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Holistic and Efficient Link Adaptation for 802.11x Wireless LANs

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Abstract

Wireless LANs (WLANs), based on the IEEE 802.11 standard, have become the standard means for indoor wireless connectivity. At the same time, the rising number of smart mobile devices, broadband access speeds, and bandwidth hungry applications (e.g., high definition video streaming) have led to an increase not only of usage but also of demand for higher data-rates. This demand for higher rates is being met with newer IEEE 802.11 standards (e.g., 802.11n/ac) that introduce new features and also increase the different possible settings for each feature.

Inherent channel variations and the possible interference conditions when operating in unlicensed spectrum necessitate adaptation of the various medium access control (MAC) and physical (PHY) layer features to ensure high performance. Selecting the values of those features to optimise a criterion such as throughput is the link adaptation problem. Link adaptation, the focus of this thesis, can play a key role in improving the performance of 802.11 WLANs. Increasing number of features and feature setting combinations with newer 802.11 standards is not only making link adaptation even more important but also more challenging.

The contributions made in this thesis significantly advance the state of the art on link adaptation for 802.11 WLANs along three dimensions. First, we show that not knowing the exact cause of loss is not an impediment to effective link adaptation. Nevertheless, actions taken in response to losses are more crucial and they ought to be holistic and not solely dependent on the exact cause of loss. Second, we make significant methodological contributions for analysing the impact of multiple parameters on a given criterion, based on comprehensive experimental measurements. The application of this methodology on 802.11n measurements, examining the interaction of the protocols various parameters on performance under varying conditions, has lead to several valuable findings on how to perform efficient link adaptation in a complex WLAN scenario like 802.11n and future 802.11 standards. Adaptation should be holistic, based on the channel quality instead of the interference scenario, and independent of loss differentiation. Based on these insights, lastly and most importantly, we propose two novel holistic link adaptation schemes for legacy 802.11a/b/g and 802.11n WLANs, termed Themis and SampleLite, respectively. Both Themis and SampleLite take a hybrid approach relying on easily accessed channel quality information at the sender side to perform holistic adaptation. The hypothesis that adaptation should be holistic is validated by our results, with both Themis and SampleLite outperforming the current state of the art.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified. Some of the material used in this thesis has been published in the following papers:

- Lito Kriara and Mahesh K. Marina. "SampleLite: A Hybrid Approach to 802.11n Link Adaptation". Under Submission
- Lito Kriara, Mahesh K. Marina and Arsham Farshad. "Characterization of 802.11n Wireless LAN Performance via Testbed Measurements and Statistical Analysis". In Proc. IEEE International Conference on Sensing, Communication, and Networking (SECON), New Orleans, LA, June 2013
- Lito Kriara, Sofia Pediaditaki and Mahesh K. Marina. "On the Importance of Loss Differentiation for Link Adaptation in Wireless LANs". In Proc. IEEE/VDE European Wireless Conference, Poznan, Poland, April 2012
- Lito Kriara, Mujahid Al-Adhami and Mahesh K. Marina. "Impact of 802.11n Link Layer Parameters on Application Performance". In Proc. ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc), Paris, France, May 2011 (poster)

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Chapter 1

Introduction

1.1 Motivation

Wireless local area networks (WLANs) based on the IEEE 802.11 standard (commonly referred to as WiFi networks) have become the de facto means for end-user connectivity in indoor environments (e.g., homes, offices, hotspots). According to a recent Internet traffic forecasting study from Cisco [1], in 2018 traffic from wireless and mobile devices will make up 61% of the overall IP traffic while it amounts to only 44% in 2013. Broadband speeds are also increasing quite rapidly. Ofcom, the UK telecommunications regulator, predicts that super-fast broadband connections will be available to 95% of households by 2018 [2]. Given that Internet access in homes is mostly via WiFi-enabled user devices, increasing broadband speeds in turn creates a need for faster WiFi speeds. The above factors are fuelling the demand for WLANs with higher and higher data rates.

To keep up with the aforementioned demand, the IEEE 802.11 standard has been continually evolving for the past decade or so with enhancements that yield higher data rates. While initially enhancements have mainly come in the form of newer and faster modulation schemes [3, 4, 5], enhancements in recent versions have become more broader both within the physical (PHY) layer and also spanning the medium access control (MAC) layer. The current 802.11n standard [6] presents a case in point. It introduced the MIMO enhancements that concern the use of multiple antennas both in the transmit and receive directions. Broadly speaking, there are two different MIMO modes in 802.11n: spatial division multiplexing (SDM) and space-time block coding (STBC). SDM targets higher data rates via multiple (up to 4) concurrent and independent data streams transmitted

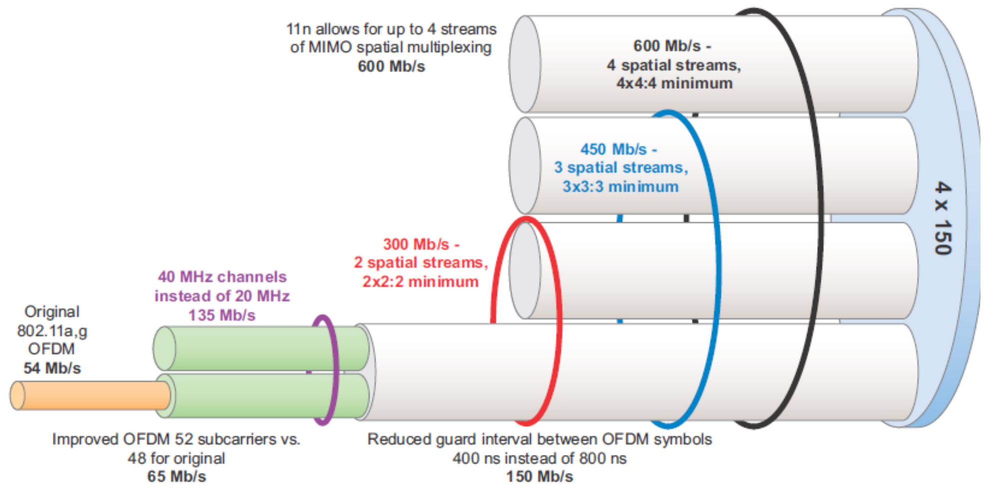
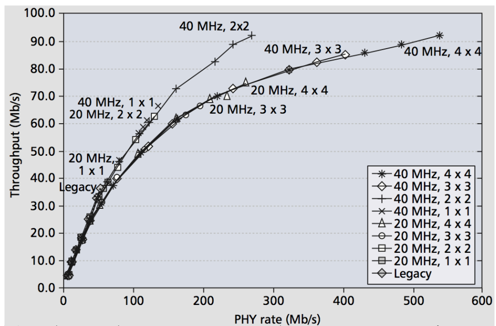


Figure 1.1: Impact of PHY layer features in 802.11n throughput performance.

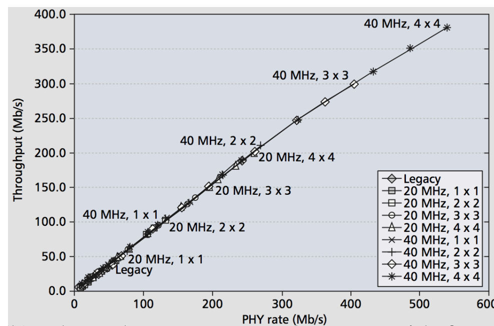
via different antennas, whereas STBC is for enhancing reliability by transmitting a single data stream across multiple antennas with redundancy. Besides MIMO, 802.11n has another new feature called channel bonding that permits doubling the channel width to 40MHz from the 20MHz width common in earlier 802.11a/b/g WLANs. Other PHY enhancements include the long and short guard intervals, as well as the replacement of a 802.11a/b/g bit-rate with a higher modulation and coding rate.

Fig. 1.1 from Altaware Inc. [7] shows the impact of each of those features on the performance of 802.11n compared to 802.11a/g. We see that the original legacy 802.11a/g can support up to 54Mbps with 48 and 65Mbps with 52 subcarriers, when using a 20MHz channel. When the channel size is doubled to 40MHz then the maximum possible data rate increases to 135Mbps. This number is multiplied by the number of available streams, reaching to 600Mbps data rate when four streams are employed. So, we see that by enabling all of these PHY enhancements 802.11n PHY data rate can reach 600Mbps compared to 54Mbps possible with 802.11a/g.

Although PHY enhancements seem to be the key sources of 802.11n's improved performance, the actual effective throughput seen above the MAC layer is limited by the protocol overhead, even more in 802.11n than legacy 802.11a/b/g. Therefore, two key MAC layer features called frame aggregation and block acknowledgements were introduced in 802.11n to improve the MAC efficiency. They enable multiple back-to-back frame transmissions upon each successful chan-



(a) Throughput vs. PHY data rate assuming no MAC changes.



(b) Throughput vs. PHY data rate with frame aggregation.

Figure 1.2: Throughput vs. PHY data rate with and without MAC changes in the 802.11n standards. Figures originally from [8].

nel access, thereby amortize the packet overhead. As shown in the study by Perahia and Stacey [8], reproduced here in Fig. 1.2, throughput above the MAC layer will get closer to the optimal value near 400Mbps only when frame aggregation (and block ACKs) are enabled (see Fig. 1.2(b)); otherwise it does not exceed 100Mbps as shown in Fig. 1.2(a).

The foregoing discussion on achievable data rates and throughput with 802.11n are based on an idealistic perspective and glosses over a key issue that faces WLANs in practice. In reality, channel conditions tend to vary over time and space and are rarely ideal. Also, given that 802.11 operates in unlicensed spectrum, WLANs are subject to interference from co-located WLANs and other unlicensed wireless devices. Like channel fluctuations, the nature of interference also exhibits spatio-temporal variability. The implication of such varying channel and interference conditions is that optimal settings for various available 802.11 features also keep varying. We refer to the problem of choosing the best feature settings on a 802.11 device at any given point in time for optimising a desired criterion like throughput or fairness as the *link adaptation problem*. Radio resource management (RRM) [9, 10] is an equivalent and somewhat broader term compared to link adaptation that is more commonly used in the context of cellular networks and broadcasting systems. It refers to the system level control of radio transmission parameter and characteristics using strategies and algorithms for controlling parameters such as transmit power, user allocation, beamforming, data rates, modulation scheme, error coding scheme, etc. with the objective of utilising

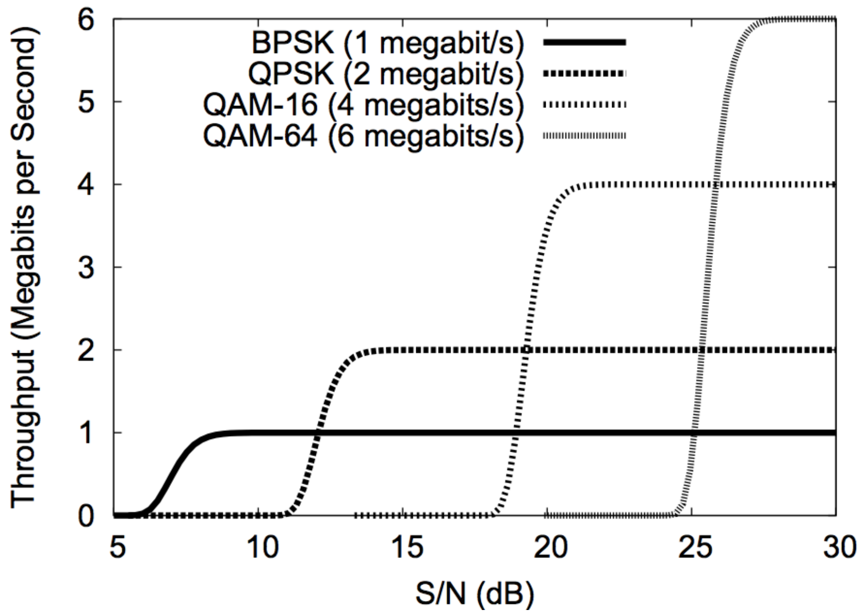
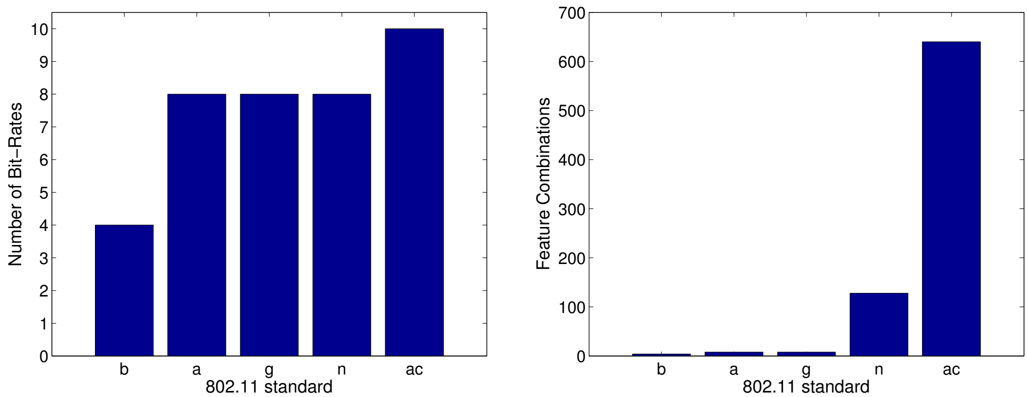


Figure 1.3: Theoretical throughput in Mbps using packets versus signal-to-noise ratio for several modulations, assuming AWGN channel and a symbol rate of 1 mega-symbol per second. Figure originally from [11].

the limited radio-frequency spectrum resources and radio network infrastructure as efficiently as possible.

The simplest case of link adaptation concerns selection of the best modulation and coding scheme (PHY bit-rate) to maximise the throughput performance in the context of a legacy 802.11 WLAN. Bicket et al. [11] use a simple theoretical framework to explain why allowing links to choose between multiple different modulation schemes can deliver improved link throughput when channel quality varies. Fig. 1.3 shows throughput in Mbps versus signal to noise ratio (S/N) for 1500-byte packets after accounting for packet losses caused by bit-errors. It clearly shows the maximum throughput yielding modulation scheme changes with the channel quality (SNR), thereby highlighting the key role of link adaptation in WLAN performance optimisation.

The key motivation underlying the research presented in this thesis is that link adaptation in 802.11 WLANs is becoming not only more important but also more challenging with each new version of the 802.11 standard. This is because the number of different MAC/PHY features and different possible settings for each of



(a) Number of bit-rates (b) MCS and other feature combinations

Figure 1.4: Increasing number of rate and feature combinations from the oldest to newest IEEE 802.11 standards.

them is increasing dramatically with recent and emerging 802.11 standards. To see this consider that the initial 802.11b [3] standard supported only 4 transmission bit-rates; this number increased to 8 with the following 802.11a/g [4, 5] standards. The current 802.11n [6] has 8 different modulation and coding schemes (MCS) like before but also has other new features like MIMO, channel bonding and frame aggregation, taking the total number of feature setting combinations to 128. With the emerging 802.11ac [12], the number of combinations goes up even more to 640 as it supports 10 different MCSs, 4 different channel width options and up to 8 spatial streams[1]. Fig. 1.4(a) and Fig. 1.4(b), respectively, illustrate the increasing number of MCSs and feature setting combinations with each new 802.11 standard.

Clearly, the more combinations there are, the more complex the link adaptation problem becomes. Let us look at the increasing importance of link adaptation with newer 802.11 standards. Consider legacy 802.11a/g WLANs with 8 different bit-rates (corresponding to different MCSs) to choose from between 6Mbps and 54Mbps (as Table 1.1 shows). Lack of link adaptation (or a poor selection of bit-rate) in this case can result in a loss in data rate by up to 48Mbps — choosing 6Mbps when the best rate setting is 54Mbps. Now consider 802.11n with the bit-rates ranging from 6.5Mbps to 600Mbps. The absence of (or poor) link adap-

[1]In the case of 802.11n there are 8 bit-rates $\times$ 4 spatial streams $\times$ 2 channel bonding $\times$ 2 guard interval options, resulting in 128 feature combinations; whereas in 802.11ac the 640 combinations are because of 10 bit-rates $\times$ 8 spatial streams $\times$ 4 channel bonding $\times$ 2 guard interval options.

802.11 protocol	Min. data rate	Max. data rate
802.11b	1Mbps	11Mbps
802.11a	6Mbps	54Mbps
802.11g	6Mbps	54Mbps
802.11n	6.5Mbps	600Mbps
802.11ac	6.5Mbps	6.75Gbps

Table 1.1: 802.11 standards theoretical minimum and maximum data reate.

tation can cause a more dramatic and order-of-magnitude loss in data rate by up to 593.5Mbps, suggesting that link adaptation is more important now than before.

1.2 Thesis Contributions

This section summarises the contributions of this dissertation.

1.2.1 Link Adaptation in Legacy 802.11a/b/g WLANs

We first look into legacy 802.11a/b/g link adaptation from a loss differentiation perspective. Loss differentiation, differentiates between the various types of frame losses that may occur (i.e., channel errors, collisions and interference – further described in section 3). Specifically, we quantify the impact of loss differentiation on legacy 802.11a/g link adaptation, since previous works (e.g., [13]) claim that link adaptation mechanisms should rely on loss differentiation in order to effectively adapt the link based on the type of frame loss (e.g., channel errors, collision losses, hidden terminal losses). Loss differentiation refers to differentiating between the various types of frame losses that may occur. Intuitively, since inappropriate responses can adversely impact performance (e.g., in terms of throughput), the various causes of losses should be considered separately when designing a link adaptation scheme. Aiming to validate this hypothesis, we examine the impact of loss differentiation on link adaptation. We show that loss differentiation has a positive impact on performance, especially in low contention WLAN scenarios. More importantly, we observe that actions taken in response to losses are more crucial and they ought to be holistic and not solely dependant on the exact cause of loss.

Taking the aforementioned observations into account, we propose *Themis*, a new link adaptation scheme for legacy 802.11a/g WLANs, with a novel bit-rate sampling process, that does not rely on loss differentiation but still is able to outperform schemes that do, especially in high contention scenarios. *Themis* does bit-rate and contention window adaptation. The key idea underlying our design is to optimise the data rate sampling process of the link adaptation scheme. It selects the rate to sample based on Received Signal Strength Indicator (RSSI) in low contention cases, whereas it randomly selects a rate to sample in high contention cases, like SampleRate [11]. In both cases, the rate used for data transmission is selected based on a statistical table created and updated by this sampling technique. *Themis* was implemented and evaluated via simulation and results show that it considerably improves performance over both the standard 802.11a/g and SampleRate in terms of throughput and fairness by reducing hidden nodes.

This work was published in the Proceedings of the IEEE European Wireless Conference (EW 2012), April 2012.

1.2.2 Experimental Characterisation of 802.11n Performance

Next, we considered the 802.11n context and we aim to understand the impact of different 802.11n features on performance, as well as the interdependencies among them. Therefore, we explore the impact of different 802.11n features across different link and interfering scenarios via a thorough experimental characterisation study. Moreover, we make the hypothesis that there is interaction and interdependence among the various 802.11n features, and therefore adaptation should be holistic (i.e., adapting multiple 802.11n features). We perform the characterisation and validate the hypothesis via an indoor 802.11n WLAN testbed and experimental measurements of link performance with respect to different metrics (including throughput, packet loss, video streaming quality and fairness). We use all possible available settings for 802.11n features, and a wide range of link scenarios, including those that model adjacent channel interference. To gain insight from the large number of measurements collected and to understand the relative impact of different 802.11n features on WLAN performance, we use regression analysis. Specifically, we use categorical regression since 802.11n features are better viewed as categorical (nominal) variables. For understanding the interdependencies among various 802.11n features in different scenarios, we use the response surface methodology (RSM) and multiple linear regression. We show that this type of characterisation can help us gain deeper understanding on how to best select the settings of each feature and the mutual interactions among features, given the channel and interference conditions.

This work improves upon earlier experimental studies of 802.11n networks [14, 15, 16, 17, 18, 19] in the following respects. It is comprehensive in the set of features, metrics and range of scenarios considered. Another aspect that sets our work apart from prior work is our goal to capture important 802.11n features for performance optimisation in different link scenarios and their mutual interaction. Our contributions and findings from this study are listed below:

- Regression-based analysis is valuable in easing the characterisation of the impact of different features on performance.
- The relative impact of different 802.11n features on performance (throughput, packet loss, video streaming quality and fairness) is scenario dependent.
- Different features are interdependent with respect to throughput and the nature of interdependence varies between scenarios.
- It is crucial to adapt the settings of all available features to obtain the best performance.

Part of this work was published in the Proceedings of the IEEE Conference on Sensing, Communication, and Networking (SECON 2013), June 2013.

1.2.3 A Hybrid Approach to 802.11n Link Adaptation

Following up on the above mentioned 802.11n performance characterisation study, we focus on link adaptation in 802.11n WLANs. Existing 802.11n link adaptation schemes are either open- or closed-loop. Open-loop schemes (e.g., [11, 15, 20, 21]) rely on some form of sampling at the sender side to actively probe with different feature settings to identify the best performing one. Their usual approach is to perform exhaustive sampling of all the possible feature combinations. This either incurs high sampling overhead (e.g., approximately 10% in the case of Minstrel HT [20] according to [21]) or tends to use sub-optimal settings for extended periods. Moreover, this type of link adaptation approach may be inefficient and impractical for use with the upcoming 802.11ac standard [12]. 802.11ac introduces more feature settings increasing the sampling space from 128[2] in the case of 802.11n, to 640[3] combinations in 802.11ac. This means that exhaustive sampling

[2] 8 rates $\times$ 4 streams $\times$ 2 channel bonding $\times$ 2 guard interval options

[3] 10 rates $\times$ 8 streams $\times$ 4 channel bonding $\times$ 2 guard interval options

in 802.11ac would mean 5-fold increase in overhead, as well as longer time to "find" the optimal feature combination. We believe none of the current open-loop link adaptation approaches would prove to be efficient in the context of 802.11ac and future standards.

On the other hand, the closed-loop approaches (e.g., [22]) measure channel quality on the receiver side and feed it back to the sender. Then the sender can use this information as a metric of how to best select the feature settings. Even though this idea would be effective in theory, it faces practical hurdles in the form of hardware restrictions and little or no support for certain necessary capabilities for precise measurement of channel state and feedback.

Taking the limitations of prior work into consideration, as well as the insights of our experimental characterization study in [23] (as described in the previous section), we propose a practical and efficient 802.11n link adaptation design that takes a novel hybrid approach and is termed SampleLite. SampleLite avoids the problems faced by existing schemes from either category. The key difference from past work is that we take an opportunistic approach. SampleLite is driven by the insight that maximum goodput yielding setting of each of the 802.11n PHY features (MIMO mode, channel bonding and MCS) exhibit monotonicity with respect to RSSI. This in turn suggests the presence of RSSI threshold(s) that separate the regions where the best value for a feature differs. We exploit this insight to limit the feature settings that need to be sampled. In practice, we only use the RSSI as a guide to decide what subset of feature setting combinations to sample and not for deciding the actual settings to use. We implement SampleLite as an additional 802.11n rate control algorithm in the ath9k driver [24] and we experimentally show that this simple yet fundamental change in sampling operation can yield large gains over the current state of the art. Results show that SampleLite reduces the sampling overhead by an average of 70% compared to the widely open-loop approach Minstrel HT [20], while increasing goodput performance by up to around 35%. Being opportunistic, SampleLite can not only cope better with varying channel and interference conditions, but it can also be applied and extended to the upcoming and future 802.11x standards (e.g., 802.11ac).

The main findings and contributions of this part of the thesis are summarised below:

- The maximum goodput yielding setting of each of the 802.11n PHY features (MIMO mode, channel bonding and rate) exhibit monotonicity with respect to RSSI, which in turn suggests the presence of RSSI threshold(s) that separate the regions where the best value for a feature differs.

- We design and implement SampleLite, a novel hybrid link adaptation scheme that adapts all 802.11n features (i.e., MIMO mode, channel bonding and rate). SampleLite uses RSSI as a guide to decide what subset of feature setting combinations to sample without risking the use of sub-optimal settings.

- Through simple analysis, we show that SampleLite reduces the sampling overhead by at least 50% compared to the widely used Minstrel HT and that it could adapt efficiently to the upcoming 802.11ac standard.

- We experimentally evaluate SampleLite on a real testbed, employing different link qualities across both stable and mobile clients, considering a wide range of controlled and real-world interference scenarios in mobile and stable clients. Results show that SampleLite significantly reduces the sampling overhead by around 70% compared to the widely used Minstrel HT scheme in 802.11n. We also show that goodput-wise SampleLite provides substantial improvements relative to Minstrel HT by up to around 35%.

  To the best of our knowledge, SampleLite is the first implementable link adaptation approach that can be efficient and extendable to upcoming WLAN standards (e.g., 802.11ac).

Part of this work is under submission.

1.3 Thesis Structure

The rest of the dissertation is structured as follows. In Chapter 2 we discuss the background of this work and the state of the art related to it. More specifically, we give an overview of the past IEEE 802.11 standards, as well as the ones in the making, explaining further the recently introduced features that provide more than a 10-fold throughput increase. Moreover, we present the statistical techniques used throughout this dissertation, namely categorical regression, response surface methodology, multiple linear regression, and a variety of machine learning classifiers. Finally, we discuss the related work on the topics of legacy 802.11a/b/g and 802.11n link adaptation, and performance characterisation.

In Chapter 3 we explore the impact of loss differentiation on legacy 802.11a/b/g link adaptation, showing that it has a positive impact on performance, especially in low contention WLAN scenarios. We next propose a legacy 802.11a/g link adaptation scheme, termed *Themis* that does not rely on loss differentiation and adapts the bit-rate as well as the contention window holistically. *Themis* was evaluated in the context of Qualnet 4.5 simulator [25] and we show that it considerably improves performance in terms of throughput and fairness, compared to both the standard 802.11a/g and SampleRate [11] by eliminating hidden nodes.

We explore the new 802.11n standard and the potential impact of link adaptation on its performance in Chapter 4. We present an extensive and methodical feature characterisation and statistical analysis of the 802.11n standard. Finally, we quantify the importance of holistically adapting all available features to maximise throughput performance, and we also show the importance of regression analysis on gaining insight from large data sets of measurements.

In Chapter 5 we introduce the design, implementation and experimental evaluation of a novel 802.11n link adaptation scheme, named SampleLite. Using RSSI thresholds, SampleLite adapts the setting of each specific feature. We experimentally show that this link adaptation algorithm is not only implementable and efficient in 802.11n WLANs by significantly minimising the sampling overhead (by approximately 70%), but currently it is the only one that could be efficiently extended to be used in the upcoming 802.11ac standard.

Chapter 6 presents additional preliminary studies on topics related to 802.11n that have not been previously explored and could be potential fruitful future work, too. We perform an initial experimental study on the fairness of the 802.11n standards compared to legacy 802.11a. Moreover, we show the feasibility of identifying the interference type at a node online using throughput measurements and a supervised machine learning based classifier. Finally, we perform an extensive characterisation study similarly to Chapter 4, using live video streaming as the traffic generation method and the frames lost as a metric metric under varying link qualities, interfering conditions and video resolution.

Finally, Chapter 7 concludes and discusses opportunities for future work.

Chapter 2

Background & Related Work

In this chapter, we provide an overview of the current 802.11 standard and a summary of the state of the art concerning the issue of link adaptation. We begin in section 2.1 with a summary of the 802.11 protocol and the specific standards we try to optimise throughout this dissertation. Section 2.2 discusses prior work in link adaptation relevant to this dissertation. Finally, section 2.3 discusses the various statistical techniques we use for analysing measurements and characterising the behaviour of the network protocol.

2.1 IEEE 802.11 Overview

802.11 and 802.11x refers to a family of specifications developed by the IEEE for wireless LAN (WLAN) technology. 802.11 specifies an over-the-air interface between a wireless client and a base station or between two wireless clients. It is a set of media access control (MAC) and physical layer (PHY) specifications for implementing wireless local area network (WLAN) computer communication in the 2.4, 5 and 60 GHz frequency bands. The base version of the standard was released in 1997 and has had subsequent amendments. Wireless LANs based on the 802.11 standard have become the de facto means for end-user connectivity in indoor environments (e.g., homes, offices, hotspots) using Wi-Fi.

Table 2.1 summarises the various amendments of the IEEE 802.11 standard. The original 802.11 applies to wireless LANs and provides 1 or 2 Mbps transmission in the 2.4 GHz band using either frequency hopping spread spectrum (FHSS) or direct sequence spread spectrum (DSSS). 802.11a is an extension to 802.11 that applies to wireless LANs and provides up to 54Mbps throughput in

802.11 protocol	Frequency (GHz)	Bandwidth (MHz)	Max. data rate per stream (Mbps)	MIMO stream number
a (1997)	5	20	54	1
b (1999)	2.4	20	11	1
g (1999)	2.4	20	54	1
n (2009)	2.4/5	20, 40	72.2, 150	4
ac (2014)	5	20, 40, 80, 160	87.6, 200, 433.3, 866.7	8
ad (2012)	60	2, 160	6912 (6.75Gbps)	1

Table 2.1: 802.11 standards.

the 5GHz band. It uses an orthogonal frequency division multiplexing encoding scheme rather than FHSS or DSSS. 802.11b (also referred to as 802.11 High Rate or Wi-Fi) provides 11Mbps throughput (with a fallback to 5.5, 2 and 1Mbps) in the 2.4 GHz band. It uses only DSSS allowing wireless functionality comparable to Ethernet. 802.11e is a wireless draft standard that defines the Quality of Service (QoS) support for LANs, and is an enhancement to the 802.11a and 802.11b WLAN specifications. It adds QoS features and multimedia support to the existing IEEE 802.11b and IEEE 802.11a wireless standards, while maintaining full backward compatibility with these standards. The next standard developed is 802.11g and it is used for transmission at up to 54Mbps in the 2.4GHz band. All the standards up to this point are referred to as legacy 802.11.

802.11n [6] is the most recent version of the standard and it is currently being widely deployed, replacing the legacy 802.11a/b/g networks. 802.11n offers PHY layer speeds of up to 600Mbps and application-level throughput (goodput) in excess of 100Mbps through a combination of new PHY and MAC layer enhancements that include the use of multiple antennas (or MIMO), channel bonding and frame aggregation. Table 2.2 shows a subset of the 802.11n PHY features and the corresponding set of bit-rates. It is clear that 802.11n goes beyond just the modulation and coding schemes (MCSs) available with the legacy 802.11a/b/g WLANs and introduces new dimensions such as spatial streams (alternatively, MIMO modes) and channel widths (20/40 MHz) that significantly influence PHY bit-rates. Besides these PHY features, frame aggregation is a key MAC enhancement in 802.11n to amortise the protocol overhead over larger frames and thereby translate high PHY bit-rates to correspondingly high goodputs. A more detailed presentation of these new features follows.

2.1.1 802.11n Features

PHY Layer

Multiple Input Multiple Output (MIMO): One of the main new features introduced in 802.11n is Multiple Input Multiple Output (MIMO). This allows stations to receive and/or transmit simultaneously through multiple antennas. Depending on the hardware used, 802.11n can define a "$T \times R$" antenna configuration, from "1×1" up to "4×4", where T and R are the number of transmit and receive antennas, respectively. Theoretically, the more the antennas an 802.11n device uses simultaneously, the higher the maximum data rate achieved. However, the number of antennas alone is not enough to maximise performance, but the signal processing techniques is very crucial too. The two main MIMO techniques are the following.

Spatial Division Multiplexing (SDM) divides a signal stream into multiple pieces and transmits them through different antennas. Each of those pieces transmitted individually along a different path is called a spatial stream. This means that each spatial stream arrives at the receiver side with different strength and delay, and given their sufficiently distinct spatial signatures, the receiver can reassemble them into the original single stream. Multiplexing for example two spatial streams onto a single channel effectively means that the capacity is doubled and thus data rate is maximised. 802.11n access points (APs) can currently support up to two or three spatial streams, although the theoretical maximum is four.

On the other hand, Space Time Block Coding (STBC) transmits only one data stream, but it transmits as many instances of the same data stream as the number of antennas available. This is possible by using up to four differently-coded spatial streams, each transmitted through a different antenna. At the receiver side the arriving spatial streams are compared and effectively the reliability is improved by reducing the error rate experienced at a given Signal to Noise Ratio (SNR). This means that frames wrongly received in one data stream but correctly received in another one, can be combined and the receiver can in the end retrieve the most correctly received frames.

Channel Bonding: Another 802.11n feature is the channel bonding. Legacy (i.e., 802.11a/b/g) standards use channels of 20MHz. 802.11n combines two neighbouring 20MHz into one channel of 40MHz width. In a bonded channel, the number of subcarriers that can transmit data are even more than the number of both single 20MHz channels, boosting theoretical throughput to more than double. This applies for both the 2.4 and 5GHz bands.

Short/Long Guard Interval (SGI/LGI): The guard interval is the time between transmitted symbols (the smallest unit of data sent at once). So far legacy 802.11a/g devices use an 800ns guard interval (i.e., long guard interval – LGI), but 802.11n devices have the option of just 400ns (i.e., short guard interval – SGI). The downside of this feature is that shorter guard interval would lead to more interference and reduced throughput in case of non ideal channel conditions (e.g., congested environments). On the other hand, a longer guard interval would lead to unwanted idle time in the medium in case of no interference in a good quality link. Short guard interval can boost data rate up to 11% while maintaining sufficient symbol separation in ideal channel conditions.

Modulation and Coding Scheme (MCS): The Modulation and Coding Scheme (MCS) index describes a combination of spatial streams, modulation type, coding rate, channel width, and guard interval, that each of the combinations results in a different data rate, as shown in Table 2.2. The combination of all these factors determines the actual PHY data rate, ranging from a minimum 6.5 Mbps to a maximum 600 Mbps (achieved by leveraging all possible 802.11n options with 4 spatial streams).

Most of current hardware can support up to two spatial streams only. Therefore, in Table 2.2 we show that there are 64 different available parameter settings for a link from a PHY perspective (16 MCS indices, 2 channel widths, and 2 guard interval options).

MAC Layer

Frame Aggregation and Block Acknowledgements: A MAC enhancement that is equally important feature to the aforementioned PHY 802.11n enhancements is frame aggregation and block acknowledgements (ACKs) [14, 16, 26]. The intuition behind frame aggregation and block ACKs is to reduce the overhead when sending multiple packets to the same receiver as well as reduce the number of ACKs that a receiver must send to a transmitter to confirm frame delivery. Legacy 802.11a/g transmitters expect an ACK for each non-multicast/broadcast frame. But 802.11n transmitters also accept block ACKs confirming the reception of multiple unicast frames.

802.11n combines frames together for transmission using frame aggregation, increasing the payload size to reduce the significance of the fixed overhead caused by inter-frame spacing and preamble. The two aggregation options are the following:

MCS Index	Spatial Streams	Modulation Scheme	Coding Rate	20MHz w/ LGI	20MHz w/ SGI	40MHz w/ LGI	40MHz w/ SGI
0	1	BPSK	1/2	6.50	7.20	13.50	15.00
1	1	QPSK	1/2	13.00	14.40	27.00	30.00
2	1	QPSK	3/4	19.50	21.70	40.50	45.00
3	1	16-QAM	1/2	26.00	28.90	54.00	60.00
4	1	16-QAM	3/4	39.00	43.30	81.00	90.00
5	1	64-QAM	2/3	52.00	57.80	108.00	120.00
6	1	64-QAM	3/4	58.50	65.00	121.50	135.00
7	1	64-QAM	5/6	65.00	72.20	135.00	150.00
8	2	BPSK	1/2	13.00	14.40	27.00	30.00
9	2	QPSK	1/2	26.00	28.90	54.00	60.00
10	2	QPSK	3/4	39.00	43.30	81.00	90.00
11	2	16-QAM	1/2	52.00	57.80	108.00	120.00
12	2	16-QAM	3/4	78.00	86.70	162.00	180.00
13	2	64-QAM	2/3	104.00	115.60	216.00	240.00
14	2	64-QAM	3/4	117.00	130.00	243.00	270.00
15	2	64-QAM	5/6	130.00	144.40	270.00	300.00

Table 2.2: 802.11n MCS index table. Note that 802.11n standard supports up to 4 spatial streams and that the highest bit-rate of 600Mbps needs the use of 4 spatial streams, SGI, 40MHz channels and highest rate combination of modulation scheme and coding rate (64-QAM, 5/6).

- MAC Service Data Unit Aggregation (A-MSDU) groups logical link control packets (MSDUs) with the same 802.11e Quality of Service, independent of source or destination. The resulting MAC frame contains one MAC header, followed by up to 7935 MSDU bytes.

- MAC Protocol Data Unit Aggregation (A-MPDU) occurs later, after MAC headers are added to each MSDU. Complete MAC frames (MPDUs) are then grouped into PHY payloads up to 65535 bytes.

Frame aggregation increases the payload that can be conveyed by each 802.11 frame, reducing MAC layer overhead from 58% to 83% when using A-MSDU and 14% when using A-MPDU [27]. Legacy 802.11a/g devices can send up to 2304 payload bytes per frame.

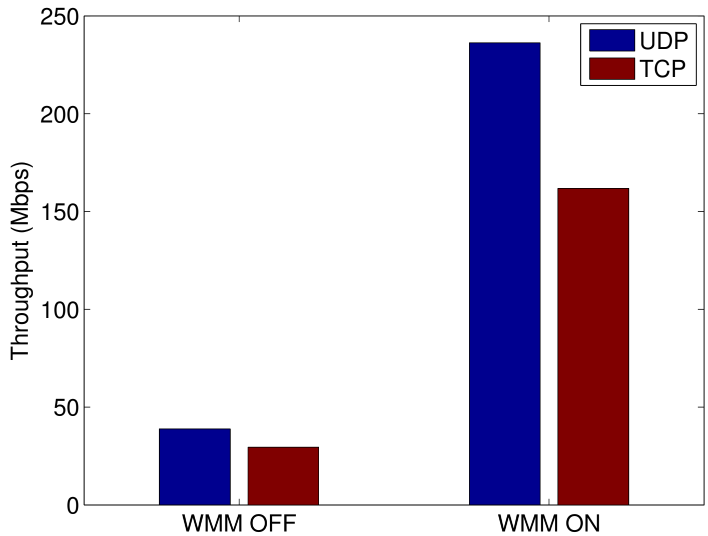


Figure 2.1: Impact of WMM on throughput performance.

WiFi Multimedia Extensions (WMM): Another MAC layer aspect that is relevant for 802.11n are the WiFi Multimedia extensions (WMM) that were originally introduced in 802.11e [28] to provide quality of service (QoS) support in 802.11 networks. This is because the use of frame aggregation requires enabling WMM, since it supports the use of block ACKs. Ranging from highest priority to lowest, the categories WMM divides traffic are the following. Firstly, giving voice packets the highest priority enables concurrent Voice over IP (VoIP) calls with minimal latency and the highest quality possible. Second priority is video related traffic; enabling support for three to four standard definition TV (SDTV) streams or one high definition TV (HDTV) stream on a WLAN. Next is best effort data packets consist of those originating from legacy devices or from applications or devices that lack QoS standards. Finally, background priority encompasses file downloads, print jobs and other traffic that does not suffer from increased latency.

We explore the impact of this feature in [29] using UDP and TCP traffic generated via iperf [30], and we find that turning off WMM implicitly disables frame aggregation, thus resulting in poor performance even in an ideal link quality as shown in Fig. 2.1.

2.1.2 Future of IEEE 802.11

The standards currently in the making extending 802.11n even further providing Gigabit throughput are 802.11ac/ad. 802.11ac builds upon previous 802.11 standards, particularly the 802.11n standard, to deliver data rates close to 1Gbps per spatial stream. Tables 2.3 and 2.4 show the MCS index settings of 802.11ac and the theoretical expected throughput per stream, respectively. The 802.11ac specification operates only in the 5 GHz frequency range and features support for wider channels (80MHz and 160MHz) and beamforming capabilities by default to help achieve its higher wireless speeds. Finally, 802.11ad is a wireless specification under development that will operate in the 60GHz frequency band and offer much higher transfer rates than previous 802.11 standards, with a theoretical maximum transfer rate of up to 7Gbps [12].

MCS Index	Modulation Scheme	Coding Rate
0	BPSK	1/2
1	QPSK	1/2
2	QPSK	3/4
3	16-QAM	1/2
4	16-QAM	3/4
5	64-QAM	2/3
6	64-QAM	3/4
7	64-QAM	5/6
8	256-QAM	3/4
9	256-QAM	5/6

Table 2.3: 802.11ac MCS index setting table.

2.2 Related Work

This section discusses previous work related to this thesis. We first consider related work on 802.11a/b/g legacy link adaptation incorporating loss differentiation (section 2.2.1). Then we discuss previous work on 802.11n characterisation (section 2.2.2) and link adaptation (section 2.2.3).

MCS Index	20MHz w/ LGI	20MHz w/ SGI	40MHz w/ LGI	40MHz w/ SGI	80MHz w/ LGI	80MHz w/ SGI	160MHz w/ LGI	160MHz w/ SGI
0	6.50	7.20	13.50	15.00	29.3	32.5	58.5	65
1	13.00	14.40	27.00	30.00	58.5	65	117	130
2	19.50	21.70	40.50	45.00	87.8	97.5	175.5	195
3	26.00	28.90	54.00	60.00	117	130	234	260
4	39.00	43.30	81.00	90.00	175.5	195	351	390
5	52.00	57.80	108.00	120.00	234	260	468	520
6	58.50	65.00	121.50	135.00	263.3	292.5	526.5	585
7	65.00	72.20	135.00	150.00	292.5	325	585	650
8	78	86.7	162	180	351	390	702	780
9	N/A	N/A	180	200	390	433.3	780	866.7

Table 2.4: 802.11ac MCS index table for a single spatial stream (in Mbps).

2.2.1 802.11a/b/g Link Adaptation

Link adaptation is key to achieving high performance WLANs. It refers to adapting one or more link/MAC and PHY layer parameters to optimise a desired criterion such as throughput or fairness. Some examples of such link/MAC parameters are contention window and frame length, and some PHY parameters are the transmission bit-rate, transmission power and carrier sense threshold.

The efficiency of 802.11 wireless networks is affected by the transmission rate selection both as far as transmission reliability and throughput are concerned. There is always a tradeoff between data rate and range, when the transmission rate is selected. The higher the transmission rate selected the higher the throughput, and the less the transmission time, but at the same time the lower the transmission range. Similarly the contention window size can either increase efficiency when efficiently selected, whereas it can increase collisions (i.e., simultaneous transmissions) or waste airtime by keeping the channel idle when set to a too low or too high value, respectively.

Different kinds of frame losses that could occur, namely channel errors, collisions and interference (hidden terminal) losses, affect the performance of the network. Differentiating between these losses is loss differentiation. Previous works (e.g., [13]) claim that link adaptation mechanisms should rely on loss differentiation in order to take a different action for every type of error and effectively adapt the link every time a certain type of loss happens. Different types of errors that may occur are the following. On the receiver side, a loss is marked as a "Channel Error" if it is caused due to a weak signal (i.e., low SNR). Otherwise, there are two possibilities. We mark a loss as due to “Collision” (synchronous interference) if it has occurred while the preamble was being received. If the preamble is correctly received but the signal is not correctly decoded then we mark the error as an “Interference” (asynchronous interference) loss instead [31, 32].

We look at link adaptation from a loss differentiation perspective in chapter 3, adapting only the two most commonly used parameters having the highest impact on performance; the contention window and the transmission bit-rate. Therefore, we are going to describe next a brief history of single parameter rate adaptation and the state of the art related to loss differentiation assisted link adaptation.

Rate Adaptation

Transmission data rate was the first and most intuitive parameter to adapt in order to maximise performance in a WLAN. Rate Adaptation algorithms that where novel for their time [11, 33, 34, 35] inspire most of the newly proposed algorithms. Lucent Technologies devices used the AutoRate Fallback (ARF) protocol [33], which is the first commercial implementation that exploits multi-rate capability. Senders decide on increasing or decreasing future transmission rates based on the number of consecutive successes or failures of past packets. This kind of algorithms perform poorly in the presence of collisions because they mistake collisions to poor channel conditions and reduce the transmission data rate, providing suboptimal performance.

Transmission bit rate adaptation schemes could also focus on the frame level. This means that they use the rate of frame errors in order to adapt the rate. ONOE [35], RRAA [34] and Sample Rate [11] also belong to this category. Sample Rate [11] is the most commonly rate adaptation mechanism used in Linux 802.11 device driver for Atheros chipsets. It is based on transmission statistics over a sliding window period. SampleRate adjusts its rate to the bit-rate that would achieve the smallest average transmission time in the last sampling interval. It starts transmitting at the highest data rate and decreases the rate immediately if it experiences four consecutive transmission failures. This scheme calculates the average transmission time per frame for different rates every 10-second period. To explore potential better channel conditions in the sampling period, SampleRate randomly selects one from all other rates whose average transmission time is less than the average lossless transmission time of the rate in use for every tenth frame.

Another set of bit rate adaptation schemes is the SNR-based ones like [36, 37, 38, 39, 40].

Contention Window Adaptation

Apart from PHY layer parameter (e.g., transmission bit-rate), the MAC layer ones (e.g., contention window) can also be part of a link adaptation algorithm in order to improve the throughput. Rate adaptation is mainly useful when channel errors occur. However, other errors like collision- and interference-based ones may happen and these errors need other ways to be handled. The Distributed Coordination Function (DCF) is the main MAC layer function in 802.11 WLANs. Various works [41, 42, 43, 44, 45, 46] have shown that the standard DCF cannot efficiently utilise the limited wireless channel bandwidth in case of high congestion in the network. The main reason is that the initial — minimum — contention window size is always the same no matter the traffic activity, whereas ideally it should be large when the number of active stations is large and vice versa.

Some of the proposed contention window adaptation mechanisms take into consideration the congestion level of the network in order to adjust the contention window settings accordingly [41, 42, 43, 44], while others initialise the control parameters (e.g., minimum contention window size) and do not further adapt them [45, 46, 47, 48, 49]. The first set of mechanisms usually incorporate a sniffer in order to monitor the surrounding activity, which adds extra processing cost and makes them harder to implement. In the latter ones, though, are easier to implement, but the existing works only consider high congestion scenarios, which is not always the case in real-life. Some of the most relevant works to this dissertation are discussed next.

Incorporating Loss Differentiation

[31, 32] show that there are multiple types of losses (channel errors, collisions, interference) and that for each loss type, different actions for link adaptation are more efficient (e.g., [13, 52]). Authors of [13] claim that link adaptation mechanisms should rely on loss differentiation, since inappropriate responses can adversely impact achieved performance (e.g., in terms of throughput). Therefore, the various causes of losses should be considered separately when designing a link adaptation scheme. In [52], authors identify the most suitable set of parameters that should be adapted for each type of loss.

As shown before, the majority of prior work on link adaptation in 802.11 networks has focused on adapting a specific parameter, usually the transmission bit-rate at the PHY layer (e.g., [53, 37, 50, 33, 11]) and contention window at the MAC layer (e.g., [46, 47, 54, 45]). Concerning loss differentiation,

	Parameters		Loss Types Considered		
	Rate	Contention Window	Channel Error	Collision	Hidden Node
SampleRate [11]	✔	–	–	–	–
RRAA [34]	✔	–	–	–	✔
CARA [39]	✔	–	–	✔	–
CHARM [37]	✔	–	–	–	✔
SGRA [50]	✔	–	–	–	✔
RAF [51]	✔	–	–	–	✔
Grant-to-send [47]	–	✔	–	✔	–
COLLIE [40]	✔	✔	–	✔	✔

Table 2.5: Parameters and loss types considered by legacy 802.11a/b/g link adaptation schemes.

most commonly, the transmission bit-rate is adapted on encountering a channel error, whereas the contention window is adapted in the event of a collision [40, 39, 55, 56].

Despite the fact that many works have focused on link adaptation with loss differentiation (e.g., [37, 50, 55, 51, 57]), we observe that none of them consider all three different kinds of frame losses seen at the MAC layer, namely channel errors, collisions and interference (due to hidden terminals); they tend to focus on only two of the three. To fill this gap in literature, also shown in Table 2.5, we are going to present a simulation-based link adaptation approach that takes into consideration all three kinds of frame losses in chapter 3; also investigating what is the actual impact of loss differentiation on link adaptation.

2.2.2 802.11n Performance Characterisation

802.11n introduces multiple new features (discussed in chapter 2.1) compared to legacy 802.11a/b/g. These new features can result in multifold increase of performance. The growing number of features means the increase to the complexity of a link adaptation algorithm since there are much more features to be adapted. Moreover, they can also result in suboptimal performance when the settings of the features are not appropriate to the given link quality. For example, intuitively one can make the hypothesis that using only one data stream (i.e., STBC) in the case of a very high quality link (e.g., the client is close to the AP and there is ab-

	Features				Interference		
	Stream Number	Channel Bonding	MCS index	Frame Aggregation	Co–Channel	Adjacent Channel	Legacy
Shrivastava [14]	–	✔	✔	✔	✔	–	✔
Pefkianakis [15]	✔	✔	✔	✔	✔	–	–
Pelechrinis [16]	✔	✔	✔	✔	–	–	–
Arslan [17]	–	✔	✔	–	✔	–	–
Deek [18]	✔	✔	✔	–	✔	✔	✔
Lakshmanan [19]	✔	–	✔	–	✔	–	–

Table 2.6: 802.11n features varied and interference cases considered in previous works.

sence of interference) would be suboptimal compared to using multiple different streams (i.e., SDM) and transmitting as many times the amount of information as the number of streams. Therefore, we see that there is the need to know the limitations and the capabilities of the various features in different link qualities and interference scenarios, so that we can appropriately adapt them in the context of an efficient link adaptation scheme.

The work of Shrivastava et al. [14] is the earliest attempt to analyse some of the key characteristics of 802.11n. Their study highlights the negative impact of legacy devices on 802.11n performance and also that channel bonding creates interference due to channel leakage. More recently, Deek et al. [18] have come to the same conclusion on the side effect of channel bonding. Both [18] and [17] focused on the impact of channel bonding. Arslan et al. [17] observed that channel bonding may be harmful even in the absence of interference for poor quality links; our results re-confirm this observation. Deek et al. [18] performed a thorough investigation of the impact of channel bonding under different types of interference and suggest the use of 20MHz channel separation in case of simultaneous transmissions between high quality links using 40MHz channels to counter the channel leakage issue mentioned above. Note that in [18] and [17], frame aggregation is disabled, which is a key shortcoming given that frame aggregation is a crucial feature affecting throughput in 802.11n networks [8].

Pelechrinis et al. [16] investigated the impact of packet size, channel width and transmission rate on 802.11n link performance. They observed that performance of SDM is highly sensitive with higher modulation and coding rates even in absence of interference, and that high rates are very susceptible to external interference and/or noise. They also suggest joint adaptation of MAC layer parameters as a way to avoid the throughput reduction with smaller packet sizes.

Pefkianakis et al. [15] discovered the non-monotonicity in the increase of throughput with increase in MCS index (Table 2.2). They then proposed a new rate adaptation algorithm called MIMO Rate Adaptation (MiRA) algorithm that takes the non-monotonicity observation into account.

More recently, Lakshmanan et al. [19] proposed a metric based on the multiplexing gain in order to adapt the bit-rate. Additionally, they observed that higher throughput can be achieved using a single stream for some link qualities and that 802.11n links are more susceptible to interference.

Table 2.6 summarises the 802.11n features studied and interference cases considered in previous work. We see that no previous work takes into consideration all features in all interfering scenarios. Therefore, in chapter 4 we aim to make a thorough and systematic characterisation of the behaviour of these newly introduced features in different link qualities and interfering scenarios to better understand what is the appropriate settings in different link and channel cases.

2.2.3 802.11n Link Adaptation

Next we focus on the existing work on the link adaptation problem in the context of the 802.11n protocol. Similarly to legacy there are multiple MAC and PHY layer features that can be adapted. However, as discussed in chapter 2.1, the increased number of newly introduced features in 802.11n compared to legacy also increases the complexity of the link adaptation schemes.

The work of Pefkianakis et al. [15] has spawned the research on 802.11n link adaptation. They were the first to identify the non-monotonicity between frame error rate and bit-rate in 802.11n networks that use both MCS *and* MIMO modes (different numbers of spatial streams for spatial division multiplexing), and this in turn explains the poor performance of schemes which assume the monotonicity to hold like the rate adaptation schemes designed for legacy 802.11a/b/g networks (e.g., RRAA [34]) and the original 802.11n rate control algorithm in ath9k [24]. [15] also proposed a 802.11n link adaptation scheme called MiRA that takes the above mentioned non-monotonicity into account and zig zags across different MIMO modes to search for the rate providing the maximum goodput. Subsequently, in [58] the same authors proposed an improved variant called WRA that searches different MCSs of all MIMO modes in parallel to find the best rate.

Minstrel HT [20] is the default link adaptation scheme in ath9k [24], the commonly used open-source 802.11n wireless driver. It does random and exhaustive sampling of all different settings for MIMO mode, channel bonding, guard interval and MCS to update the expected throughput and loss rate of each combination of settings. The combination that provides the highest expected throughput is chosen for data transmissions. However, if this selected rate turns out to be too lossy then it applies a sudden death of spatial division multiplexing rule to lower the rate by reducing the number of streams.

Differently from the schemes outlined above, RAMAS [21] takes a credit-based approach. It also divides the 802.11n features into two groups: the modulation group with different MCS values and the enhancement group that consists of number of streams, channel widths and guard intervals. RAMAS uses credit-based algorithms to adapt these groups independently of each other and combines the results together to decide the overall feature setting.

Recently, Combes et al. [59] explore the fundamental limits of sampling based rate adaptation algorithms for legacy 802.11a/b/g and MIMO-based 802.11n networks. The authors also design a family of algorithms called ORS that learn the optimal settings as fast as possible (not necessarily the same as the optimising the overhead due to sampling). For 802.11n networks, they consider adapting the rate and the number of streams simultaneously as a pair on a 2-D graph and the focus is on choosing the appropriate pairs to sample. Underlying these algorithms are certain unrealistic assumptions such as prior knowledge of the speed at which the environment is changing, which makes their implementability somewhat unclear. Also the ORS algorithms are evaluated only via trace-based simulations.

While the above discussed schemes are all open-loop schemes relying on some form of sampling, the alternate closed-loop approach has also been investigated. Even though the availability of complete channel state information (CSI) would make the 802.11n link adaptation straightforward [61], sampling and feeding it back to the sender is expensive [62]. Moreover, CSI is not widely supported across all chipsets. The ARAMIS scheme [22] is motivated by these observations. In essence, the authors devise an easy-to-obtain channel quality metric called *diffSNR* and combine it with SNR to serve as an input to a model that predicts the best setting for various 802.11n features; the setting so determined is in turn fed back to the sender to apply for the following data transmission. Although the authors attempt to use the capabilities provided in the 802.11n standard for this feedback, they report that those capabilities are not always implemented in commodity 802.11n chipsets. Moreover, as acknowledgement frames are dealt inside the firmware, accessing them on the sender side at driver level to retrieve feedback embedded in them is another practical hurdle. Finally, Chan et al. propose another link adaptation scheme for 802.11n focusing on video streaming in

	Features			
	Stream Number	Channel Bonding	MCS index	Frame Aggregation
MiRA [15]	✔	–	✔	–
Lakshmanan et al. [19]	✔	–	✔	–
RAMAS [21]	✔	✔	✔	✔
VARA [60]	✔	–	✔	–
ARAMIS [22]	✔	✔	✔	–
ORS [59]	✔	–	✔	–
Minstrel HT [20]	✔	✔	✔	✔

Table 2.7: 802.11n features considered in already proposed 802.11n link adaptation schemes.

[60]. The scheme performs Video-Aware Rate Adaptation and is called VARA. VARA adapts the PHY rate and stream number based on video streaming rate and channel quality.

Table 2.7 summarises the 802.11n features adapted in previous work on 802.11n link adaptation. We see that in most proposed schemes not all features are adapted, but even the schemes that adapt all features have some inefficiencies. The currently commercially used Minstrel HT [20], that adapts all features, wastes about 10% of the available airtime in extensive sampling [21]. Moreover RAMAS [21] was shown to perform well in the 2.4GHz band, but Deek et al. [22] show that it performs poorly in the 5GHz band in presence of obstacles and interference. Therefore, in chapter 5 we propose an efficient and practical link adaptation approach that holistically adapts all aforementioned 802.11n features and at the same time overcomes the limitations of RAMAS and significantly minimises the sampling overhead of Minstrel HT.

2.3 Statistical Techniques

In this section we explain on the statistical techniques used for characterising and classifying the behaviour of 802.11n wireless network measurements.

2.3.1 Categorical Regression

We use categorical regression in chapter 4 to study the relative impact of 802.11n features on performance. Standard multiple regression works best with continuous predictor variables. Categorical regression was developed as a method for linear regression for categorical predictor variables [63]. It relies on a method called optimal scaling that finds optimal numerical values to categorical values and in the process transforming categorical data into numerical data. The transformations of categorical variables are estimated simultaneously with the estimation of the regression coefficients using an alternate least squares procedure that maximises the squared multiple regression coefficient, R^2, on the transformed variables. As a result, categorical regression results in transformed categorical variables that have values with numerical properties and are optimal for describing the relation between the response variable and predictors. Goodness of a categorical regression can be assessed with respect to a desired level of significance (typically, 0.05). If the p-value of the ANOVA is lower than the desired level then we consider the regression result to be statistically significant.

Pratt's measure [64] is a way to quantify the importance of each predictor and is seen as much more useful metric than the standardised regression coefficient. Pratt's measure for each predictor variable is computed by taking the product of its regression coefficient and its zero-order correlation (i.e., the correlation between the transformed predictor and the transformed response in the categorical regression). These products add to R^2, so importance values are usually divided by R^2 so that they add up to 1. We use the IBM SPSS tool for this study [65].

2.3.2 Response Surface Methodology

We use response surface methodology (RSM) [66] in chapter 4 to examine the interdependence among various 802.11n features with respect to a performance metric of interest like throughput. In RSM, the response variable y (e.g., throughput) is modelled as a function of the predictor variables $x_i, 1 \leq i \leq k$ as shown in the following equation:

$$y = f(x_i), i = 1, \ldots, k$$

Broadly speaking, RSM involves two phases. In the first phase, the function f

is approximated as a quadratic function of the form:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j=2}^{k} \sum \beta_{ij} x_i x_j + \epsilon$$

In the second phase, optimisation is performed on the approximated function to determine values for the predictor variables that optimise the response. RSM has been previously used in the wireless networking context. For example, Vadde et al. [67] have used RSM to optimise the interaction between routing and MAC layers in mobile ad hoc networks.

For our purpose of understanding mutual interaction among 802.11n features, we limit our attention only to the first phase of RSM. Roughly speaking, our focus is on the statistically significant $x_i x_j$ terms in the above quadratic functional form. Specifically, we examine the ANOVA table resulting from the first phase of RSM and look at each pairwise combination of predictors to see if their p-value is lower than a desired level of significance (0.05) and if so, we conclude that the interaction between the predictors in that pair to be statistically significant. We use the SYSTAT tool [68] for our RSM based study. Note that we do not use RSM to study relative impact of different features because it does not have a suitable measure of importance like Pratt's measure with categorical regression.

2.3.3 Multiple Linear Regression

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to the observed data. Every value of the independent variable x is associated with a value of the dependent variable y. Given a data set $\{y_i, x_{i1}, x_{i2}, \cdots, x_{in}\}_{i=1}^{n}$ for n statistical samples, a linear regression model assumes that the relationship between the dependent variable y_i and the p-vector of regressors x_i is linear. This relationship is modelled through a disturbance term or error variable ε_i — an unobserved random variable that adds noise to the linear relationship between the dependent variable and regressors. Thus the model takes the form,

$$y_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i, i = 1, \cdots, n$$

where y_i is the dependant variable and x_{ip} are the input or independent variables. β is a p-dimensional parameter vector that contains the regression coefficients. Statistical estimation and inference in linear regression focuses on β.

Finally, ε is the error term that captures all other factors which influence the dependent variable y_i other than the regressors x_{ip}.

Linear regression models are often fitted using the least squares approach, but they may also be fitted in other ways, such as by minimising the "lack of fit" in some other norm, or by minimising a penalised version of the least squares loss function as in ridge regression. The least squares approach can be used to fit models that are not linear models. In our results presented in chapter 4 we use the least squares approach. We use Matlab [69] for conducting this analysis.

2.3.4 Machine Learning Classifiers

For our study on interference type classification in chapter 4, we consider four commonly used yet very different supervised machine learning classifiers: naive Bayes, multinomial logistic regression, k-nearest neighbours and C4.5 decision tree. Here we briefly describe each of them. The Naive Bayes classifier is based on the Bayes rule of conditional probability. It makes use of all the features contained in the data, and analyses them individually as though they are equally important and independent of each other. Multinomial logistic regression (also known as maximum entropy classifier) is commonly used as an alternative to Naive Bayes classifier as it does not assume statistical independence of features. C4.5 decision tree belongs to a family of decision tree algorithms that decide on the response (class in our case) for a new sample based on the values of features in the available data. The k-nearest neighbours algorithm classifies based on closest training examples in the feature space. We use the Weka data mining tool [70] for Naive Bayes, k-nearest neighbors (IBk in Weka) and C4.5 (J48 in Weka). For logistic regression, we use IBM SPSS tool [65].

Chapter 3

On the Importance of Loss Differentiation for Link Adaptation

3.1 Introduction

This chapter describes the design, implementation and evaluation of *Themis*, a new hybrid link adaptation scheme for legacy 802.11a/b/g wireless LANs that adapts both the transmission bit-rate and contention window. It uses RSSI- and random-based rate selection based on the contention level to significantly improve wireless throughput.

As mentioned in section 2.2.1, link adaptation is affected by different kinds of frame losses that could occur (i.e., channel errors, collisions and interference – hidden terminal – losses), and previous works (e.g., [13]) claim that it should rely on loss differentiation in order to effectively adapt the link every time a certain type of loss happens.

In contrast to previous works, our work is motivated by the fact that loss differentiation is a complex problem to solve at runtime, as also shown by some previous studies such as [52]. So we explore the possibility of designing an effective link adaptation scheme that does not rely on loss differentiation. Our approach towards this end is to first study the potential benefit from having loss differentiation capability. Then using insights from that study we develop a scheme that offers the same benefit but without loss differentiation.

Our primary goal in this chapter is to understand the potential benefit from loss differentiation on link adaptation, focusing on the two well studied parameters — PHY layer transmission bit-rate and MAC layer contention window. Assuming we have access to a perfect loss differentiator, we try to identify intuitively optimal parameter adaptation strategies for different kinds of losses (channel errors, collisions and interference) and quantify the resulting throughput gain under different network conditions. We find that loss differentiation has a positive impact on performance, especially in low contention WLAN scenarios.

Loss differentiation, however, is a hard problem to solve since 802.11 only gives binary feedback (success/failure of a transmission). Therefore, we explore the possibility of doing away with loss differentiation while designing an effective link adaptation scheme for WLANs. We show that it is indeed possible by synthesising a novel link adaptation scheme called *Themis* based on the insights from our study in the first part of the chapter on assessing potential gains from loss differentiation. *Themis* does bit-rate and contention window adaptation without relying on loss differentiation. *Themis* uses a sampling technique for rate selection. It selects the rate to sample based on RSSI in low contention cases, whereas it randomly selects a rate to sample in high contention cases. In both cases, the rate used for data transmission is selected based on a statistical table created and updated by this sampling technique. Simulation results show that *Themis* can considerably improve performance, in terms of throughput and fairness, compared to both the standard 802.11a/b/g and SampleRate [11] by eliminating the hidden nodes.

The remainder of this chapter is organized as follows. In section 3.2 we discuss related work and the benefit from loss differentiation is studied in section 3.3. The proposed link adaptation mechanism, *Themis*, is presented and evaluated in sections 3.4 and 3.5, respectively. Section 3.6 concludes the chapter.

3.2 Methodology

We consider the common infrastructure WLAN scenario seen in home, office and hotspot environments. We study WLAN performance focusing on throughput as the main metric. We also briefly consider the fairness metric.

We also consider an ideal loss differentiator. On the receiver side, a loss is marked as a "Channel Error" if it is caused due to a weak signal (i.e., low SNR). Otherwise, there are two possibilities. We mark a loss as due to "Collision" (synchronous interference) if it has occurred while the preamble was being received. If the preamble is correctly received but the signal is not correctly decoded then we mark the error as an "Interference" (asynchronous interference) loss instead [31, 32].

In our study, we consider various link adaptation schemes, some of which assume to have access to the aforementioned loss differentiator at the sender side. The loss differentiator uses the RSSI for estimating the current channel quality and inferring the cause of loss. In one of our schemes, called the ORACLE, instantaneous receiver-side RSSI is assumed to be available at the sender. In other loss differentiation based schemes, RSSI is obtained at the sender from the receiver via the latest ACK frame. This is more realistic, but such RSSI information could be stale in the event of prolonged transmission inactivity or successive transmission failures.

We focus on two common parameters — PHY layer transmission bit-rate and MAC layer contention window. From the literature, intuitive actions for adapting these two parameters would be to only decrease the bit-rate (henceforth, rate) in case of channel error and only adjust the contention window if loss is not due to a channel error.

We consider the following schemes for rate adaptation. Of these schemes, Loss Aware Rate Adaptation (LARA) algorithm relies on (ideal) loss differentiation.

Algorithm 1 Loss Aware Rate Adaptation (LARA) Algorithm

---

if $ChannelError$ **then**
  $rate = currRate - -$
else if $Collision||Interference$ **then**
  $rate = currRate$
else if $Frame\ transmission\ is\ successful$ **then**
  $rate = highestRateBasedOnRSSI$
end if

- *LARA (Algorithm 1)* implements the intuitive action of decreasing the rate only in case of channel error and relies on RSSI obtained via most recent ACK from receiver.
- *SampleRate [11]*
- *Static Rate* uses the best rate in terms of throughput depending on the distance between the access point and client, using a distance-dependent path loss model with no fading.
- *ORACLE* always chooses the optimal rate based on the assumed knowledge of current receiver-side channel at the sender side.

Algorithm 2 Optimized Contention Window (OCW) Adaptation [46]

Require: $retryCnt$
  if $retryCnt == maxRetry$ **then**
    $cw = cw$
  else if $successfulTx$ **then**
    $cw = max[cw/2, cwMin + 1]$
  else if $failedTx$ **then**
    $cw = min[2 * cw, cwMax + 1]$
  end if

Algorithms considered for adapting the contention window are:

- *SCW* is the **S**tandard 802.11 **C**ontention **W**indow adaptation (backoff) mechanism, which does not consider the cause of loss.
- *OCW (Algorithm 2)* is an **O**ptimized **C**ontention **W**indow mechanism based on the work of Wu *et al.* [46]. Like SCW, it also does not use loss differentiation.
- *ROCE (**R**eset CW **O**n **C**hannel **E**rror)* is a loss differentiation based contention window adaptation scheme. It sets the contention window to the minimum in case of channel error.
- *KOCE (**K**eep CW the same **O**n **C**hannel **E**rror)* is also a loss differentiation based scheme. It maintains contention window at its current value in case of channel error (as opposed to doubling it like in the SCW algorithm).

We evaluate all possible combinations of rate and contention window adaptation schemes mentioned above. For example, we combine SampleRate with SCW and OCW that are not based on loss differentiation. On top of that, we add the loss differentiation aspect in both of them like follows: SampleRate with SCW-ROCE, SCW-KOCE, OCW-ROCE and OCW-KOCE. In the case of SampleRate-OCW-ROCE, the rate is adapted based on SampleRate and the contention window based on OCW with the extra condition that if the error occurred is a channel error then the contention window size is reset to the minimum. Similarly, for the rest of the possible rate and contention wind combinations presented in Figure 3.2.

We use QualNet v4.5 simulator [25] for our study. For modelling the wireless channel, we use the common two-ray propagation model with a path loss exponent of 3.38 (based on the non-line-of-sight indoor scenario in [71]) along with

	Tx Power	*Rx Sensitivity*
6 Mbps	23 dB	-93 dBm
9 Mbps	23 dB	-91 dBm
12 Mbps	23 dB	-89 dBm
18 Mbps	23 dB	-87 dBm
24 Mbps	23 dB	-78 dBm
36 Mbps	21 dB	-76 dBm
48 Mbps	19 dB	-74 dBm
54 Mbps	17 dB	-72 dBm

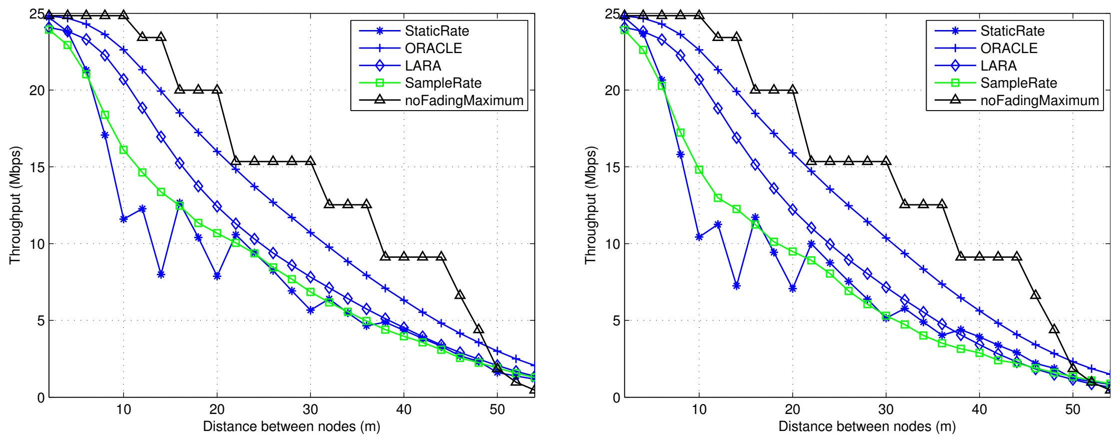
Table 3.1: Transmit power and receive sensitivity settings for Compex WLM54AG card

constant shadowing deviation of 4dB that is default in QualNet. With this channel model, the maximum distance between access point and client is 54m. We also use Rayleigh fading model with a low velocity of 1m/s to reflect WLAN scenarios with pedestrian mobility in the environment. We present results corresponding to 802.11a operation in the 5GHz band. 802.11a supports 8 rates: 6, 9, 12, 18, 24, 36, 48 and 54Mbps. Receive sensitivity values for different transmission bit-rates (modulation and coding schemes) and transmit power settings are taken from the Compex WLM54AG 802.11a card with an Atheros AR5212/5913 chipset (Table 3.2). Throughout we use a fixed packet size of 1KB and each sender-receiver pair is presented with a CBR/UDP traffic at high load of around 25Mbps, which is close to the maximum throughput possible with 802.11a.

3.3 Loss Differentiation Benefits

3.3.1 Single Link

We initially focus on the simple case of a single link between an access point and a client with varying distances of separation. The results are shown in Figs. 3.1(a) and 3.1(b) corresponding to the use of SCW and OCW contention window adaptation schemes, respectively. Each data point in the plots is an average of 5 different simulation runs, each 5mins long. Comparing Figs. 3.1(a) and 3.1(b), we observe that the contention window adaptation scheme chosen does not have any noticeable impact, as expected.



(a) Standard Contention Window (SCW) (b) Optimized Contention Window (OCW)

Figure 3.1: Impact of loss differentiation on throughput performance in the single link case with different rate adaptation and contention window adaptation schemes. The "noFadingMaximum" curve in both plots is the case where Rayleigh fading is disabled in the simulation and provides an estimate of the maximum distance till which each of the rates remains best.

We now shift our attention to looking at the impact of various rate adaptation schemes. We observe that the StaticRate scheme performs the worst as it does not consider time-varying channel conditions — spikes correspond to distances at which rate is shifted down by one level, starting from 54Mbps at the smallest distance. ORACLE and LARA, though impractical, perform substantially better than SampleRate (the practical and commonly used scheme). Note that ORACLE and LARA are both RSSI based. ORACLE performs better than LARA, as expected, since it has perfect knowledge of the specific link. These results show that having a good estimate of receiver side channel quality information at the sender and using it for rate selection is key to superior performance in the single link case. The behaviour of the noFadingMaximum algorithm near the boundary of access point coverage area in Fig. 3.1 is explained by Ren et al. in [72]. They show that the throughput rapidly decreases near the fringes of coverage in case of no fading, whereas the throughput starts to drop much earlier with Rayleigh fading but more gradually.

3.3.2 Multi–Link

In this section we study the more common case of multiple clients associated to an access point and communicating via the access point simultaneously. We model such cases by varying the number of clients associated to an access point from 1 to 50. Results are shown in Fig. 3.2. Each data point in the plots is an average of 10 simulation runs with different random node placements for each specified value of the number of clients[1].

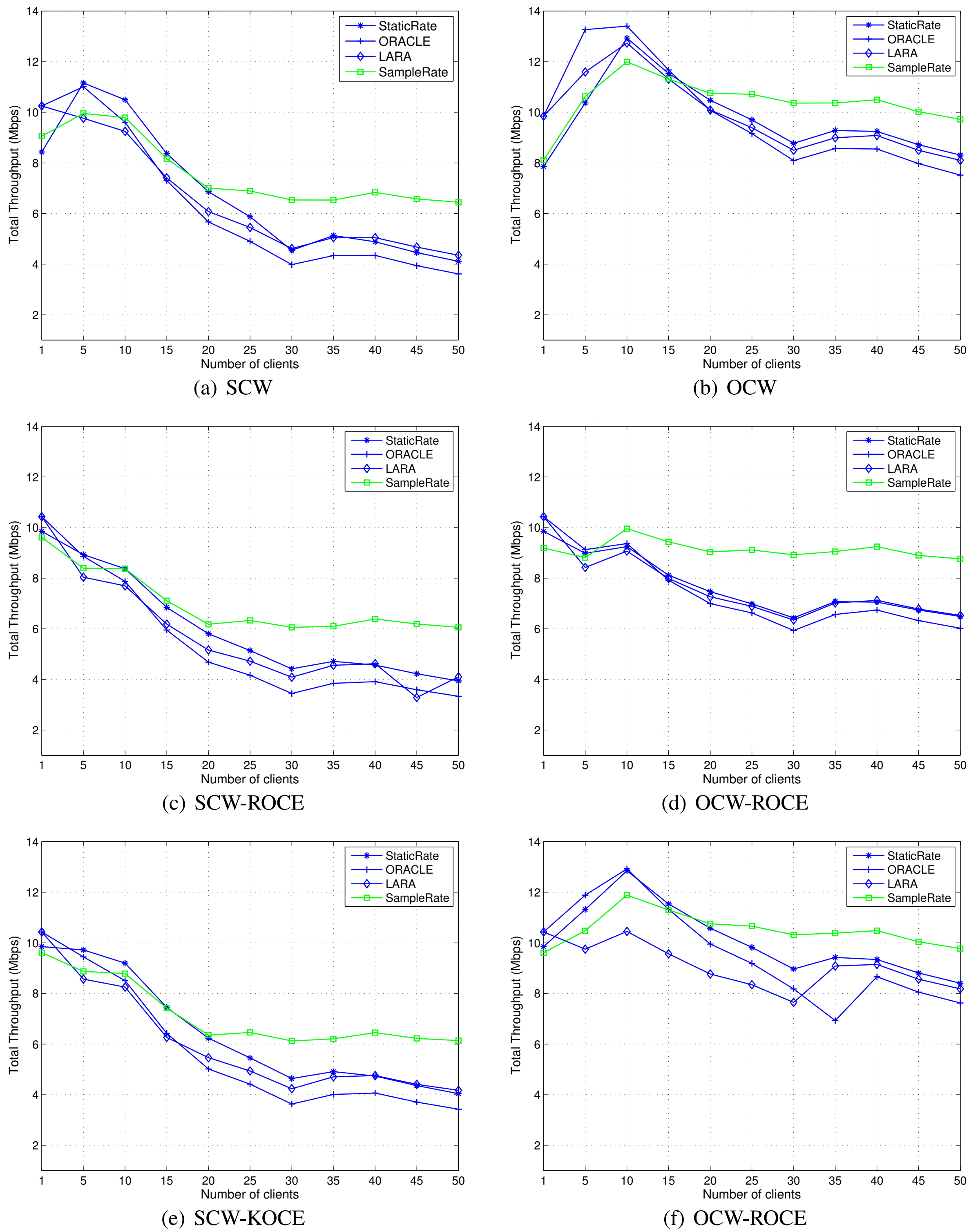
Overall, we observe that ORACLE-OCW outperforms all other schemes until a certain number of clients is reached. Thereafter the best throughput is achieved surprisingly with SampleRate. Note that neither of these schemes use loss differentiation though the former is not practical due to the assumption regarding availability of instantaneous receiver side RSSI on the sender side.

Loss differentiation based schemes (e.g., LARA with or without ROCE/KOCE) never provide superior performance. In fact, in most cases these combinations perform even worse than StaticRate that does not adapt rate, especially when the number of clients exceeds a small number. This is in part because of the use of RSSI information obtained from the receiver end through successful ACKs for estimating channel quality. As the number of clients sharing the medium increases, the channel quality information obtained increasingly becomes stale and may no longer closely reflect the true state of the channel.

Unlike the single link scenario, ORACLE is not consistently the best performing scheme. This is because it only knows the best rate for maximizing the throughput of each link in isolation, but not the rate that will maximize the throughput of the network as a whole. This agrees with the analysis by Radunovic *et al.* in [13], which shows that selfish rate selection performs poorly. In order to better understand this, we look at the distribution of losses with increasing number of clients (Fig. 3.3). We observe that interference related losses (i.e., due to hidden terminals) dominate when there are more clients in the network. Using an optimal rate for each link in such cases only contributes towards increasing interference related losses. This suggests that a holistic view of rate selection is required and that sub-optimal rates may indeed be more effective in highly dense WLAN scenarios.

Moreover, all combinations using "OCW" (Figs. 3.2 (b,d,f)) perform (or close to) the best for all rate adaptation schemes with the slight exception of StaticRate and SampleRate. For those schemes, the best performing alternatives are the

[1] As a consequence, the case with just one client does not correspond to any particular distance in Fig. 3.1 but instead represents an average across different distances.



(a) SCW (b) OCW

(c) SCW-ROCE (d) OCW-ROCE

(e) SCW-KOCE (f) OCW-ROCE

Figure 3.2: Impact of loss differentiation on throughput performance in the multi-link case with different rate adaptation and contention window adaptation schemes.

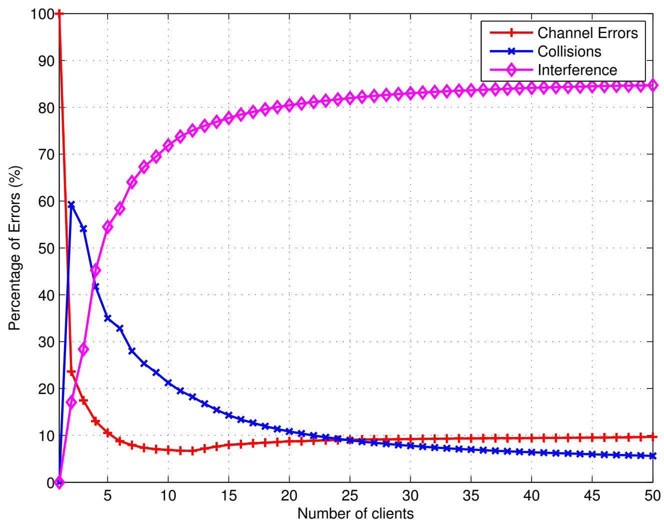


Figure 3.3: Distribution of different kinds of losses with varying number of clients. Results shown here correspond to the combination of ORACLE and SCW but similar behaviour holds for all other combinations.

ones using OCW-KOCE (Fig. 3.2(f)). However, the difference between OCW and OCW-KOCE contention window adaptation schemes is about 1% in both instances. This shows that a link adaptation scheme that is unaware of the exact causes of loss (e.g., SampleRate-OCW) can perform on average almost as well as a loss differentiation based one (e.g., SampleRate-OCW-KOCE), suggesting that loss differentiation may not be critical for optimizing WLAN throughput performance.

3.4 *THEMIS*: Effective Link Adaptation without Loss Differentiation

As shown in section 3.3, RSSI measurement errors or lost ACK frames influence the performance of the RSSI based adaptation schemes. This is obvious in the high contention cases of Fig. 3.2 that the RSSI based algorithms are the ones performing the worst. This suggests that it is helpful to use a direct indicator of receiver-side channel quality like RSSI only in low contention cases with few clients. In this section, we develop a scheme that considers RSSI in low contention cases in a way that is different from LARA. Moreover, regardless of the level of contention the proposed scheme does not rely on loss differentiation. In essence, we synthesize an effective and novel link adaptation scheme that is devoid of loss differentiation by taking into account the various observations made in the previous section.

Algorithm 3 *Themis*

Require: $RSSI\_est, contentionLevel$
Ensure: $cw\ adapted\ according\ to\ OCW.$

```
flag=FALSE
if currentRate is successful for less than T1 period then
    currentRate = currentRate
else
    flag=TRUE
end if
if currentRate fails for more than T2 period then
    flag=TRUE
end if
if flag==TRUE then
    if contentionLevel = low then
        rateToSample = highestRateBasedOnRSSI(RSSI_est)
    else
        rateToSample = selectRandomRate()
    end if
    TxTimeEst = sample(rateToSample)
    update_StatisticalTable(TxTimeEst, rateToSample)
    currentRate = bestRate(StatisticalTable)
end if
```

We call our proposed link adaptation scheme *"Themis"*[2] (Algorithm 3). *Themis* adapts both the contention window and the transmission bit-rate. The contention window is adapted according to the OCW methodology by Wu *et al.* [46]. The rate adaptation is done using a statistical table that is created and maintained by occasionally sampling various possible rates (i.e., probing or actively transmitting at different rates) in order to determine the most effective rate that permits fastest

[2]In ancient Greek mythology, *Themis* had the ability to foresee the future and was one of the Oracles of Delphi (a temple); that ability made Themis the goddess of divine justice.

transmission of data frames, similarly to SampleRate. We use the same statistics computation (i.e., estimated time of successful transmission and packet delivery ratio) as SampleRate does in order to select the optimal rate to be used for data transmission.

The main novelty of *Themis* is in the way the rate to be sampled is selected. *Themis* differentiates between low and high contention in the network and chooses a different strategy in each case. Current contention level in the network can be determined following the approach taken in WOOF mechanism by Acharya *et al.* [73] based on measurement of the channel busy time (fraction of time that the medium is utilized in a specific time interval) locally at each node. Once the current contention level is estimated, we can distinguish between low and high contention cases using a threshold.

In low contention scenarios, RSSI estimates obtained via receiver ACKs are usually reliable since few clients try to occupy the medium and the likelihood of collisions/interference is low, as indicated by Fig. 3.3. Therefore, when contention is low we choose the rate to be sampled based on the RSSI estimate at the sender node as follows. We select the *highest* rate possible with the receive sensitivity that is immediately lower than the RSSI estimate describing the channel quality ($RSSI\_est >= RX\_sensitivity(rateIndex)$ according to Table 3.2). On the other hand, in high contention scenarios, the RSSI estimate at sender side is not regarded as a trustworthy metric as explained before, so random rate selection for sampling is used instead. In either case, every time a rate is sampled, a statistical table is updated on the likelihood of the specific rate to be the fastest in successfully transmitting a typical data frame. The final rate selection is independent of the RSSI, and is only based on the aforementioned statistical table. This means that every time the rate adaptation algorithm needs to select a new rate to use, it looks up this table and selects the rate with the highest probability.

Finally, another feature of *Themis* is how often and under what circumstances should it sample in order to select a new rate, based on the updated statistics table, similarly to SampleRate. Our aim is to maintain a rate that is successful while at the same time we want to adapt quickly to changes in the environment. Moreover, we want to minimize the overhead of sampling and avoid unnecessary actions that would cause overhead. To satisfy these objectives, we define two parameters $T1$ and $T2$ as shown in Algorithm 3. As long as a rate is successful, sampling another rate is delayed for a period $T1$. On the other hand if the chosen rate is continuously failing for a period $T2$ then a new rate will be sampled. We empirically found that $T1 = 10sec$ and $T1 = 1sec$ offer the best balance between adapting quickly to environmental changes and keeping overhead low.

3.5 *THEMIS* Evaluation

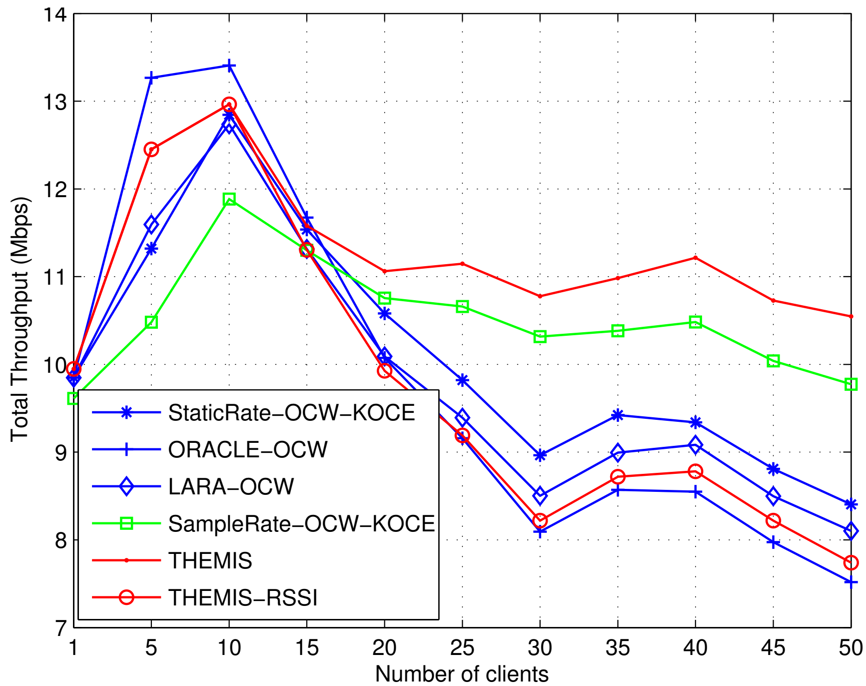


Figure 3.4: Throughput performance of *Themis* in the multi-link case relative to the top performing alternatives from the loss differentiation study.

In Fig. 3.4, the throughput performance with *Themis* is compared with the best performing variants from the multi-link study in section 3.3 (see Fig. 3.2). Only ORACLE-OCW performs slightly better than *Themis* in the low contention scenario since it has perfect knowledge of the exact channel quality and chooses the rate to use accordingly. However, when the interference increases (high contention) the RSSI and loss differentiation based schemes (ORACLE-OCW, LARA-OCW, StaticRate-OCW-KOCE and SampleRate-OCW-KOCE) are no longer effective in a dense multi-link scenario. Fig. 3.5 shows the average bit-rate chosen by various schemes including *Themis* with varying number of clients. Both Figs. 3.4 and 3.5 show the adaptability of *Themis* to varying levels of contention and distribution of losses (as previously shown in Fig. 3.3). Comparing the throughput results of *Themis* with those of standard 802.11a/b/g and SampleRate algorithm (SampleRate-SCW) from Fig. 3.2, we observe that *Themis* does up to 60% and

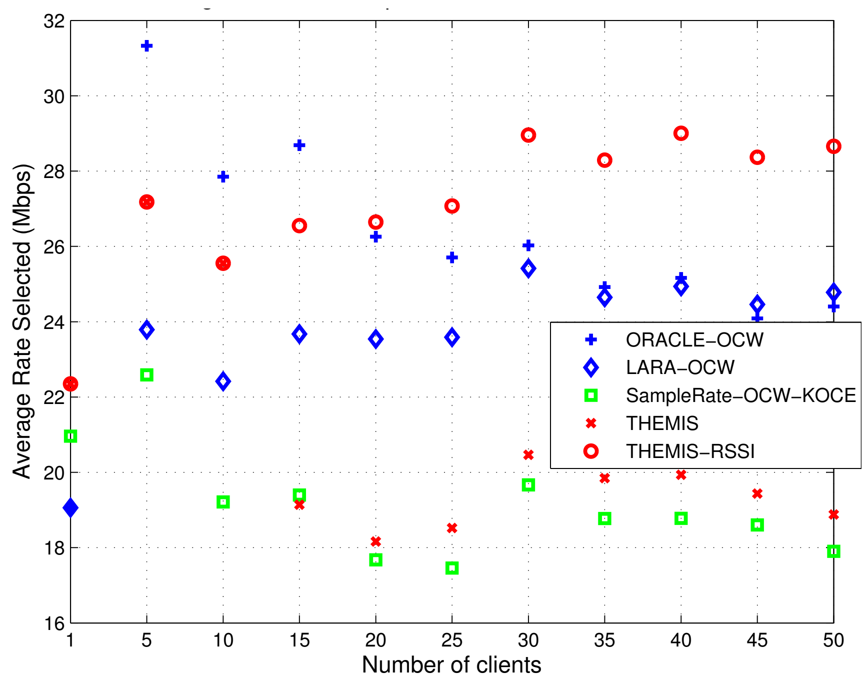


Figure 3.5: Average rate chosen by *Themis* and the top performing alternatives from the loss differentiation study with varying number of clients.

40%, respectively, better in high density settings.

In order to validate the hypothesis that selecting the rate based on the RSSI in high contention scenarios would not be fruitful, we consider a variant of *Themis* that is based on RSSI (Themis-RSSI). Themis-RSSI always selects the rate to be sampled based on the RSSI. From Fig. 3.4, we can see that it performs poorly like the RSSI– and loss differentiation-based schemes do in the high contention case. At the highest level of contention, the throughput achieved with Themis-RSSI is 27% worse compared to *Themis*.

This can be attributed to the use of stale and untrustworthy RSSI estimates in high contention scenarios. As shown in Fig. 3.5, RSSI based schemes (ORACLE, LARA and Themis-RSSI) tend to use higher rates on average at higher levels of contention, further exacerbating the hidden terminal problem and increasing interference related losses. We can see that the worst performing schemes on average (LARA-OCW and ORACLE-OCW) mostly select similar high average rates as shown in Fig. 3.5 irrespective of the number of active clients in the network. This pattern limits the transmission range of nodes to shorter using the higher rates, thus increasing the number of hidden terminal related interference losses. In general, higher rates result in shorter range of the client. This means that all the other nodes outside its reach would always assume that the channel is idle, even when it is not, and therefore attempt to transmit traffic, resulting in losses since the medium is occupied by the client with the high rate. Not that all clients try to transmit high load of traffic to the access point simultaneously. On the other hand, SampleRate-OCW-KOCE, which performs better than both of these schemes, selects the lowest average rates. This shows that the probability of successfully transmitting is higher at lower rates than with higher ones in higher contention scenarios. Lower rate suggests that more nodes in the network would know when there is a transmission, so they realize when the channel is occupied and avoid transmitting data in that time, and essentially avoiding creating losses.

The improved performance of *Themis* stems from its ability to select on average higher average rates than LARA-OCW and ORACLE-OCW in low contention scenarios, and then drop the rate with increasing number of clients, reaching similar rates as SampleRate-OCW-KOCE. Fig. 3.5 also validates the observation that RSSI does not allow for a “finegrained differentiation in the range relevant to bitrate selection”, made by Ramachandran et al. in [53], where a rate adaptation scheme optimised for congested WLANs is proposed.

ADD — Discussion of how lower rate selection affects interference and throughput in Themis.

Next, we also examine the fairness, packet loss on the MAC layer, delay and jitter of these schemes when all 50 clients were active in the network. The average results for those metrics are shown in Table 3.2. For the fairness metric we use the Jain′s fairness index [74]:

$$f(x_1, x_2, \ldots, x_n) = \frac{(\sum_{i=1}^{n} x_i)^2}{n \sum_{i=1}^{n} x_i^2} \tag{3.1}$$

where x_i is the throughput of the i^{th} link and n the total number of concurrently communicating links. The packet loss results were calculated with the following formula.

$$PacketLoss = 100 - (\frac{TotalPacketsReceived}{TotalPacketsSent}) * 100 \tag{3.2}$$

Themis outperforms the rest of the schemes in terms of fairness up to a maximum of almost 10%. This is especially true in high contention scenarios because it uses lower rates on average, increasing the number of successful transmissions

	Fairness	Packet Loss	Delay	Jitter
ORACLE-OCW	37.3%	33.7%	4.79 ms	0.105 ms
LARA-OCW	37.7%	35%	4.42 ms	0.103 ms
SampleRate-OCW-KOCE	45.8%	45.5%	7.5 ms	0.181 ms
Themis	46.6%	40.5%	4.83 ms	0.121 ms
Themis-RSSI	34.7%	42%	4.17 ms	0.107 ms

Table 3.2: Average metrics per algorithm when all 50 clients are active in the network.

for all nodes. Additionally, as Fig. 3.5 shows, *Themis* manages to use higher rates when appropriate, which is important to achieve high aggregate throughput and fairness.

Themis reduces packet loss by about 5% compared to SampleRate. As far as the average delay and jitter are concerned, we notice that *Themis* has the second highest values behind SampleRate, while Loss Differentiation-based algorithm (e.g., LARA-OCW) perform better. However, the delay and jitter measured refers to the actual successfully transmitted packets in the whole of the network. Loss Differentiation-based algorithm can have lower average delay etc, but at the same time lower fairness. This means that some clients may starve in order for others to be served and therefore improve statistics like delay and jitter.

Overall, our results show that actions chosen in response to losses are more important compared to having an accurate mechanism to discriminate between different types of losses. For a link adaptation scheme to be effective, actions taken when losses occur need to be holistic rather than being solely dependant on the exact cause of loss.

3.6 Discussion

In this chapter, we have examined the impact of loss differentiation on the performance of link adaptation in 802.11 infrastructure WLANs, focusing on adaptation of transmission bit-rate and contention window. While loss differentiation can be helpful, it is also a difficult problem given the limited feedback available to the sender in 802.11 networks. Motivated by this observation, we have developed a novel link adaptation scheme called *Themis* that does not rely on loss differentiation but still is able to outperform schemes that do, especially in high contention scenarios. Moreover, our work shows that not knowing the exact cause of loss is not an impediment to effective link adaptation. Approximately knowing the cause of loss or even just the distribution of losses is sufficient. Actions taken in response to losses are, however, more crucial and they ought to be holistic and not solely dependant on the exact cause of loss. In this chapter, we have limited our attention to legacy infrastructure-based 802.11 WLANs.

It remains to be examined if such a holistic adaptation approach can be even more effective in the IEEE 802.11n case, since there are even more parameters to consider. In the next chapter we investigate and characterise the most crucial of the newly introduced 802.11n features to find the appropriate way to efficiently adapt them.

Chapter 4

Characterization of 802.11n Wireless LAN Performance

4.1 Introduction

As discussed in section 2.1, the IEEE 802.11n standard [6] is a high performance successor to the legacy 802.11a/b/g standards. However, multiple new features were introduced by 802.11n in order to boost throughput performance, increasing the complexity of a link adaptation scheme for the specific standard. As Table 2.2 shows, there are 64 different parameter setting combinations for a link from a PHY perspective (16 MCS indices, 2 channel widths and 2 guard intervals). Combined with the simplest MAC layer setting of whether or not to enable frame aggregation, we have 128 possible configurations to choose from to optimise the performance of a link.

The key to designing a comprehensive solution for the 802.11n link adaptation problem is an understanding of the impact of different 802.11n features on performance in different link scenarios as well as interdependencies among those features. *Gaining that understanding is the aim of this chapter.* Briefly, our methodology to address this goal is as follows. Using an indoor 802.11n wireless LAN testbed, we experimentally measure link performance with respect to different metrics (including throughput and packet loss) when using different settings for 802.11n features and under a wide range of link scenarios, both for UDP and TCP traffic. To gain insight from the large number of measurements so collected and to understand the relative impact of different 802.11n features on WLAN performance, we use regression analysis. Specifically, we use categorical regression [63] since 802.11n features are better viewed as categorical (nominal) variables. For understanding the interdependencies among various 802.11n features in different scenarios, we use the response surface methodology (RSM) [66] and multiple linear regression. All statistical techniques and the testbed setup are more analytically discussed in section 2.3.

Key findings of our study are:

- Regression based analysis is valuable in easing the characterisation of the impact of different features on performance.

- The relative impact of different 802.11n features on performance (throughput, packet loss and fairness) is scenario dependent. For example, SDM is beneficial in terms of throughput only for high quality links and even that reduces in presence of adjacent channel interference (ACI), whereas channel bonding has a greater impact in scenarios with ACI.

- We find that different features are interdependent with respect to throughput and the nature of interdependence varies between scenarios. For instance, there is lesser degree of interdependence with poor quality links and in presence of interference because fewer set of features have the majority of the impact on throughput.

- We quantify the benefit of adapting multiple 802.11n features using testbed measurements that span a diverse set of scenarios differing in channel and interference conditions. We find that it is indeed crucial to adapt all features to obtain the best throughput. For example, adapting any three of the four key 802.11n features (MIMO mode, channel bonding, MCS, frame aggregation) would yield on average about 60-65% of the throughput achievable when considering all features, and adapting any one feature results in about 30% of the maximum achievable throughput. We also characterise the interactions between different features in maximising the throughput. Here we observe that all features and their interactions together determine the throughput, and this is true for all interference scenarios. We also observe that the effect of interaction among different features is more pronounced for higher quality links.

Our work improves upon earlier experimental studies of 802.11n networks [14, 15, 16, 17, 18, 19, 21] in two respects: (1) It is comprehensive in the set of features, metrics and range of scenarios considered. Table 2.6 captures the focus of previous work. (2) In terms of the underlying goal — to capture important 802.11n features for performance optimization in different link scenarios and their mutual interaction.

The rest of this chapter is structured as follows. In the next section, we describe the various elements of our methodology to perform the characterisation study as stated above. Section 4.3 presents our performance characterisation results and section 4.5 discusses interactions among 802.11n features. Finally, we conclude this chapter in section 4.6.

4.2 Methodology

Our overall goal in this chapter is to characterise the interaction between 802.11n features (frame aggregation, SDM vs. STBC, channel bonding, etc.) and their relative impact on link/WLAN performance across a wide range of scenarios, differing in channel and interference conditions. In this section, we describe the various elements of our methodology.

4.2.1 Indoor 802.11n Wireless LAN Testbed

In order to do the aforementioned characterisation experimentally, we have deployed a 802.11n wireless LAN testbed in the Informatics Forum building at the University of Edinburgh. The testbed consists of 8 nodes in total of which 6 form an infrastructure 802.11n WLAN with one access point and 5 stations. Fig. 4.1 shows the locations of these 6 nodes on the building floor plan. The placement of these nodes was done to realize diverse set of link qualities as reported in the next section. The other 2 testbed nodes are setup to be another co-located 802.11n WLAN to realize different interference conditions.

Each node in our testbed is actually a combination of a laptop and an embedded router board. The laptop is equipped with Centrino Duo 1.66GHz processor, 1GB RAM and Gigabit Ethernet interface and is setup to run Ubuntu 10.04 OS with Linux kernel version 2.6.32. The router board is a Ubiquiti RouterStation Pro [75] with 680MHz CPU, 128MB memory and 4 Gigabit Ethernet interfaces. The board hosts an 802.11n wireless interface card, specifically the MikroTik R52Hn 2x2 MIMO miniPCI card with an Atheros AR9220 chipset [76]. The miniPCI card on the board is connected to two dual band omnidirectional antennas. The laptop and router board of each node are connected through their Gigabit Ethernet interfaces and bridged via the Wireless Distribution System (WDS). We use

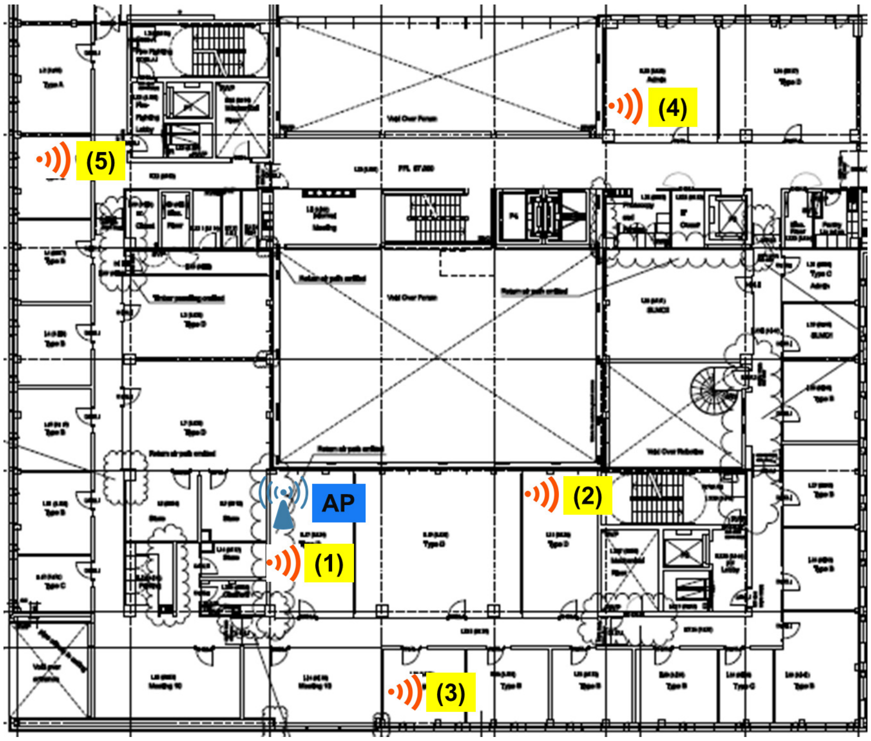


Figure 4.1: Physical layout of nodes in the 802.11n WLAN testbed — the blue coloured node is the access point and red ones numbered (1)-(5) are stations.

this particular setup with the laptop acting as the traffic source/sink because we found the link throughput to be limited by CPU on the board when it is used as a traffic source/sink and at the same time operates at 802.11n top speeds. Note that this platform bottleneck issue has been reported previously in the literature [77]. Fig. 4.2 shows a picture of our testbed node. On the board, we use the open-source ath9k driver [24].

4.2.2 802.11n Settings

We consider almost all 802.11n features — frame aggregation (FA), MIMO (SDM/STBC), channel bonding (ChB) and all available modulation and coding schemes (MCS). The only exception is the short guard interval (SGI), which is only supported for 40MHz channels in the AR9220 chipsets. We disabled SGI in our experiments for consistency. Note that we consider the effect of enabling STBC for MCS indices

Figure 4.2: Picture of a node in our 802.11n WLAN testbed.

0-7 shown in Table 2.2 while MCS indices 8-15 in Table 2.2 always refer to the use of SDM. Similar approach was also taken in [18]. In order to separately see the impact of using SDM/STBC from the use of different modulation and coding rates, we use the term MCS in the majority of this chapter to only refer to the use of the eight modulation and coding rates shown in Table 2.2 and number them 0 – 7. The use of SDM or STBC features is explicitly shown separately.

To determine the channels of operation for our experiments, we surveyed the testbed area using the WiSpy spectrum analyser [78] to look for unused channels in both 2.4GHz and 5GHz bands since 802.11n can use either. We found that only channels 149 – 161 in the 5GHz band were free of any activity at all times, so decided to use only those channels for our experiments. Also, unless specified otherwise, the transmit power for 802.11n cards is at the default setting (25dBm).

For traffic generation, we use iperf [30] UDP and TCP traffic sessions between access point and one or more client stations. Packet size is fixed at iperf default value, which is 1500 bytes. Every experiment reported in this chapter is repeated multiple times and the average value across those multiple experiment runs is taken as the measurement result.

4.2.3 Performance Metrics

We consider four metrics to quantify 802.11n link/WLAN performance in UDP and TCP traffic scenarios. In the case of UDP we consider throughput and packet loss. Throughput of a link a running iperf UDP session is measured at the server

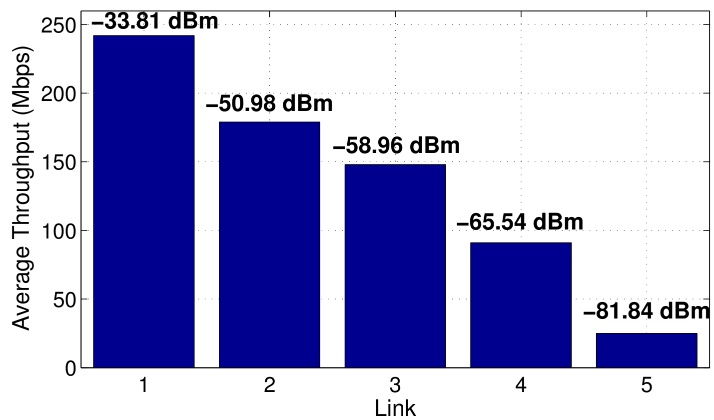


Figure 4.3: RSSI and throughput variation across links in the testbed for a specific setting of values for 802.11n features.

(receiver) side. Aggregate throughput is used as the measure when multiple links in the WLAN are concurrently active. Packet (frame) loss is computed using MAC layer statistics at the sender side. Specifically, packet loss is measured as the difference between frames sent and successfully transmitted frames as a percentage of the frames sent. As far as the TCP case is concerned, we similarly measure TCP throughput for our study.

4.3 Performance Characterisation Results

4.3.1 Baseline Results

We begin our characterisation study by verifying that links in our testbed have diverse link qualities, thus allowing us to experiment over a whole spectrum of channel conditions. For this we pick a particular configuration of values of 802.11n features for every link: frame aggregation, channel bonding and double streams (i.e., SDM) are enabled, and the default rate adaptation algorithm with Atheros ath9k driver (Minstrel HT) is used. Note that the Minstrel HT algorithm chooses between all 16 MCS values shown in Table 2.2 and also adapts the aggregated frame length size via a hardcoded table depending on the chosen MCS value.

We measure the average RSSI and throughput of different links, one at a time and in the absence of any interference. Results are shown in Fig. 4.3, which confirm that our node placement results in sufficiently different link qualities and

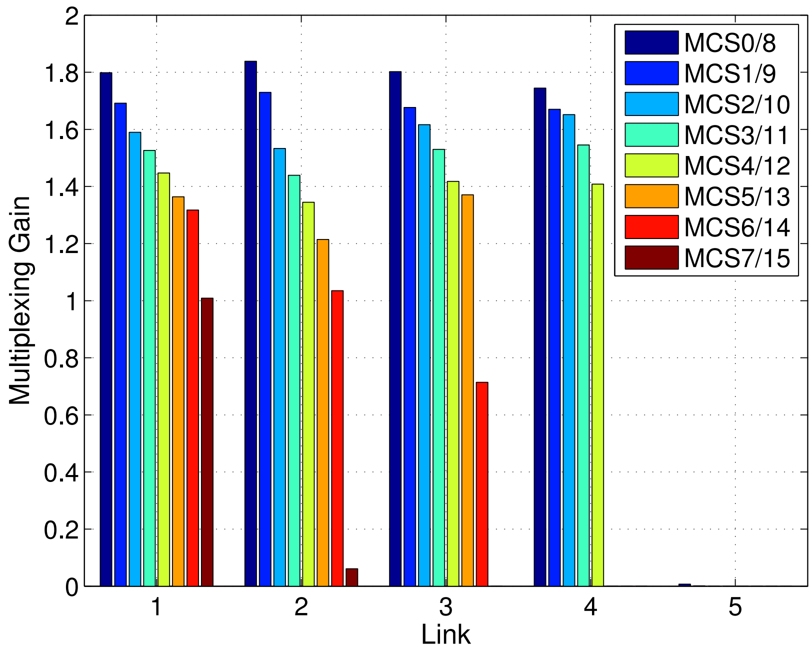


Figure 4.4: Spatial multiplexing gain across different links and MCSs. Multiplexing gain varies across modulation and code for each location and is not always equal to number of streams

throughputs across links. Our long-term RSSI measurements for these links over several days additionally show that RSSI variation for each of these links remains within a few dB of the values shown in Fig. 4.3 even during day times when there is human mobility in the environment.

We now characterise the multipath environment in the testbed area and the opportunity available for spatial multiplexing by measuring the multiplexing gain for different MCS indexes and links. We know that there is the transmission diversity (i.e., use of CSI, STBC) gain and the multiplexing (i.e., SDM) gain. Zheng et al. make a conclusion in [79] saying that "the diversity-multiplexing tradeoff achievable by a scheme is a more fundamental measure of its performance than just its maximal diversity gain or its maximal multiplexing gain alone". For this experiment, we disable frame aggregation, channel bonding, STBC and the automatic rate adaptation algorithm. Similar approach was also taken in [19]. Spatial multiplexing gain (G) is defined as:

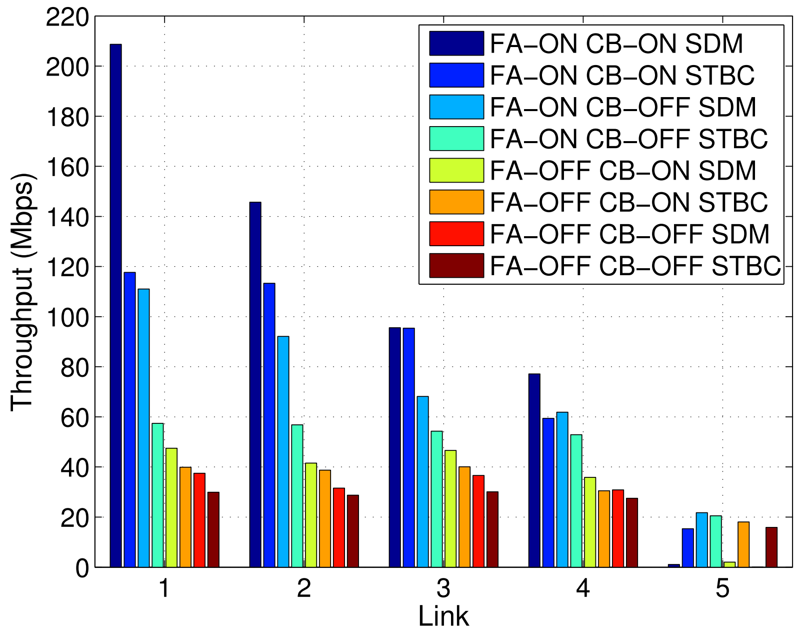


Figure 4.5: Impact of frame aggregation, channel bonding and STBC/SDM on throughput with the maximum rate possible in use.

$$G(s, m, c) = \frac{Throughput(s, m, c)}{Throughput(1, m, c)} \tag{4.1}$$

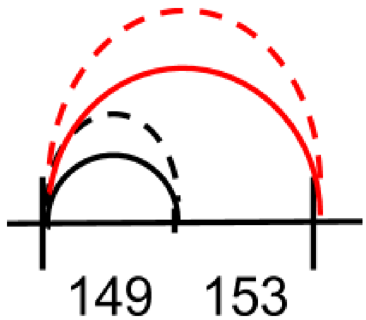
where s is the number of streams (in our scenario maximum 2), m is the modulation and c is the code rate. Results shown in Fig. 4.4 are along expected lines, and multiplexing gain drops with worsening link quality and increasing modulation and coding rates. We see that there is no multiplexing gain between STBC and SDM for certain MCS and certain links (specifically MCS7/15 on link 1). This is because without any frame aggregation or channel bonding (that are disabled for this experiment) the link already reaches the maximum capacity (approximately 30Mbps) even with one stream, so adding a second one cannot add to the throughput performance.

Having done the confirmatory experiments focusing on link qualities and the environment, we now begin to look at the impact of other settings for 802.11n features considering one link at a time with no interference. Since 3 features (frame aggregation, channel bonding and STBC) are considered each having two possible values (on/off), we have 8 possible configurations per link and 40 different configurations across all 5 links in the testbed. Results shown in Fig. 4.5 let us make certain observations such as frame aggregation is beneficial always regardless of link quality and channel bonding and SDM are helpful except when link quality is poor. However, if we also introduce a new variable (i.e., MCS (0-7)) as discussed in the previous section, which in turn has the effect of increasing the overall number of configurations to analyse by 8-fold to 320 across all links. Note that this increase in possibilities is without having any interference in the scenarios. Adding interference effects would further increase the possibilities by several fold, which motivates the need for an analysis approach that aids in easily understanding the impact of different features without the tedium of manually going through all possibilities.

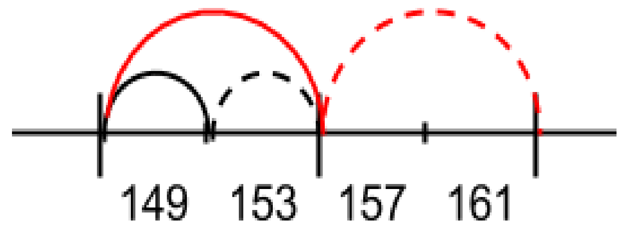
Led by this discussion, we consider regression analysis as an effective approach to ease the characterisation of the relative impact of different 802.11n features on performance in different scenarios. Given that the features under consideration are all categorical — nominal to be specific (e.g., frame aggregation ON or OFF) — categorical regression [63] is the most appropriate statistical analysis method for the problem at hand. See section 2.3.1 for a brief overview of categorical regression. For the regression based analysis, presented next, we use the widely used statistical analysis tool IBM SPSS which implements categorical regression in the function named CATREG.

4.3.2 Interference Scenarios

In this section, we can expand the number of scenarios by including various interference effects, since we can still analyze a large number of scenarios with the aid of categorical regression. Specifically, we consider co-channel interference (CCI) and adjacent channel interference (ACI) conditions besides the no interference case that was the sole focus so far. We explore the same types of interference with a legacy (802.11a) interfering link creating co-channel legacy interference (CCLI) and adjacent channel legacy interference (ACLI), too. This will effectively increase the number of scenarios being considered to 25 (5 types of interference $\times$ 5 different link qualities). To realise the effects of interference we make use of 2 additional nodes mentioned in section 4.2 to create an interfering link belonging to a co-located 802.11n WLAN with a single station. To capture the worst case of interference effects, we place the interfering link in close proximity (< 3 meters) to the access point shown in Fig. 4.1, effectively making every link under test in the testbed to experience strong interference. To create CCI, we use same channel



(a) CCI



(b) ACI

Figure 4.6: Illustration of co-channel (CCI) and adjacent channel (ACI) interference scenarios. Solid line represents the link under test while the dashed line corresponds to the interfering link. Black (red) coloured lines indicate the use of 20MHz (40MHz) channels.

(149) for both the link under test (which can be one of the links between access point and stations (1)-(5) in Fig. 4.1) and the interfering link. To generate ACI, we assign adjacent channels to the link under test and the interfering link (channels 149 and 153, respectively when channel bonding is disabled and channels 149 and 157 otherwise, as shown in Fig. 4.6). Similar measurement setup to create interference effects was used in [18]. We conduct the experiments during the night to avoid human mobility related experimental noise. Moreover, for the interference cases, we focus on TCP throughput and UDP throughput and packet loss results for the link under test.

Note that we also initially experimented with partially overlapping adjacent channels (i.e., in the case of a link in 40MHz channel, only half of it (20MHz) would overlap with another link). However, the different attributes of the primary (first 20MHz) and secondary (second 20MHz) channel of the bonded channel, made this study inconsistent and dependant on the channels selected to experiment with. For example, according to the first draft of the 802.11n amendment, a 20/40 MHz station could disregard any traffic on channels overlapping the secondary channel when transmitting. Therefore, we do not present those results analytically in this work.

4.3.3 TCP and UDP Performance

Results from applying categorical regression on UDP throughput and packet loss with respect to various 802.11n features (frame aggregation, etc.) for each of the 25 scenarios independently is shown in Fig. 4.7. The same results for TCP throughput performance are shown in Fig. 4.8. Note that we use the metric of Pratt's importance measure (see section 2.3.1) for natural interpretation of relative impact of various features. Moreover, we normalise these values so that they are comparable, and use the coefficients provided to realise the positive or negative impact of each feature in every scenario, in red and blue colour, respectively.

To associate confidence in the different regression models and verify their validity, we need to examine their significance levels, which need to be < 0.05 to be valid (as discussed earlier in section 2.3.1). Significance levels for all UDP throughput and packet loss regression models are shown in Tables 4.1 and Table 4.2, respectively, and for TCP throughput in Table 4.3. Note that significance levels for all models across both metrics satisfy the validity criterion. We have also manually verified this via detailed inspection of raw measurement results.

Frame Aggregation Impact

Frame aggregation is overall effective to be enabled in terms of both UDP (Fig. 4.7(a)) and TCP throughput (Fig. 4.8). It is quite surprising that even for poor link qualities (i.e., links 4 and 5) it does not have a negative impact as one would intuitively expect. However, the fact that frame aggregation has no significant impact in poor quality links — green colour in heat map — can be explained by the lower number of aggregated frames consisting each packet in case of a low MCS index based on the default ath9k driver. The driver allows higher number of subframes for higher MCS index; so since only low MCS values can be supported by poor quality links then only very few (i.e., 1-3) subframes will be aggregated. This means that enabling or disabling the frame aggregation in those cases would not significantly affect network performance.

UDP packet loss results, though, are more interesting (Fig. 4.7(b)). They show that the impact of frame aggregation is almost negligible, because of the linear increase of subframes number in higher MCS indexes. However, it has a high negative impact in case of good links and only legacy interference. This could be explained by the signal propagation being better in the 802.11n case rather than legacy, resulting in less hidden nodes and increasing the channel assessment (CCA) preventing simultaneous transmissions.

	Link 1	**Link 2**	**Link 3**	**Link 4**	**Link 5**
NI	0	0	0	0	0
CCI	0	$5 * 10^{-15}$	0	0	0
CCLI	0	0	$9 * 10^{-14}$	0.006	0
ACI	0	$2 * 10^{-10}$	0	$5 * 10^{-9}$	0
ACLI	0	0	$3 * 10^{-16}$	0	0

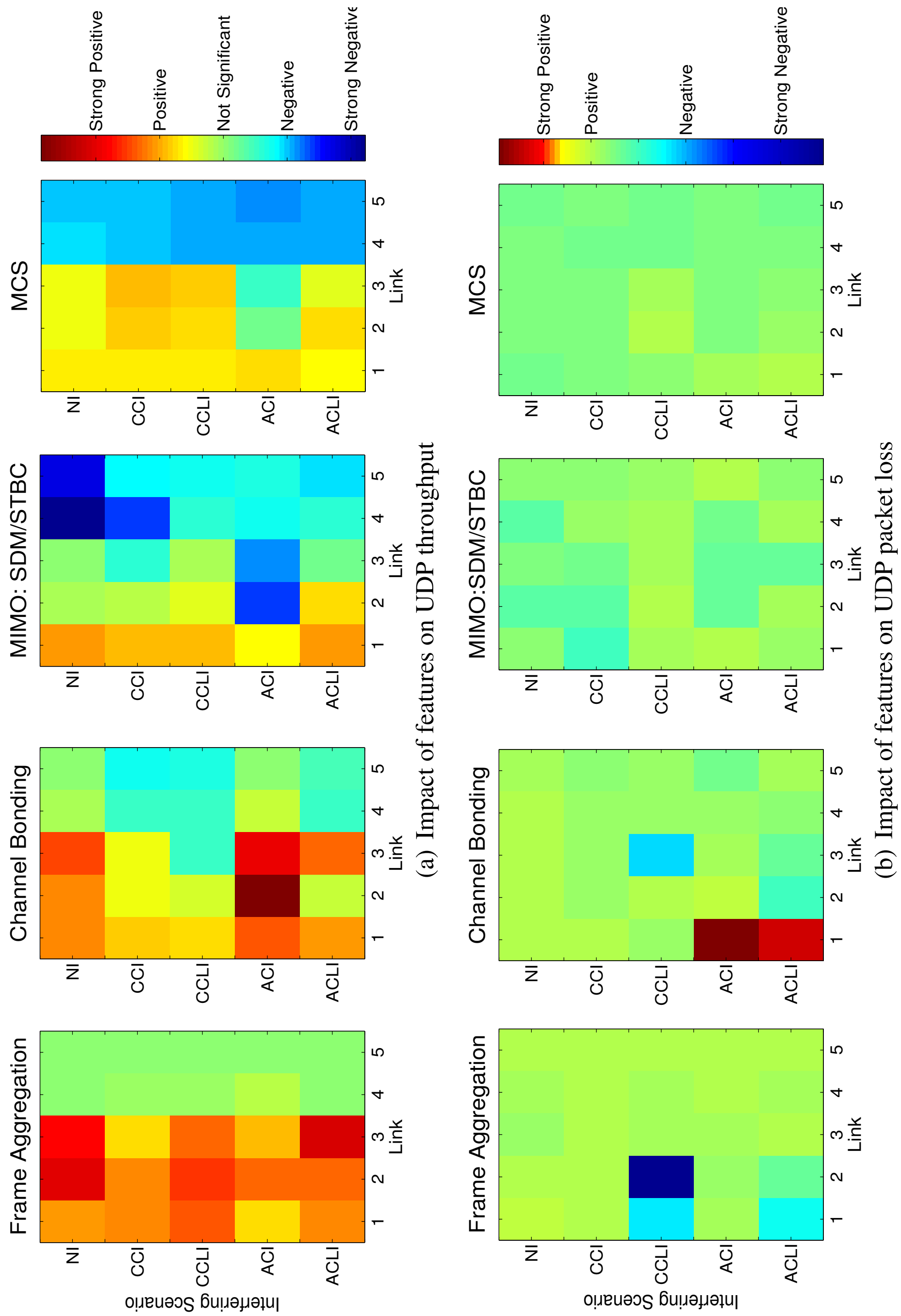
Table 4.1: Significance of UDP throughput categorical regression model for each of the scenarios.

	Link 1	**Link 2**	**Link 3**	**Link 4**	**Link 5**
NI	0	0	0	0	0
CCI	0	$8 * 10^{-11}$	0	0	0
CCLI	0	0	0	0	0
ACI	0	0	0	0	$2 * 10^{-9}$
ACLI	0	0	0	0	0

Table 4.2: Significance of UDP packet loss categorical regression model for each of the scenarios.

	Link 1	**Link 2**	**Link 3**	**Link 4**	**Link 5**
NI	0	0	0	0	0
CCI	0	0	0	0	0
CCLI	0	0	0	0	0
ACI	0	$7 * 10^{-13}$	0	0	0
ACLI	0	0	0	0	0

Table 4.3: Significance of TCP throughput categorical regression model for each of the scenarios.



(a) Impact of features on UDP throughput

(b) Impact of features on UDP packet loss

Figure 4.7: Relative impact of 802.11n features on UDP throughput and UDP packet loss performance in terms of normalised Pratt's importance measure (section 2.3.1) in different scenarios. Red, green and blue colours indicate positive, no and negative impact of the specific feature on the performance on a given link scenario, respectively.

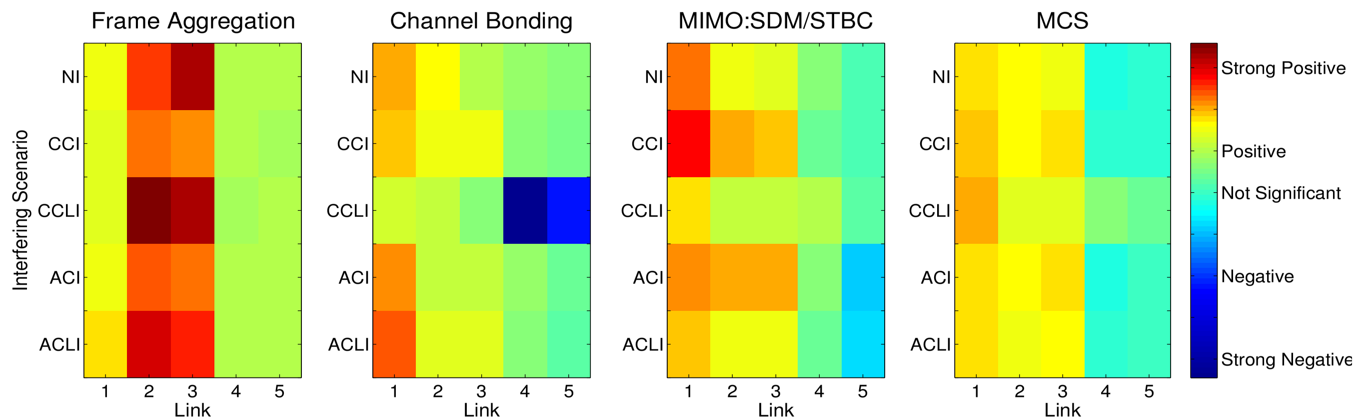


Figure 4.8: Relative impact of 802.11n features on TCP throughput in terms of normalised Pratt's importance measure (section 2.3.1) in different scenarios. Red, green and blue colours indicate positive, no and negative impact of the specific feature on the performance on a given link scenario, respectively.

Channel Bonding Impact

In terms of both UDP and TCP throughput, results show that enabling channel bonding is less effective for poor quality links. A 40MHz bonded channel has more subcarriers compared to the sum of subcarriers of two separate 20MHz channels. Therefore, transmitting over a wider channel reduces per-subcarrier transmit power, decreasing the performance of poor quality links. This phenomenon has also been observed in [17, 18]. Moreover, previous works [15, 17] have mentioned that TCP exponential backoff mechanism may degrade the throughput compared to UDP traffic. Arslan et al. [17] also mention that about 30% of the TCP experiments yield better performance without channel bonding as compared to only 10% with UDP. They attribute that to TCP being more sensitive to packet loss. However, our results show that this is not generally true, since channel bonding has mostly a negative impact on poor links in the UDP traffic case rather than in the TCP.

In presence of ACI, we observe that the importance of channel bonding in UDP relatively grows, especially for the best quality link (link 1) for packet loss (Fig. 4.7(b)). This is because CCA detects the interfering link, due to its high power and close proximity to link 1. Therefore, collisions are prevented and packet loss decreases, increasing the positive impact of channel bonding only on link 1. This is because the lower transmission power per sub-carrier limits the range of the interfering link, making all other links (i.e., 2-5) hidden nodes.

MIMO (SDM/STBC) Impact

MIMO settings have quite a different impact on UDP and TCP throughput. This is because of the different nature of UDP and TCP. TCP provides extensive error checking mechanisms such as flow control and acknowledgment of data. On the other hand, UDP only has the basic error checking mechanism using checksums. This means that TCP resends any packet that might get lost, resulting in eventually fewer packets being lost, but lower throughput performance compared to UDP. Therefore, STBC is expected to play a more important role in improving throughput performance in the case of UDP rather than TCP, since more errors may happen and hence be recovered in the case of UDP. In this way the SDM impact is stronger positive in TCP than the case of UDP throughput, since more corrected data is received. Moreover, STBC is less significant for TCP rather than UDP, since the error checking mechanisms are recovering errors anyway, limiting the impact of STBC.

Overall, the benefit of SDM (which in our case is equivalent to using double streams) is limited to only good quality links. This can be explained by the fact that transmission power is equally divided between the different antennas. With two antennas, this means power is effectively halved (reduction by 3dBm). Effective reduction of transmission power for each stream makes SDM more vulnerable when link quality is marginal. STBC is relatively more robust for marginal to poor quality links due to the redundancy it injects into a single stream. This also explains the marginal beneficial effect of STBC over SDM on packet loss (Fig. 4.7(b)). This phenomenon shows that STBC can recover frames lost due to poor link quality but it can recover less frames in presence of interference.

MCS Impact

From a throughput perspective, MCS is an overall significant factor but its impact becomes negative with worsening link quality suggesting a lowering of modulation and coding rate especially in the case of UDP traffic (Fig. 4.7(a)). The latter is expected as higher modulation/coding rates require higher SNR which is not true for poor quality links. In the presence of ACI, the effect of MCS becomes negative quickly with worsening link qualities because transmission activity from the interfering link in the adjacent channel increases the noise floor and reduces the SNR, making the lowered modulation and coding rate to be more effective, due to high channel leackage. Similar behaviour is noticed for TCP traffic (Fig. 4.8) as well. However, poor links are not affected as negatively as in UDP traffic. Again this can be explained by the extensive error checking mechanisms provided by TCP, as discussed before. UDP packet loss results in Fig. 4.7(b) show that higher MCS has a slightly negative impact — dark green colour. This means that lower MCS indices can reduce packet loss in almost all scenarios (combinations of interference types and link qualities) since lower modulation and coding rate increases link robustness.

4.4 Benefit of Adapting Multiple 802.11n Features

Several 802.11n link adaptation schemes focus on a subset of features (e.g., [15, 59, 18]). For example, MiRA [15] and ORS [59] do not consider channel bonding, whereas this was the only focus of [18]. To quantify the importance of holistic link adaptation, we first examine the benefit of adapting all features relative to cases when only a subset of features are considered. Towards this end, we obtain

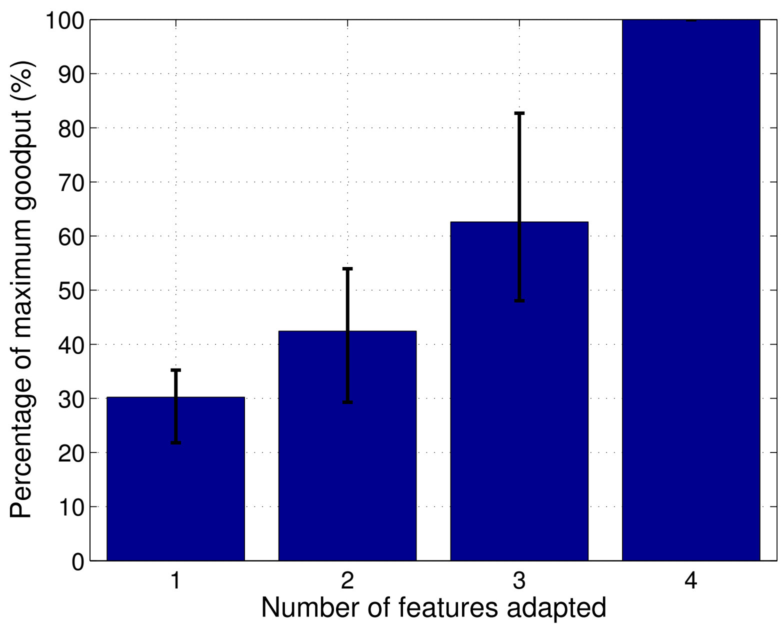


Figure 4.9: Percentage of maximum throughput obtained from adapting any 1, 2, 3 and all 4 features of FA, MIMO, CB and MCS. While the individual bars show the average gain in each case, the error bars indicate the minimum and maximum gain of each case.

goodput measurements using our testbed for each different possible feature setting combination and every link type and interference scenario. Then we have a tuple $[FA, CB, MIMO, MCS, GP]$ for each link type and interference scenario, where FA to MCS are the four different features we examine in this work and GP the goodput given by each specific combination experimentally. Moreover, using this extensive dataset, we identify the feature setting combination that yields the maximum goodput in each link and interference scenario; we use the notation $maxGP_{ij}$ to refer to the maximum goodput with link type i and interference scenario j.

We now assess the drop in goodput from adapting fewer than all available features. In case only one feature x is adapted out of the four examined in this study, we find the average goodput of $x1_{ij} = [1, :, :, :]$ and $x0_{ij} = [0, :, :, :]$, when x is enabled and disabled, respectively, averaged across all possible settings of other features. Then we compute the gain of feature x, $gain(x_{ij}) = (maxGP_{ij} -$

$max(x1_{ij}, x0_{ij}))/maxGP_{ij}$. This way we compute the gain for each of $k = 4$ features individually and then we average across all of them and across all link i and interference j scenarios as $avgGain = (\sum_{n=1}^{k} gain(x_{nij}))/k$. This is the result we report for adapting just one feature. Similarly, we repeat this process for when two, three or all four available features are simultaneously adapted.

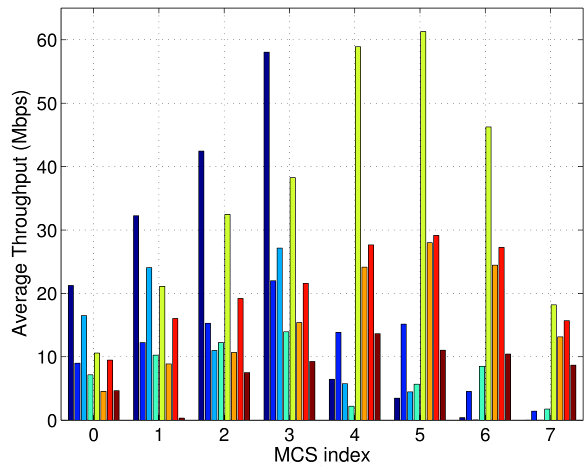
Results are shown in Fig. 4.9. Clearly, considering all 4 features gives 100% of the maximum throughput. We can observe that considering any 3 features as opposed to all 4 yields only around 60% of the maximum throughput, on average. This drops to around 40% when any 2 features are adapted and to 30% when only any 1 of the features is adapted. These results demonstrate that it is vital to adapt all available features to achieve maximum throughput performance.

4.5 Interaction among 802.11n Features

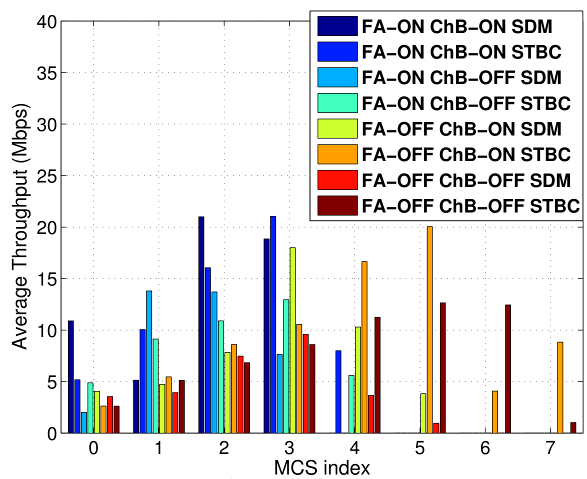
In this section, we use the response surface methodology and multiple linear regression techniques, to examine the possible interaction among different features of 802.11n protocol. Before that, though, we try to verify the existence of interaction among different features for optimising throughput or packet loss metrics, empirically, by revisiting the UDP throughput categorical regression results from section 4.3.3 and interpreting the importance values of each feature independently to choose an appropriate setting for that feature. For example, for ACI – Link 2 scenario, looking at Fig. 4.7(a), we could take the importance values to imply choosing the features as follows: frame aggregation, channel bonding and STBC enabled, and a low to moderate MCS index. However, raw measurement results for this scenario shown in Fig. 4.10(a) suggest a different setting of features for obtaining optimal throughput: frame aggregation OFF, channel bonding ON, SDM and reasonably high MCS value. As another example, consider CCI - Link 4 scenario from Fig. 4.7(a) and the corresponding raw measurement results showing the optimal configuration (Fig. 4.10(b)). Both these examples reinforce the fact that there exists potential interdependence among various features that prevents them to be treated in isolation when we aim to optimise performance.

4.5.1 Response Surface Methodology

The first way we try to quantify the interdependence among features with is by using the phase of the response surface methodology (RSM) as described in section 2.3.2 to identify significant pairwise interactions among 802.11n features given



(a) ACI link 2



(b) CCI link 4

Figure 4.10: Example scenarios for throughput suggesting interdependence among features.

a link scenario. Tables 4.4 and 4.5 summarise pairwise interactions found to be statistically significant after examination of the ANOVA table resulting from applying RSM in UDP and TCP throughput performance, respectively. These tables confirm that there is interdependence among features in every scenario, indicating features that must be jointly selected. From a practical viewpoint, results in Tables 4.4 and 4.5 suggest that for good quality links all features need to be se-

	NI	CCI	CCLI	ACI	ACLI
Link 1	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS
Link 2	FA-CB MIMO-MCS FA-MCS	FA-CB CB-MIMO MIMO-MCS FA-MCS	CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS MIMO-MCS	CB-MIMO CB-MCS FA-MIMO FA-MCS
Link 3	FA-CB MIMO-MCS	MIMO-MCS	CB-MIMO CB-MCS MIMO-MCS FA-MCS	CB-MIMO MIMO-MCS	FA-CB CB-MIMO MIMO-MCS FA-MCS
Link 4	CB-MCS MIMO-MCS FA-MCS	MIMO-MCS	CB-MIMO	MIMO-MCS	CB-MIMO CB-MCS FA-MIMO MIMO-MCS
Link 5	FA-CB FA-MIMO MIMO-MCS	MIMO-MCS	CB-MCS MIMO-MCS FA-MCS	MIMO-MCS	CB-MIMO CB-MCS MIMO-MCS

Table 4.4: Pairwise interdependence among 802.11n features in different scenarios (UDP throughput) derived via response surface methodology (RSM).

lected together, whereas for marginal to poor quality links and in the presence of interference it is sufficient to consider interaction between only a subset of the features. This observation is consistent with regression results in Figs. 4.7(a) and 4.8 showing that few features have the majority of the impact in poor quality links.

4.5.2 Multiple Linear Regression

In the previous section, RSM was used to identify significant pairwise interactions among 802.11n features given a link scenario. However, RSM only examines the pairwise feature combinations. Therefore, we use Multiple Linear Regression (see section 2.3.3) to characterise the interactions among different features in maximizing throughput, based on the regression coefficients. Our study takes four features into consideration, so we have the following model:

	NI	CCI	CCLI	ACI	ACLI
Link 1	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS FA-MCS
Link 2	FA-CB FA-MIMO MIMO-MCS FA-MCS	FA-CB MIMO-MCS FA-MCS	FA-CB CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS MIMO-MCS FA-MCS	FA-CB CB-MCS FA-MIMO MIMO-MCS FA-MCS
Link 3	CB-MIMO CB-MCS MIMO-MCS FA-MCS	FA-CB MIMO-MCS FA-MCS	CB-MCS FA-MIMO MIMO-MCS	MIMO-MCS FA-MCS	FA-CB CB-MCS FA-MIMO MIMO-MCS FA-MCS
Link 4	CB-MCS FA-MIMO MIMO-MCS FA-MCS	FA-CB CB-MIMO CB-MCS FA-MIMO MIMO-MCS	CB-MCS FA-MIMO MIMO-MCS	MIMO-MCS	FA-CB CB-MCS FA-MIMO MIMO-MCS FA-MCS
Link 5	CB-MCS MIMO-MCS	CB-MCS MIMO-MCS FA-MCS	FA-MIMO MIMO-MCS	CB-MIMO CB-MCS	CB-MCS MIMO-MCS

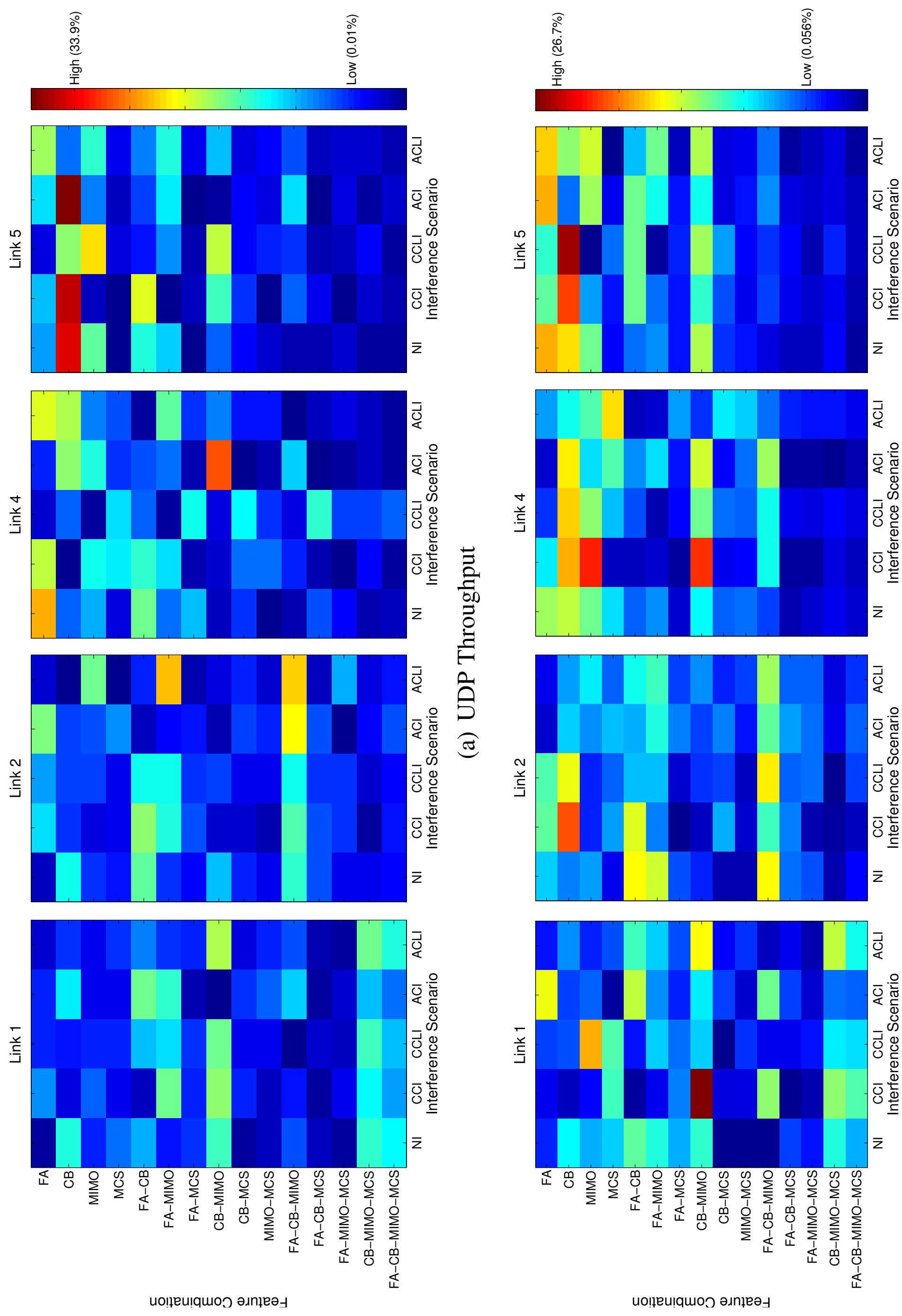
Table 4.5: Pairwise interdependence among 802.11n features in different scenarios (TCP throughput) derived via response surface methodology (RSM).

$$\begin{aligned} y \;=\; & \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \beta_4 \cdot x_4 + \\ & \beta_5 \cdot x_1 x_2 + \beta_6 \cdot x_1 x_3 + \beta_7 \cdot x_1 x_4 + \beta_8 \cdot x_2 x_3 + \\ & \beta_9 \cdot x_2 x_4 + \beta_{10} \cdot x_3 x_4 + \beta_{11} \cdot x_1 x_2 x_3 + \beta_{12} \cdot x_1 x_2 x_4 + \\ & \beta_{13} \cdot x_1 x_3 x_4 + \beta_{14} \cdot x_2 x_3 x_4 + \beta_{15} \cdot x_1 x_2 x_3 x_4 + \varepsilon \end{aligned}$$

where y is the throughput (the performance variable being optimized) and x_1, x_2, x_3 and x_4 represent features FA, MIMO, CB and MCS. The β_i's are the regression coefficients of different terms for individual features and their 2-, 3- and 4-way interactions, and ϵ is the error term.

Using the full/saturated ANOVA model (including all 1-way, 2-way, 3-way and 4-way interactions) and the backward elimination method as outlined in [80], we aim to eliminate any insignificant terms. However, we find that all terms are in fact statistically significant, which emphasises the importance of holistic adaptation. In order to understand the relative degree of importance of these different terms for optimising throughput, we normalise their corresponding coefficients (i.e., β_i's) to estimate the percentage of impact that each term has in determining the throughput. Fig. 4.11 shows the results as a heatmap. Colours closer to dark blue are the interactions that have very low or no impact on throughput, whereas colours closer to red have a higher impact. Note that in Fig. 4.11 we do not present results for link 3, due to presentational purposes and since its results are very similar to link 2.

Fig. 4.11 shows that there is no one specific interaction term that has the majority of impact. This is especially true for higher quality links. For example, in the case of UDP throughput and link 1 (Fig. 4.11(a)), the term with the maximum impact explains only 18% of the throughput, and this is taken across all interference scenarios. For lower quality links, the maximum impact of one term is relatively higher: 23%, 27% and 33% for links 2, 4 and 5, respectively. Similar behaviour is noticed for TCP throughput in Fig. 4.11(b). In other words, throughput is optimised through contributions from several different interaction terms, further reiterating the need for holistic adaptation. Moreover, we observe that three and four features combined have a higher impact in better quality links, whereas only single features or pairwise combinations are significant in poor quality links, regardless of the interference scenario. This suggests that adapting multiple features is more crucial for higher quality links than it is for poor quality links. The above observations also indicate that the link quality has a greater influence than the interference scenario.



(a) UDP Throughput

(b) TCP Throughput

Figure 4.11: Percentage of impact per feature combination on iperf UDP/TCP throughput based on regression coefficients. Red and blue colours indicate high and negligible impact of the specific feature combination on the performance on a given link scenario, respectively.

4.6 Discussion

In this chapter, we have experimentally studied how 802.11n features affect UDP and TCP performance and how they interact with each other across a wide range of scenarios differing in channel and interference conditions. We employed categorical regression based analysis for easing characterisation of relative impact of different features. We believe that this type of analysis should prove valuable and can be applied even to other 802.11 standards in the making (e.g., 802.11ac). We have also examined the interdependence among different 802.11n features in various link scenarios via response surface methodology and multiple linear regression. Our analysis showed that different features impact performance differently depending on the network scenario determined by channel and interference conditions; same is true about their mutual interaction. Finally, we have quantified the impact of holistic adaptation on network performance further stressing the importance of holistically adapting the link parameters. Our next step is to work on a detailed specification for a holistic 802.11n link adaptation mechanism that leverages insights from our analysis and with wider applicability (e.g., future standards – 802.11ac).

Chapter 5

SampleLite: A Hybrid Approach to 802.11n Link Adaptation

5.1 Introduction

This chapter describes the design, implementation and evaluation of a novel hybrid approach termed SampleLite. SampleLite leverages passive RSSI measurements on the sender side from potential destinations to identify a very small subset of promising feature setting combinations to sample for each link. SampleLite is a hybrid link adaptation scheme in the sense that it bears similarity to open-loop schemes (e.g., [15, 20, 21]) but makes use of channel quality information like closed-loop schemes (e.g., [22]). Moreover, it avoids the problems faced by existing schemes from either category. Unlike existing open-loop schemes, SampleLite dramatically reduces the search space to sample without risking the use of suboptimal settings. And differently from typical closed-loop schemes, it relies on channel quality information (RSSI) available at the sender side and therefore is easily implementable.

Elaborating further, we make the following key contributions in this chapter:

- We design SampleLite, a novel hybrid link adaptation scheme that adapts *all* available 802.11n features. It is driven by the insight that maximum goodput yielding setting of each of the 802.11n PHY features (MIMO mode, channel bonding and MCS) exhibit monotonicity with respect to RSSI, which in turn suggests the presence of RSSI threshold(s) that separate the regions where the best value for a feature differs. We exploit this insight to limit the feature settings that need to be sampled. Through simple analysis, we show that SampleLite reduces the sampling overhead by at least 50% compared to the widely used Minstrel HT [20] (that does random exhaustive sampling) across both 802.11n and future 802.11ac [12] WLAN scenarios. In using RSSI measurements at sender side, SampleLite exploits the channel reciprocity as in [37]. However, unlike [37], SampleLite uses RSSI only as a guide to decide what subset of feature setting combinations to sample and not for deciding the actual settings to use. We implement SampleLite as an additional 802.11n rate control algorithm in the ath9k driver [24]. (section 5.3)

- We extensively evaluate SampleLite over an indoor 802.11n WLAN testbed in comparison with two existing 802.11n link adaptation schemes, RAMAS [21] and Minstrel HT [20], and an ORACLE. Our evaluation spans a wide range of scenarios, including: controlled experiments with varying channel and interference conditions, mobility, and experiments with real-world interference from operational 802.11 access points and clients. In scenarios where the ORACLE alternative is considered, SampleLite yields goodput close to the ORACLE. Relative to Minstrel HT, SampleLite provides similar or better goodput but with about one-fourth or less sampling overhead. SampleLite significantly outperforms RAMAS with greater than 100% improvement in goodput in many cases. (section 5.4)

5.2 Testbed and Experiment Scenarios

Testbed. We take an experimental approach throughout this chapter for analysis and evaluation. For this, we use an indoor 802.11n WLAN testbed deployed in an office building on a floor spanning an area $30 \times 50m^2$ (Fig. 5.1), like in the previous chapter. We changed the testbed of the previous section. We remove station 3 from our study from this point on, since the results shown in chapter 4 for this station are very similar to station 2 in Fig. 4.1, so we consider it redundant. Moreover, we no longer use the WDS topology described in section 4.2. Instead we use only laptops to create a real-life scenario of users using their laptops. Each node in the testbed is a laptop with Intel Centrino Duo 1.66GHz processor, 1GB RAM and runs the Ubuntu 10.04 Linux OS kernel version 2.6.32. From 802.11n viewpoint, each node runs the well-known ath9k device driver, and is equipped with a 2×3 802.11n mini PCI express card with an Atheros AR9300 chipset; we however only use the 802.11n card in a 2×2 MIMO configuration throughout.

Figure 5.1: A snapshot of the 802.11n WLAN testbed layout on the floor map.

Also transmit power is the default setting of 18dBm.

	RSSI
Link Type A	[-33.5, -43.8] dBm
Link Type B	[-51.1, -60.2] dBm
Link Type C	[-64.8, -71.2] dBm
Link Type D	[-73.5, -81.1] dBm

Table 5.1: The range of average RSSI values (in dBm) for each link type in the testbed.

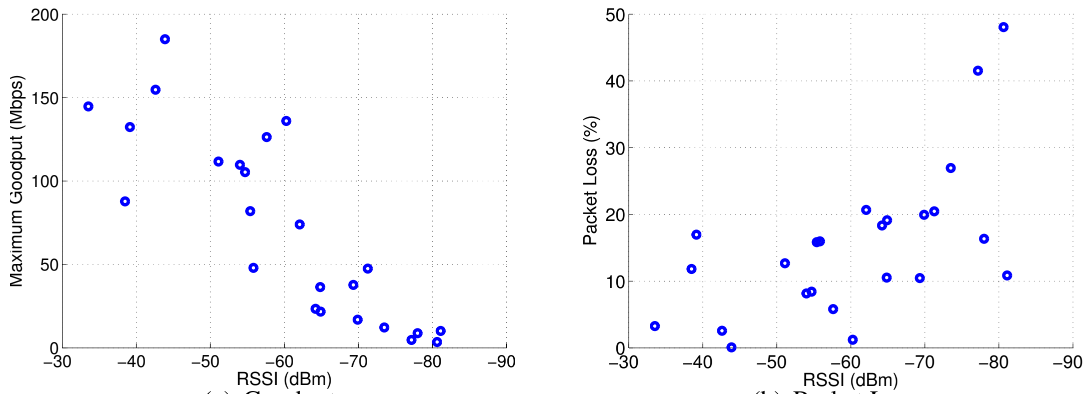
Link Types and Interference Scenarios. In order to realise a diverse set of link qualities, we experiment with several different locations for client stations while keeping the access point position fixed. A snapshot of the testbed layout on the floor map is shown in Fig. 5.1. We group the resulting links into four types based on their RSSI values as shown in Table 5.1. Using a spectrum analyser, we found that only channels 149 – 161 in the 5GHz band were free of any activity at all times in our testbed environment, so we use those set of channels for our controlled experiments. Interference scenarios we consider in our controlled experiments are same as in the previous chapter. Specifically, we consider five different interference scenarios: no interference (NI), co-channel interference (CCI), co-channel legacy interference (CCLI), adjacent channel interference (ACI) and adjacent channel legacy interference (ACLI). In all these scenarios, the interfering link consists of another access point-station pair next to the access point and station A in Fig. 5.1, and its link quality falls under the link type A (see Table 5.1). The interfering link in all our experiments uses Minstrel HT [20], which is the default link adaptation algorithm in the ath9k driver. CCI and ACI scenarios are illustrated in Fig. 4.6(a) and Fig. 4.6(b), respectively. In CCLI and ACLI scenarios, the interfering link is a legacy 802.11a link using only 20MHz channel width.

Metrics. The key performance metric we focus on is the *Goodput* (application-level throughput), which is calculated as bits delivered per unit of time without including the overheads related to protocol headers and retransmissions. We also measure sampling related probing overhead per unit of time for different link adaptation schemes. For traffic generation, we employ the commonly used Iperf tool for creating UDP traffic sessions between access point and client stations. Packet size is fixed at iperf default value, which is 1500 bytes. All our controlled experiments are conducted during late night hours to minimize experimental noise. Each data point in the results reported in this chapter is obtained from averaging across multiple runs.

802.11n features considered. We consider almost all 802.11n features available — frame aggregation (FA), MIMO mode (i.e., number of spatial streams), channel bonding (CB), and modulation and coding schemes (MCS). The only exception is again the short guard interval (SGI), which is only supported for 40MHz channels in the chipsets we use. We disabled SGI in our experiments for consistency. Table 2.2 summarises the PHY features considered in this chapter.

5.3 Hybrid Approach to 802.11n Link Adaptation

In section 4.4, we saw that adapting all key 802.11n features is essential for maximising goodput. We also saw that link quality plays an important role in determining which features and their combinations need to be adapted. From our ear-



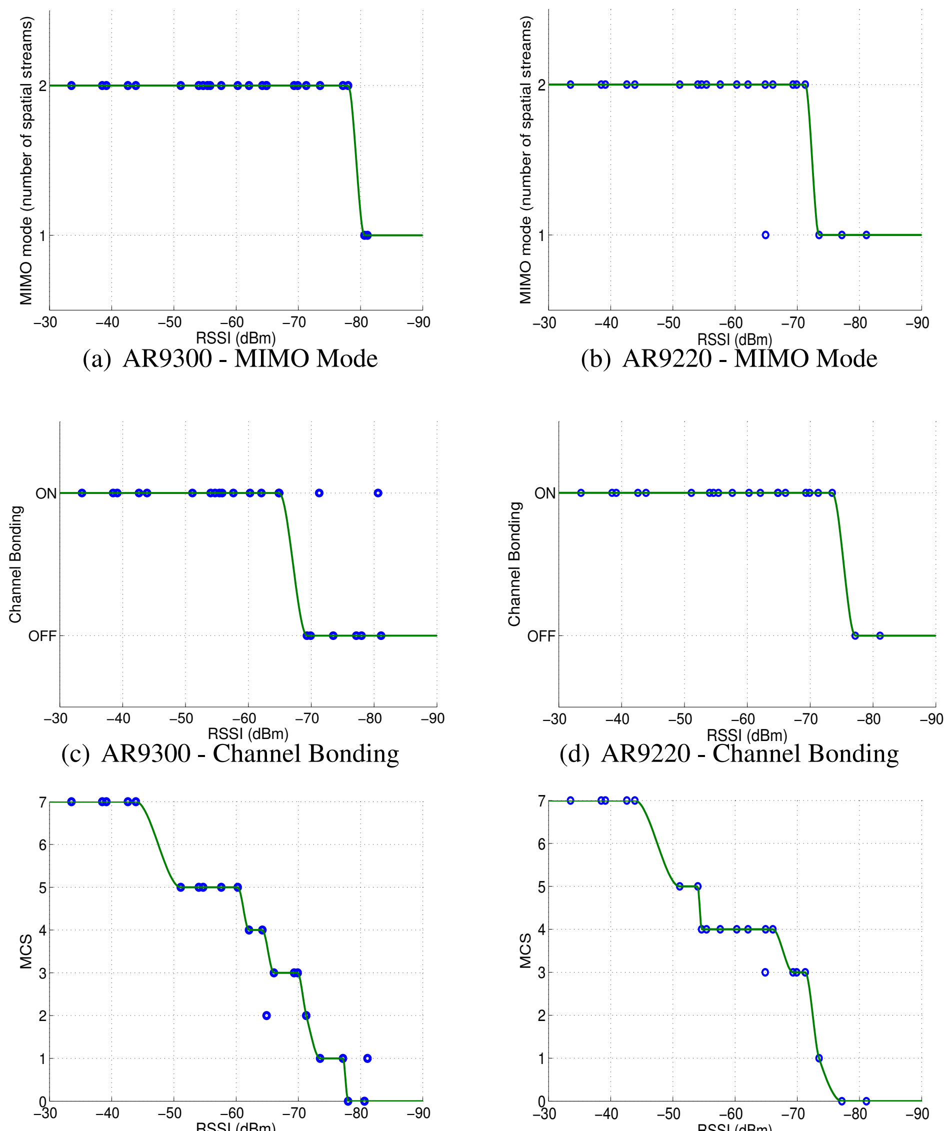
(a) Goodput (b) Packet Loss

Figure 5.2: Maximum goodput and corresponding packet loss versus average RSSI of a link.

lier discussion of existing 802.11n link adaptation schemes, we find that sampling based open-loop approaches can be inefficient while the closed-loop approaches relying on direct measurement of channel quality face practical hurdles. In this section, we propose a hybrid approach called SampleLite that combines aspects of these two approaches but avoids their limitations. We begin by detailing the key insight behind our design.

5.3.1 Key Insight

Our key insight is that the link quality as inferred by RSSI observations on the sender side can serve as a guide in significantly reducing the sampling space for open-loop schemes. While the RSSI as a channel quality indicator is simpler and easily accessible when used on the sender side, it is also shown to be an unreliable measure of packet delivery success [22, 61]. In fact, we do observe the same issue as the goodput and packet loss results in Fig. 5.2 show. Each data point in these results represents a different scenario in terms of link and interference type, and corresponds to the feature setting that gives the maximum goodput. As we can see, there is no strict monotonic relationship between RSSI and goodput or loss; meaning that we cannot derive a function of predicting the possible goodput or loss given the RSSI, due to the large spectrum that goodput/loss spans for the same RSSI. For example in the case of goodput and RSSI value of -56dBm, the various goodput measurements span from 49 to 105Mbps. For the same data,



(a) AR9300 - MIMO Mode

(b) AR9220 - MIMO Mode

(c) AR9300 - Channel Bonding

(d) AR9220 - Channel Bonding

(e) AR9300 - MCS

(f) AR9220 - MCS

Figure 5.3: Monotonic relationship between feature settings providing maximum goodput and RSSI. Each data point corresponds to a different experiment scenario in terms of link and interference type. AR9300 and AR9220 correspond to two different Atheros chipsets tested in testbeds in Fig. 5.1 and Fig. 4.1, respectively.

however, interestingly as shown in Fig. 5.3 we find that setting each feature in the maximum goodput yielding configuration shows a monotonic behaviour with respect to RSSI. We exploit this relationship between feature settings and RSSI in our approach as elaborated in the following.

Note that we do not explicitly consider the 802.11n frame aggregation feature here because we find that existing schemes like Minstrel HT [20] and RAMAS [21] already have an efficient way to adapt the frame aggregation level depending on the bit-rate as determined by the settings chosen for the underlying 802.11n PHY features (MIMO mode, channel bonding and MCS) and we could do the same. Specifically, the aforementioned schemes have a table that maps the number of subframes that an aggregated frame should have to the bit-rate — higher the bit-rate, larger the number of sub-frames[1] and thus greater the level of aggregation. This is the indeed the right strategy for adapting frame aggregation as guided by previous analytical studies (e.g., [81]).

From Fig. 5.3, we can identify reasonably clear RSSI thresholds that separate the RSSI regions where each feature should take different values to yield the maximum goodput. This suggests that we could use the current RSSI as a guide in choosing a small subset of feature setting combinations to sample and thereby drastically reduce the sampling overhead in comparison with most existing schemes that resort to exhaustive sampling. Through simple analysis, we now outline the potential savings in overhead from this idea, starting with the MIMO mode.

Fig. 5.3(a) indicates that for an average RSSI higher than -79dBm MIMO mode setting to two spatial streams should be sampled and a single stream otherwise. This reduces the sampling space for MIMO modes by 50% in the context of our 802.11n wireless cards supporting up to two spatial streams compared to commonly employed exhaustive sampling (e.g., Minstrel HT). However, the space would be reduced by 75% when up to four spatial streams can be used as specified in the 802.11n standard by requiring the sampling of only one value out of the four possible values. The impact would be even greater with the emerging 802.11ac standard [12] that supports up to 8 spatial streams, by minimising the sampling space by 87.5%.

Turning to channel bonding, Fig. 5.3(c) shows that for an average RSSI over -65dBm channel bonding enabled setting should be sampled. This means that in the case of 802.11n the sampling space for channel bonding is halved since

[1] The maximum number of subframes in an aggregated frame is however limited to 32, set by the 802.11n standard.

	802.11n	802.11ac
MIMO mode (# spatial streams)	75%	87.5%
Channel Bonding	50%	75%
MCS	62.5%	70%
Total	95.3%	99%

Table 5.2: Potential sampling overhead reduction from exploiting the monotonic relationship between best feature setting and average RSSI for 802.11n and 802.11ac cases relative to exhaustive sampling based approaches.

channel bonding (with 40MHz channels) can only be enabled or disabled. The above two observations concerning MIMO mode and channel bonding are consistent with prior work (e.g., [17, 18]) that shows that channel bonding should be disabled and single stream (or STBC) enabled for poor quality links. Continuing with sampling reduction related to channel bonding, savings will be even greater with the upcoming 802.11ac that supports more channel bonding alternatives. Specifically, with 802.11ac there are four channel width options (20, 40, 80 and 160MHz channels), so the sampling space can reduce by 75%.

Finally, Fig. 5.3(e) shows that there is high degree of monotonicity showing that a lower value of MCS should be sampled as the link quality (RSSI) decreases to achieve maximum goodput. This is also consistent with existing literature on adaptive modulation and coding (e.g., [81, 37]). We do notice outliers to this otherwise monotonic relationship, possibly due to the known challenges with using RSSI as an indicator [61]. A simple and efficient way to handle such outliers would be to sample not just the specific MCS value suggested by the average RSSI measurement but also its neighbouring ones. More generally, suppose that measured RSSI value maps to sampling the MCS value n, then for robustness, instead of just n, we could sample MCS values $\in [n-i, n, n+i]$ where i is a small number (e.g., 1, 2, 3). We experimentally determine that i = 1 works well as elaborated in the next subsection. This in turn implies sampling up to 3 MCS values. For 802.11n with 8 different MCS values, this suggests a reduction in sampling space by 62.5% and for 802.11ac with 10 different MCS alternatives savings will be up to 70%.

All the above points taken together, as few as 3 feature setting combinations need to be sampled with 802.11n from a total of 64 (8 MCS values x 2 channel bonding x 4 spatial streams), indicating a potential reduction in sampling by

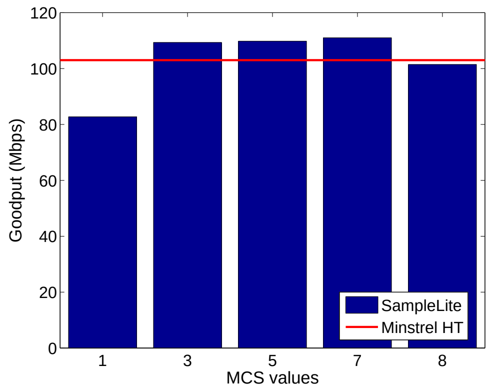
95.3% overall. The 802.11ac with 320 combinations in total (10 MCS values x 4 channel bonding options x 8 spatial streams) offers even higher potential savings by over 99% across all features. These potential savings in sampling overhead are summarised in Table 5.2. We have also experimented with a different 802.11n chipset (i.e., AR9220 used in testbed described in chapter 4 and Fig. 4.1) and found that the monotonic relationship between best feature setting and RSSI still holds regardless of the hardware. For validation purposes we present these results too in the second column on Fig. 5.3 (i.e., Fig. 5.3(b) for the MIMO, Fig. 5.3(d) for the channel bonding and Fig. 5.3(f) for the MCS settings). As we also show in our evaluations in the next section, slight widening of sampling space to address the outliers is effective with no major drop in goodput.

5.3.2 SampleLite: Design & Implementation

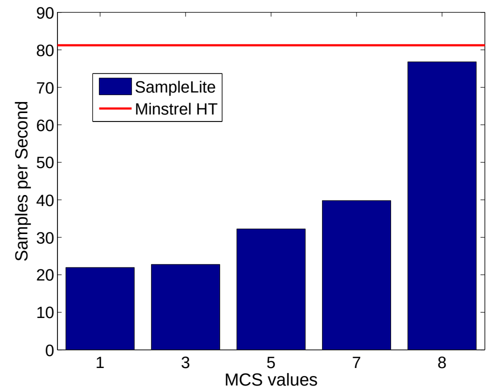
Our proposed approach named SampleLite follows directly from the insight described in the previous section on the monotonic relationship between best setting of each feature and average RSSI of a link. To exploit this insight, we need the current RSSI information. In SampleLite, average RSSI is measured on the sender side separately for each destination (link) as a sliding window of k most recent RSSI measurements obtained via passive observations of data transmissions and ACKs from the destination; k is set to 10 in our implementation. Use of sender side RSSI measurements, like we do with SampleLite, for rate adaptation in 802.11 networks is not new. For example, CHARM [37] relies on such measurements and exploits the channel reciprocity in a practical SNR-based rate adaptation scheme for legacy 802.11 WLANs in dynamic environments.

Once we have the average RSSI of a link, then relationships between best feature settings and RSSI shown in Fig. 5.3 serve as reference curves in deciding which feature setting combinations to sample as discussed in the previous section. These curves need to be calibrated for different types of hardware and receiver radio configurations (e.g., transmit power). In SampleLite, this calibration is done by tracking the packet error rates. Note that the calibration in our case is simpler than with schemes like CHARM [37] that rely on RSSI measurements to select the actual rate for data transmissions because we use them to decide only the sampling subspace. In the case of SampleLite employing different hardware, we could for example resample MCS values around the RSSI thresholds to shift them accordingly towards the left or right (compared to Fig. 5.3(e)) in case of higher losses.

We define two variants of SampleLite. In the vanilla SampleLite, we only



(a) Goodput



(b) Sampling Overhead

Figure 5.4: Goodput and sampling overhead with SampleLite for different values of i: 0, 1, 2, 3 and 7.

exploit the MCS related monotonic relationship with RSSI in Fig. 5.3(e), while in SampleLite+ we exploit all three monotonic relationships in Fig. 5.3 including MIMO mode and channel bonding. We implement both SampleLite and SampleLite+ as additional rate control algorithms in the ath9k driver [24]. We experimentally determine the parameter i in SampleLite and SampleLite+ that reflects the range of MCS values to sample around the one suggested by the RSSI for robustness against outliers as mentioned in the previous subsection. Fig. 5.4 illustrates the impact of using different values for i on goodput and sampling overhead for one of our experiment scenarios. In the figure, range of MCS values = 1 implies i = 0, range of MCS values = 3 implies i = 1 and so forth. As there are only 8 MCS values available with 802.11n, we also include the case of sampling all those values as in Minstrel HT. We see that choosing the smallest or largest value for i, respectively representing too little or too much sampling, are not appropriate from goodput or sampling overhead viewpoints. So we set i = 1 (3 MCS values) in our implementation of SampleLite and SampleLite+.

With SampleLite+, the sampling space is reduced by a factor of four compared to SampleLite with the hardware we use because it only samples one setting each for MIMO modes (number of spatial streams) and channel widths. And SampleLite with i = 1 has a sampling overhead that is 3/8ths of what is needed with exhaustive sampling schemes like Minstrel HT. Gains in sampling overhead and goodput with SampleLite in comparison with Minstrel HT are also illustrated in Fig. 5.4 for one experiment scenario. In the next section, we provide the results that span all scenarios. Note that, unlike Minstrel HT, SampleLite and SampleLite+ do not downgrade the bit-rate in response to high rate of losses. In addition, since they only focus on a small sampling subspace with fewer feature setting combinations, the rate of sampling can also be correspondingly lower. In our implementation, sampling frequency of SampleLite and SampleLite+ is reduced in comparison with Minstrel HT by a factor of four and five, respectively. The exact algorithm of SampleLite+ is presented in Algorithm 4. Finally, the MIMO, Channel Bonding and MCS index, RSSI thresholds obtained by Figs. 5.3(a), 5.3(c) and 5.3(e), respectively, are shown in Tables 5.3, 5.4 and 5.5.

RSSI Threshold	**MIMO: Number of Streams**
$avg(RSSI) \geq -79$	2
$-79 > avg(RSSI)$	1

Table 5.3: RSSI thresholds for choosing the optimal number of streams for SampleLite+, based on Fig. 5.3(a).

RSSI Threshold	**Channel Bonding**
$avg(RSSI) \geq -67$	40 MHz
$-67 > avg(RSSI)$	20 MHz

Table 5.4: RSSI thresholds for choosing the optimal channel width for SampleLite+, based on Fig. 5.3(c).

RSSI Threshold	**MCS value** $\in [0, 7]$
$avg(RSSI) \geq -45$	7
$-45 < avg(RSSI) \geq -49$	6
$-49 < avg(RSSI) \geq -61$	5
$-61 < avg(RSSI) \geq -65$	4
$-65 < avg(RSSI) \geq -70$	3
$-70 < avg(RSSI) \geq -73$	2
$-73 < avg(RSSI) \geq -78$	1
$-78 < avg(RSSI)$	0

Table 5.5: RSSI thresholds for choosing the MCS value n for SampleLite and SampleLite+, based on Fig. 5.3(e).

Algorithm 4 SampleLite+ Algorithm

```
1:  while 1 do
2:    if waitTime ≥ samplingFrequency then
3:      for MCSi = 7 to 0 do
4:        if avg(RSSI) ≥ Threshold(MCSi) then
5:          n = MCSi;
6:        end if
7:      end for
8:      if avg(RSSI) ≥ Threshold(MIMO) then
9:        streams = 2;
10:     else
11:       streams = 1;
12:     end if
13:     if avg(RSSI) ≥ Threshold(ChannelBonding) then
14:       width = 40;
15:     else
16:       width = 20;
17:     end if
18:     sampleRandomSetting S' from :
19:     [MCS ∈ [n − 1, n + 1], streams, width];
20:     updateStatisticsTable(S');
21:     reset waitTime;
22:   else
23:     waitTime + +;
24:   end if
25:   chooseOptimalSettingForTx(statisticsTable);
26: end while
```

Algorithm 4 shows the implementation of SampleLite+ (we get the SampleLite algorithm by removing lines 8–17). The sampling frequency used is explained just before. The statistics table update involves estimating the probability of successful transmission, as well as the estimated throughput to be provided with the specific setting combination. Finally, the optimal setting that is selected, is the one with maximum throughput. Note, that once the statistics information is considered old (i.e., using an exponential weighted moving average similarly to Minstrel HT), the specific entry is given a lower weight.

Although we present SampleLite and SampleLite+ as separate schemes, they could be combined into a scheme that allows switching between them to achieve further robustness in highly dynamic and interference-prone environments. This idea is along the same lines as slight widening of sampling space in SampleLite to handle outliers, which we show in our evaluations to be a fairly effective strategy. We leave further exploration of this point for future work.

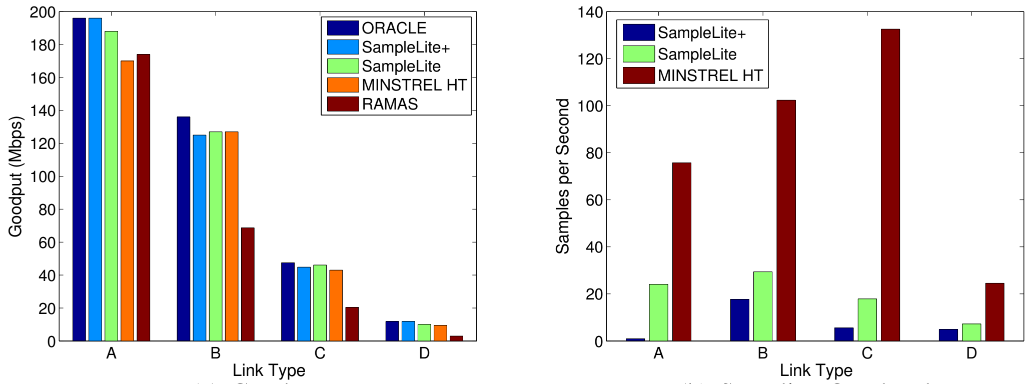
5.4 Evaluation

In this section, our main goal is to evaluate the performance of SampleLite in terms of goodput and sampling overhead. Our evaluations use the 802.11n testbed and span a wide range of scenarios including different link types and interference scenarios described in section 5.2. As alternatives in our comparative evaluation, we consider Minstrel HT [20], RAMAS [21] and an ORACLE. Note that Minstrel HT is the default scheme with the ath9k driver, whereas RAMAS was shown in [21] to outperform other link adaptation schemes including MiRA and original ath9k 802.11n rate control algorithm [24]. For RAMAS, we use the implementation made available by its authors. As per the ORACLE, it is an idealised scheme that is omniscient and with no sampling overhead. We use the ORACLE alternative, where possible, as an upper bound for goodput performance. To realise ORACLE, we measure the goodput obtained from using each feature setting combination and pick the maximum among them. Because of unavailability of implementations for other schemes like [22], we could not include them in our evaluation. Also some existing schemes (e.g., [24, 15, 59]) do not adapt channel bonding, a key 802.11n feature.

5.4.1 Controlled Experiments

Effect of Link Type

We start by looking at the impact of different link qualities in the absence of any interference. Fig. 5.5 shows the results. We can observe that both variants of SampleLite, especially SampleLite+, achieves goodput quite close to ORACLE. Compared to Minstrel HT, SampleLite+ improves goodput by up to 25% while at the same time reducing the sampling overhead by up to 98% and on average by 90%. Goodput gains with SampleLite+ over Minstrel HT can be explained by its targeted sampling and resulting reduction in sampling overhead. Relative to RAMAS, both SampleLite and SampleLite+ provide up to a 3-fold improvement



(a) Goodput (b) Sampling Overhead

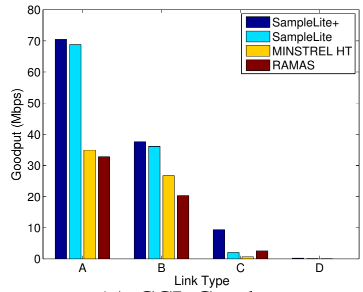
Figure 5.5: Performance in controlled experiments with varying link quality and no interference.

in goodput (which happens for link type D). Reasons for the poor performance of RAMAS are elaborated in the next subsection.

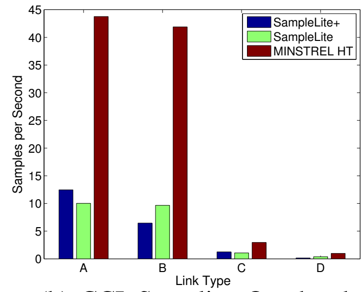
Controlled Co-Channel and Adjacent Channel Interference Effect

We now additionally consider the effect of interference using several different scenarios described in section 5.2, and Fig. 5.6 shows the results. We see that SampleLite mostly outperforms both Minstrel HT and RAMAS in terms goodput on average by 27.2% and 63.3%, respectively. Similarly, average goodput improvement with SampleLite+ compared to Minstrel HT and RAMAS is 33.7% and 94.3%, respectively. Worse performance with Minstrel HT in the presence of interference is because it responds frequently and rapidly to increase in frame losses by reducing the number of streams and rate. This compounds the effect of interference as transmissions take longer and increase the contention level and likelihood of collisions. SampleLite and SampleLite+ avoid this problem as they rely on RSSI measurements for choosing which feature setting combinations to sample and then select the combination providing maximum expected goodput for data transmissions.

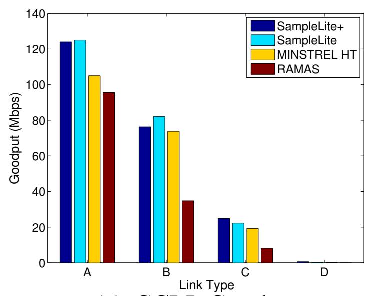
RAMAS performs poorly because its credit based scheme is conservative in adapting the number of streams, and aggressive in adapting the MCS. This mismatch, also noted in [22], causes RAMAS to often operate at sub-optimal settings with single stream and high MCS values, leading to higher losses and reduced



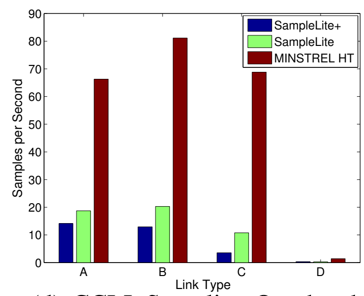
(a) CCI, Goodput



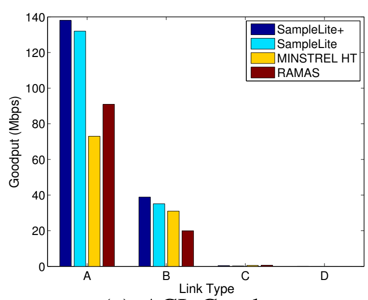
(b) CCI, Sampling Overhead



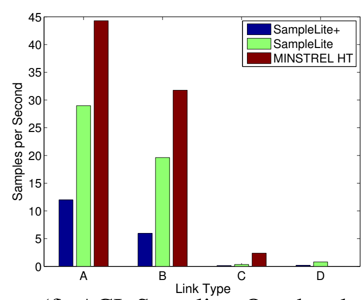
(c) CCLI, Goodput



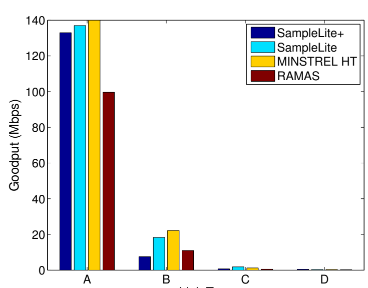
(d) CCLI, Sampling Overhead



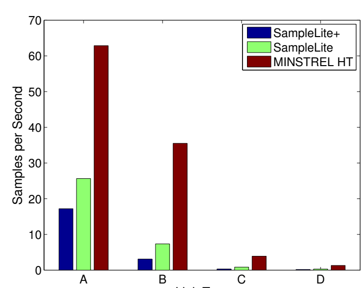
(e) ACI, Goodput



(f) ACI, Sampling Overhead



(g) ACLI, Goodput



(h) ACLI, Sampling Overhead

Figure 5.6: Performance in controlled experiments with different interference scenarios and link types.

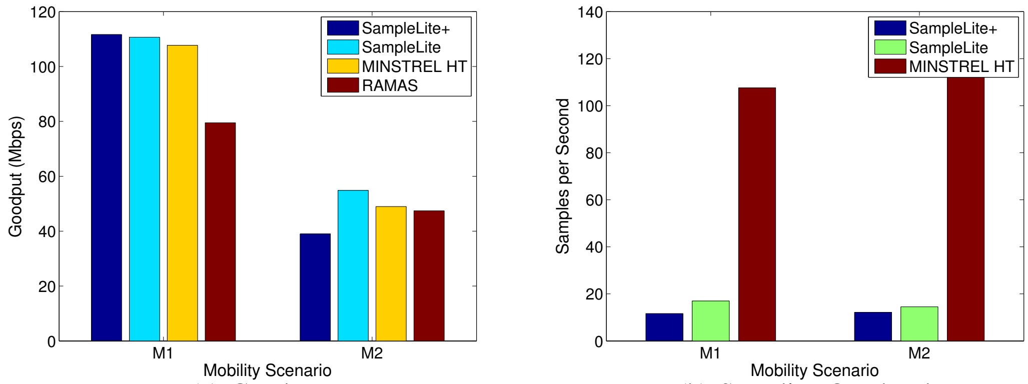
performance. This is more apparent as link quality deteriorates. Our results for RAMAS are considerably different from those reported by its authors in [21]. This is because evaluation scenarios are different, and also because RAMAS was only evaluated in 2.4GHz band, which limits the potential benefits possible with 802.11n [15, 14]. Deek et al. [22] have also observed that RAMAS performed worse than Minstrel HT in the 5GHz band for link distances greater than 5m or when there were obstacles between the access point and the station. Distances for all of our links are longer than 5m and there were obstacles in all cases other than the ideal link A.

We observe that although SampleLite and SampleLite+ outperform the other two alternatives in most of the cases, they do slightly worse in a couple of cases in the ACLI interference scenario. We believe this is because RSSI by its very nature is sensitive to interference and in highly dynamic environments as noted previously in [61], for example. In the ACLI case, where the interfering link effectively causes the hidden terminal effect, RSSI measurements can lead the sender to sample higher rate configurations than appropriate. However the resulting drop in goodput is somewhat marginal to be of huge concern.

In terms of sampling overhead, SampleLite achieves a 70.5% reduction on average compared to Minstrel HT, and a maximum reduction by 86.5%. SampleLite+ reduces the sampling overhead even more by 83% on average and up to 98.7%. This significant decrease in the amount of sampling is a result of RSSI-guided sampling approach adopted in SampleLite+ and SampleLite that is fundamentally different from the random and exhaustive sampling used by schemes like Minstrel HT. The savings in sampling overhead partially contribute to the goodput improvements with SampleLite+ and SampleLite. The minimised overhead leaves the medium available for data transmission increasing the goodput of SampleLite and SampleLite+.

Mobile Scenarios

We now study the performance of SampleLite variants with station mobility that makes the environment dynamic and causes frequent channel fluctuations. Specifically, we create two mobility scenarios M1 and M2, as shown in Fig. 5.1, where the mobile user walks at a pedestrian speed ($\sim 1m/sec$). M1 exhibits better link qualities, with RSSI $\in [-39, -52]$ dBm, compared to M2 which observes RSSI values in the range of $[-56, -68]$ dBm. Fig. 5.7 shows the results from these experiments. We can see that even in this dynamic scenarios SampleLite manages to deliver similar or better goodput relative to Minstrel HT and RAMAS but



(a) Goodput (b) Sampling Overhead

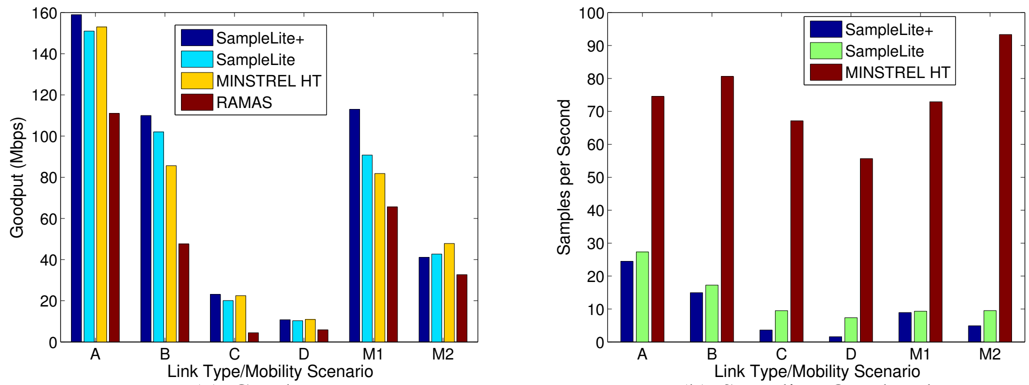
Figure 5.7: Goodput and sampling overhead in scenarios with mobility.

with a significant reduction in sampling overhead (87% on average) compared to Minstrel HT. SampleLite+ provides slightly higher reduction in sampling overhead (89% on average) but it has lower goodput than the alternatives in the M2 scenario. The explanation given for ACLI in the previous subsection also applies here. SampleLite relatively fares better in these scenarios as it samples more widely.

5.4.2 In the Wild Experiment

We now study the performance of SampleLite variants in the wild with several other access points and their associated clients coexist and share channels with our testbed nodes in an uncoordinated manner. Specifically, we configured our testbed access point and associated clients during peak office hours (2-4pm) to use channel 44 in the 5GHz band on which we found there are 12 other access points operating. Among these other access points, which act as real-world interferers to our testbed links, 5 access points were active at all times in channel 44, and 7 access points on the adjacent secondary channel (i.e., 48); 4 of the access points in channel 44 and 2 in channel 48 were 802.11n based but none of them used channel bonding during our experiment.

Fig. 5.8(a) shows the goodput results in presence of such dynamic and uncontrolled interference from other co-located access points. We observe that, even in this challenging environment, SampleLite+ provides up to 38% goodput com-



(a) Goodput (b) Sampling Overhead

Figure 5.8: Goodput and sampling overhead results in a scenario with several real-world, uncontrolled interferers.

pared to Minstrel HT and SampleLite variants outperform RAMAS by over 100% in goodput. However, in the case of mobility scenario M2, SampleLite variants are up to 15% worse than Minstrel HT for reasons similar to that explained in the previous subsection. Turning our attention towards sampling overhead, SampleLite+ and SampleLite respectively reduce the overhead by up to 97% and 87% compared to Minstrel HT in this real-world scenario.

5.5 Discussion

In this chapter, we considered the link adaptation problem in 802.11n WLANs and showed through measurement-based analysis that it is vital to adapt all key 802.11n features in order to maximize goodput. Observing that most of the existing 802.11n link adaptations schemes suffer from excessive sampling or implementation concerns, we designed an efficient and practical scheme called SampleLite that takes a novel hybrid approach. SampleLite relies on easily accessible sender-side RSSI measurements to identify a small subset of rates to sample, thereby reduce the sampling overhead. Through a testbed based evaluation considering a wide range of controlled and real-world interference scenarios, we showed both the SampleLite variants proposed in this chapter significantly reduce the sampling overhead by around 70% compared to the widely used Minstrel HT scheme. We also showed that goodput-wise SampleLite, while performing close to an OR-

ACLE scheme (in the case of no interference), it generally provides substantial improvements relative to Minstrel HT and RAMAS by up to around 35% and 100%, respectively. SampleLite also has some limitations. For example, there is the risk of omitting optimal configurations from your sampling in cases like in heavily dynamic environments (e.g., like M2 presented in previous sections). So, in highly dynamic and interference-prone environments SampleLite should adaptively widen the sampling space as needed to minimize that risk. However, this approach would have the tradeoff that sampling overhead would increase, but we still expect it to be considerably lower than Minstrel HT. Finally, including the guard interval feature in SampleLite would help to improve its performance further.

Chapter 6

Additional Studies

In this chapter we discuss additional interesting and not previously explored topics on 802.11n, that could be potential fruitful future work too. We address new challenges concerning the fairness of the 802.11n standards compared to legacy 802.11a in section 6.1. Moreover, in section 6.2 we show the feasibility of inferring interference type at a node online using throughput measurements and a supervised machine learning based classifier. Finally, we perform a characterisation study similarly to chapter 4, but the traffic examined this time is the live video streaming performance in section 6.3. Again the significance and the impact of the 802.11n features is examined, along with the interaction and interdependence among them under varying link qualities, interfering conditions and video resolution.

6.1 An Initial Look on 802.11n Fairness

Fairness in the context of 802.11n has not received much research attention. As an example to illustrate the fairness issue, Fig. 6.1 shows throughput share over time between links (2)-(4) in our testbed when they are simultaneously active in the 802.11n mode and 802.11a mode, respectively. Settings for this experiment are similar to the baseline results presented in Fig. 4.3. The only difference is that in this section we run links 2, 3 and 4 simultaneously in order to identify which one occupies the medium in the case of not equal bandwidth allocation. Unfairness with 802.11n is quite apparent, with higher quality links taking a greater share of the throughput at the expense of poor quality links. This is because higher quality links can use higher MCS values which in turn causes selection of larger

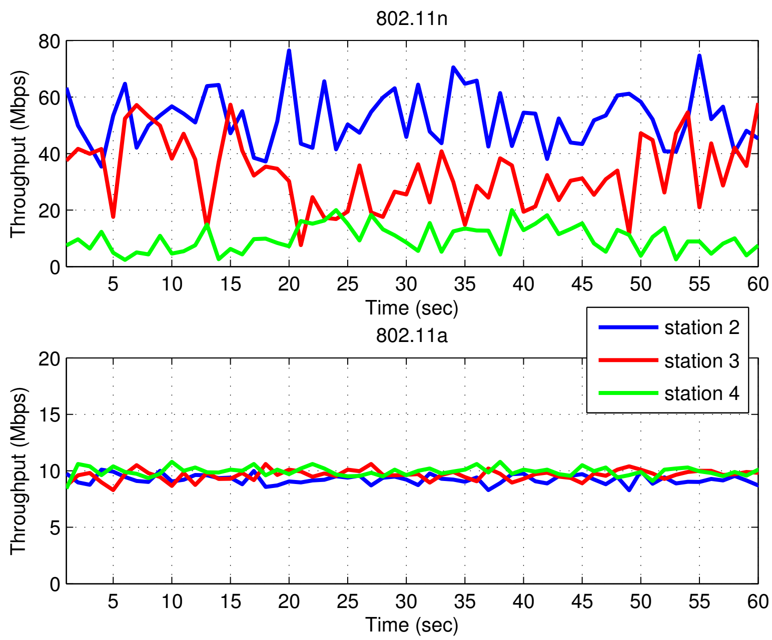


Figure 6.1: Illustration of unfairness with 802.11n compared to 802.11a.

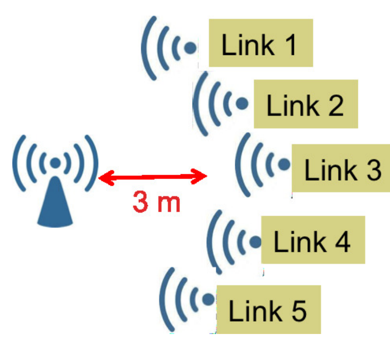
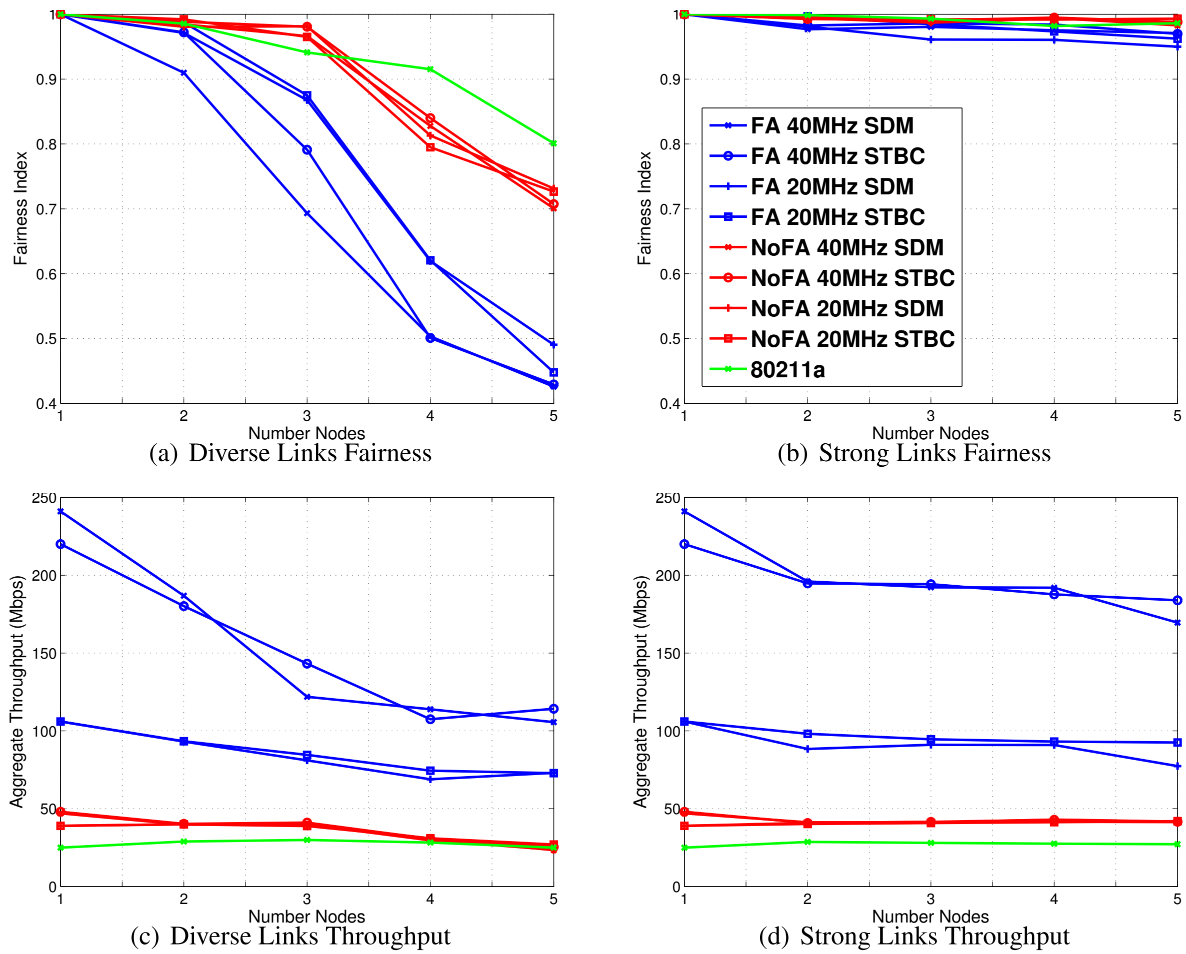


Figure 6.2: All strong links topology.

aggregated frame sizes, thus making higher quality links occupy the channel for long periods.

We compare different 802.11n settings to legacy (802.11a) fairness and network throughput performance when multiple users compete for the medium (Fig. 6.3). We consider two scenarios, one where all links have similar good link quality — $\sim 20dBm$ — (see Fig. 6.2), and another corresponding to a diverse node placement shown in Fig. 4.1.



(a) Diverse Links Fairness (b) Strong Links Fairness

(c) Diverse Links Throughput (d) Strong Links Throughput

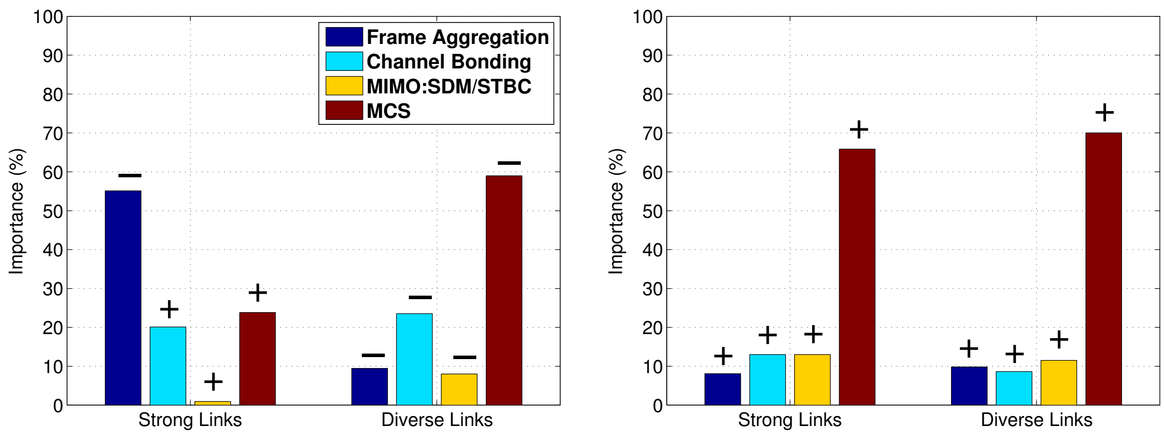
Figure 6.3: Fairness and throughput experiments for multiple users when default adaptation algorithm is enabled.

For quantifying fairness, we use the well-known Jain's index [74]:

$$f(x_1, x_2, \ldots, x_n) = \frac{(\sum_{i=1}^{n} x_i)^2}{n \sum_{i=1}^{n} x_i^2}$$

where x_i is the throughput of the i^{th} link and n the total number of concurrently communicating links.

In Fig. 6.3, it is surprising that fairness results are similar to the 802.11a ones when frame aggregation is disabled (NoFA) and the network consists of similar



(a) Impact on Fairness (b) Impact on Aggregate Throughput

Figure 6.4: Relative impact of 802.11n features on fairness and aggregate throughput performance in different network scenarios.

link qualities. In addition, no matter the scenario frame aggregation degrades fairness in case of higher network contention, because longer packets would require to use the network for longer time, creating unfairness. Moreover, when both frame aggregation and channel bonding are enabled, then fairness is about 15% worse than when channel bonding is disabled (in the diverse link scenario that different link qualities co-exist – Fig. 6.3(a)). However, in terms of aggregate throughput, enabling channel bonding provides about 50% gain. Finally, SDM combined with frame aggregation provides both the worst results in terms of fairness (on average for all the scenarios) and the highest throughput as expected.

Like with throughput and packet loss results in chapter 4, we have carried out categorical regression based analysis of the impact of different 802.11n features on fairness using the same topologies as described before. Results for fairness and aggregate throughput are shown in Figs. 6.4(a) and 6.4(b), respectively. Note that in Fig. 6.4, "+" ("-") sign indicates positive (negative) impact of a variable on the metric in question. For example, "+" sign with frame aggregation for diverse links in Fig. 6.4(b) means that enabling frame aggregation benefits throughput. Interpretation of these signs for MIMO and MCS are somewhat different. For MIMO, "-" sign suggests the use of STBC, and SDM otherwise. Note that MCS in these figures represents only modulation and coding rates (8 different possibilities as shown in Table 2.2) as already mentioned before and "+" sign for MCS suggests the use of higher modulation and coding rate and lower otherwise.

We see that relative impact of 802.11n features on fairness varies depending on the network scenario and is different from that on aggregate throughput. Fig. 6.4(a) shows that when diverse links are used, SDM with two spatial streams and high MCS indexes degrade fairness. Moreover, frame aggregation has negative impact due to longer packets requiring to acquire the network for longer time, creating unfairness. As expected, the aggregate throughput results (Fig. 6.4(b)) are the opposite from the fairness ones.

In case of different link quality combinations in the network, the behaviour and significance of the various parameters changes (Fig. 6.4). However, channel bonding has a positive impact on fairness when all links are identical. This can be attributed to the fact that the channel is wider so even long aggregated packets can be transmitted faster and release the channel for another link to get access to the channel. Consequently, frame aggregation should have negative impact as Fig. 6.4(a) shows, because longer successful transmissions result in all other clients waiting for the medium to be available. Therefore, the faster the packets are successfully transmitted the sooner the medium is going to be available for another client. This is why higher MCS index has a positive impact on fairness in this case.

6.2 Differentiating Interference Types

Results in chapter 4 suggest that the relative impact of different features and the interactions among them changes depending on the interference type a link experiences. For example, channel bonding influence grows in the ACI case. A link adaptation algorithm could exploit these observations; it would be ideal for a sending node of a link to be able to detect the type of interference it is experiencing at a given point in time (this includes no interference case as well). Motivated by this, we assess the effectiveness of differentiating between interference types using a supervised machine learning classifier model. Classes for this model are different interference types (no interference, CCI, CCLI, ACI, ACLI) and the feature vector could be $< FA, CB, MIMO, MCS, Throughput >$. Using UDP measurements like those obtained for the characterisation study of chapter 4, one could train a supervised machine learning classifier model providing it with feature vector and known class information. During the operational phase, a link could measure its current throughput and combine it with current settings for various 802.11n features and query that interference classifier model, which would

Classifier	Link 1	Link 2	Link 3	Link 4	Link 5	Average
LogisticReg	81.79%	82.02%	90.30%	91.58%	97.61%	**88.6%**
kNN	77.28%	65.14%	73.45%	83.6%	80.75%	**76.04%**
C4.5	58.77%	43.88%	54.73%	71.02%	73.64%	**60.4%**
NaiveBayes	27.04%	29.41%	36.78%	49.33%	44.35%	**37.38%**

Table 6.1: Interference type classifier accuracy for different link qualities and classifier algorithms.

output the most likely interference type, statistically speaking.

We implemented the above idea considering several different classifiers described in section 2.3.4. Results are shown in Table 6.1. We observe that the logistic classifier provides the best result with an average accuracy of 88.6% across all link qualities, suggesting that it is indeed possible for a sender node to indirectly infer the type of interference experienced by its links. Together with link quality measurements (which are relatively easier to obtain), the scenario of operation can be inferred and best settings for that scenario can be applied. Investigation of a 802.11n link adaptation algorithm based on this idea is a key aspect for future work. Also note that it is harder to infer the interference type for higher quality links, possibly because there are more combination of features that influence the performance differently when the link quality is better, making the feature space larger and classification harder.

Another interesting observation is that Naive Bayes classifier performs the worst among all the classifier algorithms considered. Since the assumption of independence between features in the feature vector is a unique aspect of Naive Bayes, its poor accuracy could be attributed to this assumption not holding true, which suggests interdependence among features, as we showed in section 4.5.

Similarly, we could also identify the link quality. Suppose we have five distinct link qualities like the five links under test of this work we can use logistic classifier to identify between these five types of link quality. In a real life scenario, links of intermediate performance can be estimated by interpolation. Table 6.2 shows that 80% accuracy can be achieved in predicting the correct link quality, and over 70% accuracy in predicting the link and interfering scenario at the same time.

So far UDP throughput was the only runtime measurement used along with the actually feature settings in order to perform the classification. UDP packet loss is another runtime metric that could also be used. In this way the feature vector

	Overall Accuracy
Link Classification	80.69%
Link Classification with Interference Scenario Knowledge	81.65%
Link and Interference Classification	71.76%

Table 6.2: Logistic classifier accuracy for different link qualities and interference scenarios.

	Overall Accuracy
Link Classification	99.55%
Link Classification with Interference Scenario Knowledge	99.55%
Link and Interference Classification	99.55%

Table 6.3: Logistic classifier accuracy for different link qualities and interference scenarios, employing packet loss along with UDP throughput.

would be $< FA, CB, MIMO, MCS, Throughput, PacketLoss >$. In this case, the accuracy that could be achieved is almost 100% as Table 6.3 shows. However, the computation time needed for this result is very time consuming and might not be feasible for a run-time application. This is an issue that can be explored further as part of future work for designing a different link adaptation scheme focusing on identifying the link and interference scenario and adapting the feature settings appropriately.

6.3 Video Streaming Performance in 802.11n WLANs

Video streaming refers to transferring video data as a continuous stream over the network. With streaming, the client can start displaying the multimedia data before the entire file has been transmitted. This is different from downloading, where the client can only view the video file once the download is completed. In this section we aim to do a characterisation study similar to chapter 4, discussing the impact of different features, as well as the interaction among them on the metric of video streaming quality.

Live streaming, which refers to content delivered live over the Internet, requires for example a camera for the media, an encoder to digitise the content, a media publisher, and a content delivery network to distribute and deliver the content. Video compression and encoding refers to reducing the size, and the bit-rate of the video. This usually means the loss of the less important data, while still maintaining high perceptual video quality. Popular video codecs include MPEG 2, ON2 (VP8) and H.264. The majority of online based streaming applications like YouTube and BBC iPlayer use the H.264/MPEG-4 AVC codec. There is also the exception of Skype which uses the Google owned ON2/VP8 codec. Various works show that H.264 outperforms other codecs like MPEG 2 [82] and this is why we also focus on video streaming using the H.264 codec in this section.

In H.264 the Group of Pictures (GOP) specifies the order in which intra- and inter-frames are arranged. GOP consists of three frame types; the Intra (I-frame), the Prediction (P-frame) and the Bi-directional (B-frames). Each GOP begins with an I-frame, which is coded independently of the rest of the frames. The P- and B-frames contain motion-compensated information compared to previously decoded frames.

Another important issue is the video quality evaluation metrics. Current techniques used to analyse and evaluate video quality include objective and subjective video quality evaluation. Subjective video quality evaluation has to do with how video is perceived by a viewer and designates the viewer's opinion on a particular video sequence. Subjective video quality tests are quite expensive in terms of time and human resources [83]. Objective video quality evaluation usually involves mathematical models comparing each frame of the transmitted and received videos in a pixel-by-pixel manner, measuring the corresponding distortion between the original video and received video. A common objective metric for video performance is PSNR (Peak Signal-to-Noise Ratio) and has been broadly used in works similar to this section (e.g., [60]). PSNR is most easily defined via the mean squared error (MSE). Given a noise-free $m \times n$ monochrome image I and its noisy approximation K, MSE and PSNR are defined as

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

$$PSNR = 10 \cdot log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

where MAX_I is the maximum possible pixel value of the image. For colour images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. PSNR is measured in decibels (dB).

For the results presented in this section we use again the testbed topology described in Fig. 4.1 and for the video transmission we use the VLC media player [84]. We use HTTP over TCP for streaming the videos with duration 30 sec. This means that the TCP error correction mechanism might recover errors happening during the transmission so they will not be accurately described in the PSNR metric, since the losses are restored in the receiver side. PSNR is a more appropriate metric in the case of RTP over UDP video streaming, where UDP does not use any error correction mechanism and therefore all losses are visible in the video received. This is why we need another metric to use for our experimental evaluation. We choose to use the number of delayed — lost — frames, to measure the efficiency of the link during the 30 second video streaming session. All frames that did not arrive in the right order in this session, or arrived after the 30 sec video duration, are accounted as delayed frames.

We aim to explore the 802.11n protocol's and its features' behaviour on video streaming performance under not only different link qualities and interfering scenarios, but also under different bit-rates. Bit-rate is the number of bits that are transmitted over a set length of time, including both the video and audio information. The different bit-rates we examine in this section are 12, 23, 48 and 70Mbps. Next we perform the same analysis as in Chapter 4 for the video streaming application.

6.3.1 Impact of Various 802.11n Features

Fig. 6.5 shows the relative impact of the 802.11n features on video streaming quality performance using the lost frames, as mentioned before, as a metric. Fig. 6.5(a) depicts these results in absence of any type of interference and Fig. 6.5(b) in presence of real-world uncontrolled interference. In the latter case we use channel 36 in the 5GHz band and a spectrum analyser tool to see the amount of interference. Using WiSpy, we find that there are another 3 and 4 access points operating in the primary (channel 36) and secondary (channel 40) 20MHz of the bonded channel, respectively. Once again there is variation in the impact of each feature not only in terms of link quality and interference scenarios like in section 4.3.3, but also in terms of video bit-rate. Tables 6.4 and 6.5 depict the significance levels for all interference-free and real world interference regression models, showing that they satisfy the validity criterion (< 0.05), so the regression results shown in Fig. 6.5 are trustworthy.

	Link 1	**Link 2**	**Link 3**	**Link 4**	**Link 5**
70Mbps	0	0	0	0	0
48Mbps	0	0	0	0	0
23Mbps	0	0	$3 * 10^{-15}$	0	0
12Mbps	0	0	$8 * 10^{-11}$	0	0

Table 6.4: Significance value of video quality categorical regression model for each of the scenarios in no interference case.

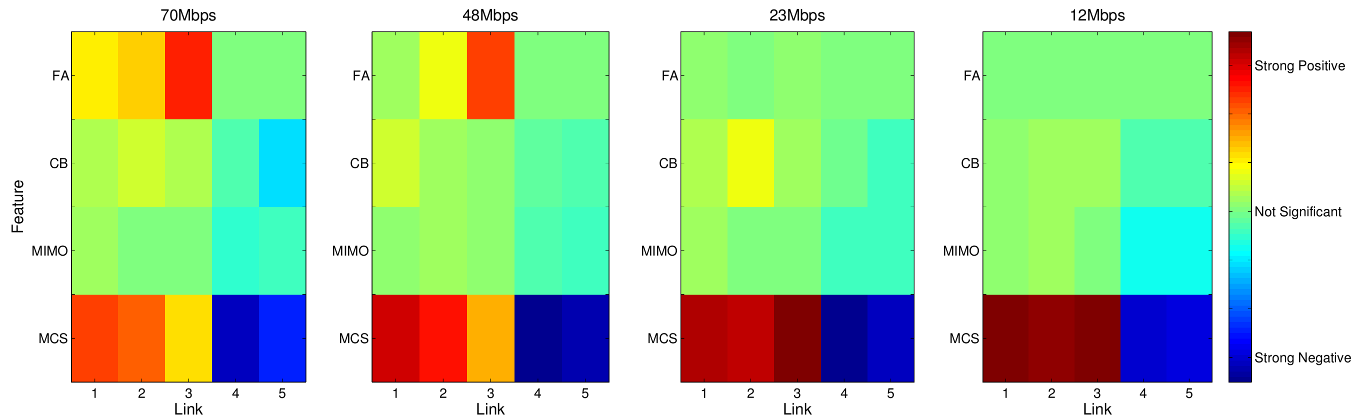
	Link 1	**Link 2**	**Link 3**	**Link 4**	**Link 5**
70Mbps	0	0	0	0	0
48Mbps	0	0	0	0	0
23Mbps	0	0.018	0	0	0
12Mbps	0	0	0	0	0

Table 6.5: Significance value of video quality categorical regression model for each of the scenarios in real-world interference case.

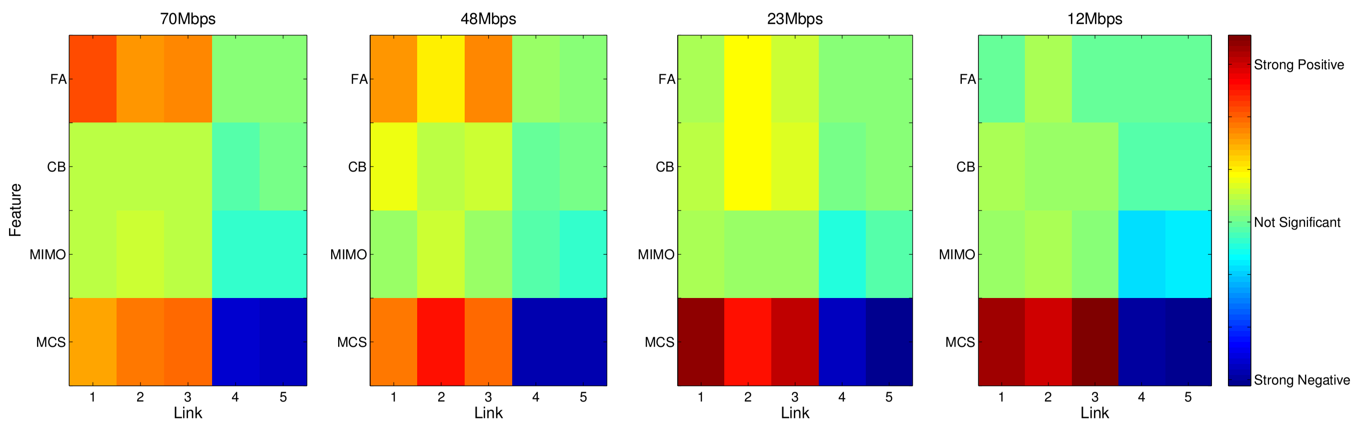
Frame Aggregation Impact

Like in the throughput results presented in Fig. 4.7, frame aggregation is efficient for video streaming in terms of both no– (Fig. 6.5(a)) and real world interference (Fig. 6.5(b)); no matter the video bit-rate. It is quite surprising that, again, even for poor link qualities (i.e., links 4 and 5) frame aggregation does not have a negative impact as one would intuitively expect. Moreover, we see that frame aggregation is even more significant for better quality links (e.g., 1, 2 and 3) and higher video bit-rates (e.g., 48 and 70Mbps). This is because higher video bit-rate means having to transmit 2 or 3 times more data as a low bit-rate video (e.g., 12Mbps) in the same time, so frame aggregation is crucial to be enabled.

The results also indicate that frame aggregation is not significant for poor quality links, since frame losses are high because of the low link quality. Another reason why this is happening is because poor quality links can only support very low MCS values (e.g., 0 and 1). In the specification of the ath9k driver [24], we have seen that the lower the MCS value, the lower the frame aggregation level. This means that for MCS value 0, for example, there is no frame aggregation happening, while for MCS 1 we only have 2 frames to be aggregated. This also explains why frame aggregation is not significant for poor link qualities (i.e., link 4 and 5).



(a) No interference.



(b) Real-world, uncontrolled interference.

Figure 6.5: Relative impact of 802.11n features on video streaming quality performance in terms of normalised Pratt's importance measure (section 2.3.1) in different scenarios. Red, green and blue colours indicate positive, no and negative impact of the specific feature on the performance on a given link scenario, respectively.

Channel Bonding Impact

Similarly, channel bonding is efficient for transmitting more data faster in good links (i.e., links 1, 2 and 3), no matter the interference scenario. However, its impact is even higher in the real world interference case. Overall, we see that channel bonding should be enabled for video streaming no matter the video bit-rate or interference case.

MIMO (SDM/STBC) Impact

The MIMO results' intuition is more similar to the throughput results than the frame aggregation and channel bonding. There should be multiple streams enabled — SDM — for good links so as to transmit more data faster, while poor links should only use one stream — STBC. However, in case of real-world interference we see that the need for multiple streams and SDM is even higher for good links and higher than legacy supported bit-rates. Once again this is because high bit-rates need more simultaneous streams in order to successfully transmit data and minimise the losses of I-frames.

MCS Impact

Finally, the MCS index behaviour is along expected lines and similar to the throughput results shown in section 4.3.3. Higher MCS indexes — transmission bit-rates — should be used for better links in lower interfering scenarios, whereas lower MCS indexes should be used for poor links and in presence of higher interference, in order to minimise the delayed frames.

6.3.2 Interaction among Different Features

In section 4.5 we showed that there is interaction among the different 802.11n features as far as throughput and packet loss is concerned. In this section, we aim to show that similarly there is interdependence among them even in the case of a different metric like live video streaming quality.

Response Surface Methodology

When exploring the pairwise only interactions using RSM we find out the following interactions for no interference (Table 6.6) and in presence of real-world and uncontrolled interference (Table 6.7). We see that there is a similar pattern with video compared to throughput in the interaction of the features.

	70Mbps	48Mbps	23Mbps	12Mbps
Link 1	CB-MCS	FA-MCS	FA-MCS	FA-CB
	MIMO-MCS	CB-MCS	CB-MIMO	FA-MIMO
		MIMO-MCS	CB-MCS	FA-MCS
			MIMO-MCS	CB-MCS
				MIMO-MCS
Link 2	FA-MIMO	FA-MCS	FA-MCS	FA-CB
	FA-MCS	CB-MIMO	CB-MCS	FA-MIMO
	CB-MIMO	CB-MCS		FA-MCS
	CB-MCS	MIMO-MCS		CB-MIMO
	MIMO-MCS			CB-MCS
				MIMO-MCS
Link 3	FA-MIMO	FA-MCS	FA-MCS	FA-CB
	FA-MCS	CB-MIMO	CB-MIMO	FA-MCS
	CB-MCS	CB-MCS		CB-MIMO
				CB-MCS
Link 4	FA-CB	FA-MIMO	FA-MIMO	FA-CB
	FA-MCS	FA-MCS	FA-MCS	FA-MCS
	CB-MCS	CB-MIMO		
	MIMO-MCS			
Link 5	FA-CB	FA-MCS		FA-MCS
	FA-MIMO	CB-MCS		CB-MCS
	FA-MCS	MIMO-MCS		MIMO-MCS
	CB-MIMO			
	CB-MCS			
	MIMO-MCS			

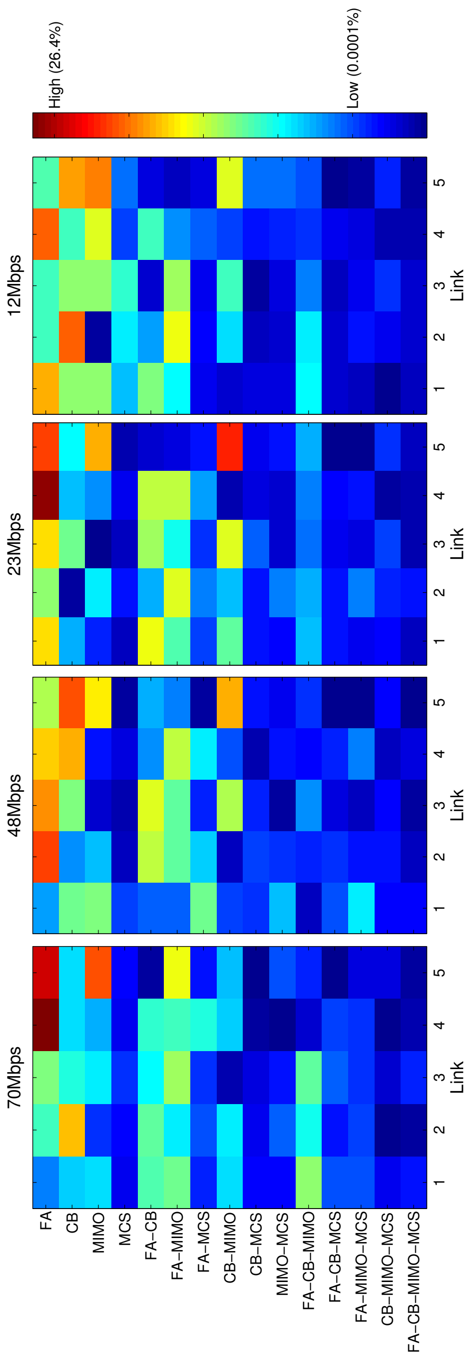
Table 6.6: Pairwise interdependence among 802.11n features in different video quality scenarios, with no interference derived via response surface methodology (RSM).

Multiple Linear Regression

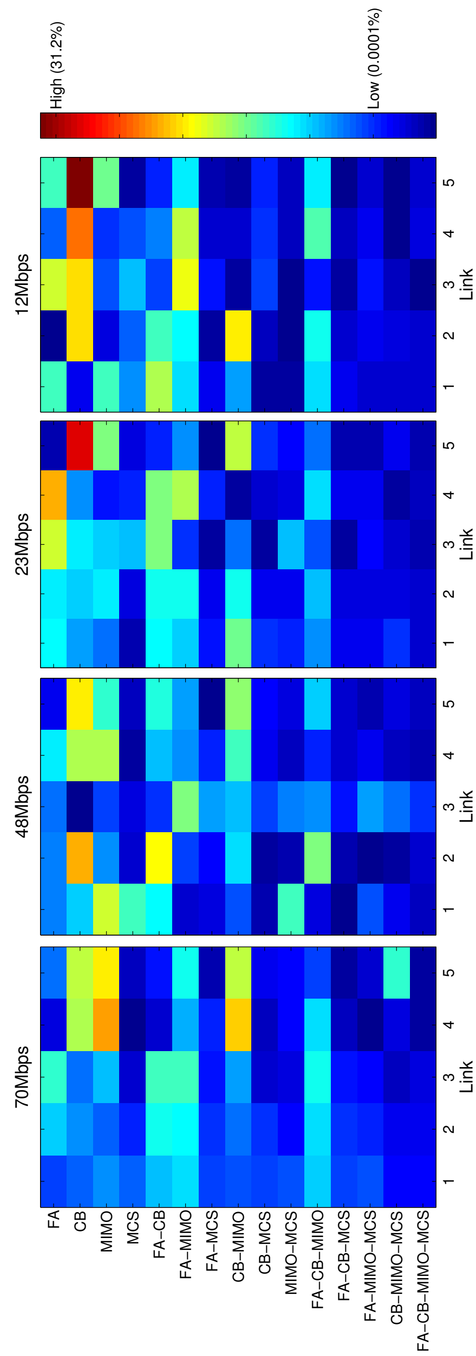
The multiple linear regression results are more interesting providing more insights on the feature interactions. Surprisingly, in Fig. 6.6 we see that better quality links do not necessarily result in higher interaction between more features like in throughput results (Fig. 4.11). Moreover, we notice that throughout all link qualities, interfering scenarios and bit-rate levels, it is the single features that have the highest impact on performance, when the feature combinations (pairwise or higher) usually have a much lower impact.

	70Mbps	48Mbps	23Mbps	12Mbps
Link 1	CB-MCS	FA-MCS	FA-MCS	FA-CB
	MIMO-MCS	CB-MCS	CB-MIMO	FA-MIMO
				FA-MCS
				CB-MIMO
				CB-MCS
				MIMO-MCS
Link 2	FA-MIMO	FA-CB	FA-MCS	FA-MCS
	CB-MIMO	FA-MCS		CB-MCS
	CB-MCS	CB-MCS		
	MIMO-MCS	MIMO-MCS		
Link 3	CB-MCS	FA-MIMO	FA-MCS	FA-MCS
	MIMO-MCS	FA-MCS	CB-MCS	CB-MIMO
		CB-MIMO		CB-MCS
		CB-MCS		
Link 4	FA-CB	FA-CB	FA-CB	FA-MCS
	FA-MIMO	FA-MCS	FA-MIMO	MIMO-MCS
	FA-MCS	CB-MCS	FA-MCS	
	CB-MIMO	MIMO-MCS	CB-MIMO	
	CB-MCS		CB-MCS	
	MIMO-MCS		MIMO-MCS	
Link 5	FA-CB	FA-CB	FA-MIMO	FA-MCS
	FA-MIMO	FA-MCS	FA-MCS	CB-MCS
	FA-MCS	CB-MCS	CB-MCS	
	CB-MIMO	MIMO-MCS	MIMO-MCS	
	CB-MCS			
	MIMO-MCS			

Table 6.7: Pairwise interdependence among 802.11n features in different video quality scenarios, with real-world uncontrolled interference derived via response surface methodology (RSM).



(a) No interference.



(b) Real-world, uncontrolled interference.

Figure 6.6: Percentage of impact per feature combination on video quality performance based on regression coefficients using the number of lost frames as a metric. Red and blue colours indicate high and negligible impact of the specific feature combination on the performance on a given link scenario, respectively.

Overall we see that video performance has different behaviour in terms of feature interaction compared to the throughput performance. Also, in chapter 4 we saw that there is a different pattern even in throughput performance results, regarding the feature interaction, between UDP and TCP throughput. This shows that the 802.11n feature interaction is not a trivial problem and needs to be further examined.

Chapter 7

Conclusions & Future Work

Even though wireless LANs is a very common medium for Internet access, todays wireless systems are not equipped to meet the demands of emerging high bandwidth applications. Currently deployed wireless LANs are highly susceptible to spatio-temporal variations in channel and interference conditions, which ultimately limits throughput and performance. This dissertation advocates a holistic approach to link adaptation not only for legacy 802.11a/b/g and 802.11n, but also for future standards (e.g. 802.11ac). We observe that it is effective to be holistic and this approach can provide large throughput gains. Based on this insight we develop two novel link adaptation schemes that adapt the features of interest in a holistic way for legacy 802.11a/b/g and 802.11n. The common grounds of both schemes are the fact that they both are hybrids relying on easily accessed channel quality information at the sender side to perform holistic adaptation. We conclude by examining the benefits of our link adaptation schemes and the remaining challenges.

7.1 Holistic & Efficient Link Adaptation for 802.11x Wireless LANs

In this dissertation we consider both legacy 802.11a/b/g and 802.11n link adaptation. In the first case, we focus on the impact of differentiating between different types of losses (i.e., loss differentiation) on link adaptation. Loss differentiation has received a lot of attention in the literature. So, we revisit this issue and show that not knowing the exact cause of loss is not an impediment to effective link adaptation (chapter 3). Thus, actions taken in response to losses are more crucial and they ought to be holistic and not solely dependant on the exact cause of loss. Motivated by this observation, we have developed a novel link adaptation scheme for legacy 802.11a/g WLANs, called *Themis* that does not rely on loss differentiation and adapts the transmission bit-rate and contention window. *Themis* uses a sampling technique for rate selection, that selects the rate to sample based on RSSI in low contention cases, whereas it randomly selects a rate to sample in high contention cases. Simulation results show that *Themis* can considerably improve performance, in terms of throughput and fairness, compared to both the standard 802.11a/g and SampleRate algorithms, by eliminating hidden nodes.

Next our goal was to understand of the impact of different IEEE 802.11n features on performance in different link scenarios as well as interdependencies among those features so as to be able to design an efficient link adaptation scheme for 802.11n WLANs (chapter 4). A significant contribution of this dissertation is the systematic methodology followed to accurately characterize the behaviour of the IEEE 802.11n standard and its newly introduced features. Our study revealed that:

- regression based analysis is valuable in easing the characterization of the impact of different features on performance.
- the relative impact of different 802.11n features on performance (throughput, packet loss, video streaming quality and fairness) is scenario dependent.
- different features are interdependent with respect to throughput and the nature of interdependence varies between scenarios.
- it is indeed crucial to adapt all features to obtain the best throughput. We can quantify the benefit of adapting multiple 802.11n features via testbed measurements that span a diverse set of scenarios differing in channel and interference conditions.

Current link adaptation designs for IEEE 802.11n and future standards are either open- or closed-loop schemes. Open-loop schemes rely on some short of sampling at the sender side to identify the best performing one. As there are a large number of feature setting combinations to search across with 802.11n, and even more with future 802.11ac, existing schemes incur high sampling overhead or tend to use sub-optimal settings for extended periods. On the other hand, closed-loop approaches measure channel quality on receiver side and feed it back to the sender and would be effective in theory, but they face practical implementation problems for precise measurement of channel state and feedback.

Motivated by the limitations of current schemes and the insights we gained during our characterization study, we design, implement and evaluate a novel hybrid link adaptation scheme termed SampleLite that adapts all 802.11n features (i.e., MIMO mode, channel width, MCS and frame aggregation level) while being efficient and practical (chapter 5). As a hybrid, SampleLite employs both sampling and the use of channel quality information. It dramatically reduces the sampling search space without risking the use of sub-optimal settings relying on channel quality information available at the sender side and therefore it is easily implementable. Via experimental evaluation we show performance gains in controlled and real-world interference scenarios for both mobile and stable stations compared to the state of the art 802.11n wireless link adaptation algorithms. Specifically we show that compared to the widely used Minstrel HT, SampleLite reduces sampling and improves throughput on average by 70% and 35%, respectively.

7.2 Remaining Challenges & Future Work

The schemes in this dissertation addressed the major challenges involved in efficiently and practically adapting the network settings based on the changes in the environment. Below, we present challenging issues that the dissertation does not solve. These are not fundamental limitations, however, and we believe they can be solved within the framework proposed in this work.

Our work raises the fairness issue of the 802.11n protocol in section 6.1. However, this was not the main focus of this work so it was not further explored. It is an interesting problem to determine what is the tradeoff in using high data-rates increasing the throughput of a link compared to maintaining a fairness threshold. Another important issue is the metric used to describe fairness. We believe that Jain's index is not a representative metric that can provide in depth information. Therefore, other more intuitive metrics should be used for future work, like airtime fairness [85, 86]. Moreover, the impact of a link adaptation scheme like SampleLite on fairness would also be useful to discover. Finally, further in depth study of this issue could provide valuable insights on what is the exact cause of the unfairness and how to mitigate it.

Moreover, a 802.11n feature that we do not consider throughout this dissertation is the long and short guard interval (LGI/SGI). This feature can also be employed in our proposed scheme, SampleLite, using chipsets that support it in both 20 and 40MHz channels. The same methodology as shown in section 5.3.1

can be followed. Based on the findings of that study, the guard interval can easily be another feature that SampleLite adapts.

The upcoming IEEE 802.11ac standard is expected to provide multi-user WLAN throughput of at least 1Gbps and a single stream throughput of at least 500Mbps. This is accomplished by extending the concepts embraced by 802.11n. For example, 802.11ac employs wider channel bandwidth (up to 160MHz), more MIMO spatial streams (up to 8), and high-density modulation (up to 256-QAM) increasing the MCS indexes from 8 to 10. We believe that SampleLite can be efficiently extended to as to support these extra settings and we expect the gains in both increasing the throughput and minimising the sampling overhead to be even greater in this case. Apart from extending the setting selection in existing features, 802.11ac introduces new ones too like the multi-user MIMO. This feature is expected to boost throughput performance. However, it is unclear how this new feature would affect interference in WLANs. Therefore, it would be very interesting to have a thorough experimental and statistical-based analysis to realise the limitations that this new feature could incur when misused. Then it can be properly handled in the context of a new holistic link adaptation scheme not only to increase throughput performance, but the fairness the users experience, too.

Finally, the video streaming delivery quality is another important issue that current and upcoming standards aim to improve, but has not received enough attention. We perform a characterisation study exploring the impact of the newly introduced PHY enhancements on the streamed video quality in section 6.3. However, it would be interesting to find out the impact of a link adaptation scheme like SampleLite on video streaming performance. Could a link adaptation scheme that is not focused on video provide results comparable to VARA [60] that targets only video related rate adaptation? RTP video streaming over UDP is an even more challenging environment than HTTP transmission over TCP (discussed in this dissertation) and it would be useful to study in future work.

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