Capacity analysis of densely deployed wireless LANs

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Abstract

Wireless LANs (WLANs) based on the IEEE 802.11 standard have become an integral part of today’s indoor wireless communication infrastructure. As WLAN deployments become more prevalent and densely deployed, the nodes in these WLANs start to create congestion and interference with each other. This congestion and interference fundamentally limits the performance of these coexisting WLANs. We analyze the capacity limits of such densely deployed WLANs.

We begin our analysis by investigating the suitability of the attributes of WLANs, namely their cooperative operation based on locally available information, for indoor high-capacity wireless access provisioning. We compare the cooperative class of wireless systems with another class of systems whose users behave selfishly.

Following this qualitative assessment, we perform a detailed, qualitative analysis of the capacity of densely deployed WLANs in terms of a number of key environmental and operational parameters. The indoor propagation environment has a significant influence on the congestion and interference that these coexisting WLANs exert on each other. Therefore we investigate the impact of propagation environment on the aggregate throughput of densely deployed WLANs. As WLANs are deployed in close proximity of each other, the transmissions in one WLAN start to influence the outcome of transmissions in other WLANs. The manner in which the access points are deployed, and the manner in which stations associate themselves with the available access points around themselves is shown to be an influential factor in the performance of these coexisting WLANs. Therefore, we investigate the impact of random versus planned access point deployment on performance of densely deployed WLANs. Similarly, we investigate the impact of stations associating with the access point with the strongest signal or with another sufficiently strong access point in their vicinity. Furthermore, we investigate the throughput of densely deployed WLANs when operating with bounded delay. More specifically we examine the case when the input traffic arriving at the transmitters are expected to reach their destination within a certain time period, thus the transmit queues cannot grow without bounded and the system should operate at a stable point.

The indoor propagation environment, creates complex interference relationships between nodes in coexisting WLANs. These complex interference relationships are compounded by the node interactions dictated by the nonlinear algorithms in the IEEE 802.11 MAC protocol, thus the problem of estimating the performance of these coexisting WLANs by means of simple analytical models becomes difficult. In contrast, detailed packet level simulations provide accurate performance estimates, although such analyses are computationally expensive. Therefore we seek to provide a model to estimate the throughput of densely deployed WLANs based on empirical throughput results of detailed simulations of such densely deployed WLANs. In addition, in our effort to develop an empirical throughput model for densely deployed WLANs, we develop a measure which we call “cell congestion” to be able to order and compare different propagation environments, and an “effective density” concept which accounts for the influence of the propagation environment on the congestion and interference experienced by a WLAN deployment of a given density. We expect these concepts to be useful in improving the operation of WLANs to be able to meet the predicted increase in demand for capacity.
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* where the term “best” is defined as it says on your coffee mug :-)

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Chapter 1

Introduction

Every new generation of wireless and mobile hardware introduces more capable devices with increased processing power and larger displays with higher resolution, enabling such services as streaming video to mobiles and cloud storage. Therefore, wireless data consumption per user and wireless data consumption in total are increasing. This rise in the actual consumption and the foreseeable demand translate into the need for a capacity increase in the order of a thousand-fold in future wireless networks, which is a hot topic of 5G broadband wireless access research at the moment. A more modest prediction of this significant demand is mentioned in [8], where the compound annual growth rate of mobile data traffic is predicted to be 66%, resulting in a total mobile data consumption of 11.2 exabytes per month in 2017. Since traffic is mostly created and consumed indoors, a significant proportion of this data consumption will take place indoors. Therefore, indoor connectivity solutions will be instrumental in addressing this demand.

Since their introduction in 1997, WLANs based on IEEE 802.11 standard, which use the trade name Wi-Fi™, have become extremely popular for indoor wireless access provisioning. An indication for the popularity of this standard can be seen in the number of WLAN chipsets shipped every year; in 2012, nearly 1.5 billion WLAN chipsets in all bands were shipped [9]. In comparison, in 2013, solely the number of shipments of 802.11n/ac dual band chipsets will exceed 1.5 billion [10]. This trend is expected to continue in the near future; the number of 802.11ac chipsets to be shipped in 2018 is predicted to reach 3.5 billion [11].

In view of the success and popularity of WLANs, which operate in unlicensed spectrum, regulators around the world have allocated and are planning to allocate more spectrum for unlicensed operation for devices such as WLANs. A recent example of spectrum allocation for unlicensed use is FCC’s making 100 MHz of spectrum available for WLANs and other unlicensed uses [12]. Furthermore, FCC is planning to make more spectrum available nationwide for unlicensed use in the near future [13]. Similar policies have been
adopted by other operators around the world, for instance, some European operators made portions of unused TV spectrum available for unlicensed use in Europe.

1.1 Problem Formulation

The IEEE 802.11 standard-based WLANs have been very successful up until today in catering to indoor wireless access needs. They are therefore very popular as a wireless access solution, which can partially be attributed to their operation in unlicensed spectrum. As a result of this popularity, the density of WLAN networks in urban areas has become fairly high so as to create increasing congestion and interference on each other [14, 15], and this density is expected to increase further. On the other hand, the WLAN MAC mechanism, which was first standardized in 1997, and which has largely remained unchanged in the IEEE 802.11 standard since then, does not make provisions for operation of WLANs when the number of such networks which are operating in close range of each other grows very large. Thus, it is not certain whether WLANs which operate in an environment containing a large number of other WLANs which are competing for the same resources, can continue to meet the soaring traffic demand. Nevertheless, in view of the current popularity of WLANs, we expect the dominance of WLANs to continue for the coming years. Therefore, we consider that engineering the operation and the deployment of indoor wireless access solutions such as WLANs in order to cater to the growing capacity demand is becoming an important issue.

The high level research question (HLRQ) we are trying to answer in this dissertation is:

**HLRQ** How can we operate and deploy an indoor, short-range wireless LAN system in unlicensed spectrum for high capacity wireless service provisioning?

In order to answer the high level problem we have defined above, we address the following four sub-research-questions (SRQ):

**SRQ-1** What are attributes that a generic multi-channel random access (MRA) system should possess for providing high capacity wireless access? Specifically, can WLANs be a suitable system for high capacity wireless access provisioning from the perspective of these attributes?

Investigating the high level research question we have posed above will be worthwhile provided that WLAN turns out to be a suitable system for high capacity wireless access provisioning. As such, first SRQ acts as a sanity-check of the remainder of the study. We note that a WLAN system is in essence a MRA system. Therefore, in SRQ-1, we examine the desirable attributes of the general class of MRA systems that will make them suitable candidates to be used in high capacity wireless service provisioning.

**SRQ-2** What is the capacity of a densely deployed system of WLANs as a function of a set of key environmental and operational parameters in realistic environments?
1.2. **HIGH LEVEL SOLUTION APPROACHES**

After WLAN systems pass the sanity-check we posed in SRQ-1, in SRQ-2 we investigate the dependence of the capacity of a densely deployed system of WLANs on a number of key parameters, because these key parameters, for instance the propagation environment that WLANs operate in and the choices made during the deployment and operation of WLANs, have a significant impact on the capacity of these systems.

**SRQ-3** What is a set of guidelines to follow when deploying WLANs for a high capacity wireless access provisioning?

Our aim in addressing this question is to provide network designers with a set of guidelines which will help them approximate with reasonably good accuracy what the capacity of a system of WLANs would be for varying infrastructure densities, propagation conditions and other operational parameters.

**SRQ-4** How can the capacity of a densely deployed system of WLANs be improved?

Considering that the demand for capacity may grow beyond the level which can be provided by increasing the density of the WLAN infrastructure, the question of how to increase the capacity of densely deployed WLANs becomes relevant.

1.2 **High Level Solution Approaches**

In order to answer each SRQ we have posed above, we follow an appropriate research approach which we briefly describe here.

**Approach to SRQ-1**

In order to answer SRQ-1, we first investigate a number of different attributes that can be associated with a multichannel system operating in unlicensed bands, which we consider to be able to render such a system suitable or not suitable for the purpose of providing high capacity wireless access. We consider three such attributes which would have a significant impact on the operation and performance of such systems; namely, whether a centralized entity dictates how the users access the spectrum resources, whether the users base their actions on local or global information on the availability and the quality of the spectrum resources, and whether users in the system care for the other users in the system or not. Here, we define each of these properties in the context of multichannel systems in unlicensed spectrum. The following definitions are taken from [16].

- A *centralized system* refers to a system in which access to system resources are controlled by a central decision making entity. In a centralized system, users are expected to, or sometimes obliged to, obey the decisions of the decision making entity.

- In comparison, in a *decentralized system* there is no central decision making entity, and users make their own decisions when accessing system resources. Therefore we sometimes refer to a decentralized system as a *distributed system*.
• A cooperative system comprises of users which form their actions so as to attain a common goal, e.g. maximizing system performance with respect to some metric, together with other cooperating users in the system. It is important to note that such a system is not necessarily centrally controlled.

• Conversely, a non-cooperative system comprises of users whose actions are not necessarily intended to attain a common goal with other users in the system. In the context of this work, we assume that non-cooperative users select their actions in order to maximize their own benefits in the system, potentially at the expense of other users’ benefits from the system. Therefore we will refer to the systems in which all the users behave selfishly as simply selfish systems.

• In a system with complete information the decision making entity or entities would have knowledge of all the necessary system states and parameters (e.g. channel gains, transmit powers, number of users, etc.) that they need in order to make a particular decision. In a centralized system, the central decision making entity, typically the access point, would have this complete information whereas in a distributed system, the users would have this complete information. Since complete information implies having knowledge pertaining to the entire system, global information is used interchangeably with complete information.

• In a system with incomplete information, decision making entity or entities would only have partial knowledge of the system states and parameters. Incomplete information would correspond to the knowledge that a user can gather about its system by observing its environment. Therefore we sometimes refer to incomplete information as local information.

We consider that a distributed system has the desirable property of not requiring as much exchange of control information as a centralized equivalent, which may have complexity and scalability issues as the number of users, channels and traffic in the system grow. Therefore, in this thesis we focus on distributed multichannel systems which operate in unlicensed spectrum. Since there is no central control entity to dictate how each user of the system will access the spectrum resources, these users will be accessing the spectrum resources in a random manner, at their own discretion; as such, we refer to a distributed wireless system operating on multiple channels in unlicensed spectrum as a MRA (multichannel random access) system. However, the lack of a central control entity in the MRA system may lead to some users behaving selfishly, which is likely to have a significant impact on the system performance. Therefore, we investigate the suitability of MRA systems for high capacity wireless access provisioning along the cooperativeness-selfishness dimension. In addition to this dimension, we also consider that whether users determine their actions on the basis of local or global information has a significant impact on system performance, therefore we also investigate the suitability of MRA systems for high capacity wireless access provisioning along the complete-incomplete information dimension. We answer SRQ-1 by analyzing the performance of different MRA systems in terms of a metric which represents how well the spectrum resources in the system
are utilized. We investigate the behavior of the system-wide resource utilization as a function of the user density in the system in order to comment on the suitability for high capacity wireless access provisioning of different MRA systems which possess different combinations of the attributes we described above. We model and analyze selfish user behavior using game theory.

**Approach to SRQ-2**

After we investigate the impact of the selected attributes on the performance of MRA systems, we observe that a distributed system with cooperative users who base their transmission decisions on local information can perform satisfactorily for the purpose of high capacity wireless access provisioning in that the utilization of wireless resources in such a system does not diminish as the number of users in the system increases. Such a system also possesses the desirable property of small amount of information exchange overhead by virtue of its distributed operation based on local information. Therefore, having made these observations, we shift our focus on analyzing the capacity of such a distributed system with cooperative users who act on local information. We note that WLANs based on the IEEE 802.11 standard can be represented in the group of distributed systems with cooperative users who act on local information. Therefore, we focus on making a more in-depth investigation of the performance of a single channel which are operating on a single common channel. Here, we consider that all constituent channels in the MRA system are accessed according to the same rules, therefore we consider that performance analysis of a single channel can be generalized trivially to multiple channels. We identify several key parameters which potentially have a decisive impact on the capacity of a system of WLANs operating on a common channel, namely the propagation environment, the method according to which WLAN infrastructure is deployed, the manner in which the users in the system of WLANs associate with different WLANs, and the rate of data arrival to transmitter nodes. We answer SRQ-2 by performing a detailed set of simulations by using a realistic MAC model and also by taking the indoor propagation environment into account. By performing a detailed set of random simulations, we observe the impact of each of the selected parameters on the capacity of a densely deployed system of WLANs.

**Approach to SRQ-3**

Following this in-depth capacity analysis, the problem which needs to be addressed from a network designer’s perspective is how to take advantage of these analysis results when deploying a system consisting of a number of WLANs on a common channel in close proximity of each other. The set of guidelines for deployment of a dense system of WLANs which is intended to provide high capacity which we develop in this thesis in order to answer this question is based on our performance analysis of a system of densely deployed WLANs. These guidelines reflect the impact of the several parameters of importance which we considered in our performance analysis. Furthermore, the set of guidelines are intended to produce estimations of densely deployed WLAN performance in a short time and depending on a reduced set of parameters. In this respect, the relation of our proposed
set of guidelines to the actual performance of a system of WLANs is comparable to a
power-law propagation model being a first-order approximation which is used in received
power calculations. That is, the guidelines we develop is a representation of the actual
system performance which is described by a reduced set of parameters and which explains
the general trends observed in the actual system performance.

Approach to SRQ-4

We approach SRQ-4 qualitatively. Again, based on our detailed performance analysis of
WLAN performance and based on the deployment guidelines we propose, we identify a
couple of key parameters which are important when describing the capacity of densely
deployed WLANs. Thus, these parameters which we highlight can act as an input for
future efforts which aim to improve the capacity of WLANs.

1.3 Contribution Summary

We can describe the contributions of this thesis as having two aspects; namely, an analysis
aspect which involves the performance analysis of generic MRA systems and concrete
WLAN systems, and a modeling aspect which involves the modeling of the performance
of a system of WLANs which constitutes the basis of the guidelines we propose for
deployment of a system of WLANs for high capacity wireless access provisioning.

Analysis aspect of the thesis contributions with respect to MRA systems involves a high-
level verification of cooperative systems acting on local information to be better
suited for high capacity wireless service provisioning compared to their selfish coun-
terparts. By virtue of WLAN systems being a member of the set of cooperative
systems with incomplete information, at a high-level, we verify that WLAN systems
are suitable for high capacity wireless access provisioning.

Contributions of this thesis due to our analysis of the capacity of a system of WLANs
include the identification of important parameters pertaining to the operation of these
WLANs and quantifying the impact of these parameters on the performance of the
system of WLANs

Modeling aspect of the thesis contributions comprises the development of an empirical
model which estimates the capacity of a system of WLANs in a range of different
propagation environments, for various operational parameters, namely deployment
and association types, and different traffic arrival patterns.

As such, the contributions in the thesis are not only descriptive, but they also have predic-
tive properties.
1.4 Overview of Constituent Articles

Here, we provide an overview of the contributions of each of the articles that constitute this thesis. We group the constituent articles in two: The first group of articles focus on the user behavior and performance analysis of a MRA system, which we consider to be a generic wireless system operating on multiple channels, whereas the articles in the second group focus explicitly on analysis and modeling of the performance of a system of WLANs.


The first article in the group articles on the analysis of user behavior in and performance of wireless system operating using multiple channels investigates the performance of an MRA system with selfish users and complete information and compares it to the performance of a similar multichannel random access system with cooperative users and complete information. This comparison illustrates the performance loss in the MRA system due to selfish behavior when all users act on complete information. The system model and the game formulation were developed in joint discussions with Omer Ileri and Jens Zander. The game theoretic analysis and subsequent simulation results were produced by the author of this thesis. Omer Ileri and Jens Zander provided valuable feedback in the refinement of the problem and the results.


These two papers in the group of articles with a game theoretic perspective investigate the performance of a MRA system with selfish users and incomplete information and compare it to the performance of a MRA system with cooperative users and incomplete information, and a MRA system with cooperative users and complete information, thereby highlighting the performance loss due to selfish behavior. The analysis in [3] extends the analysis in [2] to a MRA system with selfish users and incomplete information in which the channel statistics are not identical. The system model used in in [2] is the same as [1]. The system model used in [3] is a generalization of these models in order to account for heterogeneous channel characteristics that may be observed in a system. In both papers, the author of this thesis developed the game theoretic model and performed the game theoretic analysis and produced the simulation results. Jens Zander provided valuable feedback in the refinement of the problem and the results.
CHAPTER 1. INTRODUCTION


The first article in the group of WLAN papers investigates the limits of aggregate throughput in a system of WLANs, which uses simulations as its methodology. The novelty of the article is the combination of three features; first, the propagation environment is explicitly taken into account in the simulation analysis, second, a realistic MAC model is used, and third, a large number of transmitters are considered. The core problem in the article, that is, investigating the impact of propagation environment on aggregate throughput performance of a system of WLANs, was conceptualized in our discussions with Ki Won Sung and Jens Zander. The thesis author developed the simulation framework and produced the simulation results. In all stages of the article development, Ki Won Sung and Jens Zander provided valuable feedback.


While [4] considers only one parameter impacting the performance of a system of WLANs, namely the propagation environment, the second article in the WLAN group extends the analysis in [4] into two new dimensions, namely how AP installation locations are determined and how STAs associate with one of the many APs that they may discover. The novel aspect of [5] is the inclusion of propagation environment in conjunction with the detailed MAC model in the simulation study. The main problem of investigating the impact of deployment and association choices on performance of a system of WLANs, was initially developed in our discussions with Ki Won Sung. The thesis author developed the simulation framework and produced the simulation results. In all stages of the article development, Ki Won Sung and Jens Zander provided valuable feedback.


Our third article on WLAN performance considers both of the problems in [4] and [5] from a delay constrained traffic perspective. The article investigates capacity, i.e., the maximum possible aggregate throughput in any deployment and arrival rate combination, of WLANs subject to some delay bound. The article investigates the impact of the same set of parameters and possesses the same novel aspects as [4] and [5]. The results can be used as guidelines when deploying a dense system of WLANs for services with bounded delay requirements. The delay-bound capacity problem was conceptualized in our discussions with Ki Won Sung. Cell congestion concept was inspired by our discussions with Magnus Frodigh. The concept of cell congestion coefficient was later developed by the author of this thesis. The simulation framework was developed and simulations were performed by the author. Ki Won Sung and Jens Zander provided valuable feedback in the refinement of the problem and the results.
1.4. OVERVIEW OF CONSTITUENT ARTICLES


In the fourth article on WLAN performance, we complement the analysis in [4], [5] and [6] by proposing an empirical model for the aggregate throughput performance of dense WLANs which is based on the same set of simulation results as in our previous papers. As such, the empirical aggregate throughput model developed in this article is applicable in a range of propagation environments, deployment and association types, and traffic patterns. The novel aspect of the throughput model is that it takes the impact of the MAC mechanism on the aggregate throughput performance into account in detail. The core problem in the article, namely, developing a throughput model for WLANs which approaches the accuracy of packet-level simulations but which can produce estimates using a small fraction of the time and computational resources needed to execute packet level simulations, was initially proposed by Ki Won Sung. The author of the thesis developed the empirical models and the necessary concepts that the model builds upon. Ki Won Sung and Jens Zander provided valuable feedback in the refinement of the problem and the results.
Chapter 2

Background

In this chapter, we provide a brief review of the literature pertaining to the problems we address in this thesis, namely aggregate throughput analysis of dense WLANs and performance analysis of selfish multichannel random access. First we provide an overview of the literature on WLANs, then on selfish MRA systems.

2.1 Performance Analysis of MRA Systems

We can broadly divide the previous studies which can be related to the performance of MRA systems with selfish users into two categories as studies on selfish random access systems and studies on multichannel systems.

Random Access Systems with Selfish Users

Random access systems have been extensively studied using game theoretic approaches. One of the earliest examples is [17] which studies jamming in a multihop slotted ALOHA network by modeling the interaction between jammer and network nodes as a zero-sum game between two players. Another early example of works on random access systems with a game theoretic approach is [18], which considers a slotted ALOHA system with a single collision channel in which all users are selfish. An extension of this work to multipacket reception model is done in [19] in which the successful reception of packets is modeled statistically. Both of these works assume complete information and do not take channel state information into account.

In [20] the authors analyze cooperative and non-cooperative Aloha with capture using game theory. They assume that the users have incomplete information; the users know their own channel gains but they only know the distribution of channel gains of other users. Under this assumption they show that at the equilibrium of both the cooperative and non-cooperative games, the users employ a threshold strategy. Although the problem in [20] is fairly similar to our problem formulation, they differ in user utility and power capture models and also [20] does not treat multichannel systems.
In most analyses of random access systems with selfish users, the performance of the system when the users are cooperative turns out to be pareto-dominant to the same system when the users are selfish; in other words, cooperative systems outperform selfish systems in terms of the aggregate performance of the users. To address this problem, some works have proposed pricing mechanisms in order to influence the operating point of a selfish system so that the sum performance of the selfish system approaches to that of the cooperative system. An example of this pricing approach in selfish random access systems is [21] in which the authors consider a single channel slotted ALOHA system with selfish users and incomplete information and treat both collision channel and multipacket reception cases. In the user utilities, the authors incorporate the packet transmission cost as a function of the CSI and a network access cost charged by the network for each transmission. They show that by adjusting the network access cost, it is possible to influence the equilibrium of the selfish system to maximize throughput or revenue collected from the network access costs.

In [22] the authors analyze a single channel slotted ALOHA system with power capture in presence of selfish users. They calculate the selfish users’ transmission probability at the equilibrium of the system under complete and incomplete information assumptions. In the complete information case, only the users with more favorable channel conditions decide to transmit packets due to capture effect. The channel model in this work is somewhat simple; transmission costs for all users in all time slots are the same. The results in [22] are a subset and an extension of [23], both of which provide an extensive overview of the literature on random access systems with selfish users. In the incomplete information case the selfish users employ a threshold strategy similar to the results in [20] and [21].

**Multichannel Random Access Systems**

Multichannel random access systems have also been widely studied in literature; these works usually consider ALOHA systems [24] but occasionally other MAC methods like CSMA [25] or other novel MAC methods are considered as well [26]. Most of the earlier works treat MRA systems with a cooperative point of view, e.g. [24], but more recently MRA systems with selfish users are treated as well [25]. In [24] the steady state probabilities of the number of users in a multichannel slotted ALOHA system is calculated by Markov chain analysis and system stability is investigated. Earlier works on MRA systems such as [24] typically do not consider CSI either.

In [25] the authors consider the case where selfish users in a MRA system have multiple radios which they use to transmit on multiple channels simultaneously. Each of the channels in the system are contention based and users access these channels following the CSMA/CA protocol for medium access. They study the problem of how the selfish users would allocate their radios on the available channels and subsequently how the selfish users would access the medium following the CSMA/CA protocol. They show that the channel allocation game results in a fair and load balancing equilibrium and the channel access game leads to a Pareto-optimal Nash equilibrium. They analyze these problems under complete information assumption and provide a distributed algorithm to reach the equilibria with local information. One fundamental difference of this paper and
our analysis, other than the fact that we study ALOHA, is that in this paper selfish users do not take into account their channel state information other than the number of radios on a particular channel when they form their channel selection strategies.

One of the works which consider CSI is [26]. In this work the authors consider a MRA system with cooperative users and incomplete information and they propose a distributed MAC mechanism based on slotted ALOHA which incorporates CSI in transmission probabilities and channel allocation. They show that by selecting appropriate transmission thresholds and number of channels to transmit, the performance of the distributed system that they propose asymptotically approaches the performance of a scheduling system. Although the investigated setting is similar to our problem, we consider selfish users in our analysis.

2.2 Performance Analysis of WLANs

We can broadly categorize the performance analyses of WLANs in literature in two groups; studies that focus on a single cell and studies that focus on a set of coexisting cells.

Single Cell WLAN analyses

Articles on different aspects of the saturation throughput of a single WLAN constitute a very well investigated group within the studies on performance of WLANs. These articles employ a range of different methodologies in their investigation of WLAN performance, such as theoretical analysis, simulations and measurements. One of the fundamental articles on the subject is [27], which employs a Markov chain to analyze packet transmissions in a single WLAN. Many subsequent articles build upon the Markov chain analysis provided in [27] to investigate different aspects of a single WLAN; e.g., [28, 29]. Although such analyses provide a rigorous mathematical description of node transmissions, they typically make strong assumptions such as ignoring hidden terminals or packet capture, and they typically employ rather simplistic propagation environment assumptions in order for the theoretical analysis to be tractable. Furthermore, the results of single WLAN performance analyses cannot be easily generalized to multiple coexisting WLANs because of the nonlinear interaction of nodes in the system of WLANs.

Multi-cell WLAN analyses

Another group of articles investigate the saturation throughput of multiple coexisting wireless LANs. This group of articles as well employ a range of analysis methods such as theoretical analysis [30, 31, 32, 33, 34] or simulations [35, 36, 37]. Theoretical analysis methods that employ Markov chain analysis, stochastic geometry or other mathematical models produce results which can be applicable for a wide range of WLAN densities, however, such analyses typically do not have the accuracy of simulation studies because they tend to make simplifying assumptions such as a symmetric interference environment or a simple MAC model. On the other hand, existing simulation studies tend to investigate
the performance of a low density of coexisting WLANs, which is inadequate to represent the performance limits of a dense system of WLANs.

Similar to the volume of articles on throughput analysis of WLANs, there is a significant amount of literature on deployment of access points in a system of WLANs [38, 39] and on node association mechanisms [40, 41] in a system of WLANs. However, such existing studies also suffer in various degrees from the limitations of the above groups of articles in being accurate representations of the aggregate throughput performance of a dense system of WLANs. That is, deployment and association studies which employ theoretical methods typically lack in accuracy due to simple models, whereas other studies which employ simulation methods tend to apply to a low density of APs which is not representative of limits of the performance of a dense system of WLANs.
Chapter 3

Models

This chapter describes the models which we used in our performance analysis of WLANs and multichannel random access systems with selfish users. The models used in our aggregate throughput analysis of a system of WLANs tries to represent the MAC and PHY features of an 802.11 system in detail, whereas the models used in our game theoretic analysis of multichannel random access systems are more generic. Therefore we describe these two sets of models separately.

3.1 Performance Analysis of MRA Systems

As we described earlier, in our analysis of an MRA system, we try to determine the behavior of selfish users, and we compare the performance of such an MRA system in which users behave selfishly to a system in which users behave cooperatively. We try to answer this comparison question for particular selfish and particular cooperative systems which are representative of the properties of their respective classes of systems. Namely, we consider slotted ALOHA systems with multiple channels to reflect the properties of a MRA system with many channels. Users’ complete or incomplete information about the system is captured by the users’ exact or statistical knowledge of the channel state information (CSI) of all users in the system. The driving factors behind users’ transmission decisions are captured by the prospect of a successful transmission and the energy cost to make that transmission.

System Model

As mentioned above, we analyze a decentralized wireless system in which the users may be behaving in a cooperative or non-cooperative manner, depending on the scenario considered. In a cooperative system, the users try to achieve a common objective such as maximizing the cumulative benefit of all the users in the system, whereas in a non-cooperative system the users are behaving in such a way that will maximize their own benefit from the system, without necessarily considering the benefits of other users. We model the wireless
system that the users operate in as a random access system where there are a number of wireless channels available for users to transmit on. In the MRA system that we analyze, we consider that there are \( N \) users and \( K \) channels that the users can potentially access. The \( N \) users are trying to send packets to their respective receivers over one of the \( K \) available channels using the slotted ALOHA medium access mechanism.

In a given time slot, we assume that each user exactly knows its own instantaneous channel conditions and the statistical distribution of its own channel conditions in all time slots. This can be a reasonable assumption even for distributed systems because a user may easily keep track of its channel conditions in past time slots in order to obtain a statistical distribution of its channel conditions in an empirical way, without the need of any feedback from the access point. In a given time slot, the instantaneous channel conditions of each user are different from the instantaneous channel conditions of other users. However, depending on the similarity of the users’ speeds and movement patterns, the statistical distribution of the channel conditions of each user may be similar as well. If the users have similar speed and movement patterns, the statistical distribution of their channel conditions will be similar, therefore in this case the users will also know the statistics of the channel conditions of other users by extension of their knowledge of their own channel statistics.

The transmission choices of the users on the available channels may result in a number of outcomes. In some situations, more than one user may have chosen to transmit a packet on the same channel in a given time slot. In our model of the MRA system using slotted ALOHA medium access method, we assume that whenever there is more than one packet transmitted over the same channel in the same time slot, all the packets transmitted on that channel will fail to be received at the receiver. Thus, the only case when a packet is successfully received is when there is no other packet transmitted on the same channel and in the same time slot. Conversely, depending on channel conditions, some user may find it more preferable not to transmit at all. Thus, in some time slots, some channels may be idle.

**Receiver Model**

Our modeling of users’ utilities is related to our modeling of the receivers. We assume that in order for a packet to be successfully received, it needs to fulfill some signal to noise ratio (SNR) requirement at the receiver, which is required for some particular modulation and rate scheme. At the beginning of the transmission, the user selects an appropriate transmission power to satisfy the SNR requirement at the receiver, using its exact knowledge of its channel conditions in this time slot. To simplify the game theoretic analysis, we assume that there is no rate adaptation in the system. Alternatively, if the positive utility that a user obtains from a successful packet of any size (equivalently any rate) is the same, then the analysis in this work would still be valid.

**Utility Model**

The utility model we use is based on [23], which is similar to other utility definitions in literature, for example [21]. This definition of utility accounts for the throughput obtained
3.1. PERFORMANCE ANALYSIS OF MRA SYSTEMS

by the user in a system and the energy that the user spends in order to obtain this throughput. Furthermore, we make the following distinction between utility interpretations, thus we use two metrics when evaluating the performance of different systems and making comparisons between them. The first metric we use is the sum of the utilities of every user in a given system, which we simply refer to as sum utility. This performance metric reflects the efficiency in utilization of a system’s spectrum resources as a whole. Therefore it represents the system’s performance from the system designer’s point of view; the larger the throughput that a system achieves with less energy spent, the better system it is. The other performance metric we use in this work is the utility that an individual user obtains in a system, which we refer to as individual utility. This metric is indicative of system performance from the user’s point of view.

When a user transmits a packet and the transmission is successful, then the user gains some benefit from this transmission, which is modeled as some positive utility for the user. Naturally, the user needs to expend some energy in order to transmit this packet, which is modeled as some negative utility for the user associated with this transmission. We refer to this negative utility as the “transmission energy cost”. This transmission energy cost will vary according to the user’s channel conditions. The transmit power needed to achieve the SNR requirement will increase as the channel conditions deteriorate, i.e. the attenuation becomes more and more severe. At some point, even the maximum transmit power that the user terminal can supply will not be enough to meet the SNR requirement at the receiver. We arbitrarily model the negative utility of transmitting a packet at maximum power to be equal to the positive utility of a successfully transmitted packet. An intuitive interpretation of this modeling is that when the user has to transmit at maximum power, it will be indifferent between the actions of transmitting and not transmitting (waiting). The basis of our assumption that the positive utility of a successful transmission to be equal to the negative utility of transmission at maximum power is that the users who are located outside the nominal cell boundary (defined by the maximum transmit power) will have negative average utility from their transmissions, which complies with the notion of a cell as “the area served by one access point”.

We normalize all the positive and negative utilities with the utility of a successful transmission. Therefore, when a user transmits a packet successfully, it enjoys a positive normalized utility of 1. Similarly, when a user has to transmit a packet at full power, it incurs a normalized transmission energy cost of 1. We refer to the normalized transmission energy cost simply as the “transmission cost” and denote it as $e_{nk}$ where the subscript $n$ indicates the user index and $k$ indicates the channel index. Thus, the overall utility of a successful transmission will be $1 - e_{nk}$ whereas the utility of a failed transmission will be $-e_{nk}$.

Transmission Cost Model

We model the transmission cost of a user at a given time slot to be the ratio of the transmit power that the user needs to use in order to reach the required SNR level at the receiver to the maximum transmit power that the user terminal can supply. Thus, the transmission cost depends on the user’s channel conditions in that time slot. It is important to note
that, the user will not need to do any modeling when it is operating in the MRA system. Depending on the modulation and rate scheme and the receiver’s SNR requirement, the user will simply know its required transmit power. By dividing this required power by its maximum transmit power, the user will obtain the transmission cost. The modeling we do here is in fact not integral to the game theoretic analysis of user behavior in the MRA systems, but it is rather intended to be used in our simulations of the performance of the MRA system.

By taking into account distance dependent, shadow fading and Rayleigh fading components together, we can express the received power at a given time slot as:

\[ P_r = \frac{P_t}{D_{\text{dist}}} S R = \frac{P_t S R C_D}{d^\alpha f^\beta} \]

where \( P_t \) is the transmit power, \( D_{\text{dist}} \) is the distance dependent fading, \( S \sim \mathcal{N}(0, \sigma) \) is the shadow fading, \( R \sim \text{Exponential}(1) \) is the Rayleigh fading, \( d \) is the distance between transmitter and receiver, \( f \) is the carrier frequency, \( \alpha \) is the pathloss exponent, \( \beta \) models the frequency-dependence of the pathloss, and \( C_D \) is some constant.

As mentioned earlier, if a user is transmitting at the cell border with maximum transmit power, its average transmission cost will be equal to the positive utility of a successful transmission. This implies that, a user who is at the cell border and transmitting with \( P_{\text{max}} \) will on average just satisfy the received power requirement at the AP. This can be expressed as

\[ P_0 = E[P_r] = \frac{P_{\text{max}} S R C_D}{d_{\text{max}}^\alpha (f_{\text{max}})^{f}\beta} E[S] E[R] \]

because \( S \) and \( R \) are independent and all other quantities are constants. This expression can be further simplified as

\[ P_0 = E[P_r] = \frac{P_{\text{max}} C_D}{d_{\text{max}}^\alpha (f_{\text{max}})^{f}\beta}. \]

We define the coverage area on a given frequency as the area where a transmitter which is transmitting on that frequency using less than or equal to its maximum transmit power can in average fulfill the received power requirement at the receiver. It is interesting to note that the coverage area will be a function of the frequency of transmission. Since attenuation increases with increasing frequency, the coverage area will be reduced as frequency of transmission increases. This implies that in the regions where the distance of the transmitter is less than \( d_{\text{max}}(f_{\text{max}}) \), where \( d_{\text{max}}(f_{\text{max}}) \) is the coverage distance at the highest transmission frequency, a user will be able to transmit on all frequencies. On the other hand, if the distance of the user is between \( [d_{\text{max}}(f_{\text{max}}), d_{\text{max}}(f_{\text{min}})] \), where \( d_{\text{max}}(f_{\text{min}}) \) is the coverage distance at the lowest frequency, the user will not be able to use some of the available frequencies. In If the user is farther than \( d_{\text{max}}(f_{\text{min}}) \) then the user will not be able to communicate with the AP using any of the frequencies. Such users are not considered to be in the system.

As mentioned previously, we normalize all the positive and negative utilities with the utility of a successful transmission. We had also assumed that the positive utility
of a successful transmission is equal to the negative utility of transmitting a packet at maximum power. Thus, we can obtain the normalized transmission cost of a user on a given channel and time slot by normalizing the required transmission power with the maximum transmission power of the terminal. The transmit power required by a user transmitting on some frequency $f_k$ and at some distance $d_n$ is:

$$ P_0 = \frac{P_{SRC} C_D}{d_n^\alpha f_k^\beta} \Rightarrow P_t = \frac{P_0 d_n^\alpha f_k^\beta}{SRC_D} \quad (3.4) $$

We also know

$$ P_0 = \frac{P_{max} C_D}{d_{max}^\alpha (f_{max})^\beta} \Rightarrow P_{max} = \frac{P_0 d_{max}^\alpha (f_{max})^\beta}{C_D} \quad (3.5) $$

So we can obtain the normalized transmission cost as

$$ e_{nk} = \frac{P_t}{P_{max}} = \frac{P_0 d_n^\alpha f_k^\beta}{\frac{P_{max} C_D}{d_{max}^\alpha (f_{max})^\beta}} = \left( \frac{d_n}{d_{max}^\alpha (f_{max})^\beta} \right)^\alpha \left( \frac{f_k}{f_{max}} \right)^\beta \frac{1}{S^\cdot R} \quad (3.6) $$

Again, if we assume that the available channels are close enough in frequency so that $A(f)$ is almost constant, then we get

$$ e_{nk} = \left( \frac{d_n}{d_{max}^\alpha (f_{max})^\beta} \right)^\alpha \frac{1}{S^\cdot R} \quad (3.7) $$

which is the model used in [1] and [2].

We assume maximum transmit power of all terminals are equal by manufacturing or by regulatory rules, therefore the above result is valid for all users.

**Model Limitations**

The results of our analysis of the MRA system will depend on the distribution of the pathgains rather than the exact pathgains at any given time, and the selfish nature of the users’ behavior in the system will have a much stronger impact on system performance than the exact pathgain values. Therefore, any fading model that takes into account the essential properties of propagation would be appropriate for the analysis in this work. In the ideal case and incidentally in practice, an empirically obtained distribution of pathgains in the system considered could be used as input for the analysis done in this work, thus obtaining the most accurate representation of the selfish MRA system’s performance.

Furthermore, we try to obtain most results in closed form or in terms of integrals of CDFs and PDFs. Therefore, the results will be general, and not depend on the exact pathgains very much. Therefore the analytical results should be valid over a wide range of propagation models, if not all of them. We again highlight that we use our particular propagation model only to illustrate the performance of the system with simulations. The game theoretic analysis does not assume any particular path gain model.
CHAPTER 3. MODELS

Game Theoretic Models

In order to determine how selfish users will behave in an MRA system, we need to analyze the behavior of individual users who have potentially conflicting interests with other users in the system. Since users are selfish, they do not take commands from a central decision entity, therefore the users in the MRA system are the decision makers themselves. When a user is making transmissions in the MRA system, its transmission decisions will influence the performance that other users will experience because of the nature of radio propagation, and the performance of this user will be, in turn, influenced by the transmission decisions of the other users in the system. Therefore, each selfish user needs to take into account the possible actions of other users when it is going to make a transmission decision. Because we study the interaction between the users which are individual decision makers, and because there is this inherent antagonistic interaction between the users of a wireless system, it is fitting that we analyze the users’ behavior and the resulting system performance using game theory.

Selfish MRA System as a Strategic Game

In the MRA system, users act simultaneously because we assume slotted ALOHA is the underlying medium access method. That is to say, the users access the channel in the beginning of the time slot, so all users make their decisions at the same time. Therefore we model the interactions of the users (i.e. transmissions) in one time slot of the MRA system as a strategic game. As a logical extension of our modeling of one time slot, we model the entirety of the MRA system as a game which is played over and over again in all time slots in the system. We assume that the users make no strategic connection between the separate games which are played in each time slot. This implies that users do not take into account how their current actions may influence the behavior of other users in the subsequent time slots, which could be considered as a myopic behavior of the users. Therefore the users do not try to establish strategic connections between iterations of the game that is being played. For this reason, we do not model a sequence of transmissions as a repeated game but as a strategic game instead.

The strategic game formulation is more appropriate for the complete information assumption, in which all players are aware of the parameters related to the decision making of all other players. Our formulation of the MRA system with complete information as a strategic game is as follows:

Players: The players in the strategic game are the N users in the MRA system.

\[ \mathcal{N} = \{1, \ldots, n, \ldots, N\} \]

Here, by the word “user” we refer to the artificial intelligence on the user equipment which is tasked with making transmission decisions on behalf of the owner of the equipment, since the actual person in possession of the equipment probably will not be engaged in the decision making at the packet transmission level. Throughout this work, we use the term user and player interchangeably when it is clear from the context that the users are the decision making entities in a game.
3.1. **PERFORMANCE ANALYSIS OF MRA SYSTEMS**

**Actions**: In each time slot, a user will decide on its action in that time slot, based on its complete knowledge of its own and other users’ channel conditions. The set of possible actions for user $n$ is to transmit on any one of the available channels or to wait.

$$A_n = \{c_1, \ldots, c_k, \ldots c_K, w\}$$  \hspace{1cm} (3.9)

where $c_k$ indicates the action of transmitting a packet on channel $k$, and $w$ indicates the action of not transmitting in that time slot. Thus, the set of all action profiles is:

$$A = \times_{n \in \mathcal{N}} A_n$$ \hspace{1cm} (3.10)

**Utilities**: The preference relation of a user on action profiles can be defined by means of a utility function. In order to define the utility function $U_n : A \rightarrow \mathbb{R}$ we employ the user utilities we defined earlier, which is the normalized difference between positive utility of a successful transmission and energy cost associated with that transmission. Having complete information of all users’ channel conditions means that users know how much transmit power each user needs to transmit on each channel in the system, therefore every user knows every user’s energy costs on all channels. Thus, in the complete information case, user utility may be simply defined as

$$u_n(a) = u_n(a_n, a_{-n}) = \begin{cases} 1 - e_{nk} & \text{if } a_n = c_k, \forall a_m = a_n \ m \in \mathcal{N} \setminus \{n\} \\ -e_{nk} & \text{if } a_n = c_k, \exists a_m = a_n \ m \in \mathcal{N} \setminus \{n\} \\ 0 & \text{if } a_n = w \end{cases}$$ \hspace{1cm} (3.11)

Note that the utility of the user depends on the complete action profile $a$, that is, the action of user $n$ and actions of all other users in the system.

**Selfish MRA System as a Bayesian game**

Bayesian games are typically used to model interactions in which the decision makers are somehow not fully informed about each other’s decision making parameters. Therefore, a Bayesian game formulation is better suited to model the MRA system with incomplete information than the strategic game formulation. Below, we formulate the MRA system with incomplete information and heterogeneous channel statistics as a Bayesian game. The homogeneous channel system is a special case of this game formulation, in which all channel statistics are the same.

**Players**: Players are the $N$ users in the MRA system: $\mathcal{N} = \{1, \ldots, n, \ldots, N\}$, $|\mathcal{N}| = N$. In the context of the game theoretic analysis of the MRA system, we use the terms “player” and “user” interchangeably.

**States**: The entire set of states that the system may be in is the sample space $\Omega$, which is the set of all possible channel realizations of all the users in the system. A user’s knowledge of its channel conditions is equivalent to knowledge of its path gains, its transmit power requirements and hence its transmission energy costs on
all channels. As explained earlier, we model the channel conditions as the pathloss between the transmitter and the receiver, which is modeled as the combination of distance dependent, shadow and Rayleigh fading components, thus the possible values that pathloss can assume in our model is the positive reals. Therefore set of possible states of the system is $\Omega = \mathbb{R}^{N \times K}$. Random variable $\omega$ on $\Omega$ represents a realization of the channel conditions of all the users on all the channels in the MRA system.

**Signal functions** : A player learns its type by observing the output of the signal function. In the MRA game, the user learns its channel conditions by observing the output of its signal function, which gives the user’s pathloss on all channels; $\tau_n(\omega) = (L_{n,1}, \ldots, L_{n,k}, \ldots, L_{n,K})$. The set of all output values of the signal function is $T_n = \mathbb{R}^K$. Thus, $\tau_n : \mathbb{R}^{N \times K} \rightarrow \mathbb{R}^K$.

**Prior beliefs** : Each user’s prior beliefs about the state of the system is a probability distribution $p_n(\cdot)$ on $\Omega$. In the MRA system, a user knows the (possibly correlated) distribution of its channel conditions on all $K$ channels, and it assumes that the distribution of the channel conditions of other users is the same as its own. Furthermore, the user assumes that the distribution of channel conditions of any user is independent of the distribution of channel conditions of any other user. Thus, if we represent the joint probability density of user $n$’s channel conditions on the $K$ channels in the system as $f_{n,K}(x_1, \ldots, x_K) = f_n(x)$ then the prior belief of user $n$ about the state of nature is: $p_n(x_1, \ldots, x_n, \ldots, x_N) = \prod_{n=1}^{N} f_n(x_n) = p_n(\omega)$. We also assume that, when a user observes its type, that is, its own channel realization, the user does not obtain any information about the other users’ types. Therefore, posterior beliefs of the user will be equal to the prior beliefs. In the MRA system with homogeneous channels, we assume that every user’s channel statistics on every channel is the same.

**Actions** : The set of possible actions for each player is the different channels in the system that the user can transmit on: $A_n = \{c_1, \ldots, c_K, w\}$, $|A_n| = K + 1$. We use $c_k$ to denote the action of transmitting on channel $c_k$ and $w$ to denote the action of not making a transmission, i.e. waiting. The set of action profiles is then $A = \times_{n \in N} A_n$. We define a strategy of a player to be a mapping from the player’s possible types to the player’s possible actions. Thus, a player’s set of strategies can be denoted as $S_n = \{s_n | s_n : T_n \rightarrow A_n\}$. The set of possible strategy profiles is $S = \times_{n \in N} S_n$.

**Utilities** : The utility function of user $n$ as a function of the realization of nature $\omega$ and a strategy profile $\sigma = (s_n)_{n=1}^{N} \in S$ can be defined as follows:

$$u_n(\sigma, \omega) = \begin{cases} 1 - e_n(s_n(\tau_n(\omega)), \tau_n(\omega)) & \text{if } s_n(\tau_n(\omega)) \neq s_j(\tau_j(\omega)), \forall n \neq j \\ -e_n(s_n(\tau_n(\omega)), \tau_n(\omega)) & \text{if } s_n(\tau_n(\omega)) = s_j(\tau_j(\omega)), \exists n \neq j \\ 0 & \text{if } s_n(\tau_n(\omega)) = w \end{cases}$$

(3.12)
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where \( e_n : \mathcal{A}_n \times \mathcal{T}_n \to \mathbb{R} \) denotes the function that gives player \( n \)'s transmission cost as a function of its chosen action and its type.

Thus the Bayesian game formulation of the MRA system with incomplete information is given by the tuple \( G^B = (\mathcal{N}, \Omega, (\mathcal{A}_n)_{n=1}^N, (\mathcal{T}_n)_{n=1}^N, (\tau_n)_{n=1}^N, (p_n)_{n=1}^N, (u_n)_{n=1}^N) \). In the Nash equilibrium of the Bayesian game, player \( n \) will try to maximize its expected utility given that its type is \( t_n \).

**Scope and Discussion of Game Theoretic Models**

One archetypal solution concept in game theoretic analysis is the so-called Nash equilibrium. The solution of a game may exhibit a unique Nash equilibrium, in which case it is reasonable to assume that all the rational players that take part in this game will choose their actions indicated by this unique equilibrium. However, obtaining a single solution, that is, a unique Nash equilibrium is not the case in all games. Frequently, we come across game models that result in a multitude of Nash equilibria. In this work, when our game theoretic analysis leads to multiple Nash equilibria, we try to identify all possible Nash equilibria in the game. When it comes to making numerical simulations to obtain a representation of the system performance in terms of utilities that we discussed earlier, we make an “ensemble average” of the system performance. We consider that somehow the system will exist at one of the possible Nash equilibrium states, so we try to quantify the system performance in a way that will represent the distribution of all possible Nash equilibria that the system may be at.

In the solution of some game formulations, symmetric Nash equilibria may arise. At such equilibrium points, all players will obtain the same utilities, therefore such equilibria will inherently provide fairness. Some symmetric equilibria may exhibit other desirable properties such as being a unique equilibrium point of its kind, that is, it may happen that only a single symmetric equilibrium emerges in a game. Also, the resulting utilities at a symmetric equilibrium may be greater than utilities in a number of non-symmetric equilibria. In these cases, the symmetric equilibrium may be more preferable for the players than other equilibrium states, that is, it may be a “focal point”. Thus, the players may be expected to select their actions so as to reach this symmetric equilibrium point.

On the other hand, if there is no such focal point and there exist a number of non-symmetric Nash equilibria in the solution of a game, it is not clear why or how the players will choose actions to reach any one of these many equilibrium points. Solving this uncertainty is the subject of mechanism design, that is, creating incentives in order to compel players to choose certain actions desired by the mechanism designer. However, mechanism design is a fairly complex issue, so it constitutes a research problem in itself. Therefore we do not include mechanism design and equilibrium selection aspects in our analysis of the selfish MRA system in this thesis.

In a game, a player could be acting individually or it could be acting jointly with a group of other players. The former group of games are collectively referred to as noncooperative games whereas the latter kind of games are called coalitional games. As mentioned earlier, in this work we model the MRA system only as a noncooperative game.
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namely as a strategic game. We do not model the MRA system as a coalitional game nor investigate incentives for users to act in coalitions. The rationale behind not considering coalitional games is that, the users (players) are user terminals communicating with the AP, therefore they do not have means to communicate directly with each other, at least not on the MAC layer. Therefore the players would not be able to form coalitions in the first place. Nevertheless, two or more user terminals could potentially communicate at the application layer in order to form coalitions. We do not consider this case.

3.2 Performance Analysis of WLANs

In this chapter, we describe the various models and simplifying assumptions that we use in order to simulate the operation of WLANs as well as the metrics that we use in order to measure the throughput and delay performance of these WLANs.

Deployment and Association Models
In order to identify the impact of planning on the throughput performance of a system of WLANs, we consider two deployment regimes, which represent two different approaches to how WLANs may be deployed. In the first deployment regime that we consider, the wireless infrastructure is installed in an unplanned manner, which represents the cases where infrastructure is deployed without the involvement of a radio communication expert. For instance, the administration of or the users in an indoor premise may place APs in locations where it is convenient due to proximity to an electricity or network outlet rather than where it is favorable from a radio propagation perspective. We model such a deployment regime by randomly placing APs in our network model, following a uniform distribution.

The second deployment regime that we consider represents the cases in which wireless infrastructure is deployed in a planned manner. A planned deployment may have many different objectives; e.g., maximizing coverage area or reducing inter-AP interference or some other objective. In our analysis, we consider a planned deployment of APs such that the sum of interference powers between all pairs of APs in the system is reduced as much as possible compared to an unplanned deployment. The purpose of using this planning objective is to enable more APs to transmit concurrently compared to an equally-dense unplanned deployment in the same indoor environment, thereby increasing aggregate throughput.

While the planning regime used is one important parameter influencing the aggregate throughput of a system of WLANs, another parameter which also has a strong impact on aggregate throughput is how STAs associate with one of the several APs that they may discover in their surroundings. In a system of WLANs, especially as the number of APs in the WLAN increases, a STA will be able to communicate with several APs at the maximum data rate in absence of concurrent transmissions from other nodes. In our performance analysis, we consider two association modes, which are representative of
different precision in selecting the AP which the STA receives the strongest signal from. In one of the association modes we consider, which we define as random association, the STA chooses as its serving AP any one of the APs with which it can communicate at the maximum PHY rate. Our rationale for this random association definition is that, when a user wants to associate with a WLAN, she may see several “strong” APs which have “five out of five bars” signal quality; so the user chooses one random AP out of the set of APs that can provide the highest data rate. In the other association mode we consider, we assume that STAs are associated with the AP which they receive the strongest signal from.

We refer to this association mode as strongest association. This assumption can, for instance, correspond to a collection of open WLANs between which the users can freely and agilely roam, or an extended service set (ESS) which consists of the many APs which exist in the system.

As we have described above, in this work, we consider two deployment regimes, \( R = \{ \text{unplanned, planned} \} \), and two association modes, \( M = \{ \text{random, strongest-signal} \} \). We define the deployment-association types \( \tau \) as the combination of the deployment regime and the association mode used in a system of WLANs. Thus, we consider four such types; \( \tau \in R \times M \).

### WLAN System Model

We define the coverage area of an AP as the area in which a STA can decode 1500 octet packets from this AP with less than 1% PER at a given data rate in absence of concurrent transmissions. A representation of the 54 Mbps and 6 Mbps coverage areas of an AP are shown in fig. 3.1. We note that the actual coverage area of the AP transmitting at 6 Mbps is greater than what is shown in the figure, however, WLAN receivers ignore packets which are received at a power level lower than the CCA threshold \( P_{CCA} \), therefore the 6 Mbps coverage area shown in the figure is also the area where the signal power received from the AP is greater than \( P_{CCA} \). We denote the received power level at the edge of the 54 Mbps coverage as \( P_{54} \).

In the system model that we use in order to represent the operation of a system of WLANs, we assume that there is one STA associated with each AP. We model the location of the STA associated with an AP such that the STA is able to communicate with the AP at the highest data rate, which is 54 Mbps in our model, because we are interested in the performance limit of a system of WLANs. The assumption that each STA communicates with its respective AP at the highest data rate is reasonable for a densely deployed WLAN in which STAs associate with the strongest signal around them.

We note that this system model in which there is one STA associated with every AP can also represent the cases in which there are more than one STA associated with each AP, because at most one STA can be in successful transmission or reception within one basic service set (BSS). However, one shortcoming of our one-STA-per-AP assumption is that this model cannot exactly represent a system of WLANs in which there are more APs than active STAs. This is because the received power distribution of a system with e.g. \( x \) APs and \( x \) active STAs will not be the same as \( 2x \) APs and \( x \) active STAs, because in the 2:1 system, STAs will be relatively closer to their APs than in the 1:1 system. However, the
Figure 3.1: Example realizations of selected deployment-association type (τ) and propagation environment (ε) combinations. Each link between an AP and its intended recipient STA is represented by a red triangle connected to a green circle. (a) Low attenuation propagation environment. (b) Moderate attenuation. (c) High attenuation. (a-c) Unplanned deployment, strongest association. (d) Planned deployment counterpart of (b). Dark-shaded areas: 54 Mbps coverage area of AP1 in each system. Light-shaded areas: 6 Mbps coverage area of AP1 in each system.
3.2. PERFORMANCE ANALYSIS OF WLANS

difference between the results of one-AP-per-STA model and many-APs-per-STA model will diminish as AP densities increase, because received power statistics will increase due to increased AP density, while the CSMA/CA mechanism keeps the interference power essentially constant, thereby packet SINRs will become sufficiently large to communicate at the highest data rate in any situation.

We also assume that there is no STA left in outage in the system. The reasoning behind this modeling assumption is that, in an unplanned deployment, if there are users in need of connectivity, either the building administrator or the users themselves install an AP where the users are located, even though they do not place it necessarily in the best location from an SINR perspective. If a planned deployment is considered, the same assumption could represent the situation where nomadic users move to the area where there is connectivity, such as near a hot-spot. As the modeled deployment density increases, the assumption that there are no STAs in outage becomes very relaxed, because eventually the entire indoor area becomes covered even at the highest data rate.

In our system model, all APs operate on channel 1 on the 2.4 GHz band. We further assume that there is no adjacent channel interference, nor any interference coming from partially overlapping channels.

Propagation Model

In order to represent different propagation conditions created by various different indoor environments, we use the same propagation model as we have used in [4, 5], which incorporates the distance dependent fading and wall losses:

\[ P_r = \frac{P_0}{d^\alpha} \cdot W_k = [P_0]_{\text{dB}} - \alpha \cdot [d]_{\text{dB}} - k \cdot [W]_{\text{dB}}. \]  

(3.13)

where \( P_0 \) denotes the constant pathloss at 1 m, which depends on the transmit power \( P_t \), which we assume to be the same for all users in the system. Thus, a propagation environment may be represented by the vector \( \varepsilon = (P_t, \alpha, R) \), where \( \alpha \) is the pathloss exponent, and \( R \) is a parameter which denotes the number of rooms in the indoor environment. We model the propagation environment as a square region which has the same size in all systems we investigate in our analysis. We assume that the room dimensions that correspond to a given number of rooms in the indoor environment all come from the same distribution, which is defined by the size of the indoor environment and the number of rooms therein. Even though \( P_t \) is not an innate property of the propagation environment, we include this parameter in the set of parameters that define the propagation environment because it influences how far a transmission can reach, as do the other parameters that we use to characterize a propagation environment.

The propagation model we have described above is similar to the WINNER II indoor model, however we use slightly different coefficients, e.g. a wall loss factor of \( W = 10 \text{ dB} \). Also, we do not consider shadow fading; partly because wall losses are modeled explicitly, and partly because by keeping the propagation model simple, we aim to be able to see the impact of the parameters representing the propagation environment on dense WLAN performance more clearly. For a similar reason, we do not consider Rayleigh fading either;
CHAPTER 3. MODELS

we assume that the nodes are stationary for the small time duration that we simulate the operation of the dense WLAN system, and we intend to keep the propagation model simple.

Traffic Model

We model the data traffic in all WLANs to consist entirely of downlink traffic. As such, packet transmissions in the uplink consist entirely of ACK packets. Because of this assumption, we sometimes refer to APs and STAs as transmitters and receivers, respectively. The reason for this simplifying assumption is twofold. One of the reasons is that, we are mainly interested in estimating the capacity of systems of WLANs, and WLAN traffic is arguably dominated by downlink traffic. The other reason is that, in WLANs, both uplink and downlink transmissions share the same channel, therefore, even if we modeled the uplink and downlink transmissions explicitly, our estimate of the system capacity defined as the sum of uplink and downlink transmissions would not have been significantly different.

We model the arrival of data traffic from higher layers to the MAC layer as a Poisson process of 1500 octet-long packets. The choice of the packet length is motivated by the consideration that WLANs are typically connected to Ethernet, which carries a largest payload of 1500 octets. Also, choosing a large payload size in modeling packet transmissions downplays the impact of WLAN MAC overhead on system capacity. We model packet arrivals by directly inserting the packets into transmit buffers in our simulations; we do not model higher layer protocols such as TCP or UDP. This model enables us to identify the MAC performance in isolation of the higher layers.

PHY and MAC Model

We model the PHY used by all of the APs and STAs in the system of WLANs to be ERP OFDM. We assume that data packets are transmitted at the highest rate of 54 Mbps, whereas ACK packets are transmitted at 24 Mbps, because this rate is the highest rate in the mandatory rate set of the ERP PHY. Because we are interested in investigating performance bounds, we assume that all the WLANs in the system are ERP-OFDM-only; we do not consider a mixed PHY network, which reduces aggregate throughput performance.

We model the receivers such that received SINR values of individual bits are taken into account when determining the outcome of a packet reception. This receiver model results in packets with 1500 octet payloads to be received with a PER of less than 1% when the average SINR of the packet is more than 27 dB.

We use the 802.11 MAC model provided in OPNET Model Library “17.5 (19-Oct-2012)” in order to model the operation of the DCF which is defined in [42]. This model is a fairly faithful representation of the DCF. One minor limitation of this model is that the PLCP preamble and header are assumed to be transmitted using the same modulation and coding scheme (MCS) as the MPDU; that is, the rate used to transmit a PHY layer packet’s header and payload is assumed to be the same, while in reality the header is typically transmitted at as low a rate as possible and independently of the payload’s rate. The transmission rate of the PHY header is important because this header contains
information on the transmission duration of the payload so that in case the carrier is lost mid-transmission, the nodes which have received the header successfully can be courteous as to defer their transmissions for the duration announced in the PHY layer header. Using a low rate to transmit the PHY layer header increases the chances that this information is successfully received by a greater number of nodes. However, in our analysis, we never consider a situation in which a transmission abruptly stops before the 1500-octet payload is transmitted. Therefore, the assumption that the PHY layer header and payload are transmitted at the same rate has no impact on our simulation results. On the other hand, we make a minor modification to the OPNET model in order to account for the ACK timeout explicitly in DCF operation so that a transmitter may resume its backoff cycle if an expected ACK times out when the transmitter does not sense a collision, rather than the default implementation which assumes an ACK timeout necessarily implies a collision, which causes the transmitter to defer its transmission for an EIFS duration.

The single link throughput which results from the combination of the PHY and MAC models we use is approximately 30.8 Mbps at the highest data rate of 54 Mbps because of interframe spaces, backoff durations and packet overheads. We denote this maximum link throughput as $T_{\text{max}}$.

Other node related parameters we use in our simulations are as follows: All of the APs and STAs use a $P_{\text{CCA}} = -76$ dBm. We assume a receiver noise figure of 10 dB and an implementation loss of 5 dB as mentioned in [42]. The thermal noise power corresponding to these figures is $P_n = -90.6$ dBm. Packets which are transmitted unsuccessfully may be retransmitted 6 times, for a total of 7 transmissions.

We model transmit buffers to be infinitely large even though this is not the case in real systems, which have transmit buffers of typically a few hundreds of kilobytes. In a real system, when packets arrive from the higher layer to the MAC layer while the transmit buffer is full, these packets are dropped. However, in our investigation of the delay-throughput relationship in a system of WLANs, we are interested in identifying how much time the packets arriving at the MAC layer would spend in this layer before being successfully transmitted, or dropped due to excessive retransmissions. Therefore we model transmit buffers to be infinite. This assumption has no impact on the throughput or delay performance results of a stable system, because in a stable system there would be essentially no dropped packets, therefore the buffer size would have negligible influence on performance.

We do not consider rate adaptation; all transmissions use the highest rate of 54 Mbps. The reason for this assumption is that rate adaptation is typically beneficial in a scenario where the primary detrimental factor to successful transmission is thermal noise rather than an interfering transmission. In a dense WLAN system that we consider, rate adaptation would not be useful because the received SINR is either so high in the absence of interference that the highest rate transmission is successful, or so low in presence of interference that even a lower data rate like 6 Mbps would not be successfully received.
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Comparison between Propagation Environments

In order to observe trends in the aggregate throughput performance of a system of WLANs as a function of $\tau$ and $\epsilon$, we need to be able to compare and make an ordering between different $\epsilon$ for a given $\tau$. To devise such an ordering, we depart from the observation that different $\epsilon$ cause a given link to interact with a different proportion of all of the active links that coexist in this environment. In the context of this work, we use the term link to refer to the communication, i.e., the packet exchange, between an AP and one of its associated STAs. As such, we do not refer to the undesired packet transmission between two nodes which are not an AP and one of its associated STAs as a link but rather as interference. Thus, in a low attenuation environment, a given link will be in interaction with a large proportion of all the other active links, whereas in a high attenuation environment the given link will be interacting with a smaller proportion.

It turns out that the ratio of the average number of “neighbors” of a link, that is, the average number of links that a given link is in interaction with, to the number of all links in the system lends itself nicely to comparison of different $\epsilon$ for the given $\tau$. This ratio, which we refer to as cell congestion, can act as a measure of how much the cells in a dense WLAN system are isolated from each other. Furthermore, it does not depend on the link density, and it can easily be computed from the received power matrix $P_r$ as follows. Let $l \in L$ be a link in the set $L$, which consists of one random link, which can also be interpreted as the active link, selected from each WLAN that exists in the system. We define three sets in order to define cell congestion, $\phi(\tau, \epsilon)$. The first set represents the links such that when the APs of these links are active, they will cause the AP of link $l$ to defer its transmission:

$$S^l_1 = \{k \in L, k \neq l : P_r(AP_l, AP_k) > P_{CCA}\}$$  \hspace{1cm} (3.14)

where $P_r(AP_l, AP_k)$ denotes the power received by AP$_l$ from AP$_k$, and $P_{CCA}$ is the CCA threshold. The second set represents the links such that when the APs of these links are active, they will potentially cause the STA of link $l$ to lock onto their signal, thereby causing a concurrent transmission by AP$_l$ to fail:

$$S^l_2 = \{k \in L, k \neq l : P_r(STA_l, AP_k) > P_{CCA}\}$$  \hspace{1cm} (3.15)

where $P_r(STA_l, AP_k)$ denotes the power received by STA$_l$ from AP$_k$. The third set denotes the links such that when there is a transmission on these links, a concurrent transmission on link $l$ will fail with some significant probability, e.g. 50%, because of interference:

$$S^l_3 = \{k \in L, k \neq l : P_r(STA_l, AP_k) > P_r^{50\%}\}$$  \hspace{1cm} (3.16)

where $P_r^{50\%}$ is an interference power threshold such that if interference from a concurrent transmission on link $k$ is greater than this threshold, then $PER(\Gamma_l) > 50\%$, where $\Gamma_l$ is the SINR on link $l$, and PER is the packet error rate as a function of SINR. Using these three sets we have defined above, we can define the set of all neighbors of link $l$ as

$$S^l = S^l_1 \cup S^l_2 \cup S^l_3.$$  \hspace{1cm} (3.17)
Since the links in \( S_1 \) are determined by the position of the AP of link \( l \) in relation to the transmitters of the other links, we sometimes refer to the set \( S_{AP}^l \triangleq S_1^l \) as \( AP-neighbors \) of link \( l \). Similarly, since the links in \( S_2^l \) and \( S_3^l \) are determined by the position of the STA of link \( l \) in relation to the transmitters of the other links, we refer to the set \( S_{STA}^l \triangleq (S_2^l \cup S_3^l) \setminus S_1^l \) as \( STA-neighbors \) of link \( l \).

![Figure 3.2: Coverage and CCA ranges in an example topology with 20 links where \( \tau = (unplanned, strongest-signal) \) and \( \varepsilon = (P_t = 14dBm, \alpha = 2, R = 16) \). The 54 Mbps coverage area of AP \( l \) is denoted by the solid blue line. The points where the received power from AP \( l \) is greater than \( P_{CCA} \) is shown as the blue shaded region. The orange solid line denotes the set of points such that when a transmitter on this point transmits a packet at \( P_t = 14dBm \), the received power at STA \( l \) is greater than \( P_{CCA} \).

Thus, we can define the cell congestion as \( |S_1|/|L| \). However, this ratio is in fact a random variable since \( P_r \sim f_P(\tau, \varepsilon, L) \), where \( L = |L| \) is the number of links in the system, is random because of the randomness in the wall and link positions. Therefore, we define cell congestion as the expected value of this ratio over all possible values of \( P_r \):

\[
\phi(\tau, \varepsilon) \triangleq \mathbb{E}_{P_r} \left[ \frac{\tilde{S}}{L} \right]
\]

(3.18)

where \( \tilde{S} \) is the cardinality of the set of neighbors of a random link in a random realization of \( P_r \sim f_P(\varepsilon, \tau, L) \) as defined in (3.14-3.17). This ratio turns out to depend only on the deployment-association type and the propagation environment characterized by \( (\tau, \varepsilon) \), and not on \( L \).
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Performance Metrics

The metric that we use to represent the delay performance of a WLAN link is the mean MAC layer delay ($\tilde{d}_l$), which we define as the expected value of the time duration from the moment that a packet arrives at the MAC layer of a transmitter from its higher layer and enters the transmit buffer, to the moment that this packet is successfully delivered from the intended receiver’s MAC layer to its higher layer. Thus, delay is defined for packets which are successfully delivered for the first time; it is not defined for retransmitted packets, or packets which are dropped due to excessive retransmissions.

In order to represent the delay performance of an entire WLAN system with a certain infrastructure density ($\delta$) in a given deployment-association type and propagation environment ($\tau, \varepsilon$), we use the worst 95th percentile of all the delays that a random link in all possible such WLAN systems may experience. We can express this delay definition more precisely as follows: Let $d_l = f_d(\rho, \tau, \varepsilon, \delta, \tilde{P}_r)$ represent the mean MAC layer delay of a random link $l$ in a WLAN system with deployment-association type $\tau$ in an environment characterized by $\varepsilon$, where $\rho$ is the mean arrival rate per AP, and $\tilde{P}_r \sim f_P(\varepsilon, \tau, \delta)$ is a random realization of the received power matrix in a system of WLANs with AP density $\delta$.

Since we assumed that the indoor area where the system of WLANs exists is fixed, we take a shortcut by using infrastructure density ($\delta$) to refer to the number of APs in the system of WLANs in the fixed area in our model rather than to refer to an area density, as in number of APs/m$^2$. Thus, in our notation, $\delta = L$, and we do not explicitly indicate the indoor area size in our notation. So, we define the worst 95-percentile delay of such a WLAN system as

$$d_{95\%}(\rho, \tau, \varepsilon, \delta) \triangleq d^* : \Pr[\tilde{d} < d^*] = 0.95$$

(3.19)

$$= d^* : F_d(d^*) = 0.95$$

(3.20)

where $F_d(\cdot)$ is the CDF or the random variable $\tilde{d}$.

The metric we use to represent the throughput performance of a link, $\tilde{t}_l$, is the MAC layer throughput, which is defined as the expected value of the number of bits delivered from the higher layers of a transmitter to the higher layers of its intended receiver in unit time. In this throughput representation, only the “good” bits are accounted for; that is, packet overheads, retransmissions or duplicate receptions are not included.

In order to represent the throughput performance of an entire WLAN system, we define the aggregate throughput of the WLAN system as the expected value of the sum of throughputs of all links in the system. That is, if the infrastructure density is $\delta$, the given deployment-association type and propagation environment is $(\tau, \varepsilon)$, the mean arrival rate per AP is $\rho$, and $\tilde{P}_r \sim f_P(\varepsilon, \tau, \delta)$ is a random realization of the received power matrix in a system of WLANs, then we can denote the throughput of a single link $l$ as $\tilde{t}_l = f_t(\rho, \tau, \varepsilon, \delta, \tilde{P}_r)$. Consequently, the sum of throughputs of all links in this particular realization of a WLAN system is given by $T \triangleq \sum_{l \in L} \tilde{t}_l$. Thus, we define the aggregate throughput as:

$$T(\rho, \tau, \varepsilon, \delta) \triangleq \mathbb{E}_{\tilde{P}_r}[T] = \mathbb{E}_{\tilde{P}_r}\left[\sum_{l=1}^{\delta} \tilde{t}_l\right].$$

(3.21)
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We define stability of a WLAN system loosely as all traffic arriving to the MAC layers of all transmitters in the system being successfully delivered to their respective receivers. However, this loose definition is impractical because there is positive, albeit astronomically small, probability that some packets will be dropped due to excessive retransmissions simply as a result of thermal noise. Therefore, we use a more rigorous stability definition based on probabilities, which is as follows: A WLAN system is $x\%$-stable if more than $x\%$ of all the transmitters each can deliver more than $x\%$ of its incoming traffic to its intended receiver in more than $x\%$ of all realizations defined by a given set of parameters $(\rho, \tau, \varepsilon, \delta)$. In other words, if we let $\tilde{A} = \{ l \in L : t_l > \frac{x}{100} \rho \}$ where $t_l = f_l(\rho, \tau, \varepsilon, \delta, P_r)$, then a WLAN system with deployment-association type $\tau$, deployment density $\delta$, input arrival rate $\rho$, and which is operating in an environment characterized by $\varepsilon$ is $x\%$-stable if

$$\Pr \left| \tilde{A} \right| > \frac{x}{100} \delta > \frac{x}{100}. \quad (3.22)$$

This stability definition is arbitrary; stability may be defined in other similar ways such as the expected value of the throughput of a single random link in a random $P_r$ realization being greater than $x\%$ of the input data rate, i.e., $E_{P_r} [t_l] > \frac{x}{100} \rho$. Such similar definitions result in a slightly less or slightly more conservative stability definition, essentially leading to similar results and same conclusions.

Utilizing this stability definition, we define $x\%$-stability aggregate throughput of a system of WLANs as the maximum aggregate throughput for a given set of parameters $(\tau, \varepsilon, \delta)$ that the system is $x\%$-stable. That is:

$$T_{\text{sta}}^{x\%}(\tau, \varepsilon, \delta) = \max_{\rho, \delta} T(\rho, \tau, \varepsilon, \delta) \text{ s.t. } (3.22) \text{ is true.} \quad (3.23)$$

Similarly, we define saturation aggregate throughput as the sum of the throughputs of all links when all transmitters have full-buffers:

$$T_{\text{sat}}(\tau, \varepsilon, \delta) = \lim_{\rho \to \infty} T(\rho, \tau, \varepsilon, \delta). \quad (3.24)$$

A similar but distinct concept that we use is capacity. We define capacity of a system of WLANs as the maximum aggregate throughput that can be provided by any configuration of this system of WLANs of deployment-association type $\tau$ in a propagation environment $\varepsilon$. We define $x\%$-stability capacity as:

$$C_{x\%}(\tau, \varepsilon) = \max_{\rho, \delta} \left. T(\rho, \tau, \varepsilon, \delta) \right|_{3.22} \text{ is true.} \quad (3.25)$$

We can make a similar capacity definition based on a fixed delay constraint on the traffic carried by the system of WLANs. We define $x$ millisecond delay-bound capacity as:

$$C_{x\text{-ms}}(\tau, \varepsilon) = \max_{\rho, \delta} T(\rho, \tau, \varepsilon, \delta) \text{ s.t. } d^{95\%}(\rho, \tau, \varepsilon, \delta) < x \text{ ms.} \quad (3.26)$$

The subset of the DCF basic access mechanism that is relevant to our simulations is described in appendix A. This DCF implementation conforms to the IEEE 802.11 standard defined in [42].
Chapter 4

Methodology

This chapter describes the methodology which we use in our performance analysis of WLAN and other multichannel random access systems. In order to estimate the aggregate throughput performance of a system of WLANs, we use simulations. The reason for choosing to perform a simulation study as our main method as opposed to using analytical derivations such as a Markov chain analysis is that using analytical models sophisticated enough to represent WLAN operation in detail would be mathematically intractable, whereas using simplified analytical models would mean that our results would not represent WLAN performance accurately. An alternative to simulation studies would be implementing a testbed, but that too would be impractical because of the AP densities and the propagation environment parameters we investigate.

While in our aggregate throughput analysis of a system of WLANs we use a simulation based methodology using Monte Carlo simulations, in our game theoretic analysis of multichannel random access systems, we use a mixture of analytical derivations and simulations. Therefore we describe these two methodologies separately.

4.1 Performance Analysis of MRA Systems

In order to identify the behavior of selfish users in a MRA system, and in order to highlight the impact of selfish behavior on the performance of a MRA system we consider four distributed multichannel ALOHA systems that represent the four classes of distributed systems. Among these four systems, we analyze the behavior of selfish users under complete information and incomplete information assumptions, and compare the performance of these selfish systems to their cooperative counterparts. In our analysis of selfish systems in question, we use game theory to model and determine the behavior of selfish users in the distributed MRA systems. Since in this work we are investigating the interaction between independent decision makers whose actions affect each other, game theory was the natural choice as a mathematical analysis tool.

We formulate the MRA system with complete information as a strategic game. Using this game formulation, we identify the transmitter strategies at the Nash equilibria of this
CHAPTER 4. METHODOLOGY

For the incomplete information case, we formulate the MRA system with selfish users as a Bayesian game. For this game, we also identify the transmission strategies at the Nash equilibria. We also show that the game has a generalized ordinal potential function, so we use an iterative algorithm to calculate the transmission strategies at the Nash equilibria. In both complete and incomplete information analyses, in order to assess the system performance in terms of sum utilities and user utilities, we simulate frame transmissions under random propagation condition realizations. Using Monte Carlo simulations, we evaluate user utilities at the Nash equilibria of the MRA systems with complete and incomplete information.

4.2 Performance Analysis of WLANs

In our investigation of the throughput performance of a system of WLANs in different propagation environments, we follow a simulation based methodology. The reason for using simulations as a basis for our study is that the DCF function, when modeled to a high degree of detail, in combination with the PHY layer and propagation environment details, quickly becomes intractable to analyze theoretically. Therefore, we employ Monte Carlo simulations to estimate the performance of the system of WLANs in question.

We selected several values for evaluation in the simulations representing a range of each of the different model parameters. For arrival rates ($\rho$), we consider different arrival rates from 31 kbps up to 32 Mbps in 45 logarithmically spaced steps when calculating the stable aggregate throughputs:

$$\rho = \left\{ \frac{12000}{32 \cdot 10^6} \cdot 2^i \bigg| i = 0, 1, 2, \ldots, 5, 6, 7, \ldots, 10 \right\}$$

(4.1)

where 12000 is the number of bits in a 1500 octet payload.

For deployment-association types ($\tau$) we consider $\tau = \{(unplanned, strongest-signal), (unplanned, random), (planned, strongest-signal), (planned, random)\}$. In order to generate planned topologies, we implemented the planned deployment regime’s objective of reducing the sum of received powers between all pairs of APs by a heuristic gradient search algorithm. As such, the planned topologies we use in the simulations correspond to a local minimum with respect to the sum of interference power between APs rather than the global minimum. Nevertheless, the interference reduction by virtue of this algorithm is substantial enough to observe the impact of planning on system capacity.

The other values we considered in the parameter space of transmit power values ($P_t$), pathloss exponents ($\alpha$) and the number of rooms ($R$) in the indoor environment are the following:

$$P_t = \{100 \text{ mW}, 25 \text{ mW}\} \approx \{20 \text{ dBm}, 14 \text{ dBm}\}$$

(4.2)

$$\alpha = \{2, 3\}$$

(4.3)

$$r = \{1, 16, 256\}.$$ 

(4.4)
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Thus, the set of all propagation environments that we investigate in our simulation study comprises \( \varepsilon = P_t \times \alpha \times r \). Out of this set, we usually select for further study three propagation environments which are representative of different ends of the range of interference that may arise in these propagation environments. These selected examples interference environments are namely a high interference environment, which is characterized by \( \varepsilon = (20\text{dBm}, \alpha=2, R=1) \), a moderate interference environment, which is characterized by \( \varepsilon = (14\text{dBm}, \alpha=2, R=16) \), and a low interference environment, which is characterized by \( \varepsilon = (14\text{dBm}, \alpha=3, R=256) \). Furthermore, we arbitrarily classify propagation environments with \( \phi(\tau, \varepsilon) \geq 0.9 \) as low attenuation environments, those with \( \phi(\tau, \varepsilon) \leq 0.1 \) as high attenuation environments, and the remaining ones with \( 0.1 < \phi(\tau, \varepsilon) < 0.9 \) as moderate attenuation environments.

For AP densities \( (\delta) \), we consider \( \delta = \{1, 2, \ldots, 10, 20, \ldots, 100, 120, \ldots, 200\} \) (4.5)

APs per channel per a fixed simulation area of 100 m \( \times \) 100 m. We simulate the performance of system of WLANs operating on the same channel, however, considering a typical three channel reuse in the 2.4 GHz band, a total AP count of 600 corresponds to approximately 16.7 m\(^2\) per AP in average.

For every \( (\tau, \varepsilon, \delta) \) combination, we generated 40 random floor plans and random AP-STA location realizations:

\[
P_r = \{\tilde{P}_r\}_{i=1}^{40} \sim f_{\tilde{P}_r}(\tau, \varepsilon, \delta).
\]

For every scenario \( s \in \beta \times \tau \times \varepsilon \times \delta \times P_r \) we performed packet level simulations using OPNET Modeler “17.5A PL3 (Build 12737)”; we simulated the packet transmissions in the MAC and PHY layers of the system of WLANs in each scenario for 1.5 seconds. We discarded the first 0.5 seconds of each simulation as transient behavior of nodes until backoff window distributions converged, and obtained result statistics based on the remaining 1 second of packet transmissions. The steps followed in order to produce the simulation results are described in fig. 4.1.

In order to estimate the various performance metrics we defined in section 3.2, we use the following estimators. To estimate the mean MAC layer delay of a random link, \( \hat{d}_l \), we use the average of delays of individual packet transmissions that take place within the 1 second simulation duration. Let \( \mathcal{A} \) be the set of successful packets and \( \tilde{d}^a \) where \( a \in \mathcal{A} \) be the delay associated with successful packet \( a \):

\[
\hat{d}_l \triangleq \frac{1}{|\mathcal{A}|} \sum_{a \in \mathcal{A}} \tilde{d}^a \approx \tilde{d}_l.
\]

To estimate \( \hat{d}_{95\%}(\rho, \tau, \varepsilon, \delta) \) defined in (3.19), we use the 95-percentile of the empirical CDF of \( \hat{d}_l \) obtained from \( l \in \mathcal{L} \) and \( \tilde{P}_r \in P_r \). That is,

\[
\hat{d}_{95\%}(\rho, \tau, \varepsilon, \delta) \triangleq \hat{d}^* : \frac{1}{|\mathcal{L}| \cdot |P_r|} \sum_{l \in \mathcal{L}} \sum_{\tilde{P}_r : \tilde{P}_r \in P_r} 1(\tilde{d}_l < \hat{d}^*) < 0.95. \]
CHAPTER 4. METHODOLOGY

Figure 4.1: Simulation methodology used in WLAN performance analysis.

where \( 1(x) \) is the indicator function denoting the truth of event \( x \).

To estimate expected MAC layer throughput of a random link \( l \) in a random realization \( i \) of a system of WLANs, \( \hat{t}_i \), we use the average number of bits successfully transmitted on link \( l \) in realization \( i \) in unit time. Let \( A \) be the set of successful packets transmitted during the 1 second simulation of a random realization of a system of WLANs, and \( \beta_a \) be the size of payload associated with \( a \in A \).

\[
\hat{t}_i \triangleq \sum_{a \in A} \beta_a \approx \tilde{t}_i
\]  

(4.9)

where \( \beta_a = 12000 \) bits is assumed to be constant in our simulations.

We estimate \( T(\rho, \tau, \varepsilon, \delta) \) given in (3.21) by averaging \( \hat{t}_i \) over all links \( l \in L \) and all realizations \( \hat{P}_i \in P_r \) of the system of WLANs we simulate for the given set of parameters \( (\rho, \tau, \varepsilon, \delta) \). Thus,

\[
\hat{T}(\rho, \tau, \varepsilon, \delta) \triangleq \frac{1}{|L| \cdot |P_r|} \sum_{l \in L, \hat{P}_i \in P_r} \hat{t}_i.
\]  

(4.10)

Our estimators for the \( x \%-\)stability aggregate throughput, \( \hat{T}_{sta}(\tau, \varepsilon, \delta) \), and saturation aggregate throughput, \( \hat{T}_{sat}(\tau, \varepsilon, \delta) \), follow the definitions given in (3.23) and (3.24) respectively, but we substitute \( \hat{T}(\rho, \tau, \varepsilon, \delta) \) for \( T(\rho, \tau, \varepsilon, \delta) \) in those equations.

Our estimators for the \( x \%-\)stability capacity and \( x \)-ms delay bound-capacity follow the definitions given in (3.25) and (3.26) respectively, but we substitute \( \hat{T}(\rho, \tau, \varepsilon, \delta) \) for \( T(\rho, \tau, \varepsilon, \delta) \) and \( \hat{d}_{95\%}(\rho, \tau, \varepsilon, \delta) \) for \( d_{95\%}(\rho, \tau, \varepsilon, \delta) \) in those definitions.
Chapter 5

Selfish MRA system performance analysis

In this chapter, we present our game theoretic analysis of a MRA system with complete information [1], and incomplete information [2, 3].

5.1 MRA System with Complete Information

We consider the selfish users in the MRA system which we have described in chapter 3. We assume that the users have complete information, that is, every user knows the transmission costs of all users in the system. User utilities are modeled as described in chapter 3, which is a combination of a user’s gain from successful transmission and user’s energy cost for that transmission. We model the user interactions in the selfish MRA system as a game and analyze user behavior in the Nash equilibria of the system. We then compare the performance of the selfish MRA system with three cooperative systems; the scheduling system represents a cooperative system whose performance is optimum, the max-min fair system represents a cooperative system with fairness objective and a classic ALOHA system in which cooperative users try to maximize throughput without regard to their utilities. The performance metrics we use are sum utilities, which represent the efficiency in overall resource utilization, and individual utilities, which represent users’ benefit in the system.

For convenience, we reiterate the strategic game formulation here. The selfish multi-channel random access system with complete information, which we refer to as MRA-C, can be modeled as a strategic game \( G = \langle \mathcal{N}, (A_n)_{n=1}^N, (u_n)_{n=1}^N \rangle \) in the following way.

**Players:** The set of players is \( \mathcal{N} = \{1, \ldots, n, \ldots, N\} \)

**Actions:** The action set of player \( n \) is the set of channels that it can transmit on, \( A_n = \{c_1, \ldots, c_k, c_{K}, w\} \). The set of all action profiles is \( \mathcal{A} = \times_{n \in \mathcal{N}} A_n \).

**Utilities:** The utility of a player \( n \) for a given action profile \( a \in \mathcal{A} \) is \( 1 - e_{nk} \) if the user successfully transmits a packet, \( -e_{nk} \) if the user’s packet collides with another
transmission, and zero if the user’s action is to wait. Here, $e_{nk}$ is the transmission cost which is defined according to our channel model in section 3.

$$u_n(a) = u_n(a_n, a_{-n}) = \begin{cases} 1 - e_{nk} & \text{if } a_n = c_k, \forall a_m = a_n \ m \in \mathcal{N} \setminus \{n\} \\ -e_{nk} & \text{if } a_n = c_k, \exists a_m = a_n \ m \in \mathcal{N} \setminus \{n\} \\ 0 & \text{if } a_n = w \end{cases} \quad (5.1)$$

The mixed extension of this game can be defined as $G^M = \langle \mathcal{N}, (\mathcal{D}(A_n))_{n \in \mathcal{N}}, (U_n)_{n \in \mathcal{N}} \rangle$ in the following way.

**Players:** In $G^M$, the set of players, $\mathcal{N}$, is the same as $G$.

**Actions:** The set of actions of player $n$ is the set of mixed strategies $\mathcal{D}(A_n)$, which is the set of all possible probability distributions over $A_n$. The set of mixed strategy profiles is $\times_{n \in \mathcal{N}} \mathcal{D}(A_n)$. A mixed strategy is denoted as $\alpha_n \in \mathcal{D}(A_n)$ whereas a mixed strategy profile is denoted as $\alpha \in \times_{n \in \mathcal{N}} \mathcal{D}(A_n)$.

**Utilities:** Player $n$’s utility in a given mixed strategy profile $\alpha$ is defined as the expected value of its utility function in $G$ at that mixed strategy profile; $U_n(\alpha) = \mathbb{E}_{a \in A}[u_n(a)] = \sum_{a \in A} \prod_{a \in \mathcal{N}} \alpha_n(a_n) u_n(a)$. If we substitute (5.1) in this expected value expression, we obtain:

$$U_n(\alpha) = \sum_{k=1}^{K} \alpha_n(c_k) \left( \prod_{j=1}^{K} (1 - \alpha_j(c_k)) - e_{nk} \right) \quad (5.2)$$

Using this game theoretic formulation, we identify the Nash equilibria of $G$. We classify the Nash equilibria of $G$ into three groups; pure strategy Nash equilibria, fully mixed Nash equilibria (FMNE) and partially mixed Nash equilibria (PMNE). Pure strategy equilibria are the Nash equilibria in $G$, which can also be defined as mixed strategy Nash equilibria in which all users are employing degenerate probability distributions. FMNE are the equilibria in which all users are employing mixed strategies, that is, non-degenerate probability distributions. PMNE are the equilibria in which some users are using pure strategies and some users are using mixed strategies.

In our discussion on the existence conditions of the various Nash equilibria, we use the following notation. The set of users which “monopolize” some channels is $\mathcal{N}_m$. That is, these $|\mathcal{N}_m|$ monopolizing users transmit with probability 1 on a channel, where $|\mathcal{N}_m| = \mathcal{N}_m \leq K$. We call the channels that these users transmit on as monopolized channels, $\mathcal{K}_m$. The number of monopolized channels is $|\mathcal{K}_m| = \mathcal{K}_m = \mathcal{N}_m \leq K$. Consequently, $\mathcal{K}_f = \mathcal{K} \setminus \mathcal{K}_m$ is the set of channels which are not monopolized by users in $\mathcal{N}_m$. Let $\mathcal{M}$ denote the set of users which are using mixed strategies, and $\mathcal{X}_n$ denote the set of channels on which a mixed strategy user $n \in \mathcal{M}$ transmits. The set of channels on which some mixed strategy users are transmitting is then $\mathcal{X} = \bigcup_{j \in \mathcal{M}} \mathcal{X}_j$. Let $\mathcal{M}_k$ denote the set of mixed strategy users that transmit on channel $k \in \mathcal{X}$ and $\mathcal{N}_w = \mathcal{N} \setminus (\mathcal{M} \cup \mathcal{N}_m)$ denote the set of users who wait.
Pure strategy Nash equilibria

In this class of Nash equilibria, users are employing pure strategies; they either transmit on one of the $K$ channels in the system, or they wait. The following are the necessary and sufficient conditions for an action profile $a \in A$ to be a pure strategy Nash equilibrium.

1. If a user monopolizes a channel, then the monopolizing user is the only one to transmit on that channel.

2. User $n \in N_m$ which is monopolizing channel $k$ has $e_{nk} < 1$ and does not have lower transmission cost on any one of the non-monopolized channels. That is, $e_{nk} \leq e_{nj}, j \in K_f$.

3. Waiting users obtain negative utility if they were to transmit on any channel. That is, if a waiting user $n$ transmits on channel $k \in K_m$ then it would have a collision. If this user would transmit on a channel $k \in K_f$, then it would have negative utility; $u_n(c_k, a_n) = 1 - e_{nk} < 0$.

Fully mixed Nash equilibrium

In this equilibrium, all users assign positive probability to all actions in their mixed strategies. There exists a unique fully mixed Nash equilibrium, in which a user $n$ employs mixed strategy $\alpha_n(\cdot)$ such that

$$\alpha_n(a_n) = \begin{cases} 
1 - \frac{\prod_{j=1}^{N} e_{jk}}{e_{nk}} & \text{if } a_n = c_k \\
1 - \sum_{a_n \neq w} \alpha_n(a_n) & \text{if } a_n = w
\end{cases} \quad (5.3)$$

In order for the FMNE to exist, $0 < \alpha_n(a_n) < 1$ and $\sum_{a_n} \alpha_n(a_n) < 1$ must be satisfied.

Partially Mixed Nash Equilibria

Since we define the class of PMNE to be equilibria in which some users are using pure strategies whereas some are using mixed strategies, the existence conditions for the PMNE are a combination of pure and FMNE. The necessary and sufficient conditions for $\alpha = (\alpha_n)_{n=1}^N$ to be a PMNE are:

1. The transmit probabilities of mixed strategy users are

$$\alpha_n(a_n) = \begin{cases} 
1 - \frac{\prod_{j \in K_k \setminus M_k} e_{jk}}{e_{nk}} & \text{if } a_n = c_k, \forall c_k \in X, \forall n \in M_k. \\
1 - \sum_{a_n \neq w} \alpha_n(a_n) & \text{if } a_n = w
\end{cases} \quad (5.4)$$

2. $\prod_{a_n \in M_k} (1 - \alpha_n(c_k)) < e_{mk}, \forall k \in X, \forall m \in M \setminus M_k$. 
3. If user $n \in N_m$ is monopolizing channel $k$, and if $l \in X$, then user $n$ has less utility in monopolizing $l$ to which some users assign positive transmission probabilities. That is, $U_n((e(c_k), \alpha_{-n})) > U_n((e(c_l), \alpha_{-n}))$ where $e(a_n)$ denotes a degenerate probability distribution where user $n$ assigns probability 1 to action $a_n$.

4. If $n \in N_w$ and $k \in X$ then $\prod_{j \in M_k} (1 - \alpha_j(c_k)) - c_n k < 0$. That is, for a waiting user, changing to a mixed strategy which assigns positive transmission probability to a channel on which other mixed strategy users have assigned positive transmission probabilities results in negative expected utility.

In addition to these conditions listed above, existence conditions that apply to monopolizing and waiting users in pure strategy equilibria must also be satisfied. Furthermore, mixed strategy profiles must be valid probability distributions, i.e., $0 < \alpha_n(a_n) < 1$ and $\sum_{a_n} \alpha_n(a_n) < 1$ for $n \in M$.

**Simulation results**

The analytical results show that a multitude of equilibria exist in the MRA-C game, therefore we derived the MRA-C system performance as distributions of average sum utilities and average individual utilities. We performed snapshot simulations with random transmission cost realizations in each snapshot and obtained the distributions of sum and individual utilities using the equilibria from all simulations. We performed our simulations for small system sizes of less than 5 users and 4 channels due to the exponential growth in the number of equilibria with increasing system sizes.

Typically, in the Nash equilibria of the MRA-C system, mixed strategy users obtain zero utility whereas pure strategy users obtain positive utilities. The sum utility distribution in figure 5.1 illustrates that equilibria in which some users obtain positive utilities occur much more frequently than equilibria in which all users obtain almost zero utility. The ratio of users which obtain positive utilities can be seen in the individual utility plot in figure 5.2. Approximately 70% of the users in all Nash equilibria of the MRA-C system obtain positive utilities. Classic ALOHA system gives the worst utilities because the users try to maximize the system throughput without considering their utilities.

**Discussion**

The game theoretic analysis that we performed in this section does not assume any particular distribution for the channel statistics in the selfish MRA-C system. Therefore the analysis results are valid for MRA-C systems with both homogeneous and heterogeneous channels. However, when we obtained the simulation results of the MRA-C system, we assumed the channels to be homogeneous, i.e. identical transmission cost distributions.

The performance of the selfish system is inferior to the cooperative system, nevertheless, they are comparable for the small system size that we consider. Interestingly, the selfish system does not deteriorate to a “tragedy of commons” where the system would perform extremely poorly, although we note that the system we simulated corresponds to a
5.1. MRA SYSTEM WITH COMPLETE INFORMATION

Figure 5.1: PDF of sum utilities in the multichannel random access system with complete information and the scheduling system.

Figure 5.2: CDF of individual utilities in the multichannel random access system with complete information and the scheduling system.
low load scenario. For higher loads, due to the random access nature of the selfish system, we expect further performance degradation caused by increasing number of collisions.

Obtaining multiple Nash equilibria in the MRA-C game raises the question of equilibrium selection. Obviously, not all of the existing Nash equilibria in the MRA-C game are desirable. Therefore, investigating mechanism designs like simple policies enforced by the access point to alter the behavior of selfish users in order to eliminate undesirable equilibria will be useful in improving the performance of the selfish system.

Complete information assumption in [4] is a rather strong assumption. It is impractical because of the required information exchange between the AP and selfish users. In this respect, we don’t consider selfish MRA systems with complete information to be an alternative to centralized DSA systems. Nevertheless, we study this problem to observe the impact of selfish behavior on the performance of systems with complete information.

5.2 MRA System with Incomplete Information

In this section, we considered the problem of selfish users in a MRA system in which the users make their transmission decisions based on incomplete (local) information. In contrast to the complete information analysis above, in [2] and [3] we are interested in studying the selfish users’ behavior when they have to base their decisions on incomplete information, because having complete information is a rather strong assumption, and in practical systems selfish users will most likely have to make their transmission decisions based on local information.

The scope of the incomplete information analysis in [5] is a MRA system with homogeneous and correlated channels. Homogeneous channels implies that the statistics of channel conditions are the same on all channels in the system. This assumption applies to situations in which channel separations are smaller than coherence bandwidth of the channels. Correlated channels implies that the statistics of different channel conditions for the same user at the same time instant are correlated. The analysis in this paper focuses on the symmetric equilibrium. In comparison, the scope of the analysis in [6] is a MRA system with heterogeneous and independent channels. Heterogeneous channel assumption is a logical extension of the homogeneous channel assumption in [5], since different channels with a large frequency separation are likely to exhibit different statistics. Independent channel assumption is a simplification to reduce the complexity of the game theoretic analysis of the heterogeneous channel system. The analysis in [6] is a generalization of the analysis in [5] in that [6] considers all possible Nash equilibria, including the symmetric equilibrium. Analytical results of [6] concerning the symmetric equilibrium when the channel conditions are taken to be identical reduce to the results in [5] when the channel conditions are taken to be independent. In the following discussion, we refer to the game analyzed in [5] as MRA-I and the game in [6] as MRA-IH.

Both of the MRA systems with incomplete information which are analyzed in [5] and [6] are essentially the same system, therefore we model both of these systems using the Bayesian game formulation we presented in 3 which we reiterate below. The difference in the assumptions on channel statistics do not influence the game formulation, however
it applies to the subsequent game theoretic analysis. The MRA system with incomplete information can be formulated as follows:

**Players**: Players are the \( N \) selfish users in the MRA system: \( \mathcal{N} = \{1, \ldots, n, \ldots, N\} \), \( |\mathcal{N}| = N \).

**States**: A state of the MRA system is the path gains of all \( N \) users on the \( K \) channels. A sample space \( \Omega \) represents the set of all possible states of the system. A random variable \( \omega \) on \( \Omega \) represents a realization of path gains in a given time slot.

**Signal functions**: A user’s signal function reveals the user’s private information. Each different output value of the signal function is called a type of the user. Let the signal function of player \( n \) be a function from the MRA system’s states to player \( n \)’s types, \( \tau_n : \Omega \to \mathcal{T}_n \), and the set of types of player \( n \) be \( \mathcal{T}_n = \{ t_n : t_n = \tau_n(\omega), \omega \in \Omega \} \). When a user learns its type in the game, the user learns its path gains on all \( K \) channels in the system. We can express this as \( \tau_n(\omega) = t_n = (L_{n,1}, \ldots, L_{n,K}, \ldots, L_{n,K}) \).

**Prior beliefs**: The prior belief of user \( n \) about the state of the system is the probability distribution \( p_n(x_1, \ldots, x_n, \ldots, x_N) = \prod_{n=1}^{N} f_n(x_n) = p_n(\omega) \) where \( f_n(x) = f_{n,K}(x_1, \ldots, x_K) \) is the joint probability density of user \( n \)’s channel conditions on the \( K \) channels. We assume that when a user observes its type, it only obtains information about its own path gains; the user does not obtain any information about other players’ channel conditions. Therefore we assume that the posterior beliefs of users after they have observed their types will be the same as their prior beliefs. That is, \( p_n(\omega | t_n) = p_n(\omega) \).

**Actions**: The set of possible actions for user \( n \) is to transmit on any one of the available channels or to wait; \( A_n = \{ c_1, \ldots, c_k, \ldots, c_K, w \} \). The set of all action profiles is then \( \mathcal{A} = \times_{n \in \mathcal{N}} A_n \). Let a strategy of user \( n \) be a mapping from all possible types of user \( n \) to an action in \( A_n \), and \( S_n \) be the set of all such possible mappings: \( S_n = \{ s_n | s_n : \mathcal{T}_n \to A_n \} \). Thus, we define a strategy of player \( n \) to be a complete description user \( n \)’s choice of action for all possible states of nature. The set of strategy profiles can be given as \( \mathcal{S} = \times_{n \in \mathcal{N}} S_n \).

**Utilities**: The utility of user \( n \) as a function of a strategy profile \( \sigma = (s_n(\cdot))_{n=1}^{N} \in \mathcal{S} \) and a state of system, \( \omega \), can be expressed in the following way:

\[
 u_n(\sigma, \omega) = \begin{cases} 
 1 - e_n(s_n(\tau_n(\omega)), \tau_n(\omega)) & \text{if } s_n(\tau_n(\omega)) \neq s_j(\tau_j(\omega)), \forall n \neq j \\
 -e_n(s_n(\tau_n(\omega)), \tau_n(\omega)) & \text{if } s_n(\tau_n(\omega)) = s_j(\tau_j(\omega)), \exists n \neq j \\
 0 & \text{if } s_n(\tau_n(\omega)) = w
\end{cases}
\]

(5.5)

The Nash equilibrium of this Bayesian game will be a strategy profile \( \sigma^*(\cdot) = (s_n^*(\cdot))_{n=1}^{N} \in \mathcal{S} \) such that,

\[
 s_n^*(t_n) \in \arg \max_{s_n(t_n) \in A_n} \mathbb{E}_{\omega \sim \nu_n} [u_n((s_n(\tau_n(\omega)), (s_n^*(\tau_n(\omega))), \omega)]
\]

(5.6)
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Assuming that every player is employing strategies \( s_n(\cdot) \) that correspond to a Nash equilibrium strategy profile \( \sigma \), we can express the expected utility of a player \( n \) as a function of its action as

\[
E_{\omega_n}[u_n(a_n, \omega)] = \begin{cases} 
\bar{u}^S_{nk} - e_{nk} & \text{if } a_n = c_k \\
0 & \text{if } a_n = w_n 
\end{cases} \tag{5.7}
\]

where \( \bar{u}^S_{nk} = E_{\omega_n}[1_{n \neq s_j(\tau_j(\omega))} \forall j \neq n] \) indicates player \( n \)'s expected positive utility of successful transmission on channel \( k \) in this strategy profile \( \sigma \). The Nash equilibrium strategies resulting from this utility definition turn out to be threshold strategies in which player \( n \) transmits on the channel that gives the largest expected utility \( u^S_{nk} - e_{nk} \) if this utility is greater than the utility of waiting, and waits otherwise. So, a player’s strategy at a pure strategy Nash equilibrium can be summarized as

\[
s_n(t_n) = \begin{cases} 
c_k & \text{if } \bar{u}^S_{nk} - e_{nk} > \bar{u}^S_{nj} - e_{nj} \forall j \neq k \land \bar{u}^S_{nk} - e_{nk} > 0 \\
w & \text{otherwise.} 
\end{cases} \tag{5.8}
\]

where \( \bar{u}^S_{nk} \) is defined as \( \prod_{j=1}^{N} (1 - p_{j,k}) \) and \( p_{nk} \) indicates user \( n \)'s probability of transmission on channel \( k \) at the Nash equilibrium strategy profile \( \sigma \). Different transmission probability profiles result in different Nash equilibria. An alternative expression of the threshold strategy is the following. For a given realization of transmission costs, if the user’s cost on a channel is greater than a threshold which is the user’s probability of successful transmission on that channel, then the user will not transmit on that channel in that time slot.

In the MRA-I system, we assume that all channels have identical and correlated statistics. If we consider the situation that all the players users in MRA-I believe that all players will be transmitting with the same probability on all channels, then we arrive at the symmetric Nash equilibrium in the MRA-I game. At this symmetric equilibrium, the users’ transmission probability profile \( p_{\text{hom,sym}} = (p_n)_{n=1}^{N} \) where \( p_n = (p_{nk})_{k=1}^{K} \) will satisfy

\[
p_{nk} = p^* = F_K \left( (1 - p^*)^{N-1} \right) \frac{1}{K} \tag{5.9}
\]

where \( F_K(\cdot) \) is the CDF of the minimum of \( K \) correlated identically distributed random variables which are drawn from the distribution \( f_{n,K}(x_1, \ldots, x_K) \), which represents the player’s prior belief about channel realizations.

In the MRA-II system, the transmission probability profile \( p_{\text{het}} \) at a Nash equilibrium will satisfy

\[
p_{nk} = \int_{-\infty}^{\infty} \prod_{m \neq n} (1 - p_{m,k}) \prod_{j \neq k} \left[ 1 - F_{e_j} \left( \prod_{\ell \neq n} (1 - p_{\ell,j}) - \prod_{\ell \neq n} (1 - p_{\ell,k}) + x \right) \right] f_{e_k}(x) \, dx \tag{5.10}
\]

In the special case of the symmetric Nash equilibrium, where every player has the same transmission probabilities, the transmission probability profile \( p_{\text{het,sym}} = (p_n)_{n=1}^{N} \) where
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\[ p_n = (p_k)_{k=1}^K \] will satisfy

\[
p_{nk} = p_k^n = \int_{-\infty}^{(1-p_k^n)^{N-1}} \prod_{j \neq k} \left[ 1 - F_{e_j} \left( (1 - p_j^n)^{N-1} - (1 - p_k^n)^{N-1} + x \right) \right] f_{e_k}(x) \, dx.
\]

(5.11)

Simulation results

For both of the MRA systems with incomplete information, we evaluated system performance using numerical simulations. When we performed simulations of the MRA-I game, we considered the system performance at the symmetric Nash equilibrium. In comparison, in our simulations of the MRA-IH game, we considered random Nash equilibria. The system performance in terms of individual utilities obtained in [5] is shown in figure 5.3. Not surprisingly, scheduling system performs best out of all cooperative and selfish systems. The gap between scheduling and cooperative systems’ results illustrates the performance degradation due to lack of complete information. On the other hand, the gap between the selfish and cooperative systems indicates the performance degradation due to selfish behavior. The selfish system performs worse than its cooperative counterpart because of excessive transmission attempts of selfish users.

![Figure 5.3: Average user utilities in the MRA system with incomplete information and homogeneous channels.](image)

The results obtained for the heterogeneous channel system in [6] are in agreement with the homogeneous channel results in [5]. From figure 5.4 we observe the same trends that
we discussed above; the selfish system performance is rather inferior in comparison with the scheduling system.

![Diagram showing average user utilities in the MRA system with incomplete information and heterogeneous channels.](image)

Figure 5.4: Average user utilities in the MRA system with incomplete information and heterogeneous channels.

Regarding sum utilities, which is the metric that indicates system-wide performance, the performance results obtained [5] and [6] are in agreement with the individual utility results. As it can be seen in sum utility results in figures 5.5 and 5.6, scheduling systems greatly outperform selfish systems in terms of sum utilities as well. Interestingly, increasing system load decreases sum utility performance, which implies that performance of the selfish systems do not scale well.

5.3 Discussion

The recurring observation that scheduling and otherwise cooperative systems perform better than selfish systems indicate that the performance of selfish systems can be improved. The main reason for the poor performance of selfish systems in general is the excessive collisions due to superfluous transmission attempts from selfish users. This claim is supported by the observation that increasing the load, that is, the number users per channel, in the MRA system further decreases system performance in selfish systems. The possibility of performance improvement indicated by the gap between the selfish and cooperative system performances, combined with the existence of multiple Nash equilibria suggest a necessity
5.3. DISCUSSION

Figure 5.5: Average sum utilities in the MRA system with incomplete information and heterogeneous channels.

Figure 5.6: Average user utilities in the MRA system with incomplete information and heterogeneous channels.
for a mechanism design to force the selfish users to shape their transmission behavior in a
way that will improve system performance.

Finally, we note that the transmission cost model defined in chapter 3 implies correlated
channel costs, whereas our game theoretic analysis of the MRA-IH system assumes inde-
pendent channel realizations. Therefore applying the transmission cost model in 3 to our
performance evaluation of the MRA-IH system does not have much practical significance.
Nevertheless, we use the model in chapter 3 to achieve some coherence between simulation
results in [5] and [6]. If anything, independent channel realizations imply greater diversity,
therefore our performance analysis of the MRA-IH system in [6] will indicate an upper
bound of the performance of the MRA-IH system with correlated channel realizations.
Chapter 6

WLAN Performance evaluation

This chapter describes the aggregate throughput performance of a system of WLANs from several aspects which complement one another. Each of these different aspects of WLAN performance we discuss here have been treated in one of [4, 5, 6]. The dependence of aggregate throughput on deployment density and on different propagation environments is the focus of [4]. Developing on this theme, [5] investigates the impact of the choice of deployment regimes and association modes on the aggregate throughput performance of a system of WLANs. Finally, [6] extends the analysis in the previous two articles in order to incorporate the aggregate throughput of a system of WLANs at a stable operating point to complement the saturation operating point performance analysis in the previous articles.

6.1 Propagation Environment Dependence

We observed that the aggregate throughput of a system of WLANs operating at saturation point will exhibit the general behavior illustrated in fig. 6.1 in any propagation environment: The aggregate throughput initially increases almost linearly with each additional AP, which we refer to as “non-congestion”. Increasing the AP density further causes channel resources to be more and more fully utilized, therefore the increase in aggregate throughput by adding more APs gradually diminishes to zero; we call such a system “congested”. If we continue to increase the AP density, collisions will increase so much so that aggregate throughput starts to decrease; we call such a system “over-congested”.

The aggregate throughput performance of a system of WLANs which exist in different propagation environments can exhibit a large variation because the amount of contention and interference that coexisting WLANs create on each other is influenced by the indoor propagation environment such as existence of walls or clutter. The performance results indicate that the propagation conditions have a profound impact on aggregate throughput; as much as several tens of times increase in high attenuation environments compared to open areas. This observation also highlights the importance of taking the propagation environment into account when estimating the aggregate throughput performance of a system of WLANs.
CHAPTER 6. WLAN PERFORMANCE EVALUATION

The AP densities corresponding to the non-congested, congested and over-congested deployment regimes depend on the propagation environment, particularly on the amount of attenuation of interference between the coexisting WLANs. In topologies with little attenuation, the congested regime is reached even for small WLAN densities, as seen in the “low attenuation” curves in fig. 6.2. If the attenuation is very small such that all APs exert strong interference on each other, then high WLAN densities push the system into the over-congested regime, where area throughput degrades with increasing WLAN density. This trend can be observed in the “low attenuation” curves at higher WLAN densities. In contrast, in topologies with high attenuation, the WLANs operate in the non-congested regime even for high WLAN densities, which can be observed in the “high attenuation” curves in fig. 6.2. These trends are observed for all deployment and association choices with the interesting exception of WLAN systems which employ strongest-signal association. In these systems, when an over-congested regime is reached, aggregate throughput initially drops, but as AP density is increased further, the received packet SINRs become so strong that concurrent transmissions become almost always successful. Therefore the aggregate throughput starts to increase again, but this increase due to additional densification turns out to be very small, because the channel is occupied nearly 100% of the time, which prevents APs from transmission.

6.2 Association Mode Dependence

Strongest-signal association and random association modes result in approximately the same throughput performance when the amount of congestion and interference in the system is “low”, which implies that these two association modes perform similarly when WLANs are in non-congested state. This can be seen in fig. 6.3 where the gain is close to unity for small AP densities. In contrast, when congestion and interference increase, and consequently when WLANs move into congested and over-congested states, strongest-signal association mode always outperforms random association, as seen in all three curves in fig. 6.3. The reason is that, in a system which is operating in random association mode, as AP deployment density increases, interference becomes stronger due to more numerous and closer interfering APs while signal power statistics do not improve at all. As a consequence, APs end up deferring channel access for most of the time. Furthermore, when
an AP eventually transmits, the outcome of the packet transmission is mostly unsuccessful due to high interference levels. In contrast, in a system which operates in strongest-signal association mode, as WLAN deployment becomes denser, the improvement in received power levels exceeds the increase in interference because of diversity in AP selection. As a result even concurrent packet transmissions result in successful reception due to the improved SINR statistics. Therefore, the advantage of strongest-signal association mode over random association becomes most apparent in high AP densities where congestion and interference are also “high”. The absolute value of “low” and “high” in this context depends on the propagation environment. That is, if attenuation is low, even few APs will lead to a high congestion and interference in the system, therefore throughput improvement due to strongest-association will be apparent sooner. Whereas, if attenuation is high, both strongest-signal and random association modes will perform similarly until much higher
6.3 Deployment Regime Dependence

A planned deployment brings most gains in moderate interference environments; that is, where attenuation and AP densities are moderate, as shown in fig. 6.4. The reason is that, when AP densities are moderate, it is possible to find a better AP placement than a random one, which reduces the aggregate interference levels at each AP compared to the initial random AP placement by isolating APs as much as possible and thereby increasing concurrent transmission opportunities. However, when the AP density is low, and consequently the interference level from other APs is also low, then planned deployment does not improve the aggregate throughput performance substantially. The reason is that the AP location planning method that we consider aims to reduce the aggregate interference at each AP. Consequently, when the attenuation is very strong or when there are not so many interferers to begin with, then the aggregate interference is already quite low, therefore performance gain in aggregate throughput due to planned deployment is marginal. On the other hand, planned deployment is not very beneficial in high interference environments either; i.e. in low attenuation and high AP density settings. The reason is that large number of transmitters mean that throughput is degraded due to excessive interference to receivers. Therefore, reducing interference between APs to increase concurrent transmission opportunities does not improve aggregate throughput at all.

When we are considering a delay constrained throughput performance or a stable aggregate throughput of a system of WLANs, planning can give significant gains in moderate and high attenuation propagation environments as shown in fig. 6.5. The highest gains due to planning are obtained in moderate interference environments. We note that this outcome

Figure 6.3: Aggregate throughput gain due to strongest-signal association mode with respect to random association mode. At high AP densities, strongest-signal association improves aggregate throughput in all propagation environments.
6.3. DEPLOYMENT REGIME DEPENDENCE

Figure 6.4: Aggregate throughput gain due to planned deployment with respect to the unplanned deployment regime. Planned deployment brings most gains in moderate interference environments.

is also in line with our results pertaining to saturation aggregate throughput described above, in which we observed the greatest improvement in aggregate saturation throughput due to planning in moderate interference environments.

Figure 6.5: Relative increase in 90%-stability capacity due to planned deployment with respect to the 90%-stability capacity of an unplanned deployment in the same propagation environment.

Planned deployment always brings some amount of aggregate throughput gain at high deployment densities when the WLANs are operating in strongest-signal association mode, which can be observed in all scenarios. An example for high attenuation scenarios is provided in fig. 6.6. The reason for this outcome is that in the random deployment regime, two or more APs may be deployed too close to each other such that even the favorable SINR statistics obtained by strongest-signal association cannot achieve the SINR requirement for successful packet reception when these two APs are transmitting simultaneously. Planned deployment eliminates such extremely poor AP location realizations, thereby improving
the through performance. This gain due to planning at high AP densities is not observed in WLANs operating in random association mode.

![Diagram](image)

Figure 6.6: Aggregate throughput improvement due to planned deployment when WLANs operate in strongest-signal association mode.

### 6.4 Delay Bound Dependence

In order to determine if the impact of deployment and association choices on the aggregate throughput performance is the same in a stable operating point of a system of WLANs is the same as the saturation operating point, we analyzed the impact of delay requirement on the aggregate throughput performance. Figures 6.7-6.9 show iso-delay curves, which are \((\rho, \delta)\) pairs which result in the same \(d_{95\%}(\rho, \tau, \epsilon, \delta)\) value. The figures also present equal rate lines; along a given equal rate line, the logarithmic scale sum of the arrival rates to all APs in the system of WLANs, which has \(\delta\) APs and \(\rho\) arrival rate per AP, is constant.

For moderate interference environments, \(0.1 < \phi < 0.9\), increasing deployment density for the same traffic reduces the delay and brings the system to a stable operating point. Further increasing the density leads to very gradual reduction in the delay metric. Therefore further densification than what is needed to meet the stability or delay requirement is not very beneficial. In the low interference environments, \(\phi < 0.1\), we observe the same trend, namely increasing infrastructure density will bring a system in an unstable operation point to a stable operating point. Beyond the density which brings stability, increasing density further will result in a reduction in \(d_{95\%}(\rho, \tau, \epsilon, \delta)\), which is gradual but more pronounced than in the moderate interference environment. However, in high interference environments, \(\phi > 0.9\), increasing density will result in a larger delay value because the channel resources are almost fully in use everywhere in the system area. Therefore, in such environments, a smaller infrastructure density results in a smaller delay.

We also observed that any delay or stability requirement reduces the capacity substantially, except in high interference environments, as shown in fig. 6.10. This reduction is
Figure 6.7: Worst 95-percentile of MAC layer delay plotted as a function of $\delta$ and $\rho$ for the unplanned deployment, strongest association topology in a moderate interference environment. The worst 95% delay values are given by the labels on the contours. The figure also shows equal-rate lines; the total rate corresponding to each line is shown by a label on each line. The boundary of 90% and 95% stability regions are also shown. The numbers below the x-axis represent the percentage of area coverage at 54 Mbps (6 Mbps) for the corresponding AP deployment density.

mainly due to congestion.
Worst 95% MAC layer delay plotted as a function of $\delta$ and $\rho$ for the unplanned deployment, strongest association topology in a low interference environment. The worst 95% delay values are given by the labels on the contours. The figure also shows equal-rate lines; the total rate corresponding to each line is shown by a label on each line. The boundary of 90% and 95% stability regions are also shown. The numbers below the x-axis represent the percentage of area coverage at 54 Mbps (6 Mbps) for the corresponding AP deployment density.
Figure 6.9: Worst 95-percentile of MAC layer delay plotted as a function of $\delta$ and $\rho$ for the unplanned deployment, strongest association topology in a high interference environment. The worst 95% delay values are given by the labels on the contours. The figure also shows equal-rate lines; the total rate corresponding to each line is shown by a label on each line. The boundary of 90% and 95% stability regions are also shown. The numbers below the x-axis represent the percentage of area coverage at 54 Mbps (6 Mbps) for the corresponding AP deployment density.
Figure 6.10: Comparison of saturation capacity against stable and delay-bound capacities for the unplanned-deployment, strongest-signal-association topology.
Chapter 7

An Empirical WLAN Throughput Model

Having performed the simulation analysis of the aggregate throughput of a system of WLANs which we describe in chapter 6, we observed that functions which represent stable or saturation aggregate throughput in relation to infrastructure density in two different propagation environments resemble scaled versions of each other in x and y dimensions. So, we sought to develop an empirical model to estimate the aggregate throughput of a system of WLANs with an accuracy approaching that of packet-level simulations but at a much reduced time and computational complexity. In this chapter, we summarize the empirical throughput model that we proposed in [7].

We observe that in a system of WLANs, there may be several links in transmission at a given time. Thus, the aggregate throughput will be a function of how successful each link in transmission becomes, and how many such successful transmissions can take place concurrently. Therefore, we model the aggregate throughput as

\[ T(\tau, \epsilon, \delta) = \bar{T}_1(\tau, \epsilon, \delta') \cdot h(\tau, \epsilon, \delta) \cdot R_{\text{max}}. \]

We interpret \( h(\cdot) \) as the expected number of concurrent transmissions, and \( \bar{T}_1(\cdot) \) as the individual throughput of each of these concurrent transmissions. The quantity \( R_{\text{max}} \) denotes the maximum link throughput, and \( \delta' \) represents the “effective” infrastructure density as perceived by a link which is in transmission.

Using the aggregate throughput representation in (7.1), we transform our aggregate throughput performance estimates \( \hat{T}(\tau, \epsilon, \delta) \) which we obtained from packet-level simulations. We observe that these transformed aggregate throughput results indeed exhibit some common trends. To represent this set of transformed aggregate throughput results, \( \hat{T}_1(\cdot) \), we select a suitable function which can be expressed as

\[ \hat{M}(\tau, \phi(\tau, \epsilon), \delta') = \sum_{i \in B} b_i(\tau, \phi(\tau, \epsilon))(\delta')^i, \ B \subset \mathbb{Z}, \]

and then we perform a least-squares fit in order to estimate the coefficients of this function.
In order to make estimations of the aggregate throughput of a system of WLANs described by the parameters \((\tau, \varepsilon, \delta)\), we use the empirically obtained function \(\bar{M}(\tau, \phi(\tau, \varepsilon), \delta')\) in a manner similar to (7.1):

\[
M(\tau, \phi(\tau, \varepsilon), \delta') \equiv \bar{M}(\tau, \phi(\tau, \varepsilon), \delta') \cdot \hat{h}(\tau, \varepsilon, \delta) \cdot R_{\text{max}}
\]  

(7.3)

where \(\delta' \equiv \phi(\tau, \varepsilon)(\delta - 1) + 1\) is the effective infrastructure density observed by a random link in the system of WLANs, and \(\hat{h}(\tau, \varepsilon, \delta)\) is our estimate of how many concurrent successful transmissions there can be in the propagation environment for which we are producing the aggregate throughput estimate.

We define prediction error using and our simulation results \(\hat{T}(\tau, \varepsilon, \delta)\) and the estimate of the aggregate throughput of the system of WLANs which is obtained using our empirical model, \(\bar{M}(\tau, \phi(\tau, \varepsilon), \delta')\):

\[
e(\tau, \varepsilon, \delta) \equiv \frac{M(\tau, \phi(\tau, \varepsilon), \phi(\tau, \varepsilon)(\delta - 1) + 1) - \hat{T}(\tau, \varepsilon, \delta)}{\hat{T}(\tau, \varepsilon, \delta)}
\]  

(7.4)

An example \(\bar{T}_1(\cdot)\) obtained for 90%-stability aggregate throughput and saturation throughput are shown in fig. 7.1 and fig. 7.2 respectively.

The in low attenuation environments \((\phi \geq 0.9)\) and moderate attenuation environments \((0.1 < \phi < 0.9)\) show similar trends but both are quite distinct from the trends in high attenuation propagation environments \((\phi \leq 0.1)\). Therefore we produce one empirical aggregate throughput model for low attenuation environments and another for the combination of moderate and high attenuation environments.

We also observe that different deployment-association types, \(\tau\), lead to different trends in the transformed aggregate throughput values. Therefore we propose a different empirical aggregate throughput model for each different \(\tau\). Table 7.1 shows the set of the empirical aggregate throughput modes we obtained from the simulation results.

When we compare the aggregate throughput predictions obtained from our empirical models against the same set of simulations that these models were derived from, the empirical models turn out to be fairly accurate. Fig. 7.3 shows the prediction error corresponding to the scenarios in fig. 7.2 and 7.2. In all the set of estimations in all parameters that we consider, the prediction error is within \(\pm 10\%\) for the saturation aggregate throughput empirical models and \(\pm 20\%\) for the 90%-stability aggregate throughput empirical models.
Table 7.1: Empirical aggregate throughput models

<table>
<thead>
<tr>
<th>90%-Stable</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{M}(\tau, \phi, \delta')$</td>
<td>$\phi &gt; 0.9$</td>
<td>$\phi &lt; 0.9$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(unplanned, strongest)}$</td>
<td>$0.62(\log_{10} \delta' + 1)^{-1} + 0.97(\log_{10} \delta' + 1) + 0.31$</td>
<td>$0.62(\log_{10} \delta' + 1)^{-1} - 0.006(\log_{10} \delta' + 1) + 0.384$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(unplanned, random)}$</td>
<td>$0.32(\log_{10} \delta' + 1)^{-1} - 0.09(\log_{10} \delta' + 1) + 0.77$</td>
<td>$0.59(\log_{10} \delta' + 1)^{-1} - 0.16(\log_{10} \delta' + 1) + 0.58$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(planned, strongest)}$</td>
<td>$0.75(\log_{10} \delta' + 1)^{-1} + 0.15(\log_{10} \delta' + 1) + 1.1$</td>
<td>$0.78(\log_{10} \delta' + 1)^{-1} + 0.12(\log_{10} \delta' + 1) + 0.1$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(planned, random)}$</td>
<td>$0.13(\log_{10} \delta' + 1)^{-1} - 0.16(\log_{10} \delta' + 1) + 1.03$</td>
<td>$0.69(\log_{10} \delta' + 1)^{-1} - 0.11(\log_{10} \delta' + 1) + 0.42$</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Saturation</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau = \text{(unplanned, strongest)}$</td>
<td>$\begin{cases} -0.18 \log_{10} \delta' + 1 &amp; \log_{10} \delta' \leq \log_{10}(30) \ 0.52 \log_{10} \delta' - 0.03 &amp; \log_{10}(30) \leq \log_{10} \delta' \end{cases}$</td>
<td>$-0.15 \log_{10} \delta' + 1$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(unplanned, random)}$</td>
<td>$-0.26 \log_{10} \delta' + 1$</td>
<td>$-0.2 \log_{10} \delta' + 1$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(planned, strongest)}$</td>
<td>$\begin{cases} -0.15 \log_{10} \delta' + 1 &amp; \log_{10} \delta' \leq \log_{10}(30) \ 0.78 \log_{10} \delta' - 0.37 &amp; \log_{10}(30) \leq \log_{10} \delta' \end{cases}$</td>
<td>$-0.12(\log_{10} \delta')^3 + 0.44(\log_{10} \delta')^2 - 0.54 \log_{10} \delta' + 1$</td>
<td></td>
</tr>
<tr>
<td>$\tau = \text{(planned, random)}$</td>
<td>$-0.28 \log_{10} \delta' + 1$</td>
<td>$-0.14(\log_{10} \delta')^3 + 0.45(\log_{10} \delta')^2 - 0.58 \log_{10} \delta' + 1$</td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 7. AN EMPIRICAL WLAN THROUGHPUT MODEL

Figure 7.1: Empirical throughput models for unplanned-strongest deployment, 90%-stable aggregate throughput.
Figure 7.2: Empirical throughput models for unplanned-strongest deployment, full-buffer operating point.

Figure 7.3: Prediction error in empirical throughput models for unplanned-strongest deployment.
Chapter 8

Conclusions

This thesis is concerned with the investigation of operation and deployment of a system of WLANs in unlicensed spectrum for high capacity wireless access provisioning.

We started our investigation by verifying the suitability of WLANs for high capacity wireless access provisioning to answer SRQ-1. We considered WLANs to belong to the class of systems whose users are cooperative and whose users operate based on information locally available to them. We verified that in this class of systems, resource utilization does not diminish as number of users in the system increases. Thus, we considered WLANs to have the suitable attributes for high capacity wireless access provisioning.

Following this initial sanity-check, we conducted a substantial simulation study of these systems and investigated the dependence of their aggregate throughput performance on several key parameters in order to answer SRQ-2; namely, on the propagation environment that they operate in, on the deployment regime and association mode used in their operation, and on the traffic arrival pattern, that is to say, a given delay constraint.

With respect to the impact of the propagation environment on the aggregate throughput of a densely deployed system of WLANs, we have shown that the propagation environment has a profound impact on the performance of such networks. This result implies that, even though previous works, e.g. [27], can predict the general trends which are the non-congested, congested and over-congested regimes that we discussed, the simplistic models which do not account for the propagation environment in detail will lead to poor prediction of aggregate throughput performance. Because of the strong dependence of aggregate throughput performance on the propagation environment, the capacity of a system of WLANs also strongly depends on cell congestion; an increase in cell congestion coefficient causes the system capacity to decrease rapidly. Yet another influence of the propagation environment is in the observation that the delay constrained capacity of a system of WLANs is achieved at a small AP deployment density in low attenuation environments, whereas it is achieved at high AP deployment densities in high attenuation environments.

With respect to the impact of deployment and association choices on the aggregate throughput of a densely deployed system of WLANs, we showed that both the AP deployment regime and the STA association mode used in WLANs have varying degrees of
influence on the aggregate throughput. A system of WLANs which uses strongest-signal association mode enjoys a performance improvement compared to the random association mode in all propagation environments; the greater the improvement as deployment density increases. On the other hand, the choice of using a planned deployment brings the most performance improvement over a random deployment in moderate interference environments, with diminishing benefits as AP density increases. Furthermore, we have shown that if STAs perform random association, performance gain due to planning is insignificant. If, however, STAs perform strongest-signal association, then planned deployment can bring some throughput improvement over unplanned deployment, although this gain is not substantial. With respect to delay constrained capacity, we showed that planning increases delay constrained capacity.

In a system of WLANs serving a certain traffic demand with a delay constraint, in all environments and deployment-association types that we considered, we observed that infrastructure densification beyond what is necessitated by the traffic demand and delay constraint only brings minor improvements in delay performance.

In this thesis, we have also developed an empirical throughput model which can represent the aggregate throughput performance of a system of WLANs in a range of propagation environments, deployment densities, deployment and association types with fairly good accuracy, which constitutes an answer to SRQ-3.

Finally, we observed that the cell congestion coefficient plays a crucial role in determining the amount of congestion and interference between the nodes in a system of WLANs, therefore it influences the effective density and therefore the system capacity in a major way. Therefore, controlling this parameter, for instance by means of controlling transmit power and clear channel assessment threshold can be a key method in future studies which aim to improve the capacity of densely deployed WLANs, which constitutes an answer to SRQ-4.

8.1 Possible Extensions of this Thesis

The confidence in the results presented in the thesis would be greatly benefit from several sensitivity analyses.

- Sensitivity of the aggregate throughput performance to the accuracy in selection of the strongest AP: What is the level of accuracy which is needed for identifying the strongest AP so that performance gains due to strongest-association can be observed?

- Sensitivity of the results to different propagation models: Would using a more realistic channel model which incorporates shadow fading and Rayleigh fading change the results significantly?

- Sensitivity to different modulation coding schemes: Will the conclusions hold if a different PHY is used?
8.1. POSSIBLE EXTENSIONS OF THIS THESIS

Another possible extension of this study would be to incorporate higher layer mechanisms such as different TCP variants in the analysis. Even though delay constrained or saturation aggregate throughput performance presented in this thesis constitutes a set of performance limits with regard to the MAC layer, this MAC layer performance may not be achieved because of higher layer mechanisms.

An experimental verification using a large testbed of densely deployed WLANs would be immensely valuable. Even though we use a realistic MAC model into account, different implementation choices which are not defined in the IEEE 802.11 standard may or may not have a significant impact on the aggregate throughput performance. An experimental verification would identify the impact of such implementation choices which may prevent the MAC performance estimated in this thesis from being achieved.
Appendix A

Distributed Coordination Function Description

The following state diagrams explain distributed coordination function (DCF) operation when STAs are transmitting data frames according to DCF basic access mechanism. We do not include other MPDU types than data or the RTS/CTS protection mechanism in our description. Also, these state diagrams apply to individually addressed frames; i.e., frames which are not of broadcast or multicast type. The PHY dependent descriptions assume that all STAs are using ERP-OFDM modulation because different modulation types imply different CCA mechanisms or different CCA parameters. To make the analysis and description simple, we assume that all the STAs in the BSS are using an ERP-OFDM modulation; i.e., we consider an ERP-OFDM-only BSS. Even though we narrow down the scope to this setting we have described above, some of the description of DCF operation would be still valid for other PHY types, frame types and BSS configurations. However, the purpose of this description of DCF operation is not to give an exhaustive description of DCF operation in all configurations, but to give a description of DCF operation specifically for the scenarios simulated in our analysis.

Even though we have not performed a formal verification of the compliance of the simulation tool we used in this work to the DCF description in this appendix, we tried to ensure that our simulation tool has a high degree of fidelity to this DCF description by making some minor but necessary modifications to the original simulation tool.

References to 802.11-2007 standard

This section gives references to statements in the DCF MAC description and ERP-OFDM PHY description given in IEEE 802.11-2007 standard which were used in creating figs. A.1-A.4. The content in the 2007 version of the standard referenced here is almost exactly the same as the 2012 version, except for the occasional editorial modifications.

1a p.251 “For a STA to transmit, it shall sense the medium to determine if another STA is transmitting.”
1b p.251 “If the medium is not determined to be busy (see 9.2.1), the transmission may proceed.”

c p.251 “The CSMA/CA distributed algorithm mandates that a gap of a minimum specified duration exist between contiguous frame sequences. A transmitting STA shall ensure that the medium is idle for this required duration before attempting to transmit.”

d p.251 “If the medium is determined to be busy, the STA shall defer until the end of the current transmission.”

e p.251 “After deferral, or prior to attempting to transmit again immediately after a successful transmission, the STA shall select a random backoff interval and shall decrement the backoff interval counter while the medium is idle.”

f p.251 “A transmission is successful either when an ACK frame is received from the STA addressed by the RA field of the transmitted frame or when a frame with a group address in the RA field is transmitted completely.”

2 p.255 “Unless interrupted due to medium occupancy limitations for a given PHY or TXOP limitations for STA, the fragments of a single MSDU or MMPDU are sent as a burst during the CP, using a single invocation of the DCF or EDCA medium access procedure.”
Switch PHY to receive state.\[37\]

Valid signal in the medium with energy greater than CCA threshold? \[38, 47a\]

- Yes: PHY indicates busy medium to MAC. \[38\]
- No: PHY indicates idle medium to MAC.

If CCA becomes IDLE (a valid signal with energy level above threshold is missing) before processing of PLCP is complete, receiver returns to RX IDLE state. \[39d\]

- Receive PLCP Preamble. \[39a\]
- Is SIGNAL symbol valid (even parity correct)? \[39b\]
  - Yes: PHY sends PHY-RXEND.indicate(Unsupported Rate) to MAC. \[43a\]
  - No: PHY sends PHY-RXEND.indicate(FormatViolation) to MAC. \[43b\]

If CCA indicates IDLE before reception of the PSDU is complete, then PHY sends PHY-RXEND.indicate(CarrierLost) to MAC. \[42a\]

- Start FEC decode, receive the PSDU. \[39b\]
- Is SIGNAL (modulation and rate) supported? \[40, 42b, 47b\]
  - Yes: CCA indicates busy until end of intended packet duration. \[40, 42b, 47b\]
  - No: EIFS timer starts when CCA indicates medium idle. \[9b\]

- The STA must wait for EIFS before accessing medium. \[9a\]
- EIFS timer starts now. \[9b\]

- PHY sends PHY-RXEND.indicate(NoError) to MAC. \[8b, 41\]
- Update NAV if packet is not addressed to this STA \[3, 24\]
- Forget EIFS timer if any. \[9c\]
- DIFS starts now. \[16b, 15a\]

PHY reports busy medium to the MAC in these states.\[4, 10a, 46a, 46b\]

Figure A.3: State diagram of physical carrier sensing.
APPENDIX A. DISTRIBUTED COORDINATION FUNCTION DESCRIPTION

- STA has pending MPDU. [15a]
- STA wants to transmit initial frame of a frame exchange. [10a]
- Backoff timer not initialized or is 0.
- Set CW = aCWmin. [12a, 14]
- Set this MPDU's SRC/LCR = 0. [21]
- Set SSRC/SLRC = 0. [12b]

Defer until idle for DIFS or EIFS. [1c, 10b]

Has the medium been idle for DIFS/EIFS? [1c, 15a, 35]

Defer until the end of transmission. [1d, 10b]

Sense the medium using physical and virtual CS. [1a, 1b, 3, 4, 10a, 15b]

Wait SIFS. [7, 25a, 27, 30, 35]

No sensing or backoff. [2]

Did ACK arrive before ACKTimeout? [8b, 22a, 32, 33a, 34, 36]

Are there any more fragments or MSDUs to transmit?

Successful acknowledged transmission. [1f, 33b]
- Set CW = aCWMin. [13a, 20c]
- SSRC or SLRC to 0. [13b, 20c, 22a]
- This MPDU's SRC or LRC = 0. [22a]

Unsuccessful transmission. [6, 20b, 23c]
- Increment SRC or LRC for this MPDU and also increment SSRC or SLRC. [12c, 22a]
- CW takes the next value less than or equal to aCWmax. [12d, 14]
- If SSRC or SLRC reached respective retry limit, set CW = aCWmin. [13a]

Did SRC or LRC of this MPDU reach respective retry limit? [21, 23]

Are there more fragments? [2, 20a, 25a]

Did ACK arrive before ACKTimeout? [8b, 22a, 32, 33a, 34, 36]

Are there any more fragments or MSDUs to transmit?

Discard the MPDU and the MSDU containing this MPDU. [23]

Backoff (even if no additional transmissions are queued). [1e, 15b, 16, 20a, 20b, 20d, 31, 33a, 33c]

STA shall resume transmission when next transmission opportunity occurs. [25b]
- Retransmit this MPDU or another MPDU after backoff and contention. [26]
- If retransmitting a fragment, start with the last fragment which was not acknowledged. [29]

Figure A.4: State diagram of DCF.
Another means of distributing the medium reservation information is the Duration/ID field in individually addressed frames. This field gives the time that the medium is reserved, either to the end of the immediately following ACK, or in the case of a fragment sequence, to the end of the ACK following the next fragment.

Physical and virtual CS functions are used to determine the state of the medium. When either function indicates a busy medium, the medium shall be considered busy; otherwise, it shall be considered idle.

The NAV may be thought of as a counter, which counts down to zero at a uniform rate. When the counter is zero, the virtual CS indication is that the medium is idle; when nonzero, the indication is busy.

The medium shall be determined to be busy when the STA is transmitting.

Lack of reception of an expected ACK frame indicates to the STA initiating the frame exchange that an error has occurred. Note, however, that the destination STA may have received the frame correctly, and that the error may have occurred in the transfer or reception of the ACK frame. To the initiator of the frame exchange, this condition is indistinguishable from an error occurring in the initial frame.

The SIFS shall be used prior to transmission of an ACK frame, a CTS frame, the second or subsequent MPDU of a fragment burst, and by a STA responding to any polling by the PCF.

A STA using the DCF shall be allowed to transmit if its CS mechanism (see 9.2.1) determines that the medium is idle at the TxDIFS slot boundary as defined in 9.2.10 after a correctly received frame, and its backoff time has expired.

A correctly received frame is one where the PHY-RXEND.indication does not indicate an error and the FCS indicates the frame is error free.

A STA’s DCF shall use EIFS before transmission, when it determines that the medium is idle following reception of a frame for which the PHY-RXEND.indication primitive contained an error or a frame for which the MAC FCS value was not correct.

The EIFS or EIFS-DIFS+AIFS[AC] interval shall begin following indication by the PHY that the medium is idle after detection of the erroneous frame, without regard to the virtual CS mechanism. The STA shall not begin a transmission until the expiration of the later of the NAV and EIFS or EIFS-DIFS+AIFS[AC].”

The EIFS and EIFS-DIFS+AIFS[AC] are defined to provide enough time for another STA to acknowledge what was, to this STA, an incorrectly received frame before this STA commences transmission.”
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9d p.259 “Reception of an error-free frame during the EIFS or EIFS-DIFS+AIFS[AC] resynchronizes the STA to the actual busy/idle state of the medium, so the EIFS or EIFS-DIFS+AIFS[AC] is terminated and normal medium access (using DIFS or AIFS as appropriate and, if necessary, backoff) continues following reception of that frame.”

9e p.259 “At the expiration or termination of the EIFS or EIFS-DIFS+AIFS[AC], the STA reverts to the NAV and physical CS to control access to the medium.”

10a p.260 “A STA desiring to initiate transfer of data MPDUs and/or MMPDUs shall invoke the CS mechanism (see 9.2.1) to determine the busy/idle state of the medium.”

10b p.260 “If the medium is busy, the STA shall defer until the medium is determined to be idle without interruption for a period of time equal to DIFS when the last frame detected on the medium was received correctly, or after the medium is determined to be idle without interruption for a period of time equal to EIFS when the last frame detected on the medium was not received correctly.”

10c p.260 “After this DIFS or EIFS medium idle time, the STA shall then generate a random backoff period for an additional deferral time before transmitting, unless the backoff timer already contains a nonzero value, in which case the selection of a random number is not needed and not performed.”

11 p.260 “Backoff Time = Random() x aSlotTime where
Random() = Pseudo-random integer drawn from a uniform distribution over the interval [0,CW], where CW is an integer within the range of values of the PHY characteristics aCWmin and aCW-max, aCWmin = CW = aCWmax.”

12a p.260 “The contention window (CW) parameter shall take an initial value of aCWmin.”

12b p.260 “Every STA shall maintain a STA short retry count (SSRC) as well as a STA long retry count (SLRC), both of which shall take an initial value of zero.”

12c p.260 “The SSRC shall be incremented when any short retry count (SRC) associated with any MPDU of type Data is incremented. The SLRC shall be incremented when any long retry count (LRC) associated with any MPDU of type Data is incremented.”

12d p.260 “The CW shall take the next value in the series every time an unsuccessful attempt to transmit an MPDU causes either STA retry counter to increment, until the CW reaches the value of aCWmax. A retry is defined as the entire sequence of frames sent, separated by SIFS intervals, in an attempt to deliver an MPDU, as described in 9.12. Once it reaches aCWmax, the CW shall remain at the value of aCWmax until the CW is reset.”

13a p.261 “The CW shall be reset to aCWmin after every successful attempt to transmit an MPDU or MMPDU, when SLRC reaches dot1LongRetryLimit, or when SSRC reaches dot1ShortRetryLimit.”
13b p.261 “The SSRC shall be reset to 0 when a CTS frame is received in response to an RTS frame, when an ACK frame is received in response to an MPDU or MMPDU transmission, or when a frame with a group address in the Address1 field is transmitted. The SLRC shall be reset to 0 when an ACK frame is received in response to transmission of an MPDU or MMPDU of length greater than dot11RTSThreshold, or when a frame with a group address in the Address1 field is transmitted.”

14 p.261 “The set of CW values shall be sequentially ascending integer powers of 2, minus 1, beginning with a PHY-specific aCWmin value, and continuing up to and including a PHY-specific aCWmax value.”

15a p.261 “In general, a STA may transmit a pending MPDU when it is operating under the DCF access method, either in the absence of a PC, or in the CP of the PCF access method, when the STA determines that the medium is idle for greater than or equal to a DIFS period, or an EIFS period if the immediately preceding medium-busy event was caused by detection of a frame that was not received at this STA with a correct MAC FCS value.”

15b p.261 “If, under these conditions, the medium is determined by the CS mechanism to be busy when a STA desires to initiate the initial frame of one of the frame exchanges described in 9.12, exclusive of the CF period, the random backoff procedure described in 9.2.5.2 shall be followed.”

16 p.262 “The backoff procedure shall be invoked for a STA to transfer a frame when finding the medium busy as indicated by either the physical or virtual CS mechanism (see Figure 9-6). The backoff procedure shall also be invoked when a transmitting STA infers a failed transmission as defined in 9.2.5.7 or 9.2.8.”

17a p.262 “To begin the backoff procedure, the STA shall set its Backoff Timer to a random backoff time using the equation in 9.2.4.”

17b p.262 “All backoff slots occur following a DIFS period during which the medium is determined to be idle for the duration of the DIFS period, or following an EIFS period during which the medium is determined to be idle for the duration of the EIFS period, as appropriate (see 9.2.3).”

18a p.262 “A STA performing the backoff procedure shall use the CS mechanism (see 9.2.1) to determine whether there is activity during each backoff slot.”

18b p.262 “If no medium activity is indicated for the duration of a particular backoff slot, then the backoff procedure shall decrement its backoff time by aSlotTime.”

19a p.262 “If the medium is determined to be busy at any time during a backoff slot, then the backoff procedure is suspended; that is, the backoff timer shall not decrement for that slot. The medium shall be determined to be idle for the duration of a DIFS period or EIFS, as appropriate (see 9.2.3), before the backoff procedure is allowed to resume.”
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19b p.262 “Transmission shall commence when the Backoff Timer reaches zero.”

20a p.262 “A backoff procedure shall be performed immediately after the end of every transmission with the More Fragments bit set to 0 of an MPDU of type Data, Management, or Control with subtype PS-Poll, even if no additional transmissions are currently queued.”

20b p.262 “In the case of successful acknowledged transmissions, this backoff procedure shall begin at the end of the received ACK frame. In the case of unsuccessful transmissions requiring acknowledgment, this backoff procedure shall begin at the end of the ACKTimeout interval (as defined in 9.2.8). An unsuccessful transmission is one where an ACK frame is not received from the STA addressed by the RA field of the transmitted frame and the value of the RA field is an individual address.

20c p.262 “If the transmission is successful, the CW value reverts to aCWmin before the random backoff interval is chosen, and the SSRC and/or SLRC are updated as described in 9.2.4.”

20d p.262 “This assures that transmitted frames from a STA are always separated by at least one backoff interval.”

21 p.263 “Error recovery shall be attempted by retrying transmissions for frame exchange sequences that the initiating STA infers have failed. Retries shall continue, for each failing frame exchange sequence, until the transmission is successful, or until the relevant retry limit is reached, whichever occurs first. STAs shall maintain a SRC and a LRC for each MSDU or MMPDU awaiting transmission. These counts are incremented and reset independently of each other.”

22a p.263 “After transmitting a frame that requires acknowledgment, the STA shall perform the ACK procedure, as defined in 9.2.8. The SRC for an MPDU of type Data or MMPDU and the SSRC shall be incremented every time transmission of a MAC frame of length less than or equal to dot1RTSThreshold fails for that MPDU of type Data or MMPDU. This SRC and the SSRC shall be reset when a MAC frame of length less than or equal to dot1RTSThreshold succeeds for that MPDU of type Data or MMPDU. The LRC for an MPDU of type Data or MMPDU and the SLRC shall be incremented every time transmission of a MAC frame of length greater than dot1RTSThreshold fails for that MPDU of type Data or MMPDU. This LRC and the SLRC shall be reset when a MAC frame of length greater than dot1RTSThreshold succeeds for that MPDU of type Data or MMPDU.”

22b p.263 “All retransmission attempts for an MPDU of type Data or MMPDU that has failed the ACK procedure one or more times shall be made with the Retry field set to 1 in the Data or Management type frame.”

23 p.263 “Retries for failed transmission attempts shall continue until the SRC for the MPDU of type Data or MMPDU is equal to dot1ShortRetryLimit or until the LRC for the MPDU of type Data or MMPDU is equal to dot1LongRetryLimit. When
either of these limits is reached, retry attempts shall cease, and the MPDU of type Data (and any MSDU of which it is a part) or MMPDU shall be discarded.”

24 p.264 “STAs receiving a valid frame shall update their NAV with the information received in the Duration field for all frames where the new NAV value is greater than the current NAV value, except the NAV shall not be updated where the RA is equal to the receiving STA’s MAC address.”

25a p.264 “The SIFS is used to provide an efficient MSDU delivery mechanism. Once the STA has contended for the channel, that STA shall continue to send fragments until either all fragments of a single MSDU or MMPDU have been sent, an acknowledgment is not received, or the STA is restricted from sending any additional fragments due to a dwell time boundary.”

25b p.264 “Should the sending of the fragments be interrupted due to one of these reasons, when the next opportunity for transmission occurs the STA shall resume transmission.”

26 p.265 “When the source STA transmits a fragment, it shall release the channel, then immediately monitor the channel for an acknowledgment as described in 9.2.8.”

27 p.265 “When the destination STA has finished sending the acknowledgment, the SIFS following the acknowledgment shall be reserved for the source STA to continue (if necessary) with another fragment. The STA sending the acknowledgment shall not transmit on the channel immediately following the acknowledgment.”

28 p.265 “If the source STA does not receive an acknowledgment frame, it shall attempt to retransmit the failed MPDU or another eligible MPDU, as defined in 9.7, after performing the backoff procedure and the contention process.”

29 p.265 “After a STA contends for the channel to retransmit a fragment of an MSDU, it shall start with the last fragment that was not acknowledged. The destination STA shall receive the fragments in order (because the source sends them in order and they are individually acknowledged). It is possible, however, that the destination STA may receive duplicate fragments. It shall be the responsibility of the receiving STA to detect and discard duplicate fragments.”

30 p.265 “A STA shall transmit after the SIFS only under the following conditions during a fragment burst:

- The STA has just received a fragment that requires acknowledgment.
- The source STA has received an acknowledgment for a previous fragment, has more fragment(s) for the same MSDU to transmit, and there is enough time before the next dwell boundary to send the next fragment and receive its acknowledgment.”

31 p.265 “The following rules shall also apply:
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- When a STA has transmitted a frame other than an initial or intermediate fragment, that STA shall not transmit on the channel following the acknowledgment for that frame, without performing the backoff procedure.
- When an MSDU has been successfully delivered or all retransmission attempts have been exhausted, and the STA has a subsequent MSDU to transmit, then that STA shall perform a backoff procedure.

32 p.268 "After a successful reception of a frame requiring acknowledgment, transmission of the ACK frame shall commence after a SIFS period, without regard to the busy/idle state of the medium."

33a p.269 "After transmitting an MPDU that requires an ACK frame as a response (see 9.12), the STA shall wait for an ACKTimeout interval, with a value of \( a_{SIFS} + a_{SlotTime} + a_{PHY-RX-START-Delay} \), starting at the PHY-TXEND.confirm. If a PHY-RXSTART.indication does not occur during the ACKTimeout interval, the STA concludes that the transmission of the MPDU has failed, and this STA shall invoke its backoff procedure upon expiration of the ACKTimeout interval."

33b p.269 "If a PHY-RXSTART.indication does occur during the ACKTimeout interval, the STA shall wait for the corresponding PHY-RXEND.indication to determine whether the MPDU transmission was successful. The recognition of a valid ACK frame sent by the recipient of the MPDU requiring acknowledgment, corresponding to this PHY-RXEND.indication, shall be interpreted as successful acknowledgment, permitting the frame sequence to continue, or to end without retries, as appropriate for the particular frame sequence in progress."

33c p.269 "The recognition of anything else, including any other valid frame, shall be interpreted as failure of the MPDU transmission. In this instance, the STA shall invoke its backoff procedure at the PHY-RXEND.indication and may process the received frame."

34 p.269 "The receiver STA shall perform the ACK procedure on all successfully received frames requiring acknowledgment, even if the frame is discarded due to duplicate filtering."

35 p.270 "\( a_{SIFS} \) and \( a_{SlotTime} \) are fixed per PHY. The PIFS and DIFS are derived by the following equations, ...
\[
DIFS = a_{SIFS} + 2 \times a_{SlotTime}
\]
The EIFS is derived from the SIFS and the DIFS and the length of time it takes to transmit an ACK Control frame at the lowest PHY mandatory rate by the following equation:
\[
EIFS = a_{SIFS} + DIFS + ACKTxTime
\]
where \( ACKTxTime \) is the time expressed in microseconds required to transmit an ACK frame, including preamble, PLCP header and any additional PHY dependent information, at the lowest PHY mandatory rate.
To allow the transmitting STA to calculate the contents of the Duration/ID field, a STA responding to a received frame shall transmit its Control Response frame (either CTS or ACK), other than the BlockAck control frame, at the highest rate in the BSSBasicRateSet parameter that is less than or equal to the rate of the immediately previous frame in the frame exchange sequence (as defined in 9.12) and that is of the same modulation class (see 9.6.1) as the received frame. If no rate contained in the BSSBasicRateSet parameter meets these conditions, then the control frame sent in response to a received frame shall be transmitted at the highest mandatory rate of the PHY that is less than or equal to the rate of the received frame, and that is of the same modulation class as the received frame. In addition, the Control Response frame shall be sent using the same PHY options as the received frame, unless they conflict with the requirement to use the BSSBasicRateSet parameter.

In order to receive data, PHY-TXSTART.request shall be disabled so that the PHY entity is in the receive state.

Upon receiving the transmitted PLCP preamble, PMD_RSSI.indicate shall report a significant received signal strength level to the PLCP. This indicates activity to the MAC via PHY_CCA.indicate. PHY_CCA.indicate(BUSY) shall be issued for reception of a signal prior to correct reception of the PLCP frame.

After PHY-CCA.indicate is issued, the PHY entity shall begin receiving the training symbols and searching for the SIGNAL in order to set the length of the data stream, the demodulation type, and the decoding rate.

Once the SIGNAL is detected, without any errors detected by a single parity (even), FEC decode shall be initiated and the PLCP IEEE 802.11 SERVICE fields and data shall be received, decoded (a Viterbi decoder is recommended), and checked by ITU-T CRC-32.

If the FCS by the ITU-T CRC-32 check fails, the PHY receiver shall return to the RX IDLE state, as depicted in Figure 17-16.

Should the status of CCA return to the IDLE state during reception prior to completion of the full PLCP processing, the PHY receiver shall return to the RX IDLE state.

If the PLCP header reception is successful (and the SIGNAL field is completely recognizable and supported), a PHY-RXSTART.indicate(RXVECTOR) shall be issued. The RXVECTOR associated with this primitive includes the SIGNAL field, the SERVICE field, the PSDU length in octets, and the RSSI. Also, in this case, the OFDM PHY will ensure that the CCA shall indicate a busy medium for the intended duration of the transmitted frame, as indicated by the LENGTH field.

After the reception of the final bit of the last PSDU octet indicated by the PLCP preamble LENGTH field, the receiver shall be returned to the RX IDLE state,
as shown in Figure 17-16. A PHY-RXEND.indicate(NoError) primitive shall be issued.”

42a p.622 “In the event that a change in the RSSI causes the status of the CCA to return to the IDLE state before the complete reception of the PSDU, as indicated by the PLCP LENGTH field, the error condition PHY-RXEND.indicate(CarrierLost) shall be reported to the MAC.”

42b p.622 “The OFDM PHY will ensure that the CCA indicates a busy medium for the intended duration of the transmitted packet.”

43a p.622 “If the indicated rate in the SIGNAL field is not receivable, a PHY-RXSTART.indicate will not be issued. The PHY shall issue the error condition PHY-RXEND.indicate(UnsupportedRate).”

43b p.622 “If the PLCP header is receivable, but the parity check of the PLCP header is not valid, a PHY-RXSTART.indicate will not be issued. The PHY shall issue the error condition PHY-RXEND.indicate(FormatViolation).”

44 p.483 “PHY-RXEND.indication (RXERROR) The RXERROR parameter can convey one or more of the following values: NoError, FormatViolation, CarrierLost, or UnsupportedRate. A number of error conditions may occur after the PLCP’s receive state machine has detected what appears to be a valid preamble and SFD.”

45 p.623 In Figure 17-17, the labels are not aligned with the lines connecting the states. The label “Parity Fail” should be above the line to the left of “RX SIGNAL Parity” box, “PHY_CCA.ind(IDLE)” should be below the line to the left of “RX SIGNAL Parity” box, and there should be no line going out to the left of “RX PLCP fields” box because there is no conditional execution associated with this box. If this set of suggested changes are correct, then according to Figure 17-17, the PHY informs the MAC that the medium is idle. That is, the CCA does not indicate a busy medium. This is logical because the PHY cannot estimate the duration that the channel may be busy since it did not receive the RATE and LENGTH fields in the PLCP header. On the other hand, the PHY reports PHY-RXEND.indicate(FormatViolation) error to the MAC, which means that the STA will have to wait for EIFS duration before accessing the medium. The necessity of use of EIFS in this condition is not justified however, according to the intended purpose of the EIFS stated in [9c].

46a p.701 “The PLCP shall provide the capability to perform a CCA and report the results of the assessment to the MAC. The CCA mechanism shall detect a “medium busy” condition for all supported preamble and header types. That is, the CCA mechanism shall detect that the medium is busy for the PLCP PPDUs specified in 17.3.3 and 18.2.2. The CCA mechanism performance requirements are given in 19.4.6.”

46b p.701 “The ERP shall provide the capability to perform CCA according to the following method:
CCA Mode (ED and CS): A combination of CS and energy above threshold. CCA shall have a mechanism for CS that will detect all mandatory Clause 19 sync symbols. This CCA’s mode’s CS shall include both Barker code sync detection and OFDM sync symbol detection. CCA shall report busy at least while a PPDU with energy above the ED threshold is being received at the antenna.

47a p.702 “When a valid signal with a signal power of -76 dBm or greater at the receiver antenna connector is present at the start of the PHY slot, the receiver’s CCA indicator shall report the channel busy with probability CCA_Detect_Probability within a CCA_Time. CCA_Time is SlotTime - RxTxTurnaroundTime. CCA_Detect_Probability is the probability that the CCA does respond correctly to a valid signal. The values for these parameters are found in Table 19-5. Note that the CCA Detect Probability and the power level are performance requirements.”

47b p.703 “In the event that a correct PLCP header is received, the ERP shall hold the CCA signal inactive (channel busy) for the full duration, as indicated by the PLCP LENGTH field. Should a loss of CS occur in the middle of reception, the CCA shall indicate a busy medium for the intended duration of the transmitted PPDU.”
Bibliography


