in the disruption factor over time (Links 1 and 2), for different t_s.

Figure 4.4 shows the change in the disruption factor of links 1 and 2 over time, for different t_s, varying from 2 to 8 beacon intervals[4] of around 200ms in duration. We can see from the figure that for link 1 (the outer link), there is a marked increase in the disruption factor when link 2 becomes starved. At the same time, link 2's disruption factor decreases. This is a desired outcome, as it means that a starved link will not try to be socially conscious.

We can also observe that the value of t_s has minimal effect on the disruption factor. A smaller t_s only results in a marginally larger variance in the disruption factor. This is also a favorable outcome, as the higher t_s is, the more time a network would have to spend doing passive scanning, which leads to lower throughput. For the rest of our simulations, we set t_s to be (2×beacon interval).

[4] A beacon frame is a management frame transmitted periodically by an 802.11 AP. A beacon interval is the time between successive beacon transmissions.

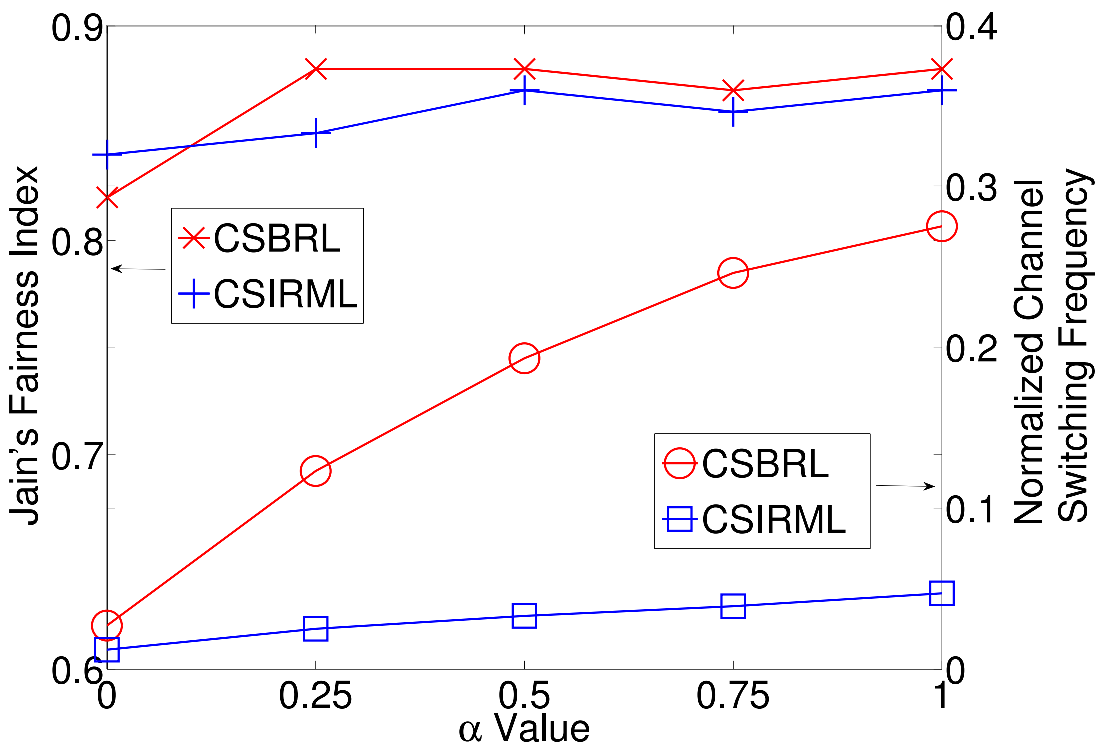


Figure 4.5: Throughput fairness (top 2 lines, left axis) and channel changing frequency (bottom 2 lines, right axis) for different α.

4.5.2 Evaluation of SC Factor α

We next investigate the effect of the SC factor α on the channel selection schemes we have proposed. As discussed in Section 4.4.5, α is directly linked to how fast a player reacts to the disruption it detects in its environment. An α value of 0 means that the player is not socially conscious at all. We compute the Jain's fairness index and channel change frequency for the networks deployed over a 1000m by 1000m area, shown in Figure 4.5.

From Figure 4.5, we can see that increasing α has the effect of improving the fairness among the networks. With social consciousness, the BR Learning scheme achieves higher throughput fairness compared to IRM learning. The tradeoff is in the channel change frequency, which represents the number of times the respective schemes trigger a change in the channel, normalized over the total number of iterations. BR learning with social consciousness results in about 5 times more changes in channel. This is to be expected, since BR learning immediately triggers a change in strategy whenever it acquires a higher utility for another strategy. This high rate of channel switching may not be desirable, as there are always costs associated with a WLAN changing its operating channel.

From the simulation result, we set the value of $\alpha = 0.5$ as the SC factor for both the CSBRL-SC and CSIRML-SC schemes in all subsequent experiments.

4.5.3 Comparison with Existing Schemes

We now evaluate the performance of our schemes against two existing channel selection schemes described in Section 2.3.1 — Hminmax [101] and No-U [35]. These 2 schemes are chosen for comparison because they do not require any explicit communication and coordination among the WLANs, and thus are suitable for use in independent WLAN deployment. They have also been shown to perform better than other existing schemes [35, 101].

Offered Load

We deployed the WLANs in a 1500m by 1500m area and varied the offered load for each AP-client link from 0.5 Mb/s to 2.5 Mb/s. Figures 4.6, 4.7 and 4.8 show the throughput fairness, aggregate throughput and minimum link throughputs of the different channel selection schemes for varying offered load.

At low traffic load, no starvation is taking place as the channels are under-utilized. Consequently, all schemes perform similarly. As the networks become more congested, unfairness becomes noticeable. Hminmax performs less well compared to the other schemes in terms of fairness, aggregate throughput as well as minimum flow throughput. This shows that information from neighboring networks that are within the communication range is not sufficient. Across the varying offered loads, we find little difference among the fairness and aggregate throughput results of CSBRL, CSIRML and No-U (within 3% difference), even though No-U requires the additional complexity of client feedback.

When we incorporate social consciousness into our schemes, we observe that CSBRL-SC and CSIRML-SC increase the system fairness (Figure 4.6) compared to their non-SC counterparts. In fact, the SC schemes result in a slightly higher aggregate throughput than their non-SC counterparts, as shown in Figure 4.7. We believe this can be

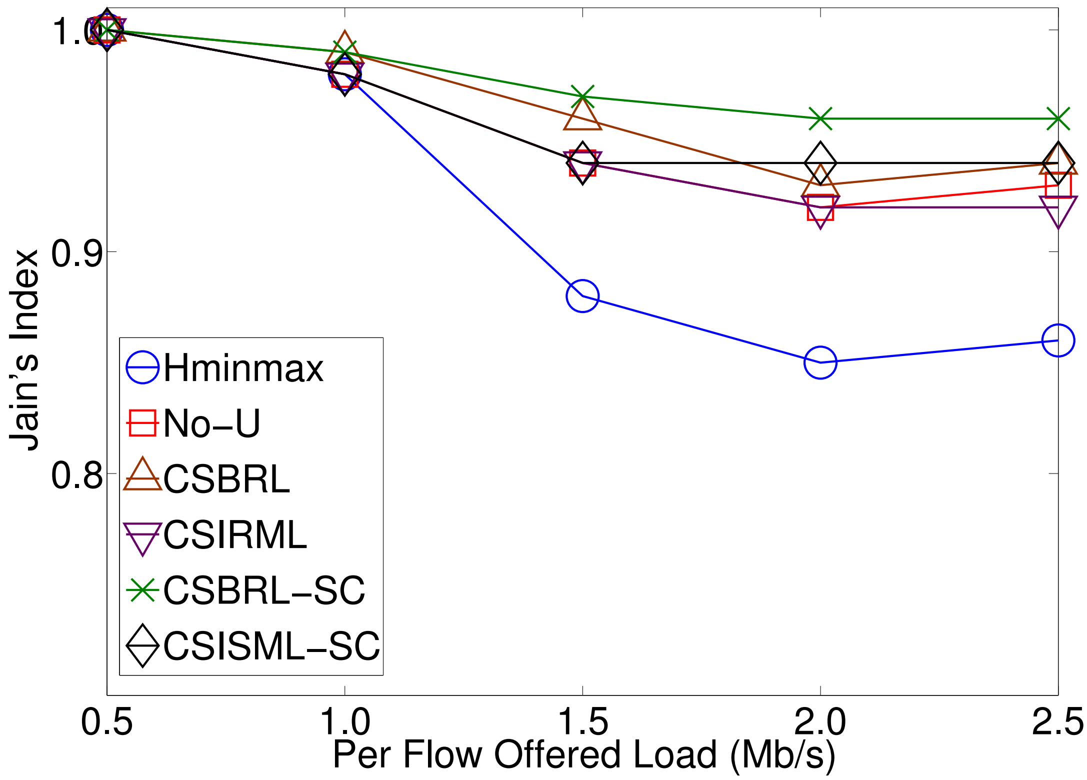


Figure 4.6: Throughput fairness for different offered load.

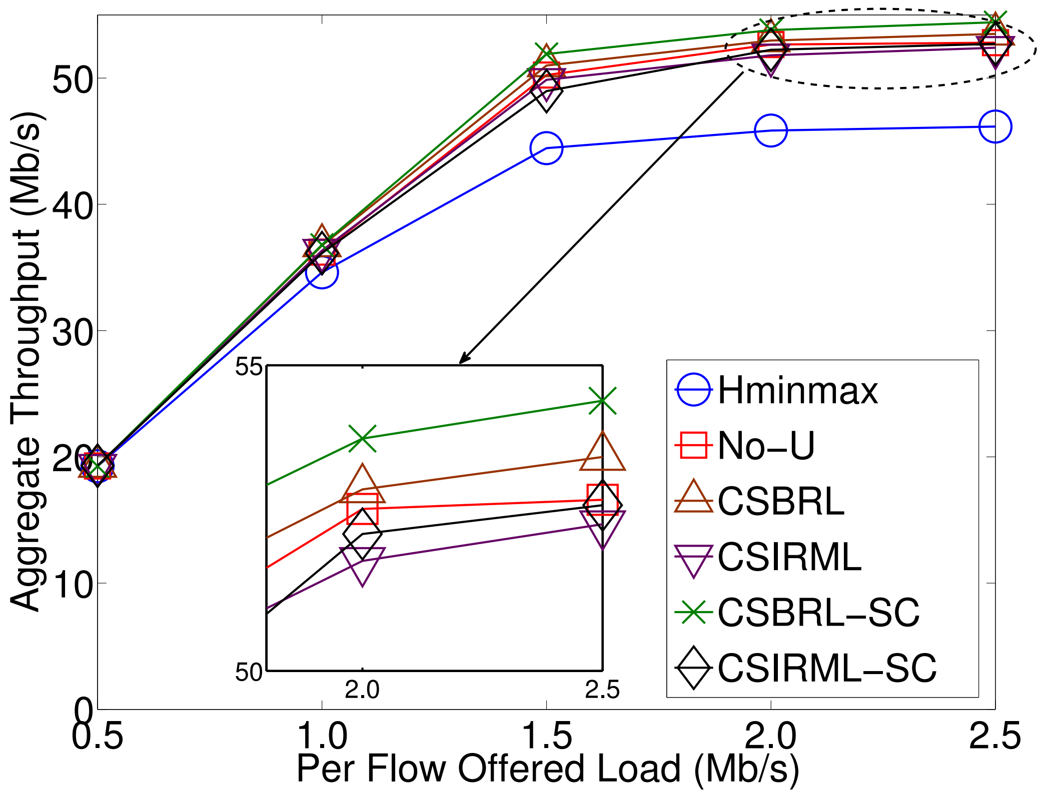


Figure 4.7: Aggregate throughput of the networks for different offered load.

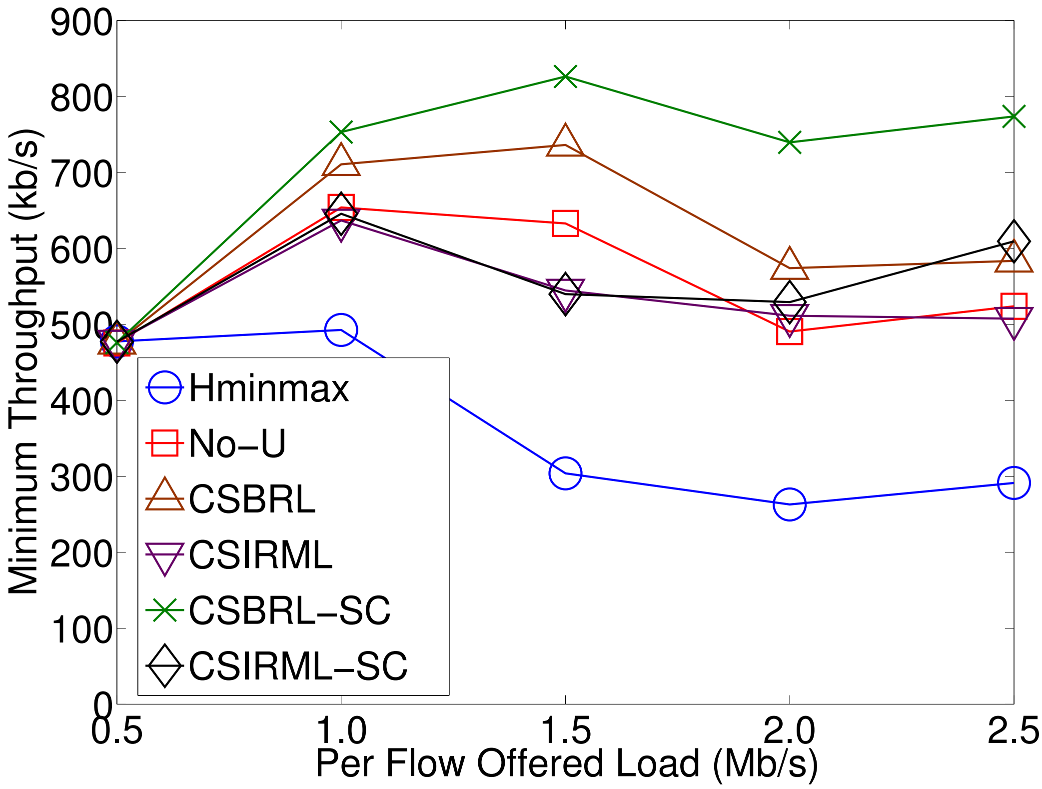


Figure 4.8: Minimum flow throughput for different offered load.

explained by cases similar to the example of Figure 4.3. Finally, the SC schemes prevent starvation by providing a much higher minimum throughput compared to the other schemes (Figure 4.8), as high as 180% when comparing with Hminmax and 50% when compared with No-U.

Since the SC schemes outperform their non-SC counterparts, only the results comparing the SC schemes with Hminmax and No-U will be shown in subsequent sections.

Network Area Size

Figures 4.9, 4.10 and 4.11 show the same triplet of performance metrics as the area where the WLANs are deployed is varied from 500m by 500m to 1500m by 1500m, with saturated traffic in all links. This gives an indication of how the different schemes perform with respect to how close the WLANs are located. In addition, the chance of uneven distribution across the area increases with the increase in the size of the deployment area. This situation is similar to actual deployment, as some areas (e.g. residential) will see a higher density of WLANs compared to others (e.g. a nearby park).

From the figures, it can be seen that the SC schemes outperform the existing schemes by as much as 12% in terms of fairness and 10% in terms of the aggregate throughput. The minimum flow throughput also increases by as much as 2.6 times.

Number of Channels

As the total number of channels provided for WLANs may vary depending on the standards (IEEE 802.11b/g or IEEE 802.11a), we evaluate our schemes with respect to the number of channels available. In our simulations, we deployed 24 WLANs consisting of an AP-client connection in a 1000m by 1000m area. The simulation time is extended to 4000s. As the number of available channels increases, we would expect an effective channel selection scheme to have better fairness and overall throughput. This is because the increased number of channels reduces the chance of networks interfering with each other.

Figures 4.12, 4.13 and 4.14 show the network fairness, aggregate and the minimum per-link throughput for different numbers of available channels. The figures show again that the SC schemes result in a higher fairness among the networks, as high

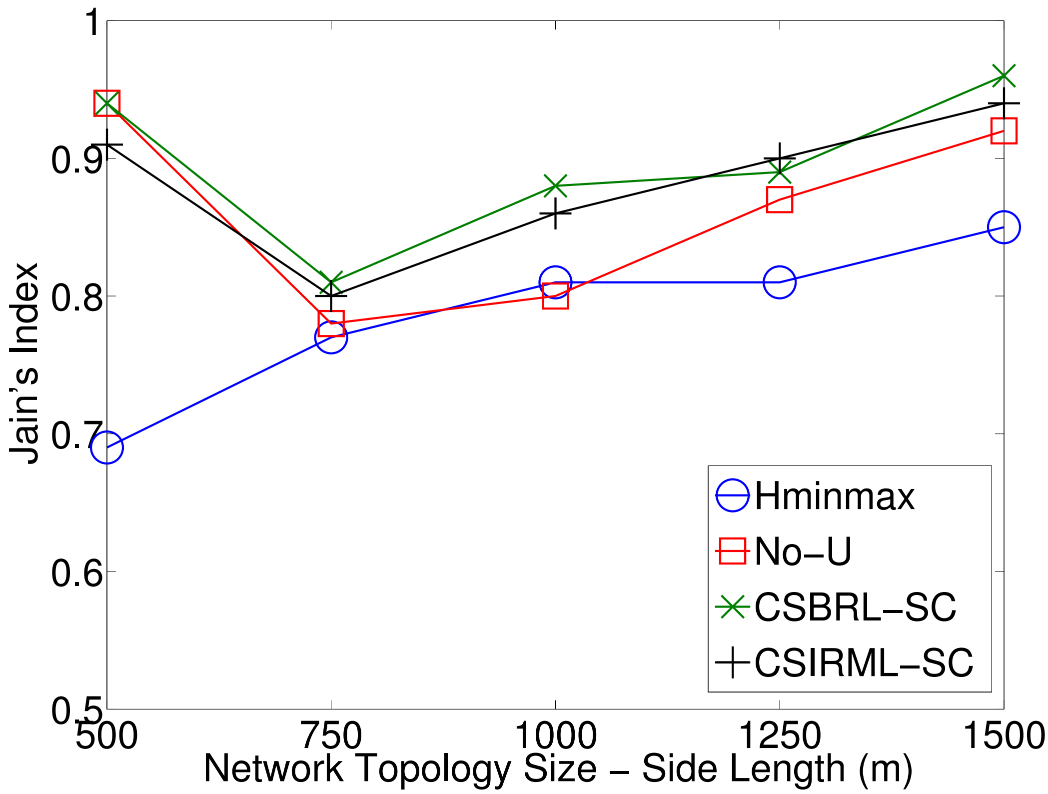


Figure 4.9: Throughput fairness for different network area size.

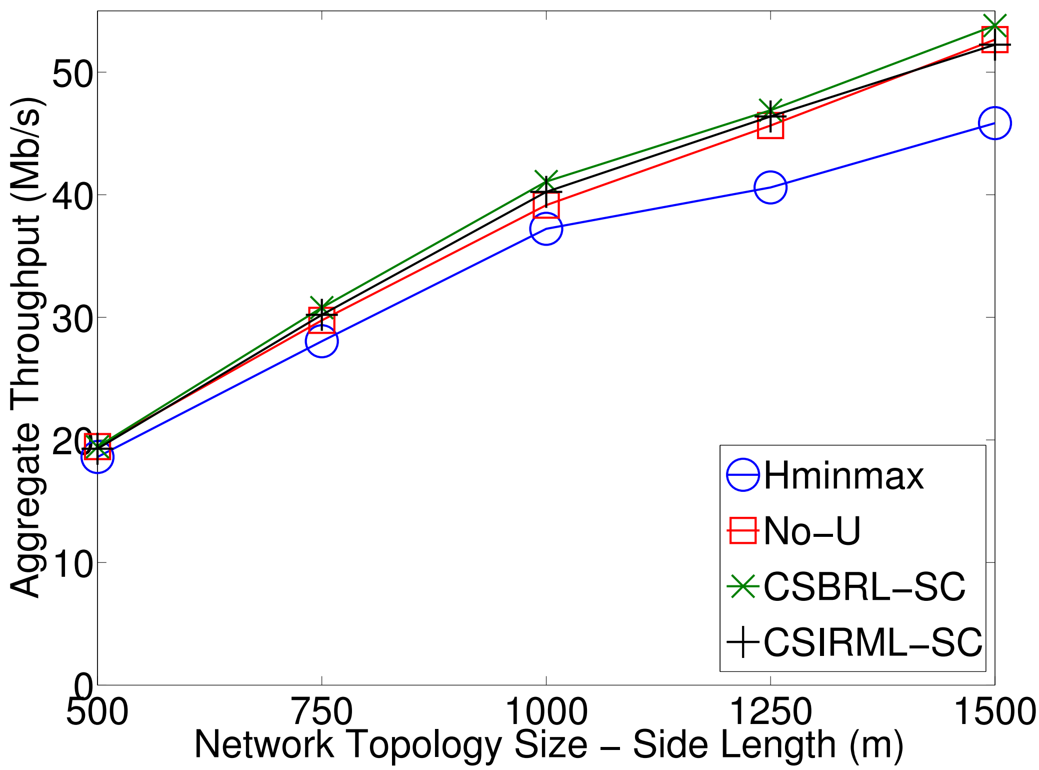


Figure 4.10: Aggregate throughput of the networks for different network area size.

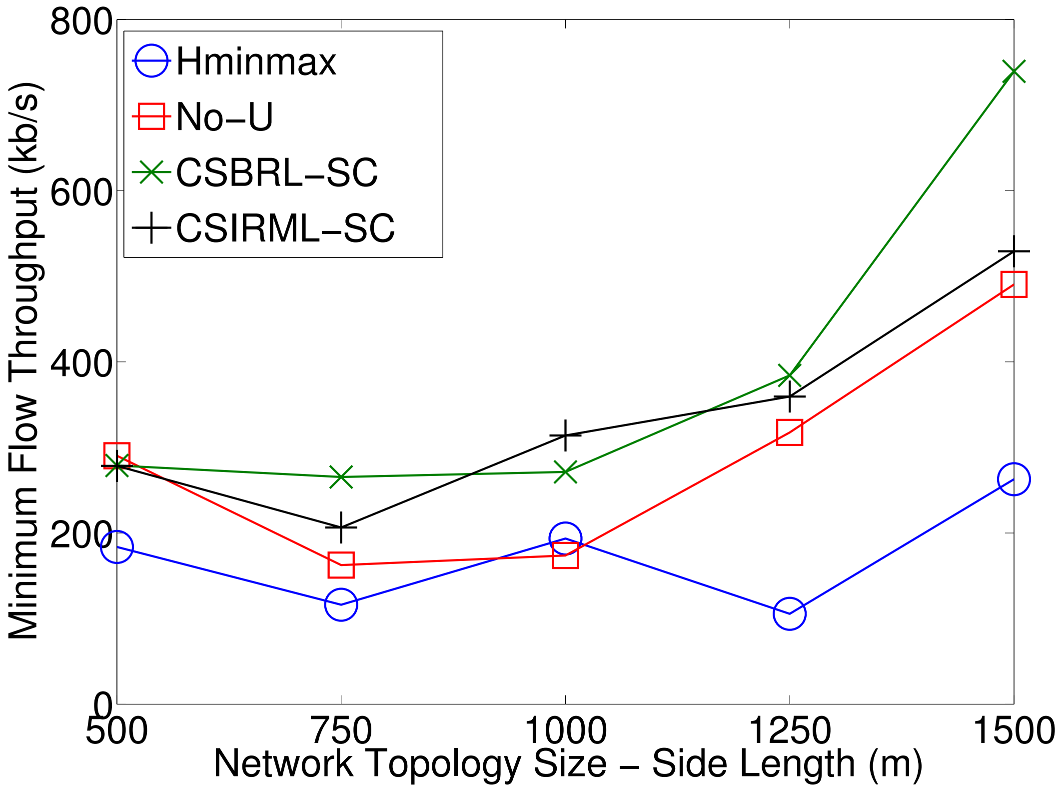


Figure 4.11: Minimum flow throughput for different network area size.

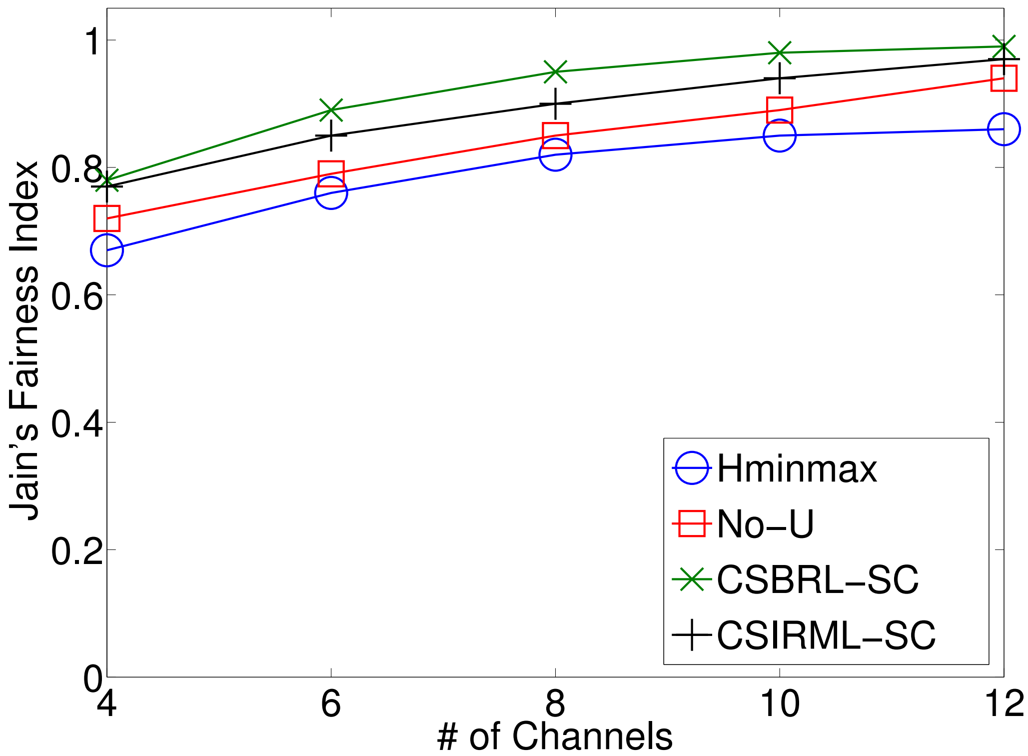


Figure 4.12: Throughput fairness for different number of channels.

as 17% compared to Hminmax and 13% compared to No-U. In terms of aggregate throughput, CSBRL-SC performs as much as 30% and 10% better than Hminmax and No-U respectively. Both SC schemes are also able to achieve higher minimum flow throughputs compared to the existing schemes.

4.5.4 Channel Switching Frequency

Figure 4.15 shows the channel switching frequencies of the different schemes for the 1000m by 1000m network area size. The channel switching frequencies indicate how often the players switch channels during the simulation run, normalized over the number of scanning periods. It shows that even though CSBRL-SC performs better compared to the other schemes, it results in more frequent channel switches. The reason for this, as discussed previously, is that the best response algorithms trigger immediate strategy change when the previous strategy results in a lower utility. This immediate change accounts for the frequent channel switch. On the other hand,

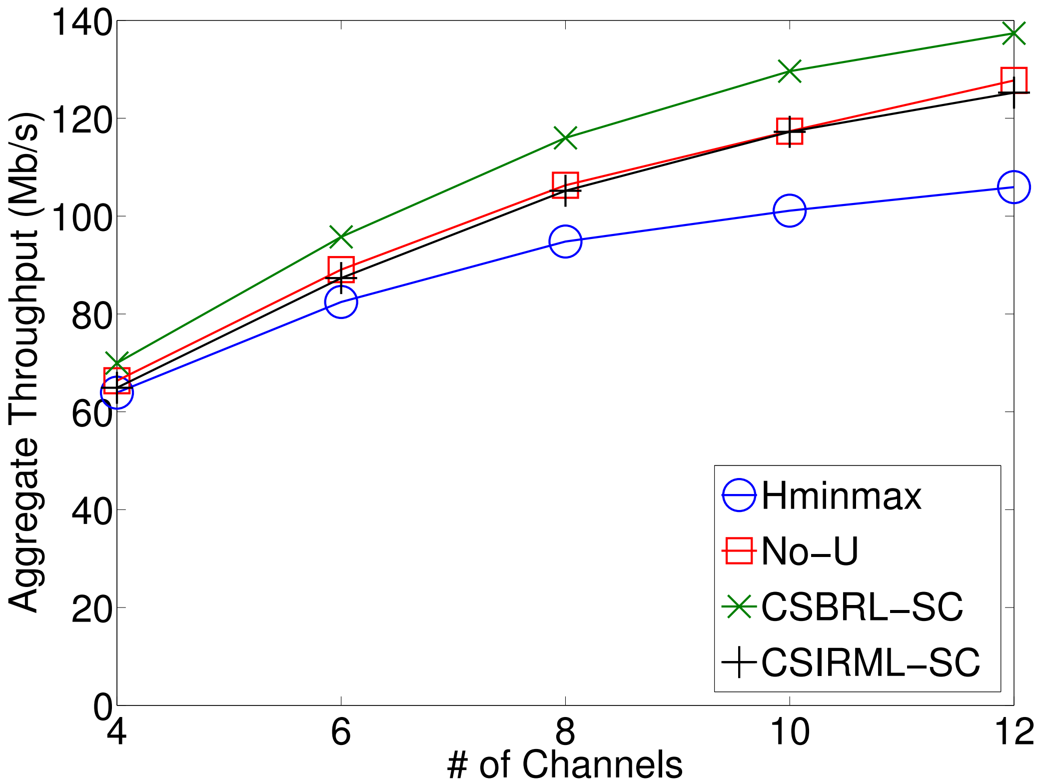


Figure 4.13: Aggregate throughput of the networks for different number of channels.

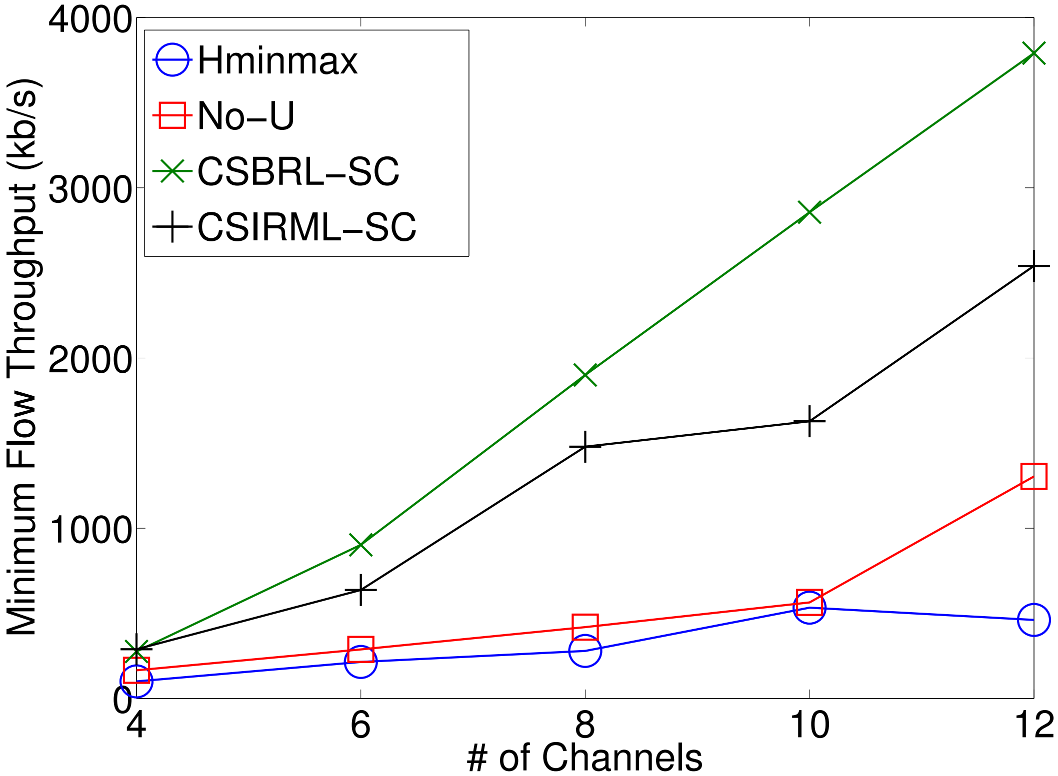


Figure 4.14: Minimum flow throughput for different number of channels.

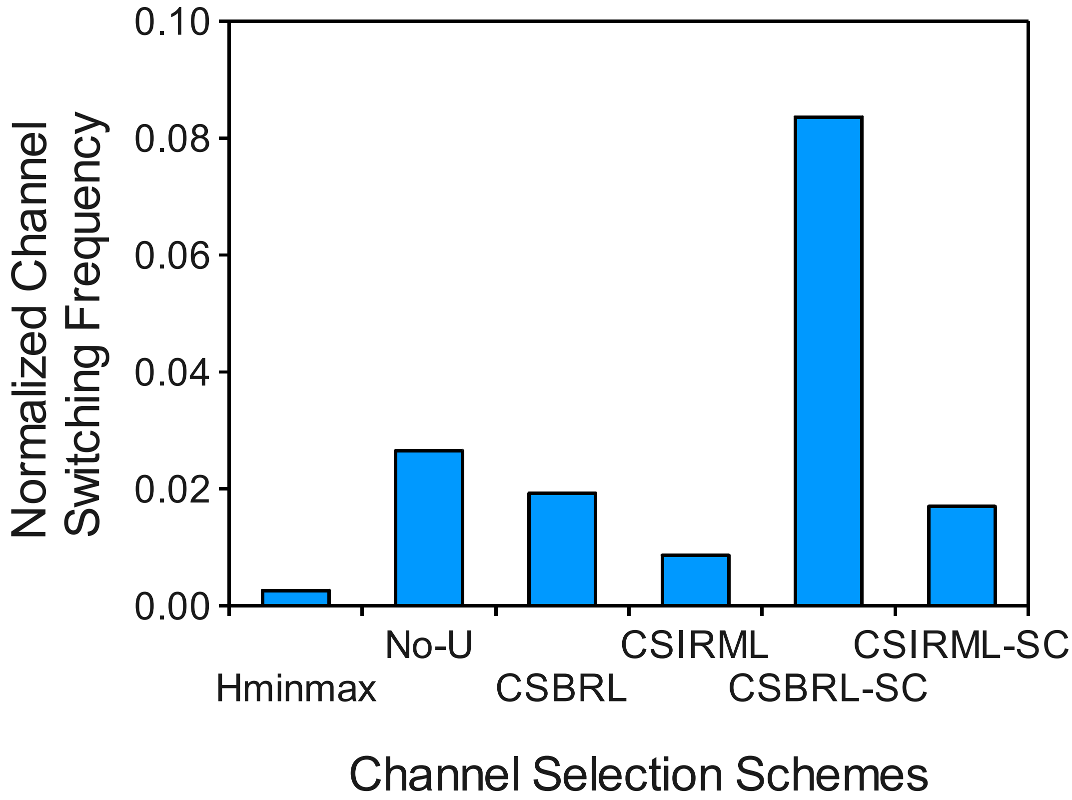


Figure 4.15: Channel switching frequencies for the different schemes.

the IRM learning algorithms are able to provide a much lower channel switching frequency at a slightly lower performance cost (at times).

This observation presents a tradeoff for the choice of channel selection schemes — if the channel switching cost is high (e.g. when the wireless devices have high channel switching time), the IRM learning schemes can be seen as better solutions. Finally, even though Hminmax has the lowest channel switching frequency, it also consistently produces the worst performance. This shows that the information it acquires is not sufficient for it to make effective channel switching decisions.

The channel switching frequency issue brings up a related question of the performance of fully-randomized channel switching schemes. Such schemes, also known as frequency-hopping schemes, have been used in Bluetooth [30] to mitigate interference in "crowded" channels. Although fairness may be improved with a randomized channel switching scheme, overall system performance (e.g. aggregate throughput) could suffer. A more detailed investigation is warranted and will be left as future work.

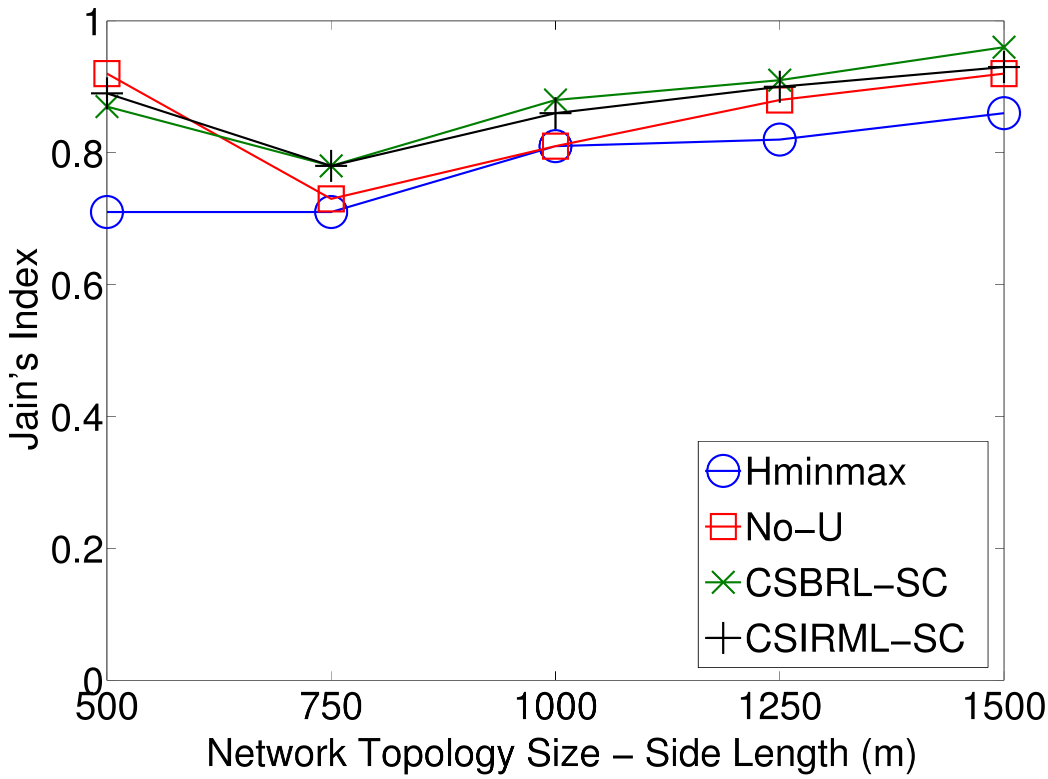


Figure 4.16: Throughput fairness for different network area size (TCP traffic).

4.5.5 TCP Traffic Evaluation

The evaluations thus far have been done using UDP traffic. The reason for this is that we believe that with the maturity of video streaming applications, the main bulk of the future network bandwidth will be taken up by UDP traffic. However, TCP traffic is still the predominant traffic type in existing networks. In fact, much of today's video traffic (e.g. youtube) is still TCP-based. For this reason, we also need to investigate how the schemes perform and compare under TCP traffic.

In order to isolate the effects the channel selection schemes have on the TCP flows, we assume that the wired connection to the traffic source is lossless and has negligible delay. While UDP traffic has a fixed offered load, the load of the TCP traffic may change, depending on the packet losses occurring in the wireless links. Figures 4.16, 4.17 and 4.18 show the performance of the channel selection schemes for different network area. They show that the similar results can be seen with TCP traffic.

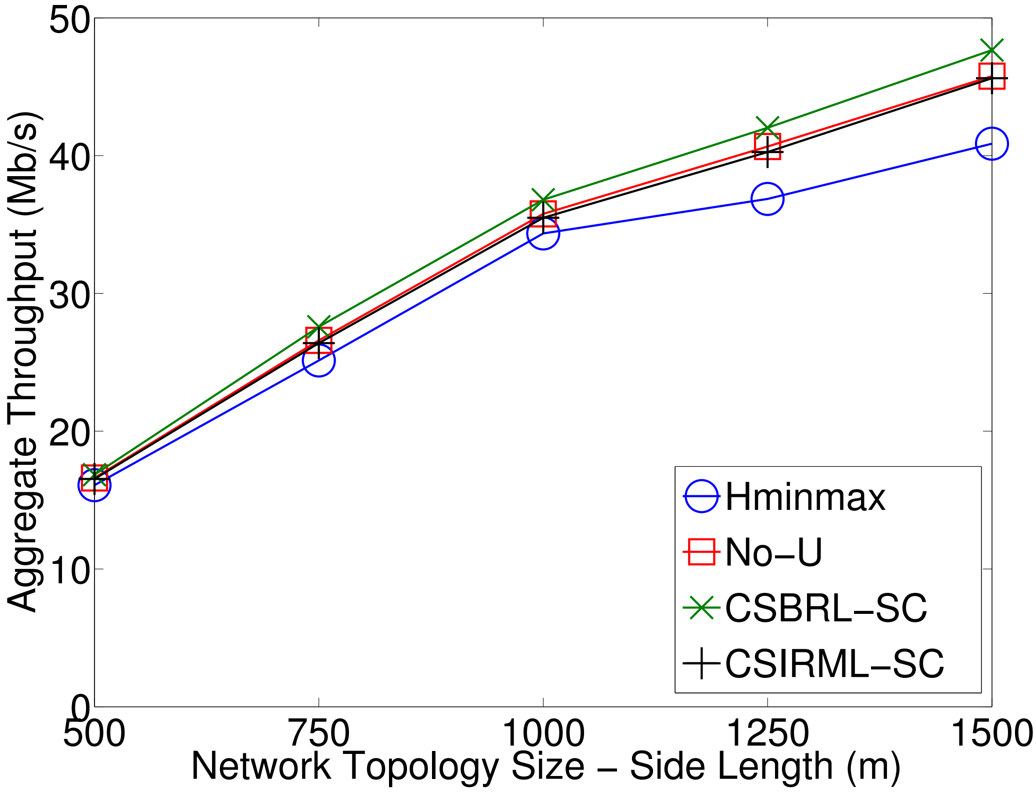


Figure 4.17: Aggregate throughput of the networks for different network area size (TCP traffic).

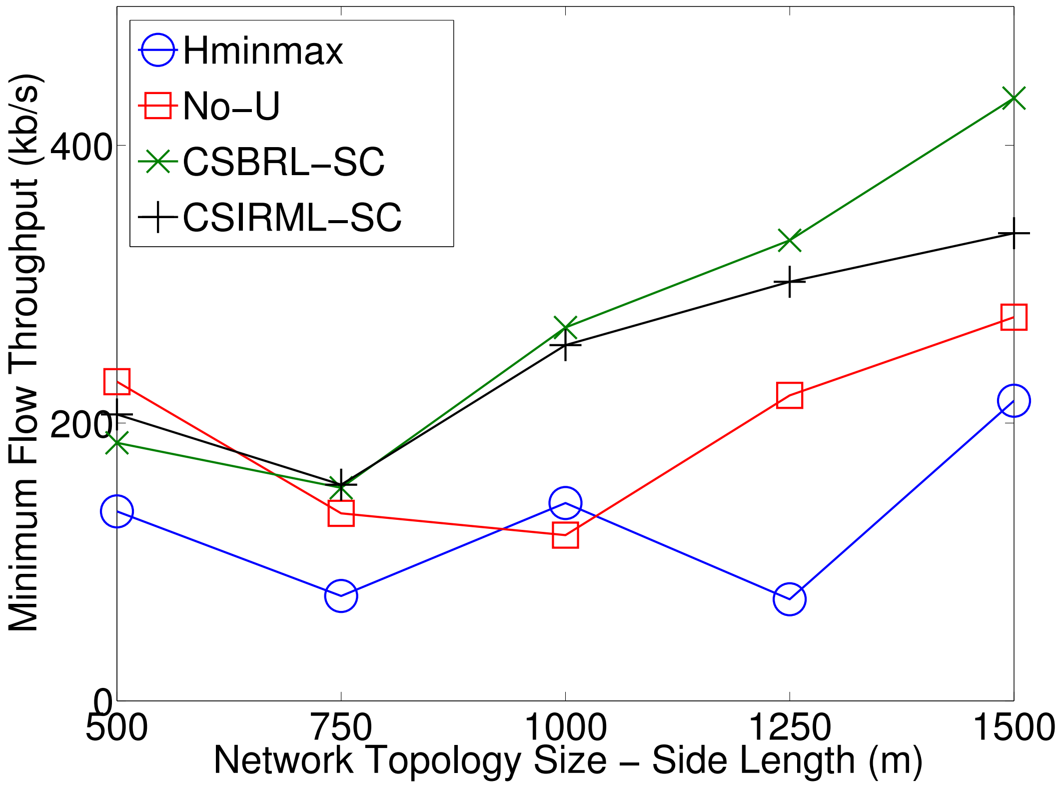


Figure 4.18: Minimum flow throughput for different network area size (TCP traffic).

4.6 Conclusion

Due to the inherent nature of the CSMA/CA mechanism in IEEE 802.11 DCF MAC, it has been shown that unfairness can occur among WLANs set up in a region spanning multiple collision domains. As more and more WLANs are being deployed, there is a need to ensure some level of fairness concerning the amount of traffic each WLAN can support. In this chapter, we look at the use of channel selection to achieve fairness. We have shown that using information gathered from networks within the communication range of a WLAN is not sufficient. As a result, we have described a number of channel selection schemes that make use of a more accurate assessment of the channel condition by using a game theoretic learning approach. We also introduce an innovative method for a WLAN to detect that it is unfairly causing starvation to a neighboring network and have incorporate this capability into the learning schemes. This has resulted in socially conscious channel selection schemes, which we have shown through simulations to perform better than existing schemes in providing improved system fairness, aggregate throughput and minimum flow throughput.

Chapter 5

Cross-Layer Resource Allocation for Independent Multihop Wireless Networks

While cross-layer algorithms have been shown to optimize the operation of multihop wireless networks, they usually assume that only one network is present. In this chapter, we apply a cross-layer resource allocation algorithm to independent multihop wireless networks in order to study its performance in a non-cooperative setting. We assume the nodes in these networks are equipped with one or more radio interfaces that allow them to operate on multiple channels. We show that there exists efficiency loss as a result of applying the algorithm to autonomous networks that neither communicate nor cooperate among themselves. In addition, we propose a simple solution that improves the performance of the algorithm when it is applied independently to each network.

5.1 Introduction

A key challenge in the operation of wireless multihop networks in general is the interference that arises among transmitting links. The operation of the links would have to be coordinated in the various domains (e.g. time, frequency and spatial) to ensure that this interference does not adversely affect the performance of the network. Attempts have been made to view this as a resource allocation problem, with solutions in scheduling [135], flow control [145], power control [108], channel assignment [134], etc. Efforts have also been made to solve a number of the above problems together, as a joint problem, e.g. [23, 36, 93, 100, 109, 116]. These, along with many other works, constitute the wide and growing field of resource allocation through cross-layer network optimization [39, 55, 96].

In Chapter 3, we show that due to the widespread adoption of wireless networks, especially those that operate on the unlicensed band, there is an increased incidence of multiple independent wireless multihop networks located within a single locality. For example, using either the IBSS (Independent Basic Service Set) or 802.11s [32] mode, different home users in an apartment block may each set up a multihop network to connect the various equipment in the home. The apartment block may in turn be located in a residential area where one or more commercial or municipal mesh networks are being deployed. In this scenario, links belonging to different independent networks interact and interfere with each other to affect the performance of the networks.

In this chapter, we are interested in the problem of cross-layer resource allocation when it is applied to more than one independent network co-located together. We assume these networks are made up of at least some nodes that are equipped with more than one radio interface, to utilize the multiple orthogonal channels available. One of the key characteristics of such networks is that although we can assume nodes within the same network will cooperate and exchange information, it is not true for nodes belonging to different autonomous networks.

The primary contributions of the work presented in this chapter are as follows:

- We investigate cross-layer resource allocation of multihop wireless networks consisting of nodes with multiple radios, specifically when it is applied to co-located independent networks that do not cooperate with each other. While such cross-layer algorithms have been extensively studied, it has been confined to a single network. We believe our work here constitutes one of the first attempts to understand how applying a cross-layer algorithm to multiple non-cooperative networks will affect its performance.

- We find that there exists efficiency loss when we apply one such algorithm, a joint congestion control, channel allocation and scheduling algorithm [100], to networks that operate independently of each other and therefore do not communicate among themselves. We show that the loss of efficiency results from an incomplete view of the contention environment.

- We propose a simple way of improving the performance of the algorithm, by incorporating a method for the networks to better estimate their link rates in the contention environment. Our modified algorithm show significant improvement in performance when compared with the original algorithm in simulations involving two independent co-located networks.

In [100], the authors model the interaction among links within an independent multi-radio, multi-channel and multihop network as an optimization problem. The aim of the problem is to maximize a system utility using a joint flow control, channel loading, interface-to-channel binding, and transmission schedule algorithm that is derived from the framework. A similar system model has also been used previously by Lin and Rasool in [93]. We will use an identical model as it closely describes the type of network we are investigating here. However, we will extend it to describe multiple independent networks.

We highlight here that even though cross-layer resource allocation algorithms that are based on network utility maximization have been extensively researched and studied, all the works are primarily focused on application to a single network. A key assumption in these works is that there exist some forms of communication among the nodes or links, such that information like shadow prices or neighbor identities can be exchanged either locally or globally. This implicitly means that the nodes or links cooperate to arrive at the desired solution. Our work here relates to the application of such cross-layer algorithms to multiple autonomous networks that have no incentive or mechanism to cooperate. We believe this is the first attempt at studying such a scenario in this area of research.

5.1.1 Chapter Outline

In Section 5.2, we describe the system model that we are considering in this work. This model follows closely to that of [100] but we extend it to multiple independent networks. We present the optimization problem arising from the system model and discuss the algorithm that can solve it in Section 5.3. In the subsequent section, we look specifically at the link-channel scheduling component of the algorithm and show why applying it to independent networks will result in efficiency losses. In addition, we present a solution to improve the situation. Following that, we evaluate the performance improvements of the proposed algorithm in Section 5.5, before ending the chapter with some discussion and conclusion.

5.2 System Model

Consider a set of multihop wireless networks $\mathcal{I} = \{1, \ldots, I\}$. Each network $i \in \mathcal{I}$ consists of a set of nodes $\mathcal{N}_i$. We define a set of unidirectional links $\mathcal{L}_i$ in each network i. Further, let $\mathcal{L} = \cup_i \mathcal{L}_i$. Each node n is equipped with R_n number of radio interfaces, which can both transmit and receive (though not at the same time). Each interface can be operating at any of the $\mathcal{C} = \{1, \ldots, C\}$ channels. Let $b(l)$ and $e(l)$ be the transmitter and receiver nodes of link l respectively. Therefore, $b(l), e(l) \in \mathcal{N}_i$ for any link $l \in \mathcal{L}_i$. It is easy to see that for traffic to flow from $b(l)$ to $e(l)$ on channel c, l must be in $\mathcal{L}$ and an interface each in $b(l)$ and $e(l)$ must be operating on channel c. In this chapter, we assume that control and data packets can be sent and received between nodes within a network, but not among nodes belonging to different networks.

In each network i, (potentially multi-hop) traffic flows are grouped according to their intended destination node, so there exists a set of $\mathcal{S}_i \subseteq \mathcal{N}_i$ *commodities*, where each member has a corresponding group of flows that are bound for the same destination. We define $\mathcal{P}_s$ as the set of nodes that are sources to the flows belonging to commodity $s \in \mathcal{S}_i$. If a node $n \in \mathcal{P}_s$, we denote the input rate as λ_n^s . Let the vector of all input rates of network i be $\vec{\lambda}_i$. Obviously, $n \notin \mathcal{P}_n$. We assume the input rates are bounded such that $\lambda_n^s \in \Lambda_n^s$, where Λ_n^s is the set of feasible input rates of commodity s in node n.

We define node n as *serving* commodity s if $n \in \mathcal{P}_s$ and/or n is an intermediate hop for flows in commodity s. Each node maintains a set of incoming and outgoing queues. For every commodity s that a node n serves, there exist one incoming queue p_n^s and C outgoing queues $q_{n,c}^s$, where $c \in \mathcal{C}$. In [100], virtual links are defined that connect each p_n^s with the corresponding C outgoing queues $q_{n,c}^s$. The rate of these virtual links are denoted as $\gamma_{n,c}^s$. For each node n, the term $\gamma_{n,c}^s$ can be seen as a decision variable relating to how much data from a commodity s is to be sent on the channel c. Let $\vec{\gamma}_i = [\gamma_{n,c}^s]$ for all $n \in \mathcal{N}_i, c \in \mathcal{C}$ and $s \in \mathcal{S}_i$. Incidentally, this notion of virtual links, used to ensure that packets are "sent" to channel queues with better channel qualities, is also found in [93].

We assume a general interference model [75, 145]. We let the interference relationships among the links in the entire system (i.e., across all the networks) be represented by a *global* contention graph G. The vertices of G are the links in the networks $l \in \mathcal{L}$ and there exists an edge between a pair of vertices if they interfere with each other when they are on the same channel. As an example, Figure 5.1 shows a network topology with 2 simple independent networks and the corresponding contention graph. Further, we denote G_i as a subgraph of G for every network $i \in \mathcal{I}$ whose set of vertices consists of just the links found in network i and where an edge exists in G_i if and only if the corresponding edge is in G and both the endpoints of the edge is in G_i. Thus G_i is the contention graph of network i, which we will call the *network* contention graph. Figure 5.2 shows the network contention graphs of networks 1 and 2 from the example in Figure 5.1.

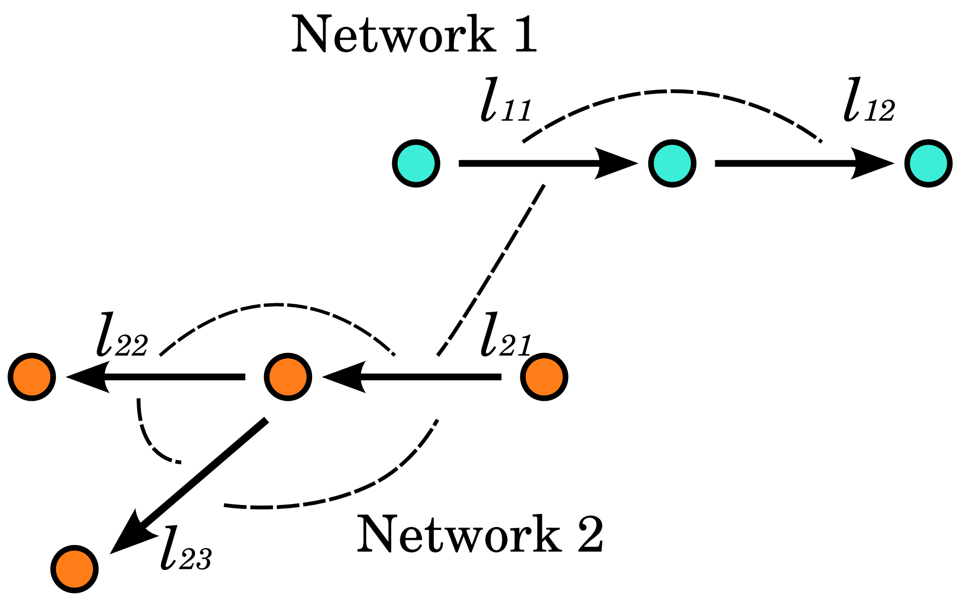
In most cross-layer algorithms, link-layer scheduling is usually done in the following manner. Time is divided into slots and they are synchronized within the network. Within each timeslot, links are scheduled such that only a subset of links are active (i.e., transmitting). To eliminate collisions, the subset of links that are active should not interfere with one another. Equivalently, this is represented by the vertices within the contention graph that form an Independent Set[1]. It has been shown [95] that algorithms that form maximal-weight schedules of the links in each timeslot have optimality properties.[2]

We assume that timeslot synchronization is possible within each independent network. This can be achieved using time synchronization protocols such as the ones proposed in [82] and [125]. However, it is not realistic for independent networks to synchronize their timeslots with one another, since the networks are uncoordinated. Nevertheless, for ease of explanation and analysis, inter-network time synchronicity is assumed initially. The effects of asynchronous timing updates will be investigated during the simulation studies in Section 5.5.

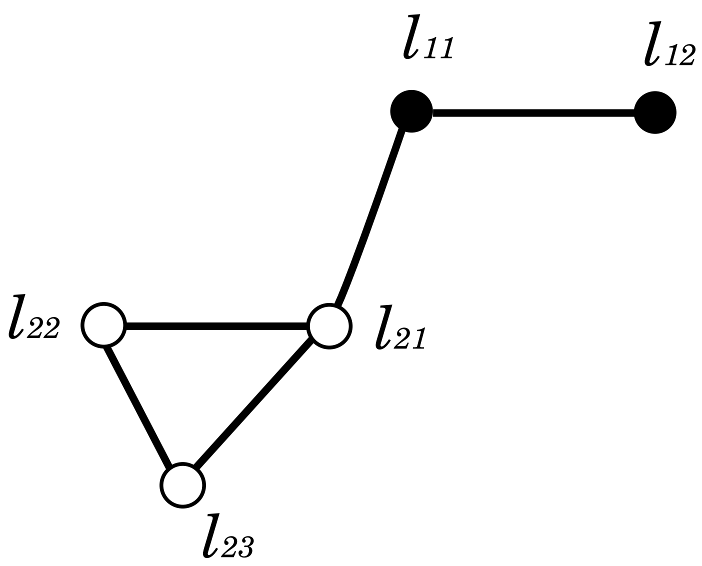
In this chapter, we assume the scheduling within each time slot takes the form of a

[1] An Independent Set of a graph is any set of vertices where no two vertices have an edge between them.

[2] There is another class of link-layer control algorithms that assigns a persistent probability of sending packets in a timeslot [86, 87]. We will not consider these algorithms in this thesis.



(a)



(b)

Figure 5.1: Example showing 2 multihop wireless networks in multiple collision domains. (a) Network topology, where the arrows represent unidirectional links and dashed lines represent interference relationships. (b) The resultant contention graph, where the solid lines represent interference relationships.

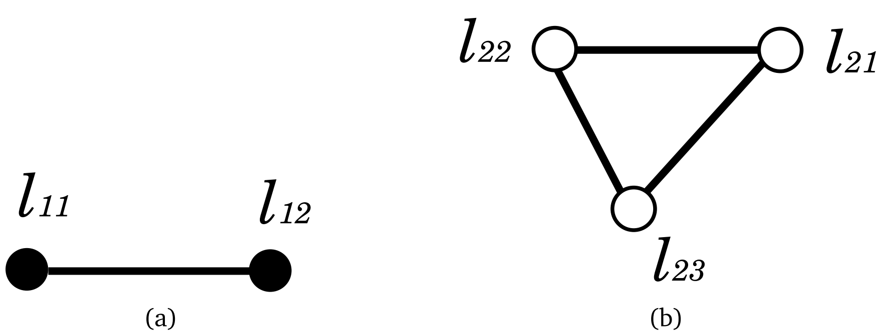


Figure 5.2: Contention graphs of the individual networks. (a) Contention graph of network 1. (b) Contention graph of network 2.

subset of links to be active in each orthogonal channel. For each network i, let the set of links scheduled to be on a channel c at a timeslot t be denoted as $\mathcal{M}_i^c(t) \subseteq \mathcal{L}_i$. We call $\mathcal{M}_i^c(t)$ the *link-channel schedule* of network i on channel c at time slot t. Further, we denote $\vec{\mathcal{M}}_i(t) = \left[\mathcal{M}_i^c(t), \forall c \in \mathcal{C}\right]$ as link-channel allocation of network i. Finally, let $\mathcal{M}_{-i}^c(t)$ be the collection of link-channel schedules of all other networks, except i, in channel c.

Within each network i, $\vec{\mathcal{M}}_i(t)$ is constrained by the number of radio interfaces present in the nodes. As an example, consider again Network 2 of Figure 5.1. Let node n be the transmitter of links l_{22} and l_{23}. If $R_n = 1$, i.e., node n only has 1 radio interface, then a link-channel allocation where $l_{22} \in \mathcal{M}_i^a(t)$ and $l_{23} \in \mathcal{M}_i^b(t)$, where $a, b \in \mathcal{C}, a \neq b$ cannot be feasible.[3] This is known as the radio interface constraint, and it restricts the set of feasible $\vec{\mathcal{M}}_i(t)$. Let Π_i be the set of feasible link-channel allocations of network i.

For each network i, let $\vec{r}_i = \left[r_{i,l,c}^s\right]$ denote the link rates, where $r_{i,l,c}^s$ is the amount of data that link $l \in \mathcal{L}_i$ sends within a timeslot on channel $c \in \mathcal{C}$, for the commodity $s \in \mathcal{S}_i$ that node $b(l)$ serves. Further let $\vec{r}_i^c$ be the elements in $\vec{r}_i$ that constitutes link rates on channel c. We assume that $\vec{r}_i^c = \Psi(G, \mathcal{M}_i^c, \mathcal{M}_{-i}^c)$, i.e., the link rates on a channel is completely determined by the contention graph, as well as the link-channel allocations of network i and all other networks.

The function $\Psi(\cdot)$ is in turn determined by the physical and link-layer model. In most related work, a general *mutually-exclusive* model is assumed. In this model, for

[3]Incidentally, in this example, l_{21} cannot be in $\vec{\mathcal{M}}_i(t)$ if either l_{22} or l_{23} is allocated. The reason is that node n cannot be both sending and receiving in a given timeslot with 1 radio interface.

a set of links (vertices) in a contention graph that forms a clique, transmission will only be successful if only one of these links is transmitting. If more than one link transmits, transmission fails for all transmitting links. We make the same assumption in our analysis. In our simulation, we will investigate a more realistic case of each network implementing an idealized CSMA model [90, 139]. For now, without loss of generality, we assume that $\sum_s r^s_{i,l,c}$ takes the form of either a constant B when there is no collision or 0 otherwise. Therefore, B is the amount of data any link l can send on a channel c in a timeslot when there are no other contending links, which will be known as the effective bandwidth. Incidentally, this means that any channel variation (e.g. due to fading or distance) is not considered here.

It should be noted that when applied over all possible combinations of $\left[\mathcal{M}^c_i, \mathcal{M}^c_{-i}\right]$, the function $\Psi(\cdot)$ constitutes the feasible rate region of the links in each network. We shall see later that in the case of non-cooperative networks, because both G and $\mathcal{M}^c_{-i}$ are not fully known, it results in an inaccurate feasible rate region. The link-channel scheduling that arises from this rate region actually constitutes a much smaller capacity region. This is the main reason behind the efficiency loss in non-cooperative resource allocation algorithms.

Table 5.1 provides a summary of the symbol definitions.

Symbols:	
$\mathcal{I} = \{1, \ldots, I\}$	Set of independent wireless multihop networks
$\mathcal{N}_i$	Set of nodes in each network $i \in \mathcal{I}$
$\mathcal{L}_i$	Set of unidirectional links in each network $i \in \mathcal{I}$
$\mathcal{L} = \cup_i \mathcal{L}_i$	Set of all links
$\mathcal{C} = \{1, \ldots, C\}$	Set of channels
$\mathcal{S}_i$	Set of commodities of network $i \in \mathcal{I}$
λ_n^s	Input rate of commodity $s \in \mathcal{S}_i$ at source $n \in \mathcal{N}_i$
Λ_n^s	Set of feasible inputs rates of commodity $s \in \mathcal{S}_i$ at source $n \in \mathcal{N}_i$
$U_n^s(\lambda_n^s)$	Utility of commodity $s \in \mathcal{S}_i$ from source $n \in \mathcal{N}_i$
$\vec{\lambda}_i = \left[\lambda_n^s\right]$	Input rates of network $i \in \mathcal{I}$
p_n^s	Incoming queue of node n for commodity s
$q_{n,c}^s$	Outgoing queue of node n for commodity s in channel c
$\gamma_{n,c}^s$	Rate of virtual link connecting p_n^s to $q_{n,c}^s$
G	Global contention graph across all the networks in $\mathcal{I}$
$G_i \subseteq G$	Network contention graph of network $i \in \mathcal{I}$
$r_{i,l,c}^s$	Rate of link $l \in \mathcal{L}_i$ for commodity $s \in \mathcal{S}_i$ in channel c
$\vec{r}_i = \left[r_{i,l,c}^s\right]$	Achieved links rates of the links in network $i \in \mathcal{I}$
$\vec{\mathcal{M}}_i = \left[\mathcal{M}_i^c\right]$	Link-channel allocation of network $i \in \mathcal{I}$
$\mathcal{M}_{-i}^c$	Link-channel schedules of all networks except i in channel c
Π_i	Feasible link-channel allocations of network $i \in \mathcal{I}$

Table 5.1: Summary of symbol definitions used in Chapter 5.

5.3 Optimization Problem

We define the following optimization problem for the above system model. For each network i, we seek to solve the following:

$$\max_{\vec{\lambda}_i, \vec{\mathcal{M}}_i, \vec{\gamma}_i} \left[\sum_{n,s} U_n^s(\lambda_n^s) \right]$$

s.t.

$$\sum_{l:\, n=e(l),c} r_{i,l,c}^s + \lambda_n^s \leq \sum_c \gamma_{n,c}^s \quad \forall n,s \tag{5.1a}$$

$$\gamma_{n,c}^s \leq \sum_{l:\, n\in b(l)} r_{i,l,c}^s \quad \forall n,s,c \tag{5.1b}$$

$$\sum_c \gamma_{n,c}^s < \Gamma_n^s \quad \forall n,s \tag{5.1c}$$

$$\vec{r}_i^{\,c} = \Psi(G, \mathcal{M}_i^c, \mathcal{M}_{-i}^c) \quad \forall c \tag{5.1d}$$

$$\lambda_n^s \in \Lambda_n^s \quad \forall n,s \tag{5.1e}$$

$$\vec{\mathcal{M}}_i \in \Pi_i \tag{5.1f}$$

where $n \in \mathcal{N}_i$, $s \in \mathcal{S}_i$ and $c \in \mathcal{C}$.

The constraints of the above problem are interpreted as follows:

- (5.1a) represents the flow conservation constraint at the incoming queue of each node, for each commodity.
- (5.1b) is the flow conservation constraint at the outgoing queue of each node, for each commodity in each channel.
- (5.1c) is the constraint on the flow in the virtual links. It is shown in [100] that with respect to the virtual link rates, a sufficient condition for the stability of the system is to let the aggregate rate be bounded by a value Γ_n^s. In order to ensure that the capacity region remains unchanged, Γ_n^s should be set to be the smallest value that is greater than the maximum possible output rate of the node. We will assume Γ_n^s to be known and constant in this chapter.
- (5.1d) is the resultant link rates from the channel assignments of all the networks in $\mathcal{I}$.

- (5.1e) is the set of feasible input rates.
- (5.1f) is the set of feasible link-channel assignments in network i.

5.3.1 Solving the Optimization Problem

Our system consists of a set of $\mathcal{I}$ networks each solving the above optimization problem. It is not difficult to see that except for constraint (5.1d), the objective function and other constraints (5.1a)—(5.1e) are decoupled with respect to flows and links respectively. A common method of solving this type of optimization problem involves solving a number of dual problems derived from relaxing constraints (5.1a) and (5.1b), as described in [95, 100].

Specifically, the Lagrange dual function that arises from relaxing (5.1a) and (5.1b) is:

$$
\begin{aligned}
L(\vec{P},\vec{Q}) = \max_{\vec{\lambda}_i,\vec{\mathcal{M}}_i,\vec{\gamma}_i} \Bigg\{ & \sum_{n,s} U_n^s(\lambda_n^s) \\
& + \sum_{n,s} P_n^s \left(- \sum_{l:\, n=e(l),c} r_{i,l,c}^s - \lambda_n^s + \sum_c \gamma_{n,c}^s \right) \\
& + \sum_{n,s,c} Q_{n,c}^s \left(-\gamma_{n,c}^s + \sum_{l:\, n\in b(l)} r_{i,l,c}^s \right) \Bigg\}
\end{aligned}
$$

where $n \in \mathcal{N}_i$, $s \in \mathcal{S}_i$ and $c \in \mathcal{C}$.[4] Also, $\vec{P} = [P_n^s]$ and $\vec{Q} = [Q_{n,c}^s]$ are the vectors of the Lagrange multipliers associated with the constraints.

[4] $\vec{\lambda}_i$, $\vec{\mathcal{M}}_i$, $\vec{\gamma}_i$ and consequently $\vec{r}_i^c$ are still subjected to constraints (5.1c)—(5.1f). However, they will be henceforth left out in the interest of notational simplification.

It is commonly known that the above function can be solved independently as a number of sub-problems, each representing a different layer [39]. This is done by rearranging the expression into:

$$L(\vec{P},\vec{Q}) = \max_{\vec{\lambda}_i}\left\{\sum_{n,s} U_n^s(\lambda_n^s) - P_n^s\lambda_n^s\right\} \tag{5.2a}$$

$$+\max_{\vec{\gamma}_i}\left\{\sum_{n,s,c}\left(P_n^s - Q_{n,c}^s\right)\gamma_{n,c}^s\right\} \tag{5.2b}$$

$$+\max_{\vec{\mathcal{M}}_i}\left\{\sum_{l,s,c}\left(Q_{b(l),c}^s - P_{e(l)}^s\right)r_{i,l,c}^s\right\} \tag{5.2c}$$

In addition, each sub-problem of (5.2a) and (5.2b) can be further decomposed with respect to each source node and virtual link respectively.

Specifically, each node n can easily solve for the optimal input rate $\lambda_n^s = \arg\max_{\lambda_n^s \in \vec{\lambda}_i}\left\{U_n^s(\lambda_n^s) - P_n^s\lambda_n^s\right\}$ for each commodity that it serves as a source, thereby solving sub-problem (5.2a). This represents the distributed congestion control component of the system. Also, to maximize sub-problem (5.2b), each node n first chooses $c^* = \arg\max_{c\in C}\left\{P_n^s - Q_{n,c}^s\right\}$ for every commodity s that it serves. It then sets $\gamma_{n,c^*}^s = \Gamma_n^s$ for all $(P_n^s - Q_{n,c^*}^s) > 0$ and $\gamma_{n,c}^s = 0$ otherwise. This allows the incoming packets to be sent to the channel queue that has the maximum Lagrange multiplier difference between the input and output queues.

Thus, sub-problems (5.2a) and (5.2b) can be easily solved in a distributed manner. On the other hand, solving sub-problem (5.2c) has traditionally been the most challenging part of the problem, as it requires the knowledge of the entire system and can only be optimally performed in a centralized manner. We will discuss this component in detail in the next section.

The last piece of the problem involves the updating of the Lagrangian multipliers. If the utility function is concave and the link rate function $\Psi(\cdot)$ produces a convex set of feasible link rates, the multipliers can be solved using a subgradient method [29]. At time slot $t+1$, the multipliers $P_n^s(t+1)$ and $Q_{n,c}^s(t+1)$ are updated as:

$$P_n^s(t+1) = \left\{ P_n^s(t) + h_p \left[\lambda_n^s(t) + \sum_{b(l),c} r_{i,l,c}^s(t) \right.\right.$$
$$\left.\left. - \sum_c \gamma_{n,c}^s(t) \right] \right\}^+ \tag{5.3}$$

$$Q_{n,c}^s(t+1) = \left\{ Q_{n,c}^s(t) + h_q \left[\gamma_{n,c}^s(t) \right.\right.$$
$$\left.\left. + \sum_{e(l)} r_{i,l,c}^s(t) \right] \right\}^+ \tag{5.4}$$

where $\{\cdot\}^+ = \max(\cdot, 0)$. In addition, h_p and h_q are positive stepsizes. In [95], it is shown that by keeping both h_p and h_q as sufficiently small values, the multipliers will converge to regions close to their optimal solutions. Setting h_p and h_q to 1 will allow the physical queue buffers to track perfectly the Lagrangian multipliers, although this increases the oscillatory behavior of the solution.

5.4 Link-Channel Scheduling

A corollary of the decoupling of the above optimization problem in the vertical (in terms of the layers) as well as horizontal sense (with respect to the nodes) is that these sub-problems could be solved in a distributed manner across the independent networks. The only issue remains the sub-problem of (5.2c). In this chapter, we will interpret it as a link-channel (L-C) scheduling problem. We first look at how the sub-problem can be (ideally but unrealistically) solved cooperatively by the networks. Following, we consider the more realistic case of networks solving this sub-problem in a non-cooperative manner and investigate the loss in efficiency that results from this. The reason for first analyzing the cooperative solution is to provide a baseline for comparison with the more practical and realistic non-cooperative algorithms.

5.4.1 Cooperative L-C Scheduling

First, let us denote $w_{l,c}^s = (Q_{b(l),c}^s - P_{e(l)}^s)$. The term $w_{l,c}^s$ can be interpreted as the weight of a link $l \in \mathcal{L}_i$ for a commodity $s \in \mathcal{S}_i$ in channel $c \in \mathcal{C}$ for every network

$i \in \mathcal{I}$. Looking at all the networks in $\mathcal{I}$, sub-problem (5.2c) can be rewritten as

$$\max_{\mathcal{M}} \left\{ \sum_{i \in \mathcal{I}} \sum_{l,s,c} w^s_{l,c}(t) r^s_{i,l,c}(t) \right\}$$

subject to (5.1d), where $\mathcal{M} = \left\{ \vec{\mathcal{M}}_1, \ldots, \vec{\mathcal{M}}_I \right\}$.

Recall that $\sum_s r^s_{i,l,c}$ is B if link l is scheduled on channel c and 0 otherwise. It is not difficult to see that for each link l, choosing the commodity $s \in \mathcal{S}_i$ that maximizes $w^s_{l,c}$ for every channel c will maximize the above equation. Therefore, in each network i, each link l could independently find $s^* = \arg\max_{s \in \mathcal{S}_i}(w^s_{l,c})$ for each channel c, giving

$$\max_{\mathcal{M}} \left\{ \sum_{i \in \mathcal{I}} \sum_{l,c} w_{l,c}(t) r_{i,l,c}(t) \right\} \tag{5.5}$$

subject to (5.1d), where $w_{l,c}(t) = w^{s^*}_{l,c}(t)$ and $r_{i,l,c}(t) = r^{s^*}_{i,l,c}(t)$. Thus, we drop the superscript s and note that at every timeslot t, there exists a commodity for each channel that will be chosen which maximizes the weight of the link at that channel. Ties are broken arbitrarily.

As mentioned before, the reason why (5.5) cannot be solved in a distributed manner is because the link rates are coupled together. Recall that in (5.1e), the rates at each link on each channel is a function of the global contention graph G and the link-channel allocations of all the networks. To optimally solve (5.5) would require a centralized algorithm that finds a maximum weight independent set, given G and $w_{l,c}(t)$ at each time slot. It has been shown in [135] that such a schedule will realize the largest capacity region, when compared with any other scheduling policy. This means that the maximum weight schedule will stably support the maximum set of incoming rates possible. Unfortunately, this is known to be an NP-complete problem.

We will therefore turn our attention to a sub-optimal scheduling algorithm that has a lower complexity. Here, we assume that nodes can exchange information with negligible time delay and cooperation exists among networks. In this case, a sub-optimal Cooperative Greedy Maximal Scheduling (CGMS) algorithm can be implemented. The following steps for the CGMS algorithm have been adapted from [93]:

i) Form a set $\mathcal{F}$ of all the link-channel pairs $(l, c), l \in \mathcal{L}_i, c \in \mathcal{C}$, for all $i \in \mathcal{I}$. Let the weight of each link-channel pair (l, c) be defined by $w_{l,c}\hat{r}_{i,l,c}$. We describe $\hat{r}_{i,l,c}$ as the amount of data link l is expected to successfully transmit if it is selected to send on channel c.[5] Begin with an empty set $\mathcal{M}(t) = \left\{[\mathcal{M}_1^c(t)], \ldots, [\mathcal{M}_I^c(t)]\right\}$.

ii) Search for the link-channel pair (l, c) with the largest weight. Add link l to $\mathcal{M}_i^c(t)$.

iii) Remove from $\mathcal{F}$ all members that cannot be scheduled due to (l, c) being scheduled. Specifically,

   a. Remove all link-channel pairs (k, c) where k shares an edge with l in G.

   b. If choosing (l, c) uses up the number of radio interfaces in the transmitter node $b(l)$ (or respectively, receiver node $e(l)$), remove all link-channel pairs $(k, c'), \forall c' \in \mathcal{C}$ where $b(k) = b(l)$ and $e(k) = b(l)$ (or respectively, $b(k) = e(l)$ and $e(k) = e(l)$). That is, we remove all link-channel pairs of links that are incident on the node that has used up all the radio interfaces available.

iv) Repeat steps ii) and iii) until $\mathcal{F}$ is empty.

The CGMS algorithm has been proven to achieve an *efficiency ratio* of $1/(\mathcal{K} + 2)$, where $\mathcal{K}$ is the maximum number of links that cannot be scheduled as a result of a given link being scheduled [93]. In other words, the CGMS performs at least a fraction $1/(\mathcal{K} + 2)$ of the optimal performance possible (i.e., by using the maximum weighted scheduling). While the above describes a centralized algorithm, distributed algorithms with time-complexity of $O(L)$ exist [94].

The achieved link rates at each timeslot is a result of the above scheduling. Since the algorithm always produces an independent set (though not a maximum weighted independent set), we can see that $r_{i,l,c} \in \{0, B\}$, assuming that all the links are backlogged. As an example to illustrate the operation, consider the 2-network contention graphs of the network in Figure 5.1, with $w_{l,c}(t)$ as shown in Table 5.2a. In this example, let there be 2 channels, where $c \in \{1, 2\}$. We also assume that each node has the same number of interfaces as the number of links incident on it. As a result of the CGMS algorithm, the links l_{11}, l_{12}, l_{21} and l_{23} will each be sending B units of data during timeslot t.

A cooperative L-C scheduling is possible if we assume that networks communicate and

[5] Under the conditions listed here, i.e., complete knowledge of G and cooperative scheduling. $\hat{r}_{i,l,c}$ can be accurately calculated to be B.

Links	$w_{l,1}(t)$	$w_{l,2}(t)$
l_{11}	20	10
l_{12}	5	2
l_{21}	10	9
l_{22}	2	1
l_{23}	8	5

(a)

Link-channel schedule	$w_{l,c}r_{i,l,c}$
$\mathcal{M}_1^1(t) = \{l_{11}\}$	$20 \times B$
$\mathcal{M}_1^2(t) = \{l_{12}\}$	$2 \times B$
$\mathcal{M}_2^1(t) = \{l_{23}\}$	$8 \times B$
$\mathcal{M}_2^2(t) = \{l_{21}\}$	$9 \times B$
$\sum w_{l,c}r_{i,l,c}$	$39B$

(b)

Table 5.2: (a) A particular $w_{l,c}(t)$ of the links in Figure 5.1. There are 2 channels available, i.e., $c \in \{1,2\}$. The $w_{l,c}(t)$ of the link-channel pairs chosen by the CGMS algorithm have been circled. (b) The link-channel schedules arising from the CGMS algorithm, including the achieved weights.

cooperate among themselves. However, as we have asserted throughout this thesis, this situation is highly unlikely among non-cooperative independent networks. The cooperative L-C scheduling will nevertheless provide a basis of comparison for the non-cooperative L-C scheduling, which is of greater interest and will be the topic of our discussion in the next section. In other words, we are interested in studying the "Price of Anarchy" [83], a term used in the game-theoretic community to describe how far the performance of non-cooperative (selfish) strategies depart from that of the cooperative (social optimum) strategies.

5.4.2 Non-Cooperative L-C Scheduling

In non-cooperative L-C scheduling, we assume the networks do not have the capabilities or incentives to communicate and cooperate among themselves. Reasons for this, as highlighted in Chapter 1, include the fact that they may be using different physical layer technologies or modulation (e.g. 802.11 and Bluetooth), and that contending links may lie outside each other's communication range. As a result, each network would be solving sub-problem (5.2c) independently. Thus, for every network $i \in \mathcal{I}$, this becomes:

$$\max_{\vec{\mathcal{M}}_i} \left\{ \sum_{l,c} w_{l,c}(t) r_{i,l,c}(t) \right\} \tag{5.6}$$

subject to (5.1d).

Given each network i only knows of its own network contention graph G_i, it can only try to solve (5.6) with this incomplete information. In addition, the network can only effect changes on its own links $\mathcal{L}_i$. We can modify the above CGMS algorithm to a Non-cooperative Greedy Maximal Scheduling (NGMS) algorithm by reducing the link set from $\mathcal{L}$ to $\mathcal{L}_i$, the contention graph from G to G_i and the resultant link-channel allocation from $\mathcal{M}$ to $\vec{\mathcal{M}}_i$. However, note that the resultant link rate $r_{i,l,c}$ is still a function of the global contention graph G, $\mathcal{M}_i^c$ and $\mathcal{M}_{-i}^c$.

Previously, the CGMS algorithm is able to produce an independent set with bounded efficiency ratio, when compared to the maximum-weighted scheduling. This is possible as we assume that the algorithm has complete knowledge of the contention graph, as well as full control over all the links, across all the networks[6]. In the NGMS algorithm, this assumption no longer holds. Because of this, the resultant link-channel allocation, when seen across all the networks, may not always produce an independent set. We will now show, by way of example, why this is so. The example will also illustrate that there is further efficiency loss when each network performs NGMS independently. In fact, the efficiency ratio can go arbitrarily close to 0.

Consider again the 2-network topology of Figure 5.1. At a particular timeslot t, let the $w_{l,c}(t)$ be as shown in Table 5.2a previously, along with the same interface configuration. Table 5.3a shows the same $w_{l,c}(t)$ values, but indicating which link-channel pairs (l, c) would have been selected if each network independently performs the NGMS algorithm instead.

Figure 5.3 shows the contention graphs when links are assigned to their corresponding channels as per the CGMS and NGMS algorithms. In the figures, the solid black edges represent *potential* contention if the end-point links are scheduled on the same channel. The colored edges represent *actual* contention due to the particular schedule. While the CGMS algorithm produces a schedule with no contention, an edge appears in the schedule produced from the independent NGMS algorithms. The NGMS ensures that there is no contention within the individual network contention graph. However, the presence of the other independent network causes the contention graph to be actually G. Therefore, when these two contention graphs are brought together,

[6]Note that this does not necessary mean that the CGMS has to be a centralized algorithm. It can still be implemented in a distributed manner, but each link has to abide by the outcome of the algorithm.

Links	$w_{l,1}(t)$	$w_{l,2}(t)$
l_{11}	20	10
l_{12}	5	2
l_{21}	10	9
l_{22}	2	1
l_{23}	8	5

(a)

Link-channel schedule	$w_{l,c}r_{i,l,c}$
$\mathcal{M}_1^1(t) = \{l_{11}\}$	20×0
$\mathcal{M}_1^2(t) = \{l_{12}\}$	$2 \times B$
$\mathcal{M}_2^1(t) = \{l_{21}\}$	10×0
$\mathcal{M}_2^2(t) = \{l_{23}\}$	$5 \times B$
$\sum w_{l,c}r_{i,l,c}$	$7B$

(b)

Table 5.3: (a) $w_{l,c}(t)$ of the links similar to Table 5.2a. The $w_{l,c}(t)$ of the link-channel pairs chosen by the networks performing NGMS algorithms independently have been circled. (b) The link-channel schedules arising from the independent NGMS algorithms, including the achieved weights.

an edge appears between links l_{11} and l_{21} since they are scheduled on the same channel, $c = 1$.

The effect this has on the weighted sum $\sum w_{l,c}r_{i,l,c}$ can be seen in Table 5.3b. Like CGMS, the NGMS algorithm is performed based on the estimated link rate $\hat{r}_{i,l,c}$, which is assumed to be B if it is scheduled. However, because of the contention, the actual achieved rates on the contending links turn out to be zero. As a result, the weighted sum $\sum w_{l,c}r_{i,l,c}$ of NGMS is significantly lower than that of CGMS (compare Table 5.2b).

In fact, the efficiency loss can become even greater. Consider now that links l_{12} and l_{23} in our example are positioned such that they contend with each other. This will introduce an edge to the global contention graph G. In Figure 5.3b, this means that a new contention edge will appear between l_{12} and l_{23}, since they are scheduled on the same channel $c = 2$. The result is that now, the achieved rates of both these links also become zero. Practically, this means that for that timeslot, even though some links are scheduled to transmit, none of them succeeds in transmitting because there are collisions on all the links. It is not difficult to construct a particular global contention graph, e.g. a complete graph[7], where at every timeslot, any schedule will result in contention on all of the links that have been chosen to send. The capacity of this system becomes arbitrarily close to 0.

[7]A complete graph is one in which an edge is present between every pair of vertices.

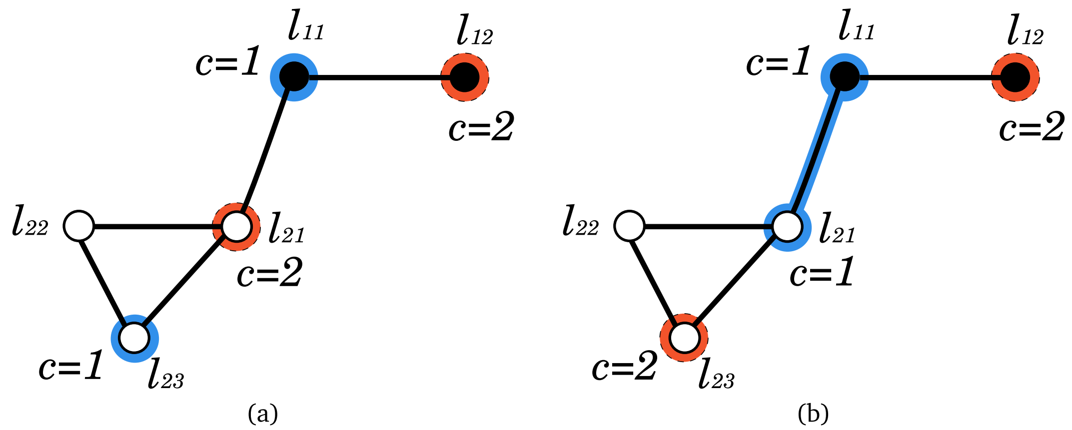


Figure 5.3: Contention graph of the 2-network topology with links colored to represent their channels. (a) CGMS algorithm – no contention. (b) NGMS algorithm – contention between links l_{11} and l_{21}.

Given that independently performing the greedy maximal scheduling in each network may result in unbounded efficiency losses, we are interested to explore ways of improving the performance. Note that the primary reason for the loss is the incomplete information about the actual contention relationship among the links. As a result, the L-C scheduling algorithm uses an inaccurate feasible rate region to compute the schedules. Instead of contention-free schedules, links from different networks may contend with each other, resulting in data loss.

One possible solution is for the networks to exchange information, in order to get a better picture of the contention relationships. However, this requires cooperation, which is a challenge in independent networks. In the next section, we propose an alternative approach of improving the efficiency of the non-cooperative scheduling algorithm, by incorporating a simple method for each link to better estimate its rate $\hat{r}_{i,l,c}$.

5.4.3 Moving Average Link Rate Updates

In this section, we propose a simple mechanism to improve the efficiency of the NGMS algorithm. We note that due to the incomplete contention information, the estimated link rate that is used in the algorithm is incorrect when multiple independent networks are co-located together. Specifically, the algorithm uses $\hat{r}_{i,l,c} = B$ as it assumes that a scheduled link is able to transmit B amount of data. However, in the presence of contentions from links belonging to other networks, the actual rate $r_{i,l,c}$ may be much lower. With the mutually-exclusive model we have assumed so far, it becomes zero. In more practical scenarios, the lower rate is a consequence of either contention management mechanisms, e.g. when a link defers transmission on sensing that the channel is busy, or of actual collisions of packets that take place when two scheduled links transmit at the same time.

We improve the rate estimation process by making use of a moving average computation, based on the actual achieved rate of the link on the channel during the previous time slots when it was transmitting. Specifically, let T denote the window size of the moving average computation. For every network $i \in \mathcal{I}$, every link $l \in \mathcal{L}_i$ and every channel $c \in \mathcal{C}$, we first define a sequence $a_k(t)$ for $k \in \{1, \ldots, t-1\}$, where $a_k(t) = 1$ if $l \in \mathcal{M}_i^c(t-k)$ and $a_k(t) = 0$ otherwise. In addition, denote $b_k(t)$ for $k \in \{1, \ldots, t-1\}$, where $b_k(t) = r_{i,l,c}(t-k)$ if $a_k(t) = 1$ and $b_k(t) = 0$ otherwise.[8] That is, $a_k(t)$ is an indicator function of whether link l was scheduled on channel c at the k-th slot before the present timeslot t, and $b_k(t)$ is the corresponding achieved rate. The sequences $a_k(t)$ and $b_k(t)$ are defined as above for all $t \geq 2$. We let $a_k(1) = 0$ and $b_k(1) = 0$ for all i, l, c.

We update $\hat{r}_{i,l,c}$ as follows: At timeslot $t \geq 2$,

$$\hat{r}_{i,l,c}(t) = \begin{cases} \frac{1}{T} \sum_{k=1}^{K} b_k(t), & \text{if } \sum_{k=1}^{t-1} a_k(t) \geq T; \\ \frac{1}{T} \left[T'B + \sum_{k=1}^{t-1} b_k(t) \right], & \text{otherwise.} \end{cases} \tag{5.7}$$

where K is such that $\sum_{k=1}^{K} a_k(t) = T$ and $T' = T - \sum_{k=1}^{t-1} a_k(t)$. We let $\hat{r}_{i,l,c}(1) = B$ for all i, l, c.

Essentially, at every timeslot t, we compute the mean of the achieved rates for the last T occasions that the link-channel pair (l, c) was scheduled, and use it as the estimated rate $\hat{r}_{i,l,c}$. If the link-channel pair was scheduled for less than T instances, the value of B will be used for the remaining times to compute the mean. We believe this will give a better estimation by taking into account the contention effect on link l on channel c (as opposed to B in the NGMS algorithm above).

[8] There are corresponding sequences $a_k(t)$ and $b_k(t)$ for each network i's link l on each channel c. For the sake of notational simplicity, we will drop the identifying terms i, l, c in our description here.

To summarize, at each timeslot t and for every link $l \in \mathcal{L}_i$, we compute the moving average estimated link rate $\hat{r}_{i,l,c}(t)$ based on achieved rates of the most recent T history that link l had been transmitting on channel c. We use $\hat{r}_{i,l,c}(t)$ to compute the weight $w_{l,c}(t)\hat{r}_{i,l,c}(t)$ for every link-channel pair (l,c), and use these weights in the NGMS algorithm. We call our modified algorithm the NGMS-MA algorithm.

The merit of the NGMS-MA algorithm is that no communication or coordination among the independent networks is required. Each link can independently compute its own estimation of the expected link rate for each channel, based on the history of its achieved rates in that channel. In the next section, we show through simulations that our proposed modification significantly improves the performance of the non-cooperative cross-layer resource allocation algorithm in multiple independent networks.

5.5 Simulations

In this section, we evaluate the performance of the NGMS and NGMS-MA algorithms using simulation. We compare NGMS and NGMS-MA with the cooperative CGMS algorithm, which will serve as the benchmark. Even though CGMS do not usually produce the optimal solution, it is a suitable candidate for comparison as it has acceptable computational complexity and has known performance bounds with respect to the optimal algorithm. In addition, this will give us an indication of the price of anarchy of the non-cooperative algorithms when compared with the cooperative one.

The network topology used in our simulation is as shown in Figure 5.4. Our topology consists of 2 independent networks co-located together, with a subset of the links contending with each other. The distance between adjacent nodes is 1 unit and the communication range is 1.01 unit. In our simulation whenever a pair of nodes m and n belonging to the same network are within communication range, we allow the possibility of a pair of unidirectional links l_1 and l_2 between them, where l_1 represents the link from node m to n and l_2 represents the reverse direction.

We set the interference range to 1.51 units. A pair of links, regardless of which network they belong to, that are within the interference range will interfere with each other. We define the distance between a pair links as the distance between the midpoint coordinates of the respective transmitter and receiver nodes the links belong to.

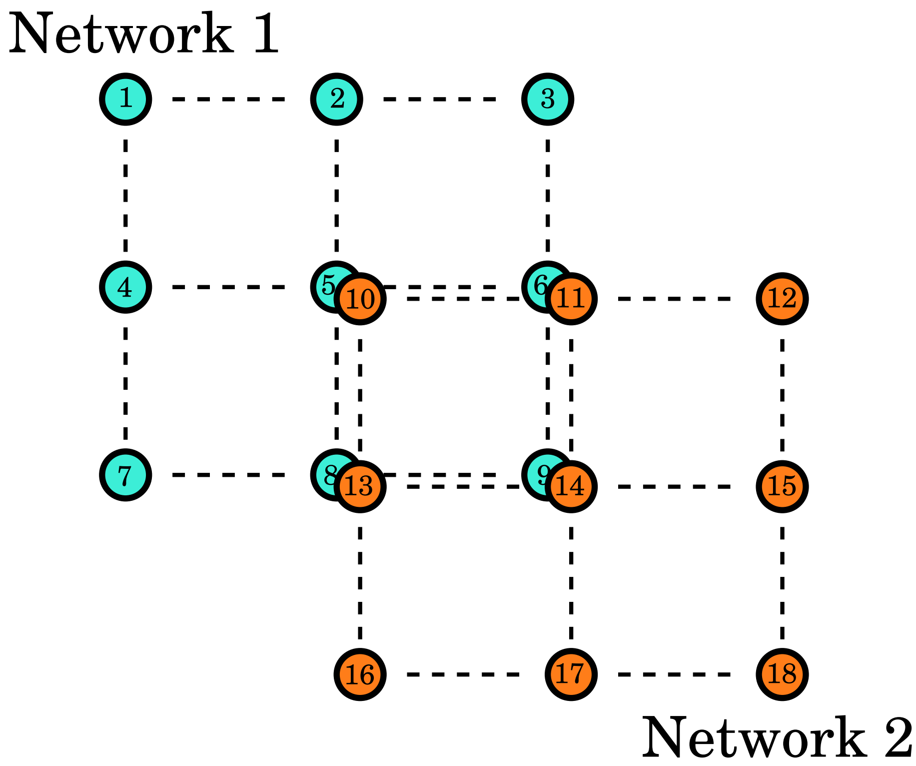


Figure 5.4: Network topology of 2 co-located networks.

This particular network topology allows us to realize the situation where 2 network are deployed in an area, but where only a subset of links from each network interfere with each other. We are interested in how the algorithms described in this chapter perform under such a condition.

In each simulation set, we run 100 independent runs, each with a fixed number of end-to-end flows set up between randomly generated source and destination nodes belonging to the same network. As such, some flows may just be between adjacent nodes, while others may extend beyond a number of hops. This gives us a varied set of different flows going through each network. We implement the cross-layer optimization algorithm, as described in Section 5.3.1, with the different L-C scheduling components as determined by the different algorithms that we discussed in Section 5.4. The utility function of every flow in the simulation is defined as $U_n^s(\lambda_n^s) = \log(\lambda_n^s)$, resulting in proportional fair congestion control. Both h_p and h_q, the Lagrange multiplier stepsizes, have been set to 0.1 in the simulations.

We first simulate the situation where the L-C scheduling timeslots are synchronized within each network as well as across the independent networks. This idealized and slightly unrealistic scenario is necessary for us to make a fair comparison of the performances of the non-cooperative L-C scheduling algorithms against the cooperative one. This is because all the algorithms essentially assume timeslot synchronization within the network running the L-C scheduling algorithm. Since the CGMS algorithm is performed by the networks cooperatively, time synchronization among these networks is a necessary condition. We will investigate the effects of asynchronicity on the non-cooperative L-C scheduling algorithms in a later set of simulations. In addition, our simulation first assumes a mutually-exclusive physical and link layer model, before we investigate the performances under a CSMA model in the later simulations.

All the simulations have been performed using Matlab and the results are collected at the end of 10000 time iterations. For each simulation set, we present the results as the mean and standard deviation of the 100 independent runs. For our NGMS-MA algorithm, we have chosen a T value of 100.

5.5.1 Comparison of Algorithms

We first compare the CGMS, NGMS and our NGMS-MA algorithms for different number of channels and interfaces. Each network sends out 4 flows for each simulation run, where the source and destination nodes of each flow are randomly chosen. Table 5.4 shows the aggregate throughputs, normalized over the effective bandwidth of B, of both networks for different number of channels and where each node in the networks have different number of radio interfaces. Note that the number of radio interfaces R_n available in each node will always be less than or equal to the number of channels available C. Otherwise, the additional interfaces would either not be used or cause interference with the interface that is already on the channel.

We show graphically a subset of the same results in Figure 5.5. We plot the total throughputs of both networks for the sake clarity in the result presentation. Comparing the performance of CGMS with NGMS on both Table 5.4 and Figure 5.5, we can see that non-cooperation in the L-C scheduling results in a significant loss in the throughput that the networks can support. As explained in Section 5.4.2, this is due to contending links belonging to different networks choosing to transmit on the same channel in a given timeslot. This lack of coordination results in collision of the data sent during that timeslot, effectively reducing the throughputs of the networks over the long run.

# of interfaces	2				
# of channels	2	3	4	5	6
CGMS	(2.436, 2.363)	(3.306, 3.213)	(4.101, 3.731)	(4.958, 4.022)	(5.448, 4.156)
NGMS	(0.768, 0.578)	(0.892, 0.857)	(1.107, 1.195)	(1.422, 1.498)	(1.521, 1.464)
NGMS-MA	(2.027, 2.008)	(2.674, 2.575)	(2.975, 3.152)	(3.466, 3.455)	(3.701, 3.718)

# of interfaces	3			
# of channels	3	4	5	6
CGMS	(3.502, 3.451)	(4.413, 4.216)	(5.051, 5.030)	(5.685, 5.266)
NGMS	(0.960, 1.079)	(1.043, 1.148)	(1.407, 1.521)	(1.618, 1.751)
NGMS-MA	(3.122, 2.923)	(3.550, 3.598)	(3.941, 4.152)	(4.331, 4.405)

# of interfaces	4		
# of channels	4	5	6
CGMS	(4.677, 4.637)	(5.309, 5.338)	(5.959, 5.799)
NGMS	(1.496, 1.207)	(1.397, 1.407)	(1.606, 1.756)
NGMS-MA	(3.899, 3.986)	(4.126, 4.368)	(4.460, 4.779)

# of interfaces	5		6
# of channels	5	6	6
CGMS	(5.554, 5.441)	(6.283, 6.252)	(6.265, 6.393)
NGMS	(1.491, 1.773)	(1.493, 1.650)	(1.468, 1.941)
NGMS-MA	(4.500, 4.477)	(4.990, 4.800)	(5.053, 4.824)

Table 5.4: Aggregate throughputs of the 2 networks for different numbers of interfaces and channels. Entries in each parenthesis are the throughputs for networks 1 and 2 respectively.

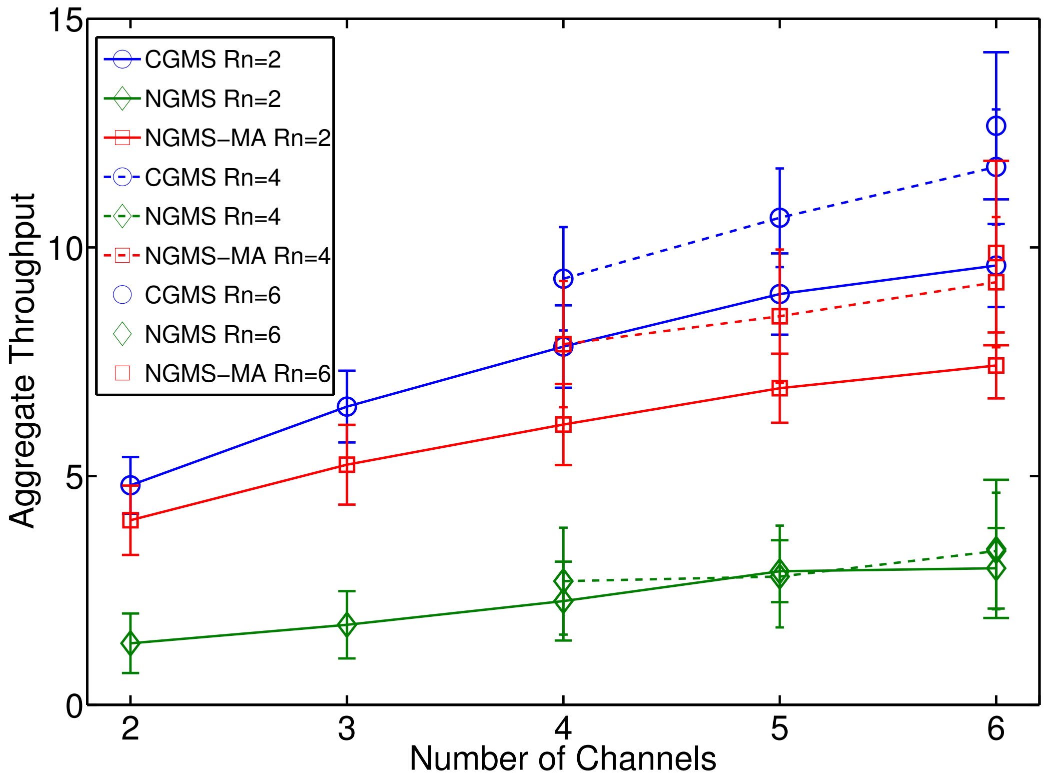


Figure 5.5: Aggregate throughputs for different number of channels and interfaces.

Increasing the number of channels does improve the throughput for NGMS, as more channels are available for the nodes to choose from. However, due to the lack of information about the contention that is coming from the external network during the L-C scheduling operation, the gains are much less than the case when networks can exchange information.

Applying the moving average link rate estimation to the L-C scheduling shows notable improvement in performance. While still not matching that of CGMS, NGMS-MA shows performances ranging from 1.4 to 2 times improvement in aggregate throughput when compared to the original NGMS algorithm. In addition, in line with the theoretic analysis of [84] and the simulation results in [100], our results show a decrease in the marginal utility of adding more interfaces to the network. However, it appears that in the case of NGMS, adding more interfaces results in much less improvement in performance than both CGMS and NGMS-MA.

5.5.2 Number of Flows

We next look at the effect the number of flows have on the performance of the algorithms. In this simulation, we set $R_n = 2$ for each node in both networks and vary the number of flows in each network. In addition, we also vary the number of channels available to the networks. Figure 5.6 shows the aggregate throughputs of both networks for the different number of flows and channels.

We can see that again, NGMS shows a substantial loss in efficiency when compared to the cooperative LC-scheduling algorithm. The NGMS-MA is able to improve the aggregate throughput by as much as 3.2 times when compared to NGMS. This shows that our scheduling algorithm can support a higher number of flows in a network that is co-located with other contending networks.

5.5.3 CSMA Model

Essentially, the mutually-exclusive model that we have used so far in our analysis and simulations assumes that each link, when chosen on a channel, will occupy the entire timeslot. Besides simplifying the analysis, we believe that it provides a worst-case performance scenario. In a practical situation, especially with unlicensed-band networks, some form of MAC protocol would be present. The MAC protocol ensures

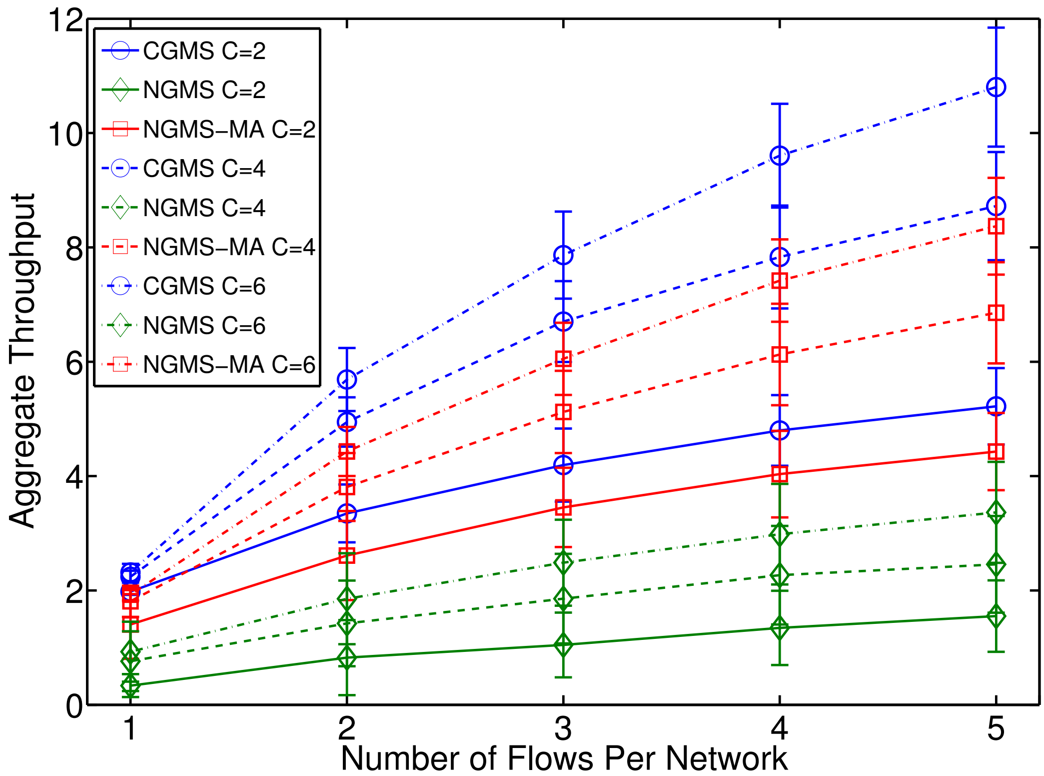


Figure 5.6: Aggregate throughputs for different number of flows and channels.

that links belonging to the same collision domain are able to share the medium. In addition, an effective MAC protocol provides some form of mechanism that allows links to respond to collision situations. It would therefore be of interest to compare the performance of the algorithms under a more realistic physical and link-layer[9] model.

In the case of multiple co-located autonomous networks, it is unrealistic to assume that *all* the networks will have the same technology (e.g. 802.11) or even employ the same MAC. In this section, we investigate the case when networks use an idealized CSMA MAC. The main reason of choosing CSMA for our evaluation is that most unlicensed-band networks employ some form of CSMA-like MAC protocol (e.g. 802.11 and 802.15.4). While not entirely realistic, it will provide us with some insights on how MAC protocols affect the performance of cross-layer optimization algorithms. Interactions among different MAC protocols, an interesting direction, will be left to future work.

Essentially, unlike in the more general mutually-exclusive model, links contending with one another may not get zero rates when they transmit on the same channel in the same timeslot. The main challenge relates to the determination of these rates. As described in Chapter 4, it has been shown that the rate allocation of the links in a network (or in our case, multiple networks) is often a function of the global contention graph. Models and algorithms have been proposed to solve for these rates with varying degrees of computation complexities [53, 90, 139]. For our simulation, we have used a method proposed by Liew et al. [90]. This method has been shown to be low in complexity, yet gives surprisingly accurate link rate allocations when compared with experimental results. Given a contention graph, their proposed algorithm, known as BoE, is able to compute the share of the channel bandwidth for each link.

In each timeslot of our simulations, we convert the link-channel schedules into a set of C contention graphs, one for each channel. Using the BoE method, we are able to compute the rate that each of the active links will achieve during that time slot. Thus, $r_{i,l,c} \in [0, B]$ instead of $r_{i,l,c} \in \{0, B\}$ as in the previous case. In addition, we also study the case when there are inefficiencies that are related to multiple links sharing a channel, which we will call the CSMA efficiency loss[10]. Take 802.11 DCF as

[9] Since a MAC protocol often assumes some form of physical characteristics, we shall loosely use the terms "MAC" and "physical and link-layer" interchangeably.

[10] Note that this is not to be confused to the efficiency loss in the scheduling algorithm that we have

an example. When two contending 802.11 links transmit at the same time, they are unlikely to each get half of the effective bandwidth B. Each transmitter of the link has to wait for a DIFS duration every time the channel becomes free again (after the completed transmission of the contending link). Thus the presence of a contending link has the effect of reducing the time available for a link to transmit data, reducing the rate to a value that is less than $\frac{B}{2}$. We denote this CSMA efficiency loss as ϵ, such that if a link is sharing the channel with other links, its share of the channel bandwidth (as computed by the BoE algorithm) will be multiplied by $(1-\epsilon)$. Thus ϵ gives an indication of how efficient different CSMA-like protocols utilize the channel in the presence of interference. We evaluate the performance of the algorithms with ϵ values of 0, 0.1 and 0.2.

Our simulation involves every node with $R_n = 2$ and each network sending 4 flows. Figure 5.7 shows the aggregate throughputs of the networks under different number of channels and different ϵ value. Note that since the CGMS algorithm allows links to always be scheduled without contention, there is no efficiency loss in the sense of what has been described above. Comparing Figure 5.7 with Figure 5.5 (mutually-exclusive model), we see that the presence of a CSMA MAC improves the performance of the non-cooperative algorithms with respect to the cooperative one. The reason for this is that the MAC ensures contending links share the bandwidth, so that data are not completely lost. However, the non-cooperative nature of the networks still results in efficiency losses of as much as 32%. Nevertheless, NGMS-MA is still able to improve the aggregate throughputs of the non-cooperative algorithm by as much as 21%.

As expected, we see that an increase in the CSMA efficiency loss ϵ results in the corresponding decrease in the performance of the non-cooperative algorithms. This motivates the design of efficient MAC protocols that can help to improve the system capacity of the independent networks.

5.5.4 Evaluation of Link Rate Estimation

In this section, we study the merits of the moving-average approach in estimating the link rates $\hat{r}_{i,l,c}$. Using results from a particular set of simulations, we first analyze the link rate estimation error – the difference between the estimated rate $\hat{r}_{i,l,c}$ and the eventual achieved rate $r_{i,l,c}$, of every link l from every network i that is scheduled

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been discussing

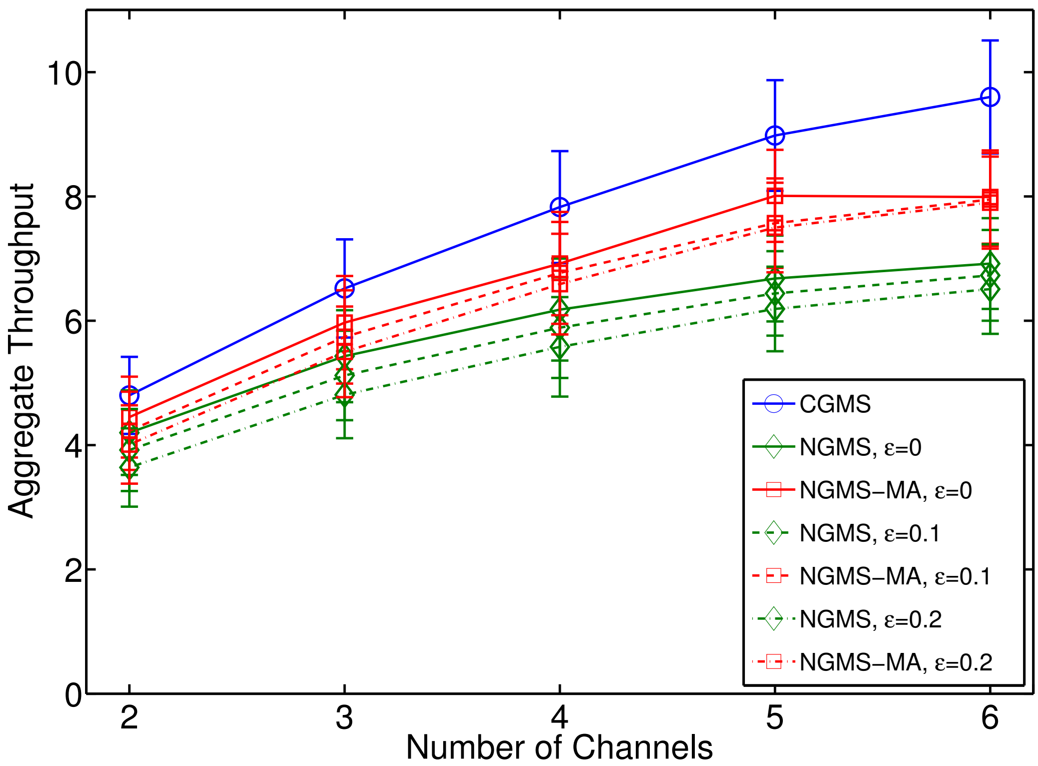

Figure 5.7: Aggregate throughputs for different number of channels and CSMA efficiency loss ϵ.

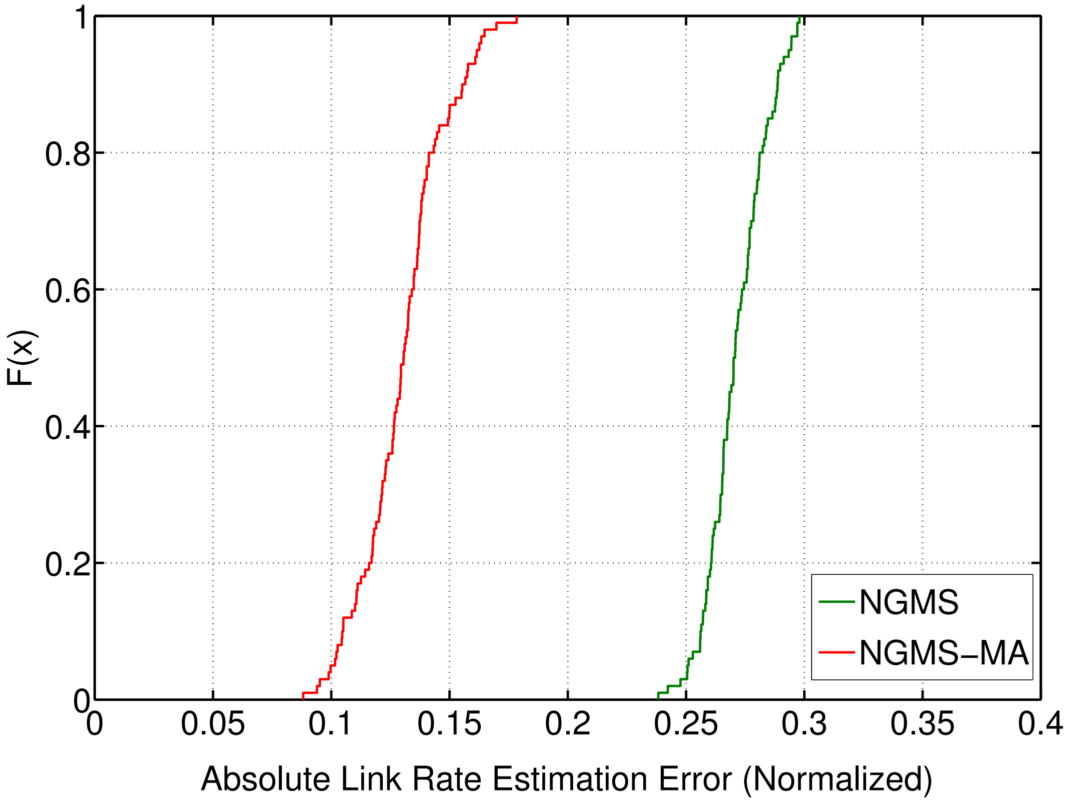

Figure 5.8: Cumulative distributive function of the link rate estimation error.

on a channel c. Following that, we investigate if the moving-average component is indeed a necessary part of our proposed NGMS-MA scheme, which helps to improve its performance. To achieve this, we compare the performance of the NGMS-MA algorithm against other possible ways of computing $\hat{r}_{i,l,c}$.

Link Rate Estimation Error

From our simulations, we take the particular setting of 4 flows per network, where $R_n = 2$, $C = 4$ and a CSMA model with $\epsilon = 0$, and compute the absolute difference between $\hat{r}_{i,l,c}$ and $r_{i,l,c}$ for all the links that have been scheduled during each simulation run. Figure 5.8 shows the cumulative distributive function of the average estimation error, normalized over the effective bandwidth B, for the 100 independent runs. The lower estimation errors for all the links show that by using the moving-average approach, the NGMS-MA algorithm is able to compute a better estimate of the eventual link rates, when compared to the NGMS algorithm.

NGMS-Realistic

As the NGMS algorithm always assumes that the rate of a link is B whenever it is scheduled, one may wonder if this overly-optimistic link rate assumption is in fact the main reason behind the performance degradation in NGMS. What happens when the link rate estimation takes values other than B? Essentially, this means that the algorithm now assumes that there is a possibility that a scheduled link may achieve a rate that is less than B, possibly due to the presence of contending links belonging to external networks.

To evaluate how the NGMS algorithm will perform under such a link rate estimation scheme, we modify the original NGMS to select $\hat{r}_{i,l,c}$ values from a probability density function (pdf). In our simulation, in each timeslot t, for every link l of network i in channel c, $\hat{r}_{i,l,c}$ is randomly selected from a beta distribution with a pdf that is expressed as follows:

$$f\left(x;\alpha,\beta\right) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\mathcal{B}(\alpha,\beta)}$$

where the beta function, $\mathcal{B}(\alpha,\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt$, serves as a normalization constant so that the total probability integrates to 1.

By setting $\beta = 1$, a monotonically increasing function is realized, where the rate of increase is determined by the value of α. Figure 5.9 shows the pdf of the beta distribution for $\beta = 1$ and $\alpha = 2$, 5 and 10. It is not difficult to see that when a link rate estimation scheme selects $\hat{r}_{i,l,c}$ randomly from this distribution, it assumes that the link rate is closer to B most of the time. However, there is still a non-zero probability, albeit a smaller one, that the rate is much less than B. For this reason, we name this modification the NGMS-Realistic.

It should be noted that NGMS-Realistic does not estimate the link rate from any measurement of the channels. It also does not use any past history to aid its estimation. It merely adds a more realistic assumption to the fixed $\hat{r}_{i,l,c}$ of the original NGMS. Thus, it will provide insights to how the availability of more choices (in fact, a continuous range) of values for link rate estimation affects the peformance of the NGMS algorithm, as well as how this compares against NGMS-MA. Indeed, if NGMS-Realistic performs favorably when compared to NGMS-MA, one could argue that it is a better

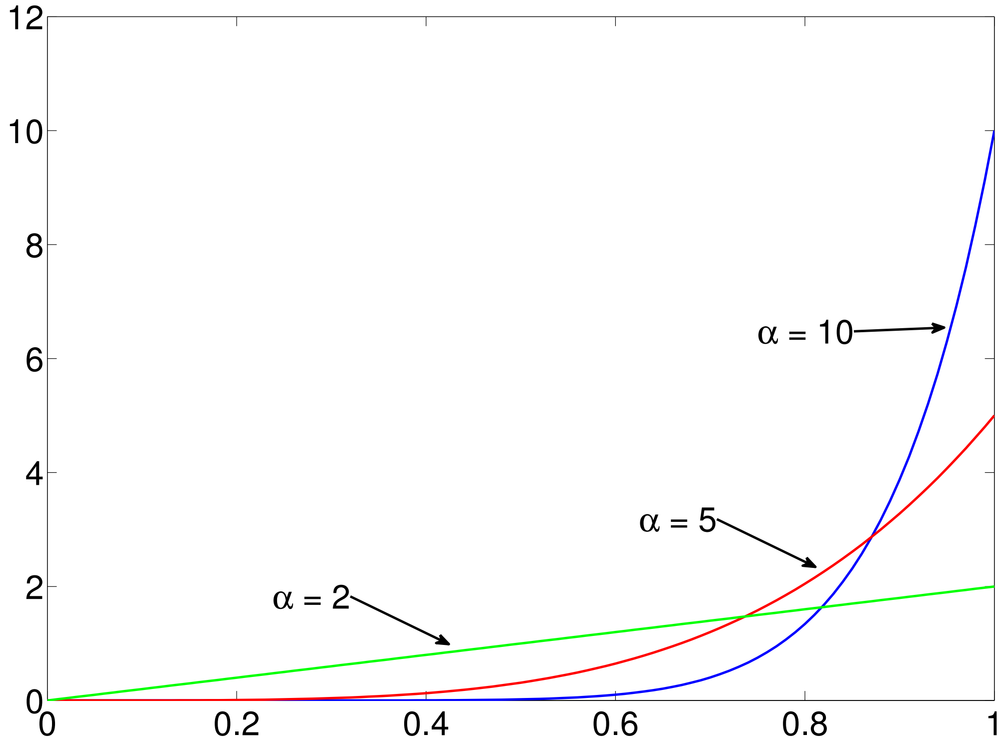

Figure 5.9: PDF of the beta distribution, where $\beta = 1$.

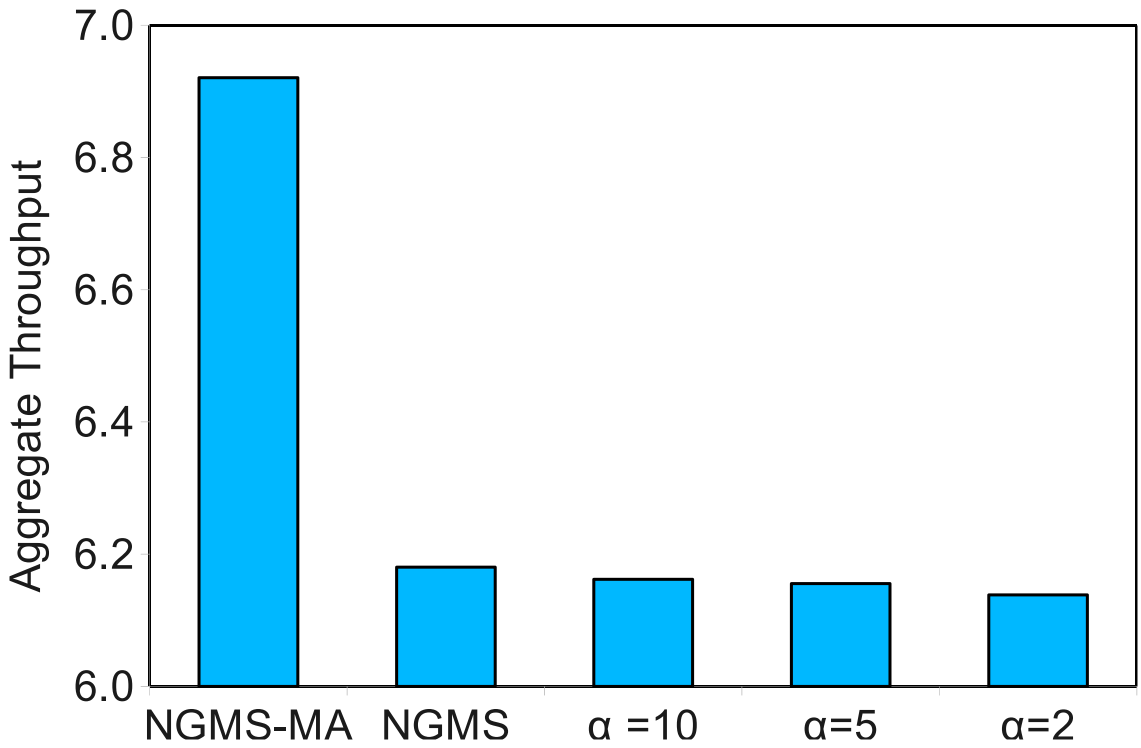

Figure 5.10: Aggregate throughputs for NGMS-MA, NGMS and NGMS-Realistic.

algorithm, since no measurement is necessary and it requires much less computation than NGMS-MA.

For this set of simulations, we use the same setting of 2 networks, with 4 flows in each network, $C = 4$ and $R_n = 2$. We again use the CSMA model with $\epsilon = 0$. We compare NGMS-Realistic, for $\alpha = 2$, 5 and 10, with the original NGMS and NGMS-MA algorithms. Incidentally, a higher α corresponds to a more optimistic view of the channel conditions, where the algorithm believes that the links can achieve rates closer to B.

Figure 5.10 shows the aggregate throughputs, averaged over 100 independent simulation runs. We can see that providing more choices for $\hat{r}_{i,l,c}$, without correlating it to the actual channel conditions, does not improve the performance of NGMS. Therefore, by considering the rates in the previous instances when a link was scheduled, NGMS-MA is able to achieve a far better aggregate throughput.

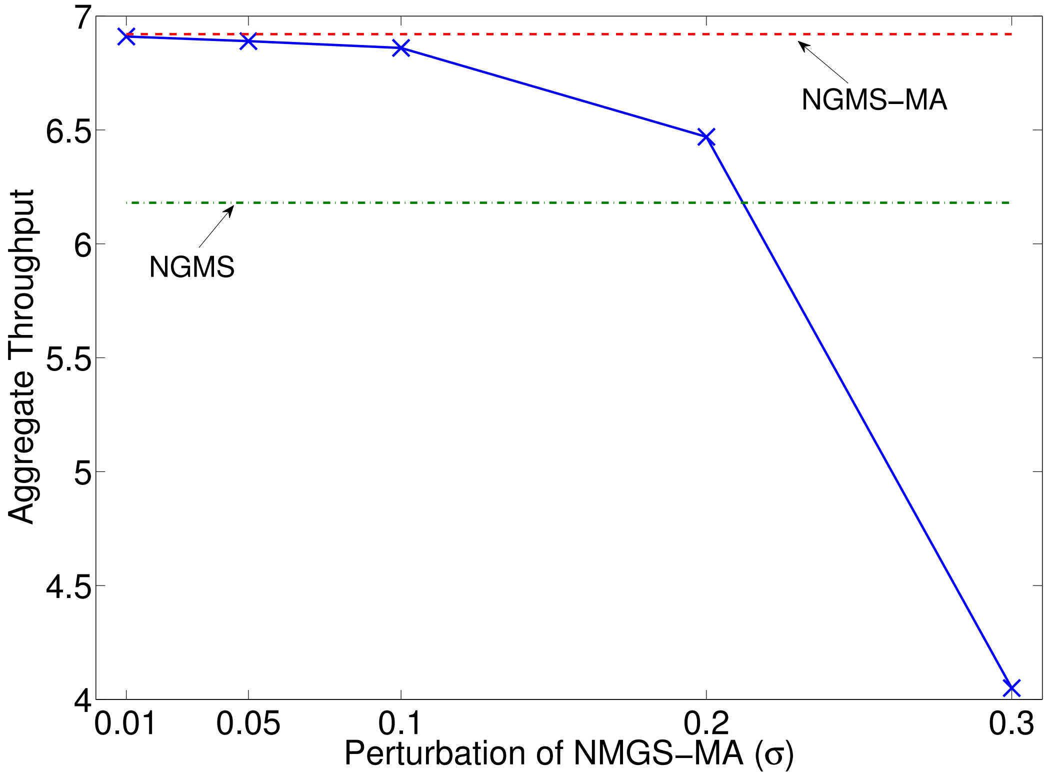

Figure 5.11: Aggregate throughputs for different degrees of perturbation.

Effects of Moving-Average Estimation Accuracy

Next, we would like to study the effects the accuracy of the moving-average estimation have on the performance of the NGMS-MA algorithm. To achieve this, we artificially introduce perturbation to the estimated link rate $\hat{r}_{i,l,c}$ that is computed using the moving-average algorithm. To be precise, instead of using the actual value as calculated by the update equation of (5.7), we choose a value from a normal distribution that is centered around the computed value. By using different standard deviation σ for the normal distribution, we control the degree of perturbation to the moving-average algorithm.

We use the same simulation setting as before. Figure 5.11 shows the aggregate throughputs for perturbations with different values of σ, normalized to B, compared with the original NGMS and NGMS-MA.

We can see that the performance of NGMS-MA degrades correspondingly with the increase in the deviation from the estimated link rate values. This serves to highlight the merit of the moving-average updating scheme in contributing to the performance gains that are achieved by the NGMS-MA algorithm. Fortunately, Figure 5.11 also shows that a small degree of deviation or error in the link rate estimation can still be tolerated by the algorithm. In fact, a perturbation with a standard deviation of $0.2B$ still performs better than the NGMS algorithm.

5.5.5 Asynchronicity

As mentioned in Section 5.2, it is not realistic to assume that the timeslots are synchronized across the networks. We now evaluate the effects of a particular form of asynchronicity in the timeslots on the operation of the non-cooperative cross-layer algorithms. Since the cooperative algorithm assumes timeslot synchronization, CGMS does not come into the picture here.

We first introduce the basic asynchronous model. Given the two independent networks in our simulation, we assume the duration of each timeslot is the same for both networks. We define an asynchronization degree value, which determines the degree of offset between the time instances the networks perform the updates in the algorithm. As shown in Figure 5.12, an asynchronization degree of 0 means that the timeslots of the networks are perfectly synchronized. An asynchronization degree of 0.1 means that the timeslots of the networks are mismatched by 0.1 of the timeslot duration, and so on. Since the asynchronization degree from 0 to 0.5 is a mirror image of that from 0.5 to 1, we evaluate the performance of the cross-layer algorithms over the range of 0 to 0.5.

We study the case when the 2 networks have 4 flows each and each node within the networks have 2 radio interfaces. There are 6 available channels. We use the idealized CSMA model defined above in our simulation here. Figure 5.13 shows the aggregate throughput of the 2 networks, comparing the non-cooperative algorithms for different asynchronization degrees. As we can see from the figure, the performances of the algorithms remain relatively unchanged when there is a mismatch in the updates of the algorithm between the 2 networks.

The section only explores the stability of the non-cooperative algorithms in the presence of a specific type of asynchronicity — i.e., when the timeslot duration is the

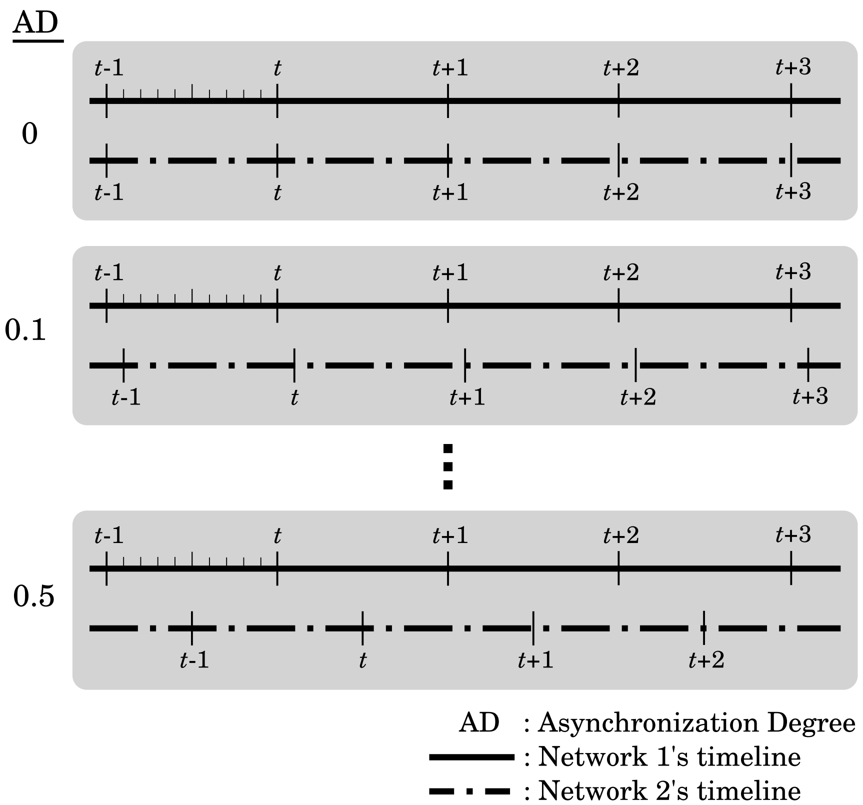

Figure 5.12: Timeline offset for different asynchronization degree.

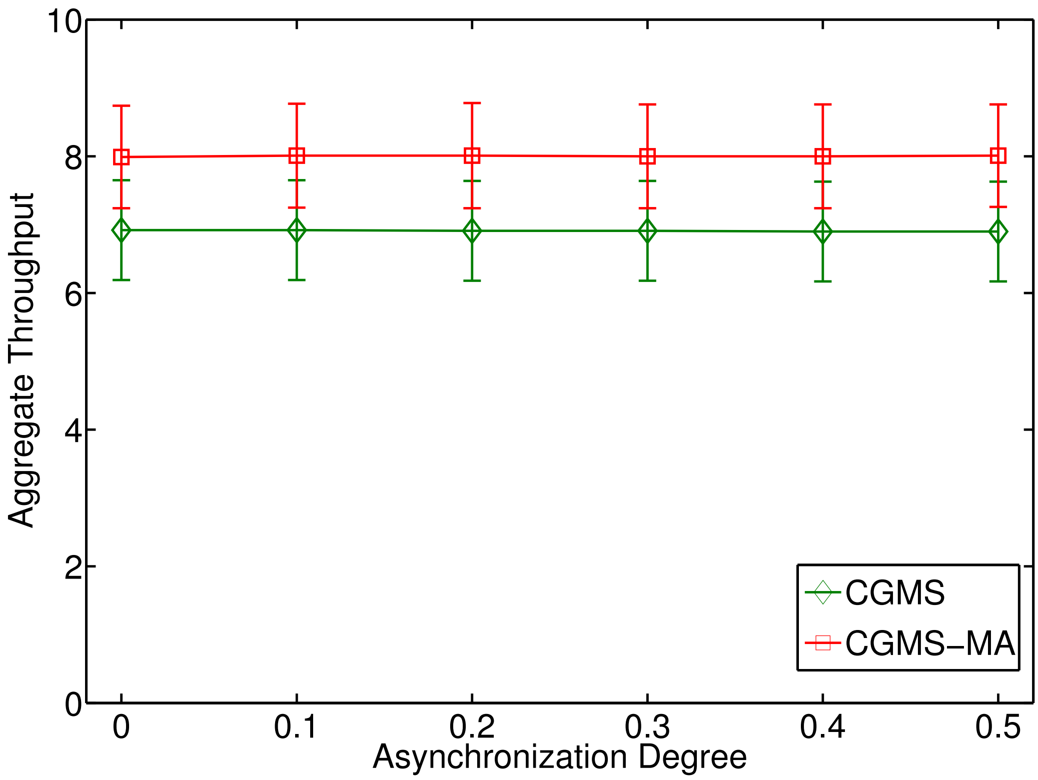

Figure 5.13: Aggregate throughputs for different asynchronization degrees.

same and the asynchronicity occurs between the networks. There exists other forms of asynchronicity in timeslots, e.g. where the timeslot durations are different, or when asynchronicity occurs within the same network [145]. Their investigation will be left for future work.

5.6 Discussion

This section discusses a number of issues related to the our proposed cross-layer algorithm described in this chapter.

1. Although the algorithms in this chapter arise from the perspective of Network Utility Maximization, the presence of independent networks suggests that the solution can be cast back to and be reinterpreted as a coexistence game, as described in Chapter 3. One can see that each network only has control over its own actions, i.e., link-channel schedule and rate allocation at the sources and virtual links. However, its performance (or utility) is a consequence of its actions, as well as the actions of other networks.

2. The moving-average algorithm described here can be thought of as a form of learning, where each link tries to predict the contention level of its environment in each channel through its achieved rates in the past. There exist other methods to make better and more accurate predictions, including other forms of contention inputs (e.g. RSSI or channel busy time at the physical layer). We will explore these in the future.

3. One undesirable outcome of our simple moving-average algorithm is that when a link consistently achieves low or zero rates in a channel over a long period of time, its rate estimation will ultimately go to zero. This renders the link-channel pair to be never scheduled from then on, since the algorithm concludes that the contention at the link in that channel is too high. Thus it cannot respond to situations when the contention condition improves, e.g. due to shut down of the contending networks or long-term changes in usage pattern. Borrowing the techniques used in the game-theoretic algorithms that we have discussed in the preceding chapters may help improve the situation. This is also left as part of our future work.

5.7 Conclusion

Cross-layer resource allocation algorithms that are based on network utility maximization theory have been proposed to improve performance of multihop wireless networks. Many of these algorithms provide attractive solutions to the problem of managing the network resources in an interference-limited environment, as they have provable performance results and can be modified into distributed algorithms with some level of efficiency loss. However, most of the algorithms assume the presence of one network with a common objective.

In this chapter, we study the application of cross-layer resource allocation algorithms to the case of multiple independent non-cooperative wireless networks. Communication does not exist among these networks and they have no mechanism and incentive to cooperate. We specifically look at an algorithm that is able to perform joint congestion control, channel allocation and routing in networks with multiple radio operating on multiple channels. We present a system and optimization model incorporating the non-cooperative networks and show that when an existing cross-layer algorithm is applied, it leads to efficiency loss. We propose an improved algorithm that is able to improve the performance of the existing non-cooperative algorithm significantly.

Chapter 6

Conclusion

In this chapter, we provide some concluding remarks to this thesis and discuss possible future research directions.

6.1 Conclusion

Driven by the growth of inexpensive IEEE 802.11 devices and the relative ease of deploying an unlicensed band network, there was a time when many had a vision of multiple networks blanketing an entire city. Some of these networks could be set up by municipal and city councils, others by network service providers. Still other networks may be deployed by businesses (e.g. cafes, bookshops [40], restaurants [148]), community groups [2, 4, 5], campuses and even individual home users. The dream was that a myriad of single-hop Wi-Fi hotspots and multihop wireless mesh networks will provide connectivity to everyone in every corner of a town or city.

Unfortunately, to date this dream remains unrealized. Municipal wireless networks have either been scaled back or abandoned entirely [136]. Besides the lack of a viable business model, one of the key challenges remains the issue of interference experienced by the networks [89]. The challenge is made tougher by the fact that many of these networks are independently set up, with little concerted effort to ensure that they exist harmoniously together. Nevertheless, with the increase in personal devices like smartphones and laptops equipped with WiFi-enabled hardware [63], there remains a motivation to overcome the challenges, and finally make the vision a reality. This thesis constitutes such an effort.

In this thesis, we investigated the issue of non-cooperative coexistence of independent wireless networks that operate in the unlicensed band. While the interference of links within a single wireless network has been extensively studied, interference among different non-cooperative networks offers different challenges. We discussed these challenges throughout the thesis, for both single-hop as well and multihop wireless networks. We were also interested in how these autonomous networks can use radio resource allocation schemes like channel assignment, transmit power control etc., to improve coexistence. Our solution fell broadly into the class of utility-based network optimization techniques.

In Chapter 3, we looked at the coexistence issues of co-located independent multihop wireless mesh networks. We motivated the problem and defined a game theoretic framework that we believe can be used to study the interactions among such networks. Using the framework, we analyzed a particular case for non-cooperative mesh networks that lie within a single collision domain. In addition, we proposed the use of game theoretic learning algorithms to allow the networks to arrive at desirable channel selection outcomes.

We turned our attention to single-hop 802.11 WLANs in Chapter 4. We showed that due to the inherent characteristics of 802.11 DCF MAC, individually-managed WLANs can exhibit unfair degradation in performance due to their relative positions. We proposed a class of practical channel selection schemes that allow the WLANs to coexist in a socially conscious manner, where fairness is improved. Our simulation showed that our schemes are able to achieve better fairness when compared to existing channel selection schemes, with comparable aggregate throughput.

In Chapter 5, we returned back to non-cooperative wireless multihop networks. We discussed the issues of extending cross-layer resource allocation algorithms that are based on network utility maximization to such networks. We showed that there exists efficiency loss due to the incomplete information of the contention environment, resulting in an incorrect feasible rate region. The link-channel scheduling component of the algorithm, when implemented non-cooperatively will result in contention or collisions, reducing the capacity region. We proposed a method for building a more accurate feasible rate region that can be used by the link-channel scheduling algorithm to increase the capacity region. Simulation results showed that our modified algorithm improves the performance of the non-cooperative resource allocation algorithm significantly when applied independently in co-located networks.

6.2 Future Research Directions

The work presented in this thesis is by no means complete. Besides the future work that has been highlighted in each of the chapters, below is a list of the areas that the work in this thesis could be extended:

1. This thesis represents the first steps in the study of non-cooperative networks. We have only focused on a particular form of radio resource control mechanism, namely channel selection and assignment. Moving ahead, we would like to extend our investigation to other control mechanisms, such as transmit power control and rate adaption. An important direction would involve the analysis of how a group of non-cooperative networks, each operating with different radio resource control mechanism, interact with one another in a game theoretic perspective.

2. Having entirely non-cooperative networks is not the only possible scenario. Another situation involves a group of networks that cooperate, in the presence of other networks that are competitive. Game theoretic analysis could be extended in this case by looking at a cooperative game, or games involving coalitions. The latter can be used to describe groups of networks that do not cooperate, even though networks within each group are cooperative.

3. The rich array of learning algorithms in the game theoretic and artificial intelligence community will provide us opportunities to explore how other algorithms can be applied to our learning schemes in Chapters 3 and 4. Future work involves investigating the suitability of some of these algorithms, given their various requirements (e.g. complexity, online responsiveness, non-cooperative or cooperative), making modifications where necessary, in order to come up with better schemes for problems similar to the ones we have defined in this thesis.

4. There has been substantial work related to the study of fairness within a single multihop network [138, 139], as well as among multiple single-hop networks [78, 104]. Maintaining fairness among co-located multihop networks will prove to be a much greater challenge. One reason for this is that not only

is fairness affected by the contention at the link-level, the flow-level rate adaptation (e.g. through the use of congestion control mechanisms) will also affect the throughput distribution of the flows in each network. In addition, in the case of multiple networks, should fairness be maintained at the flow level or network level? Therefore, an effective method of defining the problem, along with solutions to ensure (either flow or network-level) fairness will constitute interesting topics for future research.

5. In this thesis, we are primarily interested in the coexistence of non-cooperative networks that make use of the unlicensed band. In general, the frequency spectrum allocated for these bands is fixed and free for use by everyone. We believe it is possible to extend the work in this thesis to study a new class of networks, known as cognitive radio networks [22, 68]. In cognitive radio networks, there usually exists a primary user that has preference over the use of the frequency band or spectrum. Secondary users are allowed to make use of the spectrum without causing performance degradation to the primary user. The additional challenges in such situations include the changing availability and size of the frequency spectrum, the fact that different users may be using different physical and MAC protocols, and the potentially non-cooperative nature of these networks. A related direction is the performance issues of multihop cognitive radio networks.

Appendix A

A Cut-through MAC for Multiple Interface, Multiple Channel Wireless Mesh Networks

We present here a standalone piece of work that has been produced during the course of the author's Ph.D. candidature. Although it does not relate directly to the coexistence of non-cooperative networks, it illustrates how a MAC protocol could be designed to complement the increased capacity that arises from a channel assignment scheme that is implemented on a multiradio multichannel wireless mesh network.

A Wireless Mesh Network (WMN) that utilizes multiple interfaces and multiple channels has been shown to improve network performance by reducing the interference and increasing the available bandwidth. However, the *contention delay* experienced by a frame along every hop of the WMN can still limit the performance. In addition, *cross-layer delay* occurs when a frame has to travel up and down the protocol stack to access different interfaces. In this work[1], we motivate the need for a MAC in a multi-interface backhaul WMN and propose a cut-through MAC that is able to reduce the end-to-end delay of data frames in the network. Preliminary simulation results show that this MAC scheme gives higher goodput and lower end-to-end delay in a chain topology, when compared to IEEE 802.11 DCF MAC. This work also highlights key challenges that need to be addressed in the design of a cut-through MAC for multihop

[1]Part of the work here has been presented in the IEEE WCNC 2007 [91].

wireless networks.

A.1 Introduction

Using the IEEE 802.11 Distributed Coordination Function (DCF) as the MAC protocol for wireless multi-hop networks has been shown to result in sub-optimal performance. This is because the broadcast nature of the wireless medium creates inter-flow as well as intra-flow interferences [143]. Solutions to this problem have focused on two main approaches – modifying the MAC layer (e.g. [16, 146]) and increasing the number of interfaces available to mesh routers [121].

When collisions and interference occur, delay is experienced as the frames have to be retransmitted. Essentially, a MAC protocol tries to coordinate the access of the shared channel so that multiple transmitters can send frames with minimal delays. To do this, the MAC employs additional mechanisms that trade a slight increase in overheads for a more efficient use of the channel. This constitutes the *contention delay* experienced by a node in a network. Examples of contention delays include times spent on control messages (e.g. RTS/CTS) and backoffs in contention-based MAC, as well as timing synchronization overheads in TDMA-based MAC. In a multi-hop WMN, a frame experiences this contention delay at every router on its way to the destination or gateway, resulting in an increased end-to-end delay.

Introducing multiple wireless interfaces to each mesh router can reduce the number of routers (or interfaces) contending for the same wireless channel. However, each frame entering into the network would still have to contend afresh for the channel at every hop. If the channel could be reserved in advance, this multi-hop contention delay would effectively be reduced. Moreover, multiple interfaces introduce an additional delay when the packets traverse across the different layers of the protocol stack and the different interfaces within each router. In this work, we term this delay as the *cross-layer delay*. If not managed efficiently, this could increase the overall delay and reduce the throughput available to the network [80]. A suitable MAC protocol is therefore needed to reduce the multi-hop contention delay and the cross-layer delay.

Having motivated the need for a MAC protocol in a multiple interface WMN, we propose a cut-through MAC that seeks to increase the overall network performance. We start by stating some assumptions on our WMN architecture in Section A.2, before introducing our cut-through MAC in Section A.3. Section A.4 contains some results from simulations that we have conducted to evaluate our scheme. We highlight the challenges involved in developing a cut-through MAC for multihop wireless networks in Section A.5. In Section A.6, we discuss several related works, followed by some concluding remarks in Section A.7.

A.2 Assumptions on WMN Architecture

Our cut-through MAC scheme is designed specifically for *backhaul* WMN consisting of mesh routers whose primary role is to forward the network traffic in a fast and efficient manner. Besides the dedicated mesh routers, there are mesh APs providing connections to wireless clients and mesh gateways with physical connections to external networks. We assume in this work that the interfaces used for connection of clients are separated from those used for the forwarding of the backhaul traffic, using exclusive channels[2].

In backhaul WMN, it makes sense to aggregate the traffic from different clients together if they are bound for the same destination. Even when the final destinations are not the same, e.g. different hosts on the other side of the Internet, there is still a common destination as far as the WMN is concerned – a mesh gateway. Traffic aggregation helps to efficiently transport the packets over the network. A common way of doing aggregation is to use a MPLS[126]-like scheme that "groups" packets destined for the same egress gateway using a label that identifies them at layer 2. Distinguishing packets with such labels within the WMN has the added advantage of reducing the cross-layer delay since the packets do not have to move up to the network layer and down again. It has been shown that this delay can take up to 60% of the processing delay in a networking device [80]. The details of such a scheme are outside the scope of this work [3]. We assume that such a scheme is implemented in the WMN, allowing a mesh router to mark the MAC frame with a particular label, and forward the frame using the right interface at layer 2. Table A.1 shows a typical Label Switching Table (LST) that would be present in a mesh router with such a capability. In the example, an incoming frame on interface 1 tagged with label L_{xy} will be transferred

[2]For example, the backhaul interfaces may employ IEEE 802.11a at 5 GHz, while the access interfaces may use IEEE 802.11b/g at 2.4 GHz

[3]The reader is referred to the vast literature on MPLS for details on such label switching schemes, and the propagation of the label information.

Table A.1: Example of a Label Switching Table (LST)

INCOMING			OUTGOING		
I/F	**Label**	**MAC Addr.**	**I/F**	**Label**	**MAC Addr.**
1	L_{xy}	AA:AA:AA	2	L_{wz}	CC:CC:CC
...	...	...	...	...	...

to interface 2 and tagged with a label of L_{wz}. In this way, an intermediate mesh router does not have to look at the network layer packet header to determine the next hop.

We make the following assumptions on the WMN architecture that is suitable for applying our MAC scheme:

1. The mesh routers are static.
2. Each mesh router can have multiple interfaces (≥ 1).
3. The channel for each interface has been independently computed and assigned.
4. A layer 2 label switching protocol is in placed.

A.3 Cut-through MAC

In this section, we describe our proposed Multiple Interface Advance Channel Reservation (MIACR) protocol, a cut-through MAC that allows a MAC frame to traverse over multiple hops with minimum delay. The main aim of MIACR is to reduce the delay a frame experienced in each multi-interface mesh router. The label switching mechanism discussed above helps to reduce the cross-layer delay within a mesh router. To reduce the multi-hop contention delay, MIACR introduces the concept of advance collision avoidance by reserving the channel on the next interface in advance.

To describe the operation of MIACR, we will first introduce the control frames required, a channel state table that a mesh router maintains for each interface, followed by an example on how they would be used to reserve the channel in advance.

A.3.1 Control Frames

The control frames in MIACR serve similar functions as those in IEEE 802.11 DCF — to acquire the channel for the collision-free transmission of the data frames, and to inform neighboring nodes of this acquisition. The main difference is the ability to make advance reservation of the wireless medium.

Channel Reservation Request (CRRQ) This acts like the RTS in IEEE 802.11 DCF. In addition to the fields found in RTS, the CRRQ includes the label (l), the reservation id (id_r), the reservation time (t_r) and the reservation duration (d_r). It is worth noting here that t_r is the *offset* time after the CRRQ is received at the receiver. This way of representing the time of an action is similar to the *duration* field in RTS/CTS frame that is used to calculate the Network Allocation Vector (NAV). The rest of the fields will be explained in the example below.

Channel Reservation Reply (CRRP) This acts like the CTS in IEEE 802.11 DCF. Similar to CRRQ, it contains l, id_r, t_r and d_r, in addition to the CTS fields. Note that the reservation time and duration represented by t_r and/or d_r in the CRRP may be different from that requested by the CRRQ. This happens when the receiver proposes another reservation time and/or duration.

Channel Reservation Confirm (CRCF) When the replied reservation time and/or duration is different, the requesting router must confirm with a CRCF to agree or cancel the reservation. This contains the updated t_r, d_r and a *reservation_cancel* flag set if the reservation is to be canceled.

Similar to the RTS/CTS/Data/ACK operation in IEEE 802.11 DCF, the CRRQ/CRRP/[CRCF][4] operation in MIACR is a contiguous series of frames with a short interframe space (SIFS) separating them.

A.3.2 Channel State Table

Each router maintains a channel state table (CST) for each of its interfaces. The CST contains the reservation information of the channel that the interface is on. From the control frames received, a router will update the CST with the time and duration the channel will be busy because of a successful reservation, either by its upstream router,

[4]The CRCF frame is optional since it is only required if the reservation request had been changed by the receiver.

Channel x		Channel y	
Time Occupied	**Duration**	**Time Occupied**	**Duration**
τ_{r1}	t_{data1}	τ_{r2}	t_{data2}
...	...	...	...

Table A.2: Example of a Channel State Table (CST)

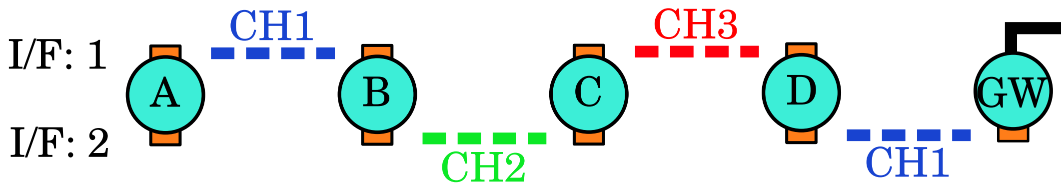

Figure A.1: A topology for the example. The gateway, GW has a wireless interface and a physical connection to a wired network.

or by a neighboring router using the same channel. Table A.2 shows an example of a CST.

A.3.3 Operating Example

In this section, we provide an example of how advance reservation is accomplished in MIACR to achieve cut-through. Figure A.1 shows the topology of a chain WMN used in this example. In this example, mesh router A needs to send traffic to the Internet via the gateway GW. On looking up its LST, it finds that it must send the data frames to router B using interface IF1, which is on channel CH1. A sends a CRRQ to B's interface IF1 requesting for channel time t_{r1} after the CRRQ frame, for a duration of t_{data1}.

Router B, on receiving the CRRQ, computes the actual reservation time requested by adding the offset t_{r1} to its actual clock time and checks its CST to ensure that channel CH1 is not occupied at that time. It updates the CST with this reservation accordingly and sends back to A a CRRP with the channel time of t'_{r1} after the CRRP frame.

From the label contained in the CRRQ, B knows that this data from A is bound for GW. Checking its own LST shows that the data should be forwarded to router C on channel CH2 using IF2. Even while the transmission of the data on channel CH1 is going on, B can begin to reserve the channel CH2 by sending a CRRQ to C. The time

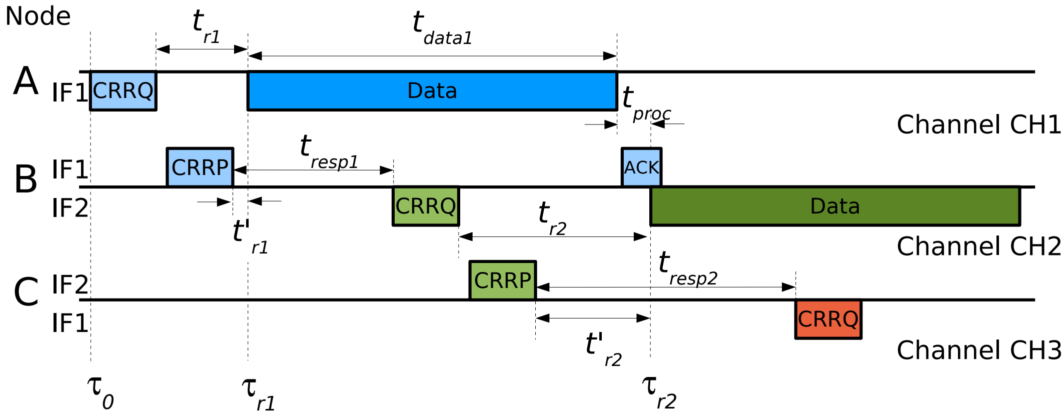

Figure A.2: Timing diagram of the interaction between the interfaces of A, B and C. Each side of the horizontal line represents an interface of a node, e.g. the top side of the second line represents Interface IF1 of node B (communicating with Interface IF1 of A) and the bottom side represents Interface IF2 of node B. τ_x represents actual timings and t_x represents relative offset times.

requested for reserving channel CH2 should be as close as possible to the completion of the transmission of the data in channel CH1. Ideally, upon receiving the data on IF1, it could be switched onto IF2 for transmission after a short processing delay, t_{proc}. The value of t_{proc} is the time needed to process the data at layer 2, including changing the header information and transferring the data from one interface to the next. As discussed in Section A.2, t_{proc} is typically less compared to when layer 3 routing is used. Figure A.2 shows the timing diagram for the reservation of channel CH1 between A and B and CH2 between B and C.

There might be situations when the channel/time requested has already been reserved for another transmission. For example, when the CRRQ from router C reaches router D, the CST of D's IF1 indicates that a prior reservation overlaps with the requested time. The new request would not be accepted as it would disrupt the existing reservation. Hence, router D will reply with a CRRP containing a *proposed* new reservation (offset) time of t'_{r3}. If this new reservation time is acceptable to C, it will send a CRCF with the new adjusted time. Otherwise, it will send a CRCF with *reservation_cancel* flag set. Figure A.3 shows the timing diagram of such an interaction.

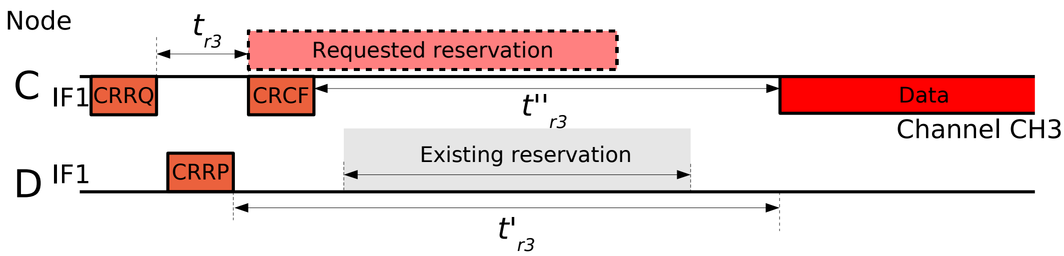

Figure A.3: Timing diagram of the interaction between router C and D. Since part of the requested time has been reserved, D propose a new reservation time, which is accepted by C.

A.3.4 Key Features and Salient Points

We will now highlight some key features and salient points of the protocol here.

1. MIACR makes use of IEEE 802.11 PHY as its physical layer. Modification is performed on the MAC layer in terms of the operation and frame formats. This allows the possibility of implementing the scheme on platforms like SoftMAC [110].

2. The broadcast nature of the control frames allows neighboring routers with interfaces on the same channel to be aware of the reservations. This is also the reason why a CRCF frame has to be sent if there are any changes to the original reservation request. Similar to the RTS/CTS mechanism in IEEE 802.11 DCF, this reduces the effects of the (in)famous hidden-node problem. For example, in Figure A.3, the pre-existing reservation may not involve node D, but two other neighbors that could interfere with any communication with D.

3. The reservation scheme in MIACR uses offset timing derived from the instance when the frame is received at the receiver. This removes the necessity of global clock synchronization, a challenging issue in reservation protocols. However, some timing allowances have to be factored into the offset to account for the propagation delay of the frames to nodes at different distances from the transmitted.

4. MIACR tries to reserve the channel of the next hop (on the next interface) in advance in order to minimize the delay a data frame encounters within each hop. A key parameter is the time between the reception of a CRRP on one

interface and the transmitting of CRRQ on the next interface, represented by t_{resp1} and t_{resp2} in Figure A.2. A delay that causes the next-hop CRRQ to be sent after the complete reception of the data frame will approach the performance of IEEE 802.11 DCF, while too small a value (e.g. if IF1 of C sends out CRRQ before τ_{r2}) runs the risk of reservation wastage if the previous hop data transmission had not taken place as planned. We plan to investigate the effects this delay as part of our future work. In this work, we assume $t_{resp} = 0$.

5. Within a reservation duration, the transmitter could potentially send out more than one data frame. This will further decrease the delay as the overheads associated with each transmission are reduced. Issues like fairness and acknowledgment granularity (i.e., whether to acknowledge after each frame or each reservation duration) would have to be investigated. In this work, we assume each reservation contains one data frame.

A.4 Simulation Results

In this section, we describe preliminary results of simulation experiments conducted to analyze the performance of MIACR. The topology used in the simulation is a chain topology with number of nodes N varying from 3 (2 hops), to 7 (6 hops). The first and last nodes of the chain have a single wireless interface and the intermediate nodes contain two wireless interfaces. We believe this simple network layout will provide some insights into the performance of the scheme without the influence of other issues on more complex topologies, e.g. the effects of different channel assignments.

We assume the number of non-overlapping channels is limited to three – a valid scenario applicable to the popular IEEE 802.11b/g standards. In our experiments, we assume that the channels have been a priori assigned to each interface. The optimum channel assignment in a chain topology would then be assigning channel 1 to the link between the first node and one interface of the second node, channel 2 to the link between the second interface of the second node and the first interface of the third node, and so on. The sequence is repeated once the total number of available non-overlapping channels has been assigned. Essentially, Figure A.1 represents an instantiation of such a channel assignment with $N = 5$.

We implement MIACR on the QualNet network simulator [129] and compare it with

Table A.3: Relevant Simulation Parameters

Simulation Time	600s (10mins)
Application Traffic	Constant Bit Rate (CBR) UDP
PHY Data Rate	11 Mb/s
PHY Tx Power	15dBm
PHY Rx Sensitivity	-83dBm
Approx Tx Range	283.554m
Propagation Pathloss Model	Two-Ray
Inter-nodal Distance	250m

the IEEE 802.11 DCF MAC protocol, both using the IEEE 802.11b PHY layer. Besides providing a realistic lower layer platform (including propagation, interference and error models), this allows us to focus on the comparison and analysis of the MAC performance. Table A.3 shows the relevant simulation parameters used. Traffic is injected at the source at one end of the chain, bound for the destination at the other end. This is like aggregated traffic from a mesh access point (source) traveling over one or more mesh routers to a mesh gateway (destination) that is connected to the Internet.

The metrics compared are the *goodput* – the application layer throughput achieved by the CBR traffic, and the *end-to-end delay* – average delay experienced by the application layer packets between the source and destination. In each simulation scenario, 10 trials have been performed with the metrics averaged over these trials.

Figure A.4 shows the goodput and end-to-end delay experienced by the CBR traffic for a chain topology with 6 wireless links. In this layout, it should be noted that each non-overlapping channel is reused once. We see that the end-to-end delay of the packets is less in MIACR compared to IEEE 802.11 DCF. The advance reservation allows each frame to spend less time in the network. This also enables the network to sustain a higher overall goodput (the network-saturation goodput). This can be seen from the goodput performance — as we increase the offered load, the network-saturation goodput is higher for MIACR. This is because getting the frames through the network as fast as possible allows the channel to be free more often, thereby increasing the opportunities that a new frame could be transmitted.

It should also be noted that the end-to-end delay of interest is during the non-saturated condition, i.e. below 3 Mb/s offered load in MIACR and 2 Mb/s offered load in

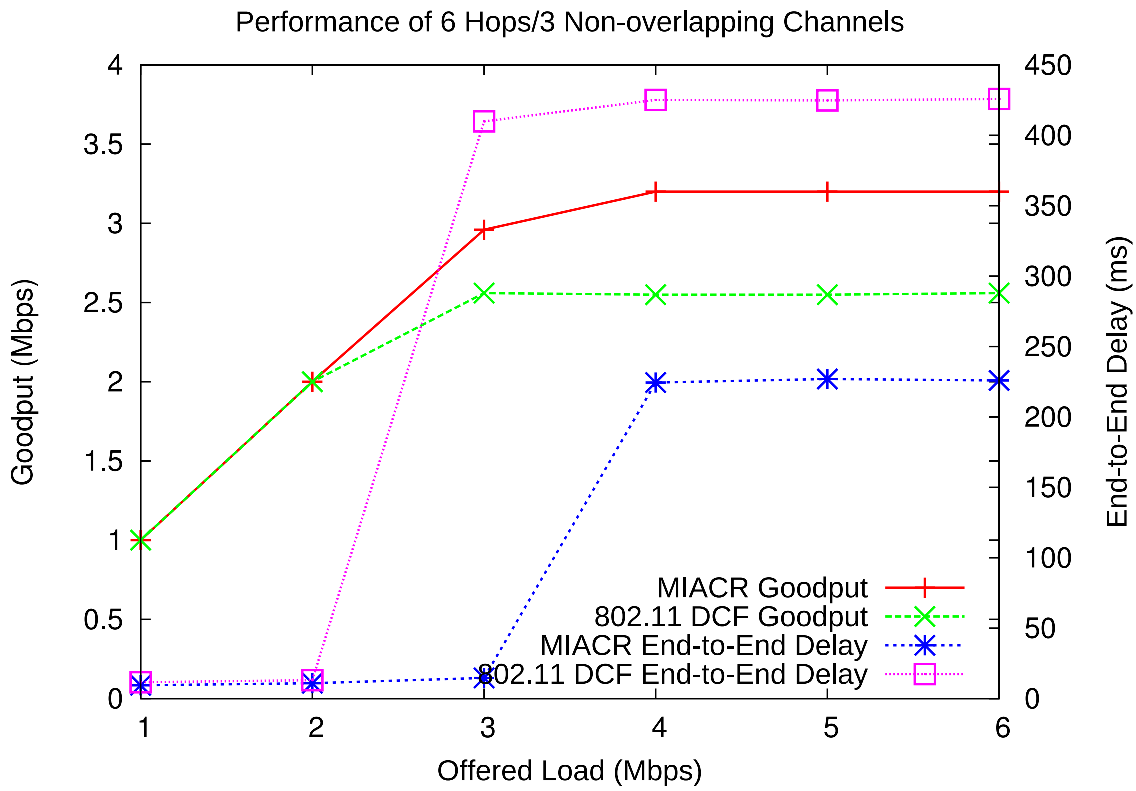

Figure A.4: Goodput and end-to-end delay for different offered loads in a 6-link chain topology.

IEEE 802.11 DCF. During network saturation, the high delay would likely render the application layer packets useless at their destination. This is especially the case for real-time traffic where certain delay bound has to be kept and for TCP/HTTP traffic where timeout occurs after excessive delays. In Figure A.4, we see that besides achieving a lower end-to-end delay, MIACR allows a higher offered load to be transmitted before this high saturation delay occurs.

We next study the performance of MIACR when compared to IEEE 802.11 DCF for different chain lengths. Figure A.5 shows the network-saturation goodput for chains of different lengths (hops). We can see that there is little difference in the goodput when there are enough non-overlapping channels. This is because under network saturated condition, MIACR performs in a similar manner to DCF, with no advance reservation possible. The slightly lower goodput is a result of the extra overhead used in MIACR. However, once the channels are reused, MIACR performs much better than DCF. Here, the channel reservation allows for a more efficient management of the channel collision space, which accounts for the better performance.

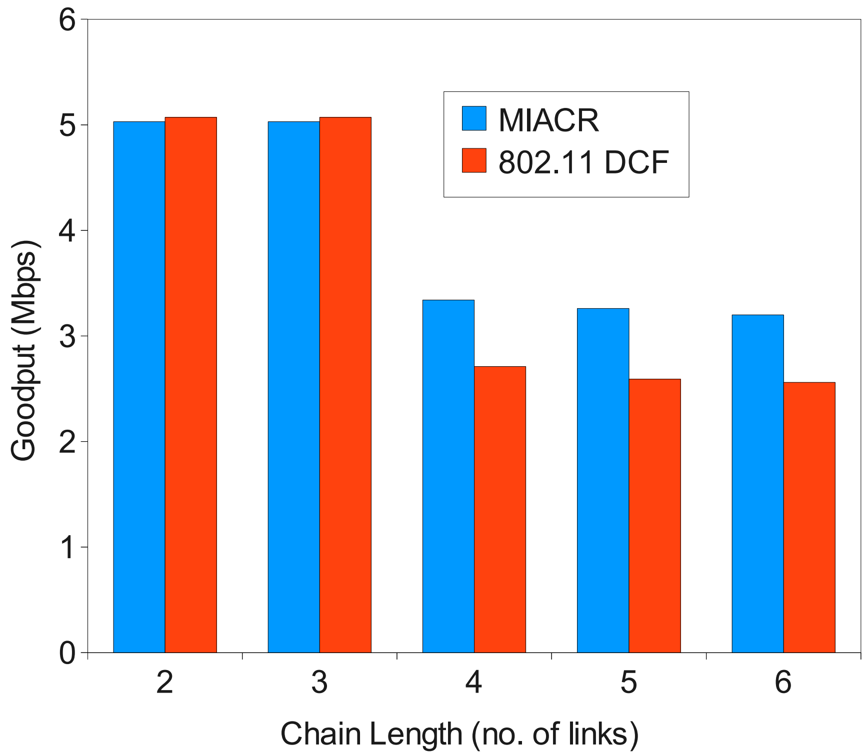

Figure A.5: Network saturation goodput for different chain lengths.

Figure A.6 shows the non-saturated end-to-end delay. The average end-to-end delay experienced is lower for MIACR and the performance is improved for higher length chains. Thus MIACR allows the frame to spend less time in the chain network due to cut-through.

A.5 Challenges of Cut-Through MAC

While a cut-through MAC protocol has the potential to improve the performance of multihop wireless networks, challenges are still present, especially when extending it to WMN utilizing multiple interfaces. In this section, we highlight some of the key challenges faced when developing a cut-through MAC.

A.5.1 Hidden Node Problem

The hidden node problem typically occurs when the interference range of a node's transmission is larger than its communication range, i.e. the distance within which

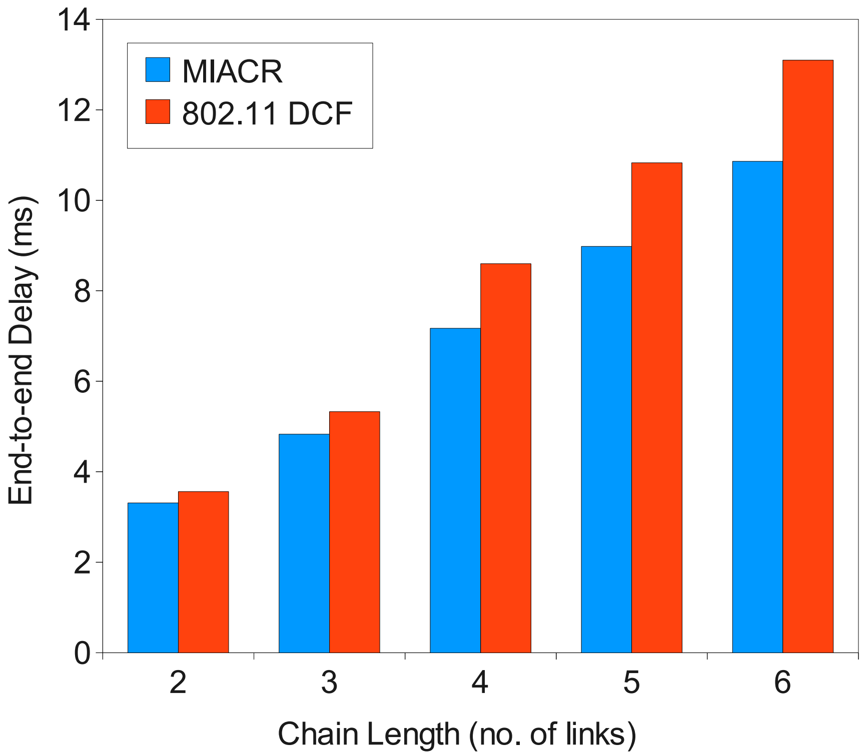

Figure A.6: Non-saturated end-to-end delay for different chain lengths.

the signal can be correctly decoded. In IEEE 802.11 DCF, this problem is only partially alleviated using the RTS/CTS mechanism [143]. When advance reservation is used in cut-through MAC, a neighboring node that did not receive the reservation frame and transmits a frame during the reserved time could disrupt the data communication. This occurs when the node is out of the communication range of the node making the reservation, but is still within the interference range of the reservation. As discussed above, the CRRQ/CRRP/[CRCF] handshake in MIACR tries to reduce this hidden node problem, similar to the RTS/CTS mechanism.

A way to further limit the effects of hidden nodes in cut-through MAC is to set aside a separate, orthogonal control channel for reservation purposes. Reservation frames sent over this channel should be of higher transmit power so that they could be heard by all the nodes within the interference range. This channel can be of a narrower bandwidth in order to conserve the valuable channel resources. In [18], Acharya et al. propose another way to reduce this problem, by using an adaptive learning mechanism.

A.5.2 Traffic Dependency

Cut-through MAC attempts to reduce the time spent by a frame when contending for the channel along each hop in its path to the destination. This works well under low/medium network traffic load. However, as shown by the simulation results, there is little gain in doing advance reservation when the network becomes saturated, since the frames are being sent back-to-back. In fact, advance reservation requires additional overheads (e.g. longer headers) compared to IEEE 802.11 DCF. This may lead to under-performance when the network is overloaded.

This observation points to the conclusion that cut-through mechanism should not be used for all traffic types. It opens the possibility of a MAC protocol that performs advance reservation for high priority, non-elastic traffic to achieve cut-through, with per-hop RTS/CTS-like channel contention for low priority, best effort traffic.

An alternative way to adapt cut-through MAC for higher traffic load is to provide reservation for multiple frames when the traffic is bursty. Some commercial Wireless LAN chipsets [27] already implement a similar idea that allows the transmission of more than one data frame within a transmission opportunity. It should however be noted that multi-frame reservation requires the frames to be buffered in the source node as the reservation is being set up. This may lead to a higher latency for some of the frames, countering the advantage of cut-through.

A.5.3 Frame Loss Management

In cut-through MAC, reservation is done for the transmission duration of a data frame, potentially for several hops forward. If the data frame is lost in an upstream hop, subsequent downstream reservations will not be utilized, and the channel is left idle. This is expensive in terms of the channel resources, which could be otherwise used to transmit frames from neighboring nodes. There is therefore a need to have a mechanism to free the reservations over the hops in the forwarding path.

A.5.4 Timing Synchronization

In doing reservation over multiple hops, timing synchronization among the nodes is a critical issue. Global timing synchronization is often difficult, if not impossible, due to clock drifts within each node. The challenge is to develop an efficient synchronization mechanism that can allow reservations over multiple hops to take place. In MIACR, we propose a relative synchronization approach that is similar to the way the duration field in IEEE 802.11 DCF is set.

A.5.5 Fairness Issues

Finally, fairness is a key challenge when we allow a frame to have access over multiple hops of a forwarding path. Admittedly, we have neither addressed nor investigated the issue of fairness in the MAC proposed in this paper. As part of our future work, we plan to look at this issue and propose ways to maintain a level of fairness in cut-through MAC.

A.6 Related Work

In [17], Acharya et al. describe an architecture incorporating MPLS with an enhanced IEEE 802.11 DCF MAC where the RTS frame for the next hop is transmitted concurrently with the Ack frame of the previous hop. This reduces the time a frame needs to spend in a node due to channel contention. Similar cut-through schemes have also been proposed by [119] and [70]. These approaches have applications to a single channel network environment, while MIACR is specifically designed to perform cut-through in a multiple interface, multiple channel network. In addition, MIACR also provides an advance reservation mechanism that is able to extend beyond the immediate next hop.

Carlson et al. [33] present a distributed reservation protocol to support real-time services in WMN. In their approach, they assume all the routers have global synchronized timings. MIACR's reservation scheme makes use of relative offset timings to set up advance reservation. The reservation protocol in [33] also does not take into account multiple interfaces and channels.

A.7 Conclusion

We motivate the need for a cut-through MAC protocol in a WMN with multiple interfaces and multiple channels. MIACR, a cut-through MAC suited for this type of application is proposed. The cut-through mechanism makes use of advance channel reservation on different interfaces in forward hops to reduce the delay a frame encounters in its passage through the network.

We include preliminary results of simulations that we have performed to evaluate the effectiveness of our scheme, comparing it to the incumbent IEEE 802.11 DCF MAC in a simple chain topology with CBR traffic. We plan to extend this investigation to more complex network setups as well as realistic traffic types. We also plan to analyze the effects of various parameters that may affect the performance of our scheme, e.g. the time to activate the next hop reservation (t_{resp}) and the number of frames to transmit in each reservation. Issues like how fairness can be maintained in such a scheme will also be studied.

A.8 Acknowledgement

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