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Coexistence of Wi-Fi and 5G NR-U in the Unlicensed Band

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Abstract

The communications industry continues to evolve to meet the ever-growing demands of fast connectivity and higher energy-efficiency and has emerged the concept of Internet of Things (IoT) systems. IoT devices can be run on Wi-Fi or cellular network, helping businesses to receive higher return on investments.

As billions of devices on cellular networks operate on the limited licensed spectrum, it is becoming scarcer. Mobile network operators are investigating to access the immense unlicensed spectrum, on which Wi-Fi is prominently operated. Managing this coexistence between the cellular and Wi-Fi networks poses several challenges.

One challenge is the spectrum sharing that affects the network capacity and the spectrum efficiency by properly allocating the available resources for each technology. A second challenge is to maintain the quality of service (QoS) while maximizing the aggregated throughput. A final challenge is to reduce the power consumption of cellular base stations by creating a sleep/wakeup policy, thereby lowering the capital and operating expenses for the mobile network operators.

To this end, this thesis proposes various optimization modeling for the coexistence mechanisms in the unlicensed spectrum, as well as intelligent techniques to manage the increasing power consumption with increased usage. First, this thesis develops optimization modeling techniques to properly allocate resources for the coexistence of the Wi-Fi and cellular networks by improving the aggregate throughput, while maintaining the minimum required power consumption. Next, this thesis implements the coexistence mechanism by simulating real-time traffic information to maximize the aggregate throughput, while satisfying the QoS for each user. Finally, this thesis investigates the use of machine learning techniques to predict the traffic behaviour of base stations; this will determine the sleep/wakeup schedule, thereby minimizing the power consumption while maintaining the QoS for each cellular user.

Keywords: Coexistence, Cellular Network, Unlicensed Band

Summary for Lay Audience

The amount of devices that connect to the Internet are exponentially increasing that users are now competing with each other to access the limited cellular network. To solve the cellular spectrum scarcity while users are demanding faster connectivity as well as higher energy-efficiency, network operators are investigating the unlicensed spectrum.

The main challenge of network operators shifting their focus on utilizing the unlicensed spectrum, which is prominently used by Wi-Fi, is that the cellular devices overpower the Wi-Fi systems, not allowing the Wi-Fi technology to be accessible.

This thesis proposes a coexistence mechanism to allow the cellular system to communicate alongside with the Wi-Fi systems without degrading the performance, as well as intelligent techniques to manage the increasing power consumption with increasing usage.

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In loving memory of my late father; Saud Khader Zimmo, this is for you.

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List of Abbreviations

3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
ABS	Almost Blank Subframe
ADF	Augmented Dickey Fuller
ANN	Artificial Neural Network
AP	Access Point
ARIMA	Autoregressive Integrated Moving Average
B5G	Beyond 5G
BIP	Binary Integer Programming
BS	Base Station
CAPEX	Capital Expenditures
CO2	Carbon Dioxide
CSAT	Carrier Sensing Adaptive Transmission
CSI	Channel State Information
CSMA/CA	Carrier Sensing Multiple Access with Collision Avoidance
D2D	Device-to-Device
DCF	Distributed Coordination Function
DES	Discrete-Event Simulation
eMBB	Enhanced Mobile Broadband
eNB	Evolved NodeB
FCC	Federal Communications Commission
FTP	File Transfer Protocol
GBR	Guaranteed Bit Rate
gNB	Next Generation NodeB
HA	Heuristic Algorithm
ID	Identification
IEEE	Institute of Electrical and Electronics Engineers

ILP	Integer Linear Programming
IoT	Internet of Things
ISM	Industrial, Scientific and Medical
ITU	International Telecommunication Union
LAA	License-Assisted Access
LBT	Listen-Before-Talk
LTE	Long Term Evolution
LTE-M	LTE for Machine-Type Communication
MCS	Modulation and Coding Scheme
MIMO	Multiple Input, Multiple Output
MINLP	Mixed-Integer Non-Linear Programming
ML	Machine Learning
MLP	Multilayer Perceptron
mMTC	Massive Machine-Type Communication
NFV	Network Functions Virtualization
NGBR	Non-Guaranteed Bit Rate
NLOS	Non-Line-Of-Sight
NP	Non-deterministic Polynomial-time
NR-U	New Radio-Unlicensed
OFDMA	Orthogonal Frequency Division Multiple Access
OP	Optimization-based Programming
OPEX	Operational Expenditures
PADF	Partial ADF
pdf	Probability Density Function
PL	Path Loss
QoE	Quality of Experience
QoS	Quality of Service
R13	Release 13 of 3GPP
RAN	Radio Access Network
RB	Resource Block
RMSE	Root Mean Square Error
ROI	Return on Investment
SARIMA	Seasonal ARIMA
SC-FDMA	Single Channel Frequency Division Multiple Access
SLA	Service Level Agreement
SNR	Signal-to-Noise Ratio

SP	Service Provider
SVM	Support Vector Machine
TTI	Transmission Time Interval
UMi	Urban Microcell
U-NII	Unlicensed National Information Infrastructure
URLCC	Ultra-Reliable and Low Latency Communication
VoIP	Voice over Internet Protocol
Wi-Fi	Wireless Fidelity
WRV	Wireless Resource Virtualization

Chapter 1

Introduction

Nowadays, there are more cellular subscribers than there are people on our planet [2]. The ever-growing demand for faster speed connection and reduced latency continue to improve and evolve the cellular technology. Cellular users enjoy the anywhere, anytime untethered connection with their portable mobile device. Cisco reports nearly two-thirds of the global population will have Internet access by 2023, and over 70% of the population will have mobile connectivity which is a 5% increase from 2018 [3]. Also, 5G devices and connections will be over 10% of all devices by 2023 [3].

However, this increase of data traffic can be problematic as the radio spectrum of the mobile network is finite and is subject to spectrum scarcity, which will affect the user's quality of service (QoS). Furthermore, the mobile network is running on a limited licensed spectrum, and expanding the licensed spectrum to increase the network capacity can be very costly[4]. Finally, increasing the number of cellular users will affect the power consumption of the mobile devices as well as the cellular base stations.

To that end, this thesis proposes various optimization modeling for a coexistence mechanism in the unlicensed spectrum as well as machine learning techniques to manage the power consumption of the base stations. The first part of this thesis introduces optimization modeling techniques to allow the Wi-Fi and cellular network to coexist in the same spectrum by improving the aggregate throughput while satisfying the minimum required power consumption. The following section of the thesis tests the coexistence mechanism using traffic simulation to maximize the aggregate throughput while satisfying the quality of service for each user. Finally, the last part of the thesis proposes the use of machine learning techniques to be integrated into base stations to minimize the power consumption while maintaining the quality of service for each cellular user.

1.1 Motivation

Cellular users around the world expect a fast secure access to information on the go. Cisco calculated that in 2022, more Internet traffic is created than in the 32 years since the Internet was developed [1]. Fig. 1.1 shows the trends in 2017 and 2022 to visualize the growth in five years. The deployment of 5G devices have been faster than previous cellular standards [5]. However, there is a diminishing access to the limited license spectrum due to increasing number of devices connected to the cellular network. Furthermore, providing spectrum for new services or expanding existing services is challenging as most of the spectrum has already been assigned [6]. In addition, the FCC white paper reported that there is unused resources for access due to not utilizing the spectrum efficiently [7]. As a result, cellular standard organization bodies have utilized the unlicensed spectrum which is primarily utilized by Wi-Fi and Bluetooth to address the spectrum scarcity [8]. Therefore, this thesis introduces a mechanism to allow cellular users to access the unlicensed spectrum while maintaining a coexisting relationship with the Wi-Fi network. In addition to the coexistence, the mechanism will exploit the capacity to efficiently access the spectrum.

As videos, gaming and multimedia will take more than 85% of all traffic, especially with the growing demand for virtual and augmented reality, the next challenge is to consider the quality of service for each user [3]. 5G applications and use cases focus on high-speed connections with ultra-high reliability and low latency communication [9, 10]. Ericsson conducted a study

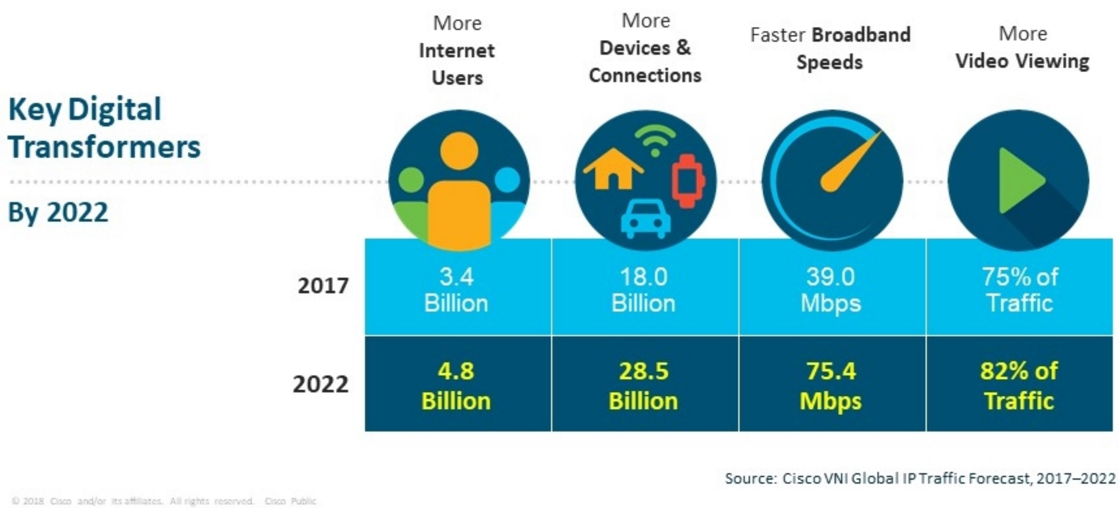


Figure 1.1: Global Internet Growth and Trends by 2022[1]

on the 5G business potential for operators showing that, between 2020 and 2024, the potential revenue will grow from $14 to $129 billion[11]. This thesis will implement the traffic scenario to the modified coexistence mechanism to meet the delay constraints.

A third challenge is the edge computing. Ericsson expects a significant investment in extended reality use cases to drive the need for time-critical communication services [11]. Edge network provides solutions to low latency with high bandwidth by keeping the resources close to the end users. However, keeping resources close require utilizing the cellular base station, which already consume high source of power. Over 90% of network costs are spent on energy including fuel and power [12], where more than 70% of the energy is consumed in base stations [13, 12]. Therefore this thesis will utilize machine learning techniques for traffic prediction for the cellular base stations to conserve power while meeting the quality of service constraints.

1.2 Thesis Objectives

This thesis can be decomposed into three different projects. The first project proposes a coexistence mechanism, the second project simulates the traffic scenario on the coexistence mechanism. The last project focuses more on the cellular network using real traffic data.

The first project proposes the coexistence of Wi-Fi and cellular network as cellular network moves to unlicensed spectrum to increase the network capacity. Also, the wireless resource virtualization is implemented to improve the spectrum efficiency. The goal is to use the optimization model and compare with the heuristic algorithm to find the maximum aggregated throughput while maintaining the power consumption.

The second project creates a practical scenario for the coexistence mechanism created in the first project by implementing traffic simulation. The goal is twofold: first, the coexistence mechanism is modified to maintain the delay constraints, and, second, the goal is to also maximize the throughput while maintaining the quality of service.

The third project has more emphasis on the cellular network, more specifically on the base station. In this project, machine learning techniques are used to predict the traffic behaviour to determine the sleep/wakeup schedule of the base station. The goal is to minimize the power consumption while still maintain the quality of service.

1.3 Thesis Organization

The thesis is composed of five chapters. Chapter 1 provides an overview of the thesis about the need of coexistence of cellular and Wi-Fi technologies as well as to maintain the quality of service for each user as technology evolves. Moreover, the importance of adopting optimization modeling and machine learning techniques to improve a variety of systems and processes is highlighted. Additionally, the thesis contributions are summarized and outline is provided.

Chapter 2 formulates the optimization problem for the cellular and Wi-Fi power-aware coexistence. Since the problem is a Mixed-Integer Non-Linear Programming problem, it is divided into four smaller linear programs, each of which is solved to optimality. Two lower complexity heuristic algorithms to solve the power allocation problems are introduced.

Chapter 3 implements the discrete event simulation to meet the delay constraints. This chapter also formulates a resource allocation optimization problem for the cellular and Wi-Fi coexistence while meeting the quality of service constraints. The problem is a Integer Linear Programming problem, therefore is decomposed into a pair of Binary Integer Programming problems using a Lagrangian dual decomposition method. Two low-complexity heuristic greedy-based algorithms are introduced.

Chapter 4 tests various machine learning techniques to predict the traffic behaviour of each base station. This chapter propose a new scheme for prediction, while considering the practical scenario by including communication and computing overhead needed to have the edge server back fully functional.

Finally, chapter 5 concludes the thesis, provides the summary of the findings and discusses some potential future works.

1.4 Thesis Contribution

Major contribution of the thesis is as follows:

1.4.1 Contributions of Chapter 2

- Propose a coordinated coexistence mechanism for LTE and Wi-Fi in time domain-based Wireless Resource Virtualization.

- Formulate an optimization problem that maximizes the throughput and minimizes the transmission power as a Mixed-Integer Non-Linear Programming Problem (MINLP).

- Decompose the MINLP into a pair of Binary Integer Programming (BIP) problems for each technology using the Lagrangian dual decomposition method.

- Propose two low-complexity heuristic algorithms to solve each of the formulated optimization subproblems.

1.4.2 Contributions of Chapter 3

- Propose a time domain-based WRV coordinated coexistence mechanism for 5G and Wi-Fi.
- Formulate an optimal formulation of QoS-aware resource allocation that maximizes the throughput while meeting the QoS constraints as a Integer Linear Programming Problem (ILP).
- Decompose, using the Lagrangian dual decomposition method, the formulated ILP problem into a pair of Binary Integer Programming (BIP) problems.
- Propose two low-complexity heuristic greedy-based algorithms to solve each of the formulated optimization sub-problems.

1.4.3 Contribution of Chapter 4

The contribution is to consider the wake-up and association time and determine the threshold time to keep it awake while maintaining the QoS and increasing the energy efficiency.

Chapter 2

Power-Aware Coexistence of Wi-Fi and LTE in the Unlicensed Band using Time-Domain Virtualization

2.1 Introduction

The rising use of smartphones and Internet of Things (IoT) devices increased the global mobile data traffic by 71% in 2017 [14]. By 2022, mobile devices will represent 20% of the total IP traffic [14]. This rapid surge is causing the limited licensed bands, which are exclusive to cellular operators, to be congested. Expanding the licensed band can improve the network capacity and provide users with better Quality of Experience (QoE). However, acquiring additional spectrum in the licensed band is costly [15]. Instead, exploring shared access with the unlicensed band is a potential solution to address the licensed spectrum scarcity problem. The unlicensed band has a wider frequency range that is free. However, it is susceptible to spontaneous interference noise as it is shared with many technologies such as 802.11 (Wi-Fi), 802.15.1 (Bluetooth) and 802.15.4 (ZigBee). Therefore, the recent trend focuses on the fifth generation, known as 5G, which includes spectrum sharing in 5 GHz and higher. The 5GHz band is an unlicensed band, which is dominated by Wi-Fi technology.

The 5G is the next generation of advanced mobile capability focusing on faster connections, higher reliability, lower costs to serve and a higher density of devices. The mobile broadband standard Third Generation Partnership Project (3GPP) has taken part in 5G standardization by focusing on enhanced mobile broadband. The 3GPP introduced LTE (Long-Term Evolution) in Release 8 as a 4G telecommunication standard operating on a licensed band and is looking into evolving LTE to coexist in unlicensed spectrum in Release 13 as a solution to spectrum scarcity [16, 17]. The goal is to offer cellular operators with the option to utilize the unlicensed spectrum with a unified network. Although operating on a licensed band offers a better user experience, accessing the unlicensed band will allow for potential cost savings and improved spectral efficiency.

Despite the merits resulting from the previously proposed inter-technology coexistence mechanisms, such mechanisms face several challenges including inter-technology coordination and mutual interference management [18]. Almeida *et al.* found that without any coexistence mechanism, the throughput of Wi-Fi decreased by 96.63% and LTE was not significantly affected as the throughput decreased by 0.49% [19]. Although each technology has an interference management mechanism, these mechanisms do not work well among other technologies.

Similarly, Wireless Resource Virtualization (WRV) has been proposed as one potential solution for meeting the continuously growing demand for mobile data traffic and spectrum access. WRV entails the sharing of available resources, such as wireless resources, hardware, and software dynamically and efficiently. Employing WRV has various benefits. Firstly, WRV can help providers reduce their Capital and Operational Expenditures (CAPEX and OPEX) as the initial investment and the maintenance costs are shared among the providers [20]. Secondly, the sharing of radio resources can facilitate resource aggregation, which in turn can lead to providers being able to support higher peak rates [20]. Finally, due to the increased number of users, a multi-provider multiplexing gain is introduced with the deployment of WRV [21]. However, the proposed coexistence mechanism with WRV will result in a higher throughput and power consumption in portable mobile devices. Thus, any proposed approach should also include a power consumption management mechanism, particularly for battery-operated devices.

Power savings or energy efficiency is one of the aspects that is critical for 5G networks [22, 23, 24]. The demand for high data rates with high Quality of Service (QoS) and QoE will draw more power from mobile devices [22]. As a result, this increase in power consumption will have a significant environmental impact due to the high emission levels of CO2 [25, 26]. Furthermore, a reduction in power consumption can decrease the CAPEX and OPEX of the cellular Service Providers (SPs) [27]. Therefore, there are financial and environmental gains associated with reducing power consumption.

Accordingly, this work proposes a coexistence configuration based on the throughput between the two technologies that uses time-sharing to ensure fairness. Additionally, it uses WRV to allow for more resources to be available for both Wi-Fi and LTE to use. Lastly, an additional mechanism to minimize the power consumption is needed to reduce the interference caused by LTE technology when sharing the unlicenced band with the Wi-Fi technology. Therefore, the focus of this paper is to propose a mechanism that increases the network capacity while maintaining the spectrum efficiency and reducing the power consumption of the mobile devices. The proposed solution schedules the coexistence of both LTE and Wi-Fi with WRV. This paper extends our previous work by considering the power consumption as part of the formulated optimization model and proposing a power-aware heuristic algorithm [28]. The key contributions of this work are as follows:

- Propose a coordinated coexistence mechanism for LTE and Wi-Fi in time domain-based WRV.
- Formulate an optimization problem that maximizes the throughput and minimizes the transmission power as a Mixed-Integer Non-Linear Programming Problem (MINLP).
- Decompose the MINLP into a pair of Binary Integer Programming (BIP) problems for

each technology using the Lagrangian dual decomposition method.

- Propose two low-complexity heuristic algorithms to solve each of the formulated optimization subproblems.

This paper is organized as follows. Section II discusses some of the related work done in the literature. Section III presents the system model as well as the channel model. The problem formulation is presented in Section IV. The heuristic algorithms are described in Section V. The scheduling algorithm is demonstrated in Section VI. Section VII presents the simulation parameters and results. Finally, Section VIII concludes the paper.

2.2 Related Works

2.2.1 Coexistence Mechanism

Coexistence and interworking are two different ways to enable the use of different wireless technologies on the same spectrum [18]. Coexistence methods involve the definition of boundaries for the occupation of radio resources by the network. On the other hand, interworking is the exchange of information between the technologies to coordinate spectrum usage amongst each other [29]. This work focuses on coexistence as a sharing mechanism with interworking being beyond the scope of this paper.

Fig. 2.1 provides an overview of the different sharing methods between LTE in the licensed and unlicensed band and Wi-Fi in the unlicensed band. The operators can choose to offload the traffic in three ways. Firstly, Wi-Fi offloading is a method introduced by 3GPP Release 10 to unload the licensed traffic onto Wi-Fi to reduce congestion via interworking [30]. Secondly, link aggregation was introduced in R13 to increase the throughput and the total system capacity via interworking [31]. Link aggregation uses licensed LTE and Wi-Fi, both belonging to the same operator. Thirdly, carrier aggregation was introduced in R10 where LTE is operated over the unlicensed band to increase reliability and boost data rates via coexistence [32].

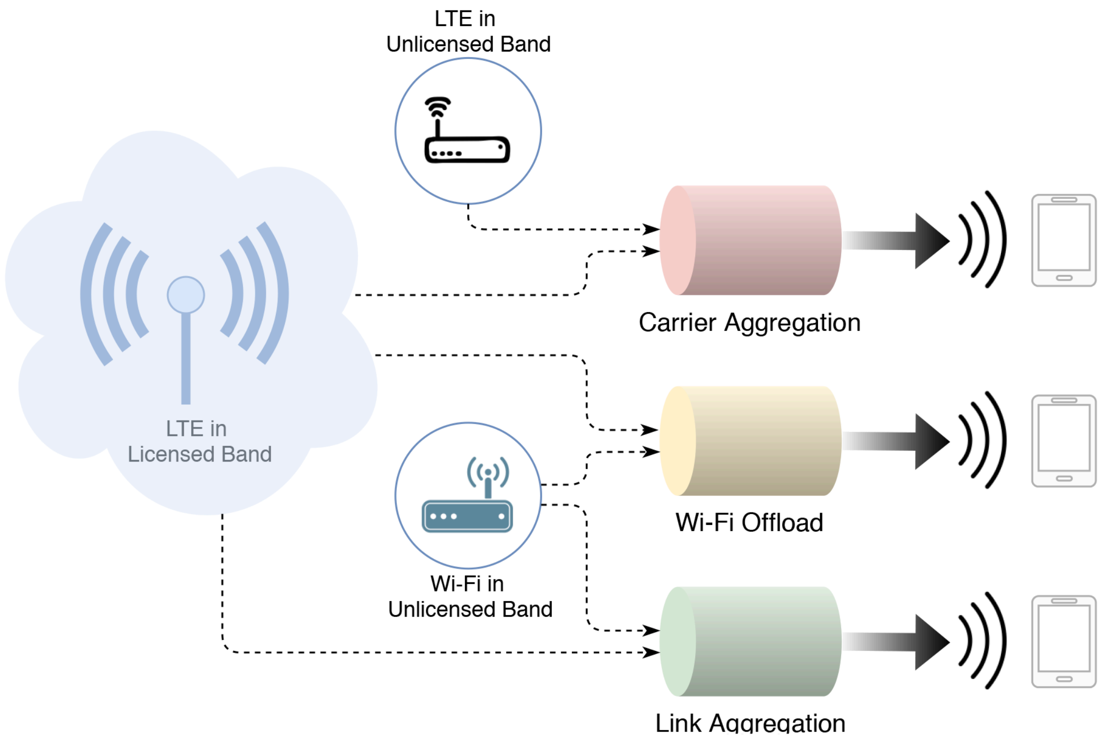


Figure 2.1: Sharing Techniques

Operators can choose to use carrier aggregation, such as LTE-U and License-Assisted Access (LAA). LTE-U, based on R10-12, uses carrier sensing adaptive transmission (CSAT) to coexist with WiFi and uses duty cycle to silence LTE to allow WiFi to access the band. LTE-U is regulated in the US, and is operated only on downlink. LAA is another type of carrier aggregation that is standardized version of LTE-U by 3GPP. LAA was introduced in R13 and is regulated globally [33].

Existing approaches to enable coexistence between LTE and Wi-Fi can be categorized into frequency domain-based and time domain-based approaches. Frequency domain-based approaches divide the spectrum between technologies while time domain-based approaches use the time to determine the spectrum sharing on the unlicensed band.

Some time-domain approaches in the literature have investigated the protocols involving sensing the carrier before transmitting [34, 35, 36, 37]. This approach includes the Listen-Before-Talk (LBT) protocol in LAA and the Carrier Sensing Adaptive Transmission (CSAT) protocol in LTE-U [36, 38, 39]. Rather than sensing the carrier, several works utilize a time-partitioning approach where LTE users are offloaded by occupying several subframes to Wi-Fi users in the form of duty cycle to allow Wi-Fi users to transmit data [19, 40, 41, 42, 43]. By occupying subframes to Wi-Fi users, the authors used the almost blank subframe (ABS), introduced in 3GPP Release 10, to keep channel state information (CSI) data, and still allow for LTE to send subframes without interfering with the Wi-Fi communication [19].

On the other hand, frequency domain-based approaches use the frequency as a variable for coexistence. This approach allows the LTE and Wi-Fi to exploit the available bandwidth by operating on separate and non-overlapping channels in the unlicensed spectrum. Sagari *et al.* developed coordinated dynamic spectrum management for a heterogeneous-traffic scenario of LTE and Wi-Fi [44]. Chen *et al.* also presented a dynamic spectrum allocation that is adaptive based on the SP of LTE and Wi-Fi and the market response [45]. Finally, Yuan *et al.* investigated the dynamic spectrum allocation using the human satisfaction of Wi-Fi and LTE throughput [46].

To summarize, the time domain-based approach allows different frequency carriers to use the unlicensed spectrum efficiently. On the other hand, the frequency domain-based approach may not efficiently utilize the spectrum due to the utilization of an entire frequency needed for Wi-Fi.

2.2.2 Wireless Resource Virtualization

Several researchers have previously proposed WRV in a variety of systems and scenarios to assist with spectrum efficiency. WRV can be done across multi-size cells, where the LTE users at macro and microcells can share resources [47]. Kalil *et al.* proposed a WRV framework in an LTE system [20], where SPs aggregate and share their spectrum bands while maintaining their scheduling policies. Based on simulation results, WRV offered throughput gains to all users. The authors further extended their framework by proposing an efficient low-complexity scheduler to achieve fair and proportional access [48]. Simulation results showed that the proposed scheme ensured the access fairness among the SPs while simultaneously achieving higher throughput when compared to the static sharing scenario.

Similarly, Moubayed *et al.* combined WRV in an LTE system with Device-to-Device (D2D) communication to further improve spectrum efficiency and resource utilization [21]. Through simulations, the authors showed the positive impact of combining WRV with D2D communication, especially to combat worsening channel conditions [21].

It is important to note that WRV is used for practical purposes, especially with the emergence of virtual SPs, to allow for the technologies to utilize the spectrum more efficiently.

2.2.3 Power-Aware Allocation

Existing research work includes power-aware communication to reduce power consumption without affecting the performance of mobile devices. Hussein *et al.* proposed a framework to minimize the total transmission energy for all users by sharing resources across the SPs in the LTE uplink system [49]. Due to this, the authors found the battery life can be prolonged by up to 53%.

Kalil *et al.* proposed a power-efficient resource allocation framework for LTE uplink communication. This framework is achieved by minimizing the total transmission power while maintaining the LTE uplink physical layer constraints and QoS requirements [50]. Also, this paper included the transmission power constraints in the BIP as well as the iterative scheduler and found that they were able to reduce the transmission power and satisfy the QoS requirements using both algorithms [50].

Finally, Moubayed *et al.* considered power-aware resource allocation with WRV while sharing with D2D communication underlaying cellular network [26]. Simulation results showed that adopting the power-aware allocation scheme into resource allocation has saved up to 42% of the transmission power for LTE systems and close to 75% for D2D communication [26].

Table 2.1 summarizes the related works and highlights the contribution of our work.

Table 2.1: Comparison with related works (✓: satisfied, ×: not satisfied)

Reference	LTE	Wi-Fi	WRV	PC
[19]	✓	✓	×	×
[20]	✓	×	✓	×
[21]	✓	×	✓	×
[26]	✓	×	×	✓
[34]	✓	✓	×	✓
[35, 36, 37, 38]	✓	✓	×	×
[39]	✓	✓	×	✓
[40, 41, 42, 43]	✓	✓	×	×
[44, 45, 46]	✓	✓	×	×
[48]	✓	×	✓	×
[49]	✓	×	×	✓
[50]	✓	×	×	✓
Our work	✓	✓	✓	✓

WRV: Wireless Resource Virtualization, PC: Power Control

2.3 System Model

The approach proposed in this work is to adopt a power-aware time domain-based WRV mechanism for LTE and Wi-Fi coexistence. Within the context of this work, time-virtualization refers to the process of assigning dedicated subframes to each technology, *i.e.* the time domain resources are being shared (in a similar fashion to the concept of virtualization) between the two technologies. Thus, the scheduler involves utilizing the ABS with the duty cycle method to silence LTE for the Wi-Fi network, which relieves the co-channel interference. Fig. 2.2 shows the proposed scheduler, running such that four subframes are assigned to Wi-Fi, and one subframe is assigned to LTE. This configuration was chosen based on the previous paper to ensure time-sharing fairness between the two technologies by limiting the LTE users overpowering the Wi-Fi users [28]. Zooming into the LTE subframe, the LTE is broken up into Resource Blocks (RBs) that are assigned to each SP. Three cases of RB allocation are shown in this figure. The left shows no allocation to the user, the middle shows the case of no WRV, and the right shows the case of WRV. Additionally, when an RB is allocated to a user without any virtualization, any users belonging to the first SP will be assigned in the first six RBs, and

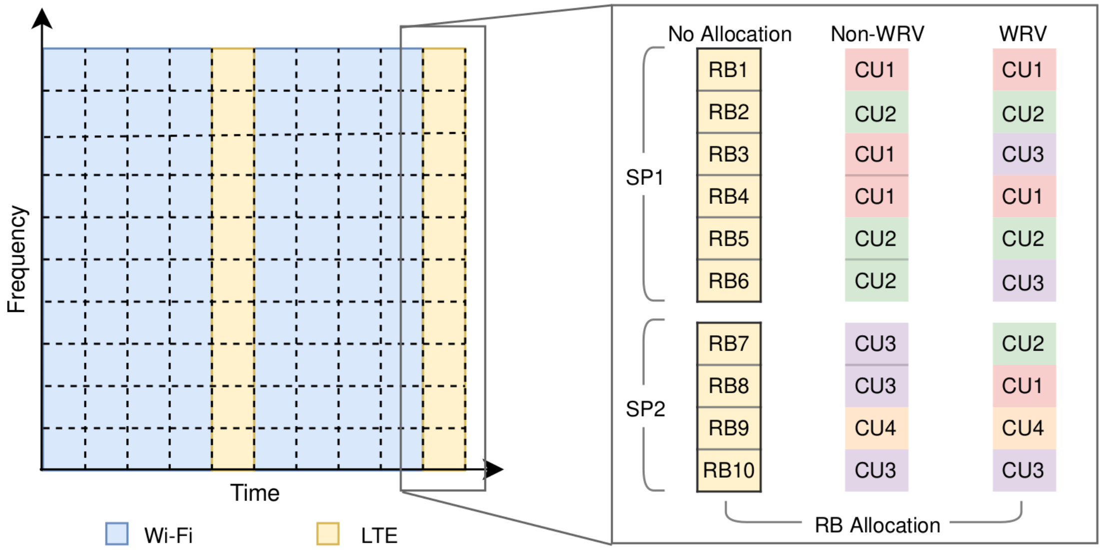


Figure 2.2: Proposed Scheduler

any users belonging to the second SP will be assigned in the last four RBs. Finally, if there is WRV, then any users can be allocated to any RB regardless of SP. In turn, this would maximize the RB pool available for a user, increasing their chances of getting a better channel.

2.3.1 Problem Definition

This work attempts to maximize the data rate of each user assigned to LTE or Wi-Fi, as well as to minimize the power required to transmit data over the unlicensed band using the lowest Signal-to-Noise Ratio (SNR) of the chosen modulation and coding scheme.

2.3.2 Channel Access

The 5GHz band is the frequency band of most interest for LTE to operate on the unlicensed band, due to the high availability of bandwidth in the spectrum [31]. The regulatory regulation to access the frequency range of 5150-5925 MHz varies in different regions in the world. Due to this, the transmission power is limited in the 20-30 dBm range, depending on the carrier frequency. To simulate a scenario in Canada and the United States, a carrier frequency of 5.8 GHz is used, with the maximum transmission power of 30 dBm [51, 33].

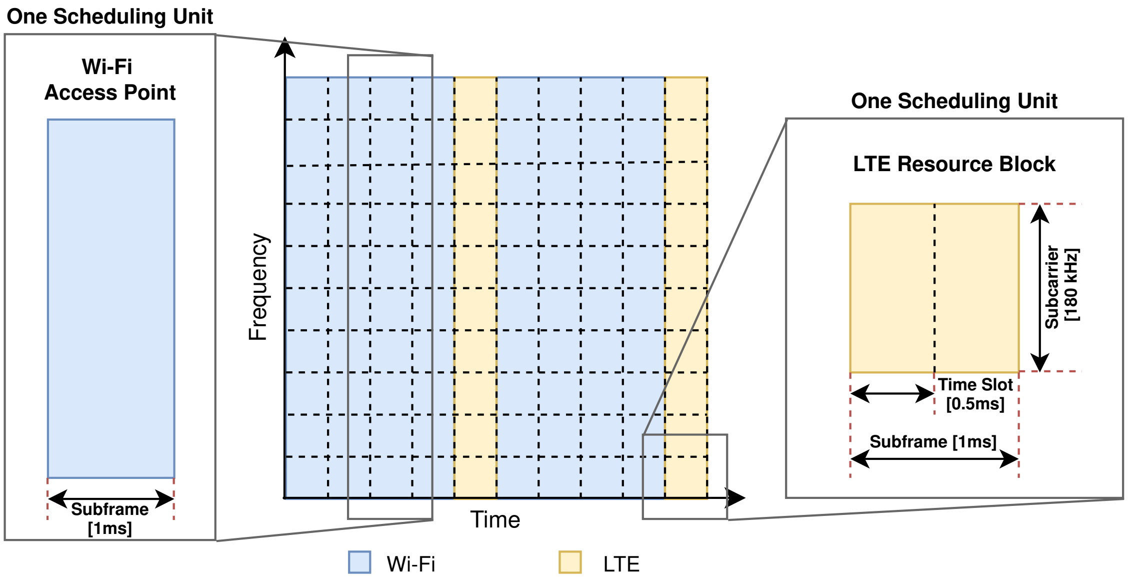


Figure 2.3: How users can access the spectrum

Fig. 2.3 illustrates how users of LTE and Wi-Fi utilize a spectrum. The scheduler allocates scheduling units to each user to ensure the expected throughput for each user. The scheduler is performed in a base station, commonly known as Evolved NodeB (eNB). The LTE scheduler has two different access schemes to allocate for uplink and downlink. Downlink carrier utilizes Orthogonal Frequency-Division Multiple Access (OFDMA) where users can access any RB in the time-frequency grid. Uplink carrier utilizes Single Channel Orthogonal Frequency Division Multiple Access (SC-FDMA), where the RBs are allocated with consecutive subcarriers. The eNB is managed by the infrastructure provider, which has a set of SPs. The infrastructure provider has a Service Level Agreement (SLA) with each SP to determine the minimum number of RBs assigned to each SP, based on the pre-agreed access ratio between the SPs. The scheduler that assigns the RB to users is done in the hypervisor.

Unlike in the LTE system where channel access is done by schedule, nodes in the Wi-Fi network use Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) and transmits over the entire available bandwidth [15]. The overview of CSMA/CA is to allow the user to listen the channel before transmitting, where if the channel is sensed to be busy, the user must wait at a random time, and if it is sensed to be free, then the user may transmit. Moreover, the Wi-Fi network transmits at the maximum power regardless of the amount of channel interference.

To operate on the 5GHz frequency band, IEEE 802.11ac is the wireless standard used in this simulation, although the implementation of 802.11 wireless standards is similar. IEEE 802.11ac was finalized in 2013 and is currently implemented in most devices. It is also backwards compatible with older Wi-Fi standards. All 802.11 protocol implements CSMA/CA access method, and this paper exploits a Distributed Coordination Function (DCF), which is a random access scheme that utilizes CSMA/CA method and binary exponential backoff rules [52]. Moreover, binary exponential backoff rules determine the time needed for the packets to re-transmit when the packets collide.

In summary, the eNB in the LTE network schedules the channel access, whereas the Access Points (APs) in the Wi-Fi network utilize the channel using CSMA protocol[36]. In uncoordinated coexistence, the continuance of the LTE communication blocks the Wi-Fi channel access, causing Wi-Fi to be in a listening mode almost indefinitely. Thus, Wi-Fi suffers the interference from LTE, and when Wi-Fi has a chance to communicate, LTE suffers interference from Wi-Fi due to the maximum transmission power of the Wi-Fi system [53].

2.3.3 General Model

The coexistence scenario is proposed in Fig. 2.4. The general model is set up such that there is one LTE microcell eNB that is shared among SPs. This model assumes the existence of continually active users. The scenario is to implement the downlink in the LTE system running in the 5GHz frequency band, with Wi-Fi APs spread in the transmission range of the eNB. The process of scheduling the access of the Wi-Fi and LTE users and minimizing the power transmission is done in the hypervisor, which is in the physical eNB. The microcell eNB is used in urban areas with hexagonal deployment and simulated in an indoor/outdoor model with the radius of 500m. The eNB can reach as far as 2000m, but to simulate a real-world application, the scenario is limited to a 500m radius, with the eNB attached on a multi-floor building. The channel condition assumes indefinitely backlogged data and assumes minimal to no interference between each technology except for the interruption of the Wi-Fi transmission caused by LTE. It is assumed that the hypervisor is in the physical eNB, and it will coordinate between the cellular SPs as well as between cellular and Wi-Fi transmission. Also, the same SPs offer cellular connection and Wi-Fi connection.

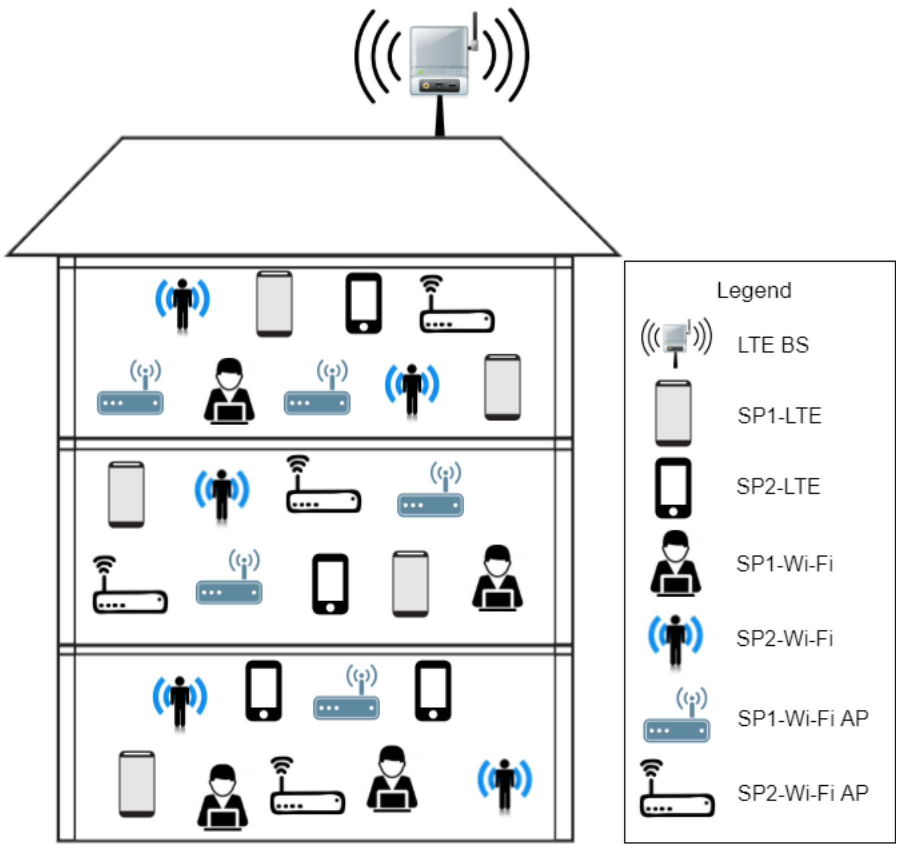


Figure 2.4: Proposed Coexistence Scenario

2.3.4 Channel Model

Both macroscopic and microscopic path loss will be considered for the mathematical model. Macroscopic path loss is dependent on the distance, and microscopic path loss is randomized which includes fading effects.

For LTE channel model, the distribution of the macroscopic shadow fading path loss is log normal with its standard deviation is given as [51, 54, 55]:

$$L_{dB}^{L}(d) = 36.7\log_{10}(d) + 22.7 + 26\log_{10}(f_c) \tag{2.1}$$

The path loss model is obtained from 3GPP standard which utilizes non-line-of-sight (NLOS) urban microcell (UMi), with hexagonal deployment. To implement the building penetration path loss of 23dB [55] and simulate indoor and outdoor model, the revised equation is given as [51]:

$$L_{dB}^{L}(d) = 36.7\log_{10}(d) + 45.7 + 26\log_{10}(f_c) \tag{2.2}$$

where f_c is the carrier frequency in MHz, d is the distance between the microcell eNB and the user, and the eNB antenna height is 10m as specified in 3GPP TR36.814 v9.20 [51].

On the other hand, the macroscopic shadow fading path loss for Wi-Fi channel model between the AP and the user at distance d is defined as [51, 56]:

$$L_{dB}^{W}(d) = 36.7\log_{10}(d/1000) + 22.7 + 26\log_{10}(f_c) \tag{2.3}$$

The microscopic path loss is the log-normal shadow fading path loss X_j of user j; the path loss component for LTE and Wi-Fi has a Gaussian distribution, a mean of 0.5, and standard deviations of 4dB and 3.58dB, respectively. Thus, adding both macroscopic and microscopic path loss, the total path loss for each technology between a transmitter i (eNB or AP) and a receiver j (users) is:

$$PL_{dB,(i,j)}(d) = L_{dB}(d) + \log_{10}(X_j) \tag{2.4}$$

Accordingly, the linear gain between the transmitter and receiver is:

$$G_{(i,j)} = 10^{-PL_{dB,(i,j)}/10} \tag{2.5}$$

2.4 Problem Formulation

The objective function is twofold. First, each technology aims to maximize its throughput and second, to minimize the transmission power. Therefore, the problem can be formulated as follows:

$$\min_{P}\max_{x}\Bigg[\beta_i \sum_{m=1}^{M}\sum_{c=1}^{|C_m|}\sum_{l=1}^{|L|} B\, x_{c,l}^{m} \log_2\left(1+\frac{P_{BS,c}^{m} G_{(BS,c)}^{m,l}}{N_0}\right) + (1-\beta_i)\sum_{a=1}^{A}\sum_{w=1}^{W}\frac{\alpha}{W+1} x_{w,a} B \log_2\left(1+\frac{P_{a,w} G_{(a,w)}}{N_0}\right)\Bigg] \tag{2.6}$$

subject to

$$\sum_{m=1}^{M}\sum_{c=1}^{|C_m|} x_{c,l}^{m} = 1 \tag{2.7}$$

$$\sum_{l=1}^{|L|}\sum_{c=1}^{|C_m|} x_{c,l}^{m} \geq \rho_{min}^{m}|L| \tag{2.8}$$

$$\sum_{l=1}^{|L|} B\, x_{c,l}^{m} \log_2\left(1+\frac{P_{BS,c}^{m} G_{(BS,c)}^{m,l}}{N_0}\right) \geq r_{min,c} \tag{2.9}$$

$$P_{BS,c}^{m} \leq P_{eq(BS,c)}^{m} \tag{2.10}$$

$$\sum_{l=1}^{L} \frac{P_{BS,c}^{m} G_{(BS,c)}^{m,l}}{N_0} \geq \gamma_{th,c}^{m} \tag{2.11}$$

$$\sum_{a=1}^{A}\sum_{w=1}^{W} x_{w,a} = 1 \tag{2.12}$$

$$\sum_{a=1}^{A} \frac{\alpha}{W+1} x_{w,a} B \log_2\left(1+\frac{P_{a,w} G_{(a,w)}}{N_0}\right) \geq r_{min,w} \tag{2.13}$$

$$P_{a,w} \leq P_{eq(a,w)} \tag{2.14}$$

$$\sum_{a=1}^{A} \frac{P_{a,w} G_{(a,w)}}{N_0} \geq \gamma_{th,w} \tag{2.15}$$

Notations used in model are defined in Table 2.2. Constraint (2.7) is such that only one RB can be allocated to a user. Constraint (2.8) is the minimum number of RBs for each SP. Constraints (2.9) and (2.13) defines the minimum rate for each user for LTE and Wi-Fi respectively.

Constraint (2.12) states that Wi-Fi user can only be connected to one AP. Constraints (2.10) and (2.14) shows that the transmission power of eNB and AP, respectively, allocated to users cannot be greater than the equal power distribution. Constraints (2.11) and (2.15) state the minimum SNR required for the power transmission of LTE eNB and Wi-Fi AP, respectively.

Table 2.2: Parameters used in the model

Parameters	
β_i	Binary indicator of assigning LTE or Wi-Fi to a subframe i
N_0	Noise Figure and Thermal Density at Receiver
B	Bandwidth
LTE Resource Allocation and Power Allocation	
M	Set of service providers (SPs)
C	Set of LTE cellular users
L	Set of resource blocks (RBs)
m	Index number in the set of M SPs
c	Index number in the set of C LTE users
l	Index number in the set of L RBs
$x^m_{c,l}$	Binary decision variable to assign LTE user to an RB
$P^m_{BS,c}$	Transmitted power from the eNB to each LTE user belonging to each SP
$G^{m,l}_{(BS,c)}$	Linear gain between each LTE user and the eNB
$r_{min,c}$	Minimum rate required for each LTE cellular user
$r^m_{c,ach}$	Achieved rate for the LTE user after RB allocation
ρ^m_{min}	Minimum number of RBs per SP
$P^m_{eq(BS,c)}$	Equal power distribution of eNB for each LTE users
$\gamma^m_{th,c}$	Minimum SNR required for power transmission of eNB
Wi-Fi Throughput Allocation and Power Allocation	
A	Set of access points (APs)
W	Set of Wi-Fi users
a	Index number in the set of A APs
w	Index number in the set of W Wi-Fi users
α	Wi-Fi bandwidth efficiency
$x_{w,a}$	Binary decision variable to assign Wi-Fi user to an AP
$P_{a,w}$	Transmitted power from the APs to each Wi-Fi user
$G_{(a,w)}$	Linear gain between each Wi-Fi user and the APs
$r_{min,w}$	Minimum rate required for each Wi-Fi user
$r_{w,ach}$	Achieved rate for the Wi-Fi user after AP allocation
$P_{eq(a,w)}$	Equal power distribution of AP for each Wi-Fi users
$\gamma_{th,w}$	Minimum SNR required for power transmission of AP

The problem is a Mixed-Integer Non-Linear Programming problem (MINLP), which is NP-hard. The logarithm in our objective function can be estimated to arbitrary polynomial and is proven to be NP-hard in [57]. For further proof of NP-hardness based on the class this belongs to can also be found in [58].

Since we are unable to solve this problem simultaneously, this problem is divided into four sub-problems. Two sub-problems for LTE are the RB allocation for each user and the power allocation. Likewise, the last two sub-problems for Wi-Fi are the access point allocation for each user and the power allocation. Based on the time-sharing mechanism, each technology will calculate the joint power control and RB or AP allocation problem. Furthermore, the two sub-problems are linear integer programming problems to maximize the throughput for both LTE and Wi-Fi through RB allocation and AP allocation, respectively. The other two sub-problems are also linear integer programming problems to minimize the power transmission for both LTE and Wi-Fi. Therefore, these subproblems are solved to optimality after decomposition. To illustrate the relationship between the algorithms, the SNR obtained from the resource or throughput allocation is used in the power allocation to determine the lowest SNR of the corresponding MCS. Once the power allocation is performed, the results of these algorithms are placed in the scheduler.

Based on previous work, to ensure fair sharing between two technology, scheduling is done such that four subframes are allocated to Wi-Fi, and one subframe is allocated to LTE [28].

2.4.1 The LTE Network

LTE Resource Allocation Problem

The optimization problem to allocate the RBs to the LTE users to maximize the throughput is formulated as follows:

$$\max \sum_{m=1}^{|M|} \sum_{c=1}^{|C_m|} \sum_{l=1}^{|L|} B\, x_{c,l}^{m} \log_2 \left(1 + \frac{P_{BS,c}^{m} G_{(BS,c)}^{m,l}}{N_0}\right) \tag{2.16}$$

subject to

$$\sum_{m=1}^{|M|}\sum_{c=1}^{|C_m|} x_{c,l}^{m} = 1;\ \forall\ l \in L \tag{2.17}$$

$$\sum_{l=1}^{|L|}\sum_{c=1}^{|C_m|} x_{c,l}^{m} \geq \rho_{min}^{m}|L|;\ \forall\ m \in M \tag{2.18}$$

$$\sum_{l=1}^{|L|} B\, x_{c,l}^{m} \log_2\left(1 + \frac{P_{BS,c}^{m} G_{(BS,c)}^{m,l}}{N_0}\right) \geq r_{min,c};$$
$$\forall\ c \in C_m;\ \forall\ m \in M \tag{2.19}$$

where B is the bandwidth of an RB, $x_{c,l}^{m}$ is a binary decision variable to determine if the user c is assigned an RB l, and ρ_{min}^{m} is the pre-agreed access ratio for each SP. Constraint (2.17) represents that an RB can only be allocated to one user. Constraint (2.18) guarantees that each SP has a minimum number of RBs according to the SLA. Constraint (2.19) ensures that each user's minimum required rate is met.

The search space for this subproblem is $2^{|MLC_m|} - 1$. The problem considers L different possible resource allocation combinations for each user, minus one to remove no allocation combination. For example, consider $M = 2$ SPs, $L = 12$ RBs, and $M \times C_m = 10$ cellular users, (i.e., 5 cellular user per SP). The worst case search space is 1.329×10^{36}.

LTE Power Allocation Problem

After determining the optimal resource allocation problem, the minimum transmitted power that eNB should allocate to each user as shown in the following:

$$\min \sum_{m=1}^{|M|}\sum_{c=1}^{|C_m|} P_{BS,c}^{m} \tag{2.20}$$

subject to

$$P^m_{BS,c} \leq P^m_{eq(BS,c)} \tag{2.21}$$

$$B\, x^m_{c,l} \log_2\left(1 + \frac{P^m_{BS,c} G^{m,l_{min}}_{(BS,c)}}{N_0}\right) \geq r^m_{c,ach} \tag{2.22}$$

Constraint (2.21) ensures that each power transmitted is below the equal distributed power. Constraint (2.22) represents that the power required for each user meets the minimum rate requirement. Since the equation of Constraint (2.22) is not a linear problem, this equation was rearranged to determine the minimum power required as follows:

$$P^m_{(BS,c)} \geq \frac{N_0 B(2^{\frac{r^m_{c,ach}}{Bx^m_{c,l}}} - 1)}{G^{m,l_{min}}_{(BS,c)}}; \forall c \in C_m; \forall m \in \mathcal{M}_{\mathcal{SP}} \tag{2.23}$$

2.4.2 The Wi-Fi Network

Wi-Fi Throughput Allocation Problem

Based on the DCF mechanism for CSMA/CA with binary exponential backoff rules and the interruption of Wi-Fi transmission caused by LTE, the Wi-Fi channel efficiency α is assumed to be 50% [52, 59, 42]. Inspired by Sagari's model which is characterized using the Markov chain analysis given in Bianchi's model [44, 52], and accounting for the interference of LTE coming on when Wi-Fi is communicating, the Wi-Fi throughput maximization problem is formulated as follows:

$$\max \sum_{a=1}^{|A|} \sum_{w=1}^{|W|} \frac{\alpha}{W+1} x_{w,a} B \log_2\left(1 + \frac{P_{a,w} G_{(a,w)}}{N_0}\right) \tag{2.24}$$

subject to

$$\sum_{a=1}^{|A|}\sum_{w=1}^{|W|} x_{w,a} = 1 \tag{2.25}$$

$$\sum_{a=1}^{|A|} \frac{\alpha}{W+1} x_{w,a} B \log_2\left(1 + \frac{P_{a,w}G_{(a,w)}}{N_0}\right) \geq r_{min,w} \tag{2.26}$$

where B is the system bandwidth, $r_{min,w}$ is the minimum throughput and $x_{w,a}$ is a binary decision variable to determine if the user w is connected to an AP a. Constraint (2.25) represents that a Wi-Fi user can assigned to only one AP. Constraint (2.26) guarantees each user has the minimum rate requirement.

For this subproblem, the search space is $2^{|AW|} - 1$. In this case, the subproblem considers the possibility of allocating the AP to each user, where there is only two options for A to be connected to each user. The subtraction removes the combination of no allocation as every user is assumed to connect to AP. Assuming $|A| = 2$ and $|W| = 10$, the worse case search space is 1.049×10^6.

Wi-Fi Power Allocation Problem

After optimizing the throughput of each Wi-Fi user, the optimal transmission power of Wi-Fi users is found by solving the following problem:

$$\min \sum_{a=1}^{|A|}\sum_{w=1}^{|W|} P_{a,w} \tag{2.27}$$

subject to

$$P_{a,w} \leq P_{eq(a,w)} \tag{2.28}$$

$$\alpha x_{w,a} B \log_2\left(1 + \frac{P_{a,w}G^{min}_{(a,w)}}{N_0}\right) \geq r_{w,ach} \tag{2.29}$$

Constraint (2.28) ensures that each power transmitted is below the equal distributed power. Constraint (2.29) represents that the power required for each user meets the minimum rate requirement. Similar in LTE power allocation problem, the constraint (2.29) is not a linear problem, therefore the equation is rearranged as follows:

$$P_{a,w} \geq \frac{N_0 B(2^{\frac{r_{w,ach}}{Bx_{w,a}}} - 1)}{G_{(a,w)}^{min}}; \forall w \in W \tag{2.30}$$

The search space for LTE allocation problem prompts the need for an heuristic algorithm as it is in the order of 36, whereas the search space for Wi-Fi allocation is six times less of the order of search space of LTE.

2.5 Heuristic Algorithm

2.5.1 LTE Resource Allocation

The modified version of the heuristic algorithm proposed in [21] is demonstrated in Algorithm 1. Moubayed *et al.* developed a low-complexity heuristic algorithm and found that the performance of this heuristic algorithm achieved close to the optimal results of resource allocation as the optimization-based programming in Section 2.4.1. The algorithm is a greedy-based algorithm to allocate the RBs to meet minimum rate requirement for each LTE user, and then when this condition is met, RB is allocated to meet the SLA agreement. The first phase describing the allocation of RB to meet the minimum rate requirement is shown in line 1-13. More specifically, the algorithm will find the best channel condition in $G_{BS,c}^{m,l}$ for each user, assign an RB for that user by setting the decision variable $x_{c,l}^{m}$ to 1. This is repeated until the rate requirement is met. To determine the second phase, the number of assigned RBs is calculated, denoted as N_c^m. The second phase in line 14-21 will allocate the remaining unallocated RBs L^m to m SPs according to the SLA constraint with priority given to the SP with the highest access ratio. Therefore, for each unallocated RB, find the best channel condition in the remaining $G_{BS,c}^{m,l}$ and set the decision variable $x^m_{c,l}$ to 1 for that RB and user. The order of complexity of this algorithm is $O(|L \times C|)$ where L is the number of RBs and $|C|$ is the total number of LTE users in the system, $|C| = \sum_{m=1}^{M} |C_m|$. This is attributed to the fact that in each iteration for each user, we search among a list of L possible RBs.

Algorithm 1 Heuristic Algorithm for LTE Users' Resource Allocation

$M_{sp} = \{1, 2, .., M\}$
$L_{tot} = \{1, 2, .., L\}$
for $m \in M_{sp}$ **do**
  for $c \in C_m$ **do**
    while $r^m_{c,ach} < r^{LTE}_{min}$ **do**
      find $g^m_{c,l} = \max_{l \in L_{tot}}(G^{m,l}_{BS,c})$
      set $x^m_{c,l} = 1$
      calculate $r^m_{c,ach}$
      update $L_{tot} = L_{tot} \setminus l$
    end while
  end for
  calculate $N^m_c = \sum_{c=1}^{|C_m|} x^m_{c,l}$
end for
for $m \in M_{sp}$ **do**
  calculate $L^m = \rho^m_{min}|L_{tot}| - N^m_c$
  for $l \in L^m$ **do**
    find $g^m_{c,l} = \max_{l \in L_{tot}}(G^{m,l}_{BS,c})$
    set $x^m_{c,l} = 1$
    update $L_{tot} = L_{tot} \setminus l$
  end for
end for

2.5.2 LTE Power Allocation

Constraint 2.23 was manipulated into the heuristic algorithm as shown in Algorithm 2. The heuristic algorithm achieves the same execution as the optimization problem, as shown in Equation (2.20). The algorithm determines the minimum power needed to transmit using the Γ to find the lowest modulation and coding scheme (MCS), and its corresponding SNR is based on the 802.11ac protocol, using channel width of 20MHz [60]. The corresponding SNR is used to determine the transmitted power of the eNB to the user.

Algorithm 2 Heuristic Algorithm for LTE power-aware function

$M_{sp} = \{1, 2, .., M\}$
for $m \in M_{sp}$ **do**
  for $c \in C_m$ **do**
    find $\Gamma_{min,c} = \min \Gamma_{eff,c}$ with same MCS
    calculate $p^m_{c,l} = [N_0 * \Gamma_{min,c}]/(G^{m,l_{min}}_{BS,c})$
    calculate $P^m_{BS,c} = p^m_{c,l} * n^m_c$
  end for
  calculate $P^m_{BS} = \sum_{c=1}^{|C_m|} P^m_{BS,c}$
end for

At each iteration, the algorithm calculates the power needed to allocate for one LTE user; therefore, the order of complexity of this problem is $O(|C|)$ where $|C|$ is the total number of LTE users in the system.

2.5.3 Wi-Fi Power Allocation

Similar to LTE power-aware function, Constraint (2.29) is a non-linear equation. The execution of the Wi-Fi Power Allocation in Equation (2.27) performs the same pattern as this heuristic algorithm. Therefore, the heuristic algorithm that performs similar results are shown in Algorithm 3.

Algorithm 3 Heuristic Algorithm for Wi-Fi power-aware function

for $w \in W_m$ **do**
  find $\Gamma_{min,w} = \min \Gamma_{eff,w}$ with same MCS
  calculate $p_w = [N_0 * \Gamma_{min,w}]/(G^{min}_{a,w})$
end for
calculate $P_a = \sum_{w=1}^{|W|} p_w$

When determining the minimum power needed to transmit, the lowest modulation and coding scheme (MCS) is used, and its corresponding SNR is based on the 802.11ac protocol, using channel width of 20MHz [60].

For each iteration, the algorithm determines the power allocation for one Wi-Fi user; therefore, the order of complexity of this problem is $O(|W|)$ where $|W|$ is the total number of Wi-Fi users in the system.

Table 2.3: Different Coexistence Configurations

	Subframe Number									
Coexistence	0	1	2	3	4	5	6	7	8	9
LTE Only	L	L	L	L	L	L	L	L	L	L
1 by 4	W	L	L	L	L	W	L	L	L	L
1 by 2	W	L	L	W	L	L	W	L	L	W
1 by 1	W	L	W	L	W	L	W	L	W	L
2 by 1	W	W	L	W	W	L	W	W	L	W
4 by 1	W	W	W	W	L	W	W	W	W	L
Wi-Fi Only	W	W	W	W	W	W	W	W	W	W

2.6 Scheduling Algorithm

There are different scheduling algorithm scenarios to be evaluated, as shown in Table 2.3. The Wi-Fi-by-LTE configuration is the number of Wi-Fi is assigned to subframes before the number of LTE is assigned. Algorithm 4 represents 4 by 1 configuration, where four subframes are assigned to Wi-Fi communication, and one subframe is assigned to LTE communication. To change the configuration, the modulo is changed to the total number of assigned Wi-Fi and LTE in the configuration (*i.e.* to simulate 4 by 1 configuration, the modulo is 5). For example, a 4 by 1 configuration assigns four subframes of Wi-Fi throughput and one subframe of LTE throughput. Note that only two sub-problems will be performed in each subframe, which are the RB or AP allocation and the power allocation. This time-sharing scheduling allows for no interference between the two technology except when switching technology for that subframe.

Algorithm 4 Scheduling Algorithm for 4 to 1 Allocation

$T_{subframes} = \{1, 2, .., T\}$
for $t \in T_{subframes}$ **do**
  if $t\%5 == 0$ **then**
    optimize $r_w = \max(Throughput_w) \times x_{w,a}$
    assign r_w to t subframe
  else
    optimize $r_l = \max(Throughput_l) \times x^m_{c,l}$
    assign r_l to t subframe
  end if
  update $sumThroughput_w+ = r_w$
  update $sumThroughput_l+ = r_l$
end for

2.7 Performance Evaluation

2.7.1 Simulation Parameters

The system model is simulated in MATLAB using Intel(R) Core(TM) i7-3770 CPU @ 3.40 GHz, 12 GB RAM computer on Windows 10 Enterprise. The time elapsed is normalized since the computer setup is too slow and do not represent the actual setup. The simulation parameters are given in Table 2.4.

Table 2.4: Simulation Parameters & Values

Parameters	**Values**
Scenario	Downlink
Carrier Frequency	5.8 GHz
Noise Figure and Thermal Density at Rx	10^{-13}
LTE Parameters	
Number of SP	2
Bandwidth per SP	10 MHz
Number of RBs	100
Number of subcarriers per RB	12
Subcarrier Spacing	15 kHz
RB Bandwidth	180 kHz
eNB Tx Power	1 W
eNB Antenna Height	10 m
Subframe Duration	1 ms
Cell-level User Distribution	Uniform
Log-normal Shadowing Standard Deviation	4 dB
Service Level Agreement Vector	[0.6 0.4]
Wi-Fi Parameters	
AP Tx Power	20 dBm
Channel Bandwidth	20 MHz
Channel Efficiency	50%
Log-normal Shadowing Standard Deviation	3.58 dB

2.7.2 Results & Discussion

The results of the throughput for each LTE and Wi-Fi user is presented in the first portion, while the power savings is discussed in the last portion of this section.

Throughput Results Discussion

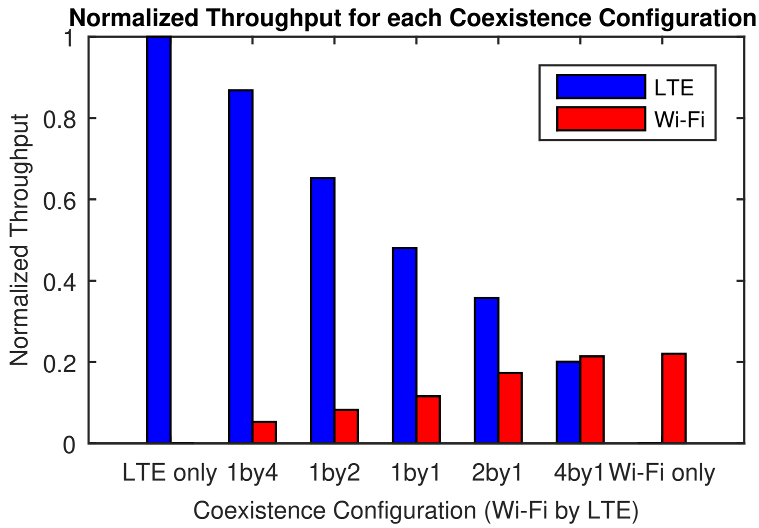


Figure 2.5: A normalized throughput simulation for each coexistence configuration model

Fig. 2.5 shows the normalized throughput of each LTE and Wi-Fi communication, with coexistence configuration based on Table 2.3. The number of LTE and Wi-Fi users is assumed to be constant and set at 50 for each configuration. As expected, the throughput of LTE or Wi-Fi is at its highest in no coexistence configuration. Overall, LTE has a higher throughput than Wi-Fi due to its reliability of scheduling its resources. Moreover, as the number of subframes assigned to Wi-Fi increases, the throughput of LTE decreases and the throughput of Wi-Fi increases. For similar throughput of both technologies, 4 by 1 is the preferred coexistence configuration, even though at this configuration, there is a decrease throughput of 80% and 3% for LTE and Wi-Fi, respectively.

It is important to note that LTE is operating in the unlicensed band, which is primarily used for Wi-Fi users. Even though there is a loss of 80% throughput for LTE users in coexistence, the minimum required rate was met.

Fig. 2.6 shows the average normalized throughput for each SP by changing the number of LTE users, keeping the number of Wi-Fi users constant at 50. It is expected as the number of LTE users increases, the fewer RBs are available for each user, thus decreasing the throughput. Not shown here, but increasing the number of Wi-Fi users while keeping the number of LTE

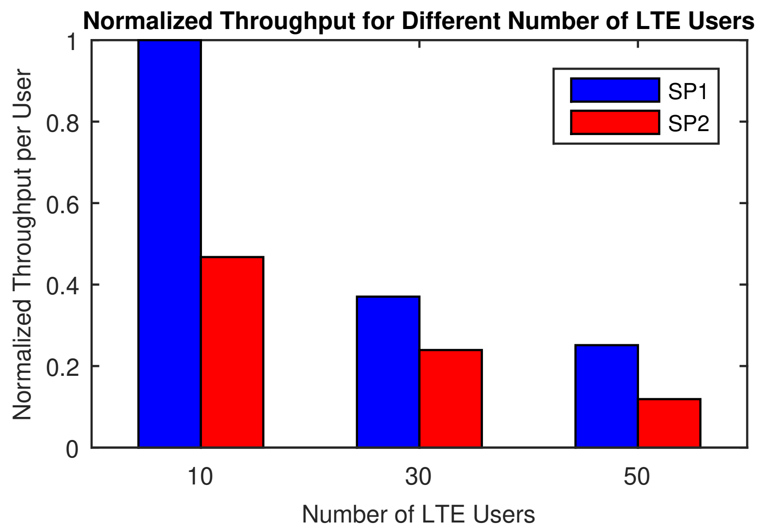


Figure 2.6: A normalized average throughput per user as a function of number of users

users constant follow a similar pattern.

Fig. 2.7 shows the difference of using WRV and not using WRV for each SP. The result shows that WRV does improve the throughput for each SP. The aggregate bandwidth resulting from WRV would amount to 40-80 MHz, thus matching the deployments of WiFi in modern systems. The impact of using WRV shows there is better throughput for each technology. For LTE users, there is a larger pool of RBs; therefore there is a higher probability of getting better channels. For Wi-Fi users, there is a bigger pool of APs that have higher throughput to access better channels. SP_{noWRV} represents no WRV in the LTE or Wi-Fi system, which means that there is no resource sharing between SP1 and SP2. In other words, for LTE users, no WRV means that users belonging to SP1 can only access to 60 RBs, and users belonging to SP2 can only access to 40 RBs. As a result, for LTE users, there is 0.14% improvement in SP1 if WRV is used, and 0.10% improvement in SP2. Similarly, for Wi-Fi users, there is an improvement of 91% and 79% in SP1 and SP2, respectively. Baswade *et al.* reported the throughput of the Wi-Fi users affected by the LTE on DCF mechanism, and using the 4 by 1 configuration, the authors found that the throughput to be about 22-24 Mbps [43]. The average throughput for Wi-Fi users in this work is 58Mbps, which is double the authors' throughput due to WRV. This is further supported by the results shown in Fig. 2.7 which shows that the average gain

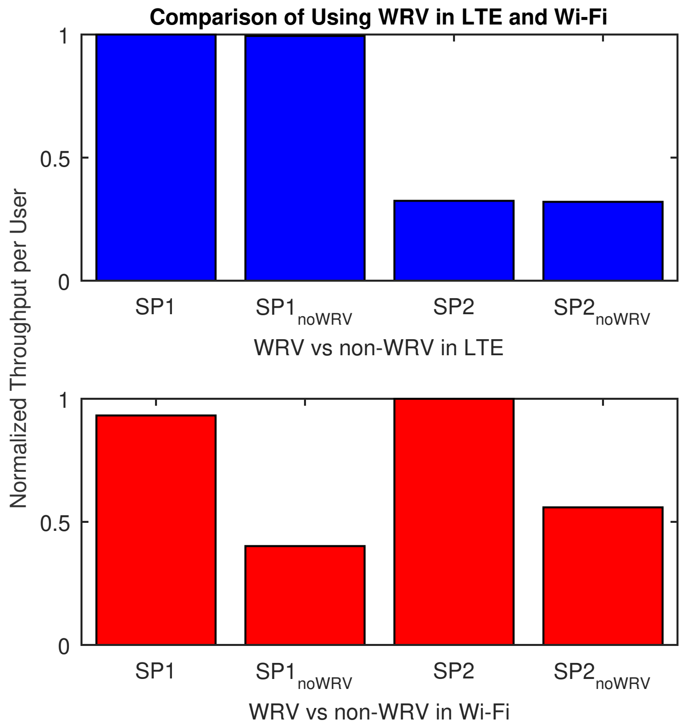


Figure 2.7: A normalized average throughput per user with and without WRV

for Wi-Fi due to WRV is almost double for both service providers. Also, Moubayed *et al.* reported their throughput for LTE users to be about 55 Mbps with 50 RBs [21]. The average LTE throughput found in this simulation is 170 Mbps, which is comparable to the throughput from Moubayed *et al.*, as in this simulation, the number of RBs is twice as much thus allowing the WRV at least double the throughput and to access better channels.

Power Savings Results Discussion

Table 2.5 shows the difference of applying the WRV to not having WRV with respect to the channel condition. There is an improvement of power savings using the WRV, 64.4% power

Table 2.5: Power Savings Comparison of using the WRV for LTE and Wi-Fi.

WRV / Tech	with [Watts]	without [Watts]	difference
Wi-Fi	0.0586	0.0963	64.39%
LTE	0.4561	0.4631	1.54%

savings for Wi-Fi users, and 1.54% for LTE users. As is expected, the trend follows that as the channel gets worse, the power savings is lower due to low channel condition causes the users to use lower MCS, which results in lower SNR.

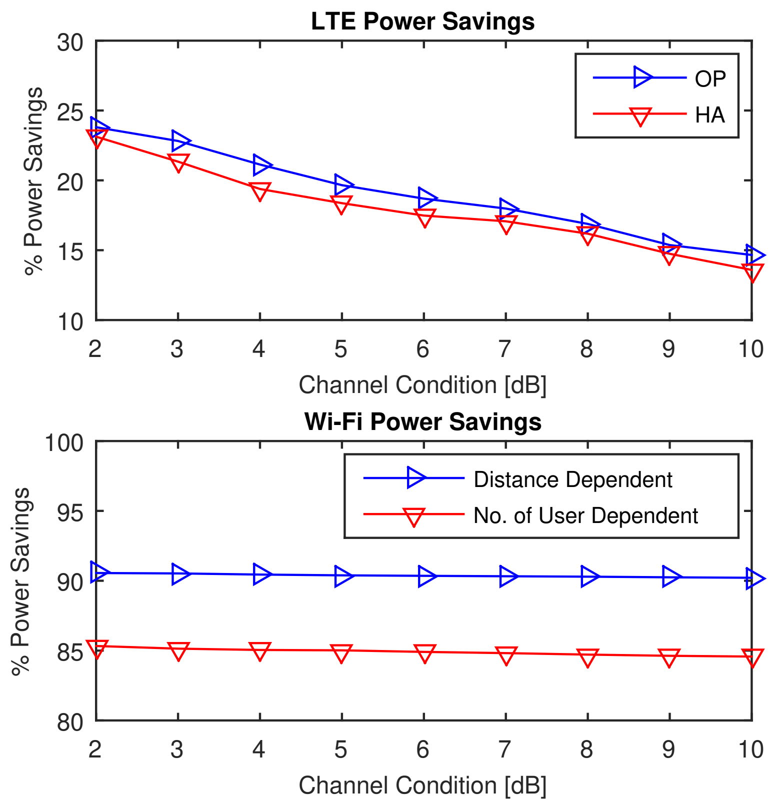


Figure 2.8: Percent Power Savings for LTE and Wi-Fi

Fig. 2.8 shows the power savings of each technology as the channel condition gets worse. It is noticed that as the channel condition gets worse, the power savings gets worse. In the top graph, two different solutions are solved for resource allocation, which is the optimization-based programming (OP) and the heuristic algorithm (HA). It is expected that the optimization-based programming has better power savings due to optimal results, although heuristic algorithm may solve the problem 10x faster. Heuristic algorithm solved the problem in 0.003 seconds, whereas the optimization-based programming was solved in 0.057 seconds. In the bottom graph, two different variables have an effect on the Wi-Fi user's power savings. The equal distributed transmitted power for each user is calculated using 1) the average distance between the AP and users and 2) the number of users. The results show that distance has more effect on the channel, which is why the power savings is higher. Moubayed *et al.* utilized heuristic algorithms on power allocation for two technologies and reported a power savings up to 42% for LTE users, and up to 75% for D2D users [26]. Wi-Fi power savings are significantly higher than the reported D2D savings due to sharing the channel condition, whereas in this work, each technology will use the entire channel for a short period of time, thus allowing Wi-Fi to transmit without interference. However, there is a difference in LTE power savings due to different available transmission power, where Moubayed *et al.* transmitted at 20W and this work simulated at 1W[26].

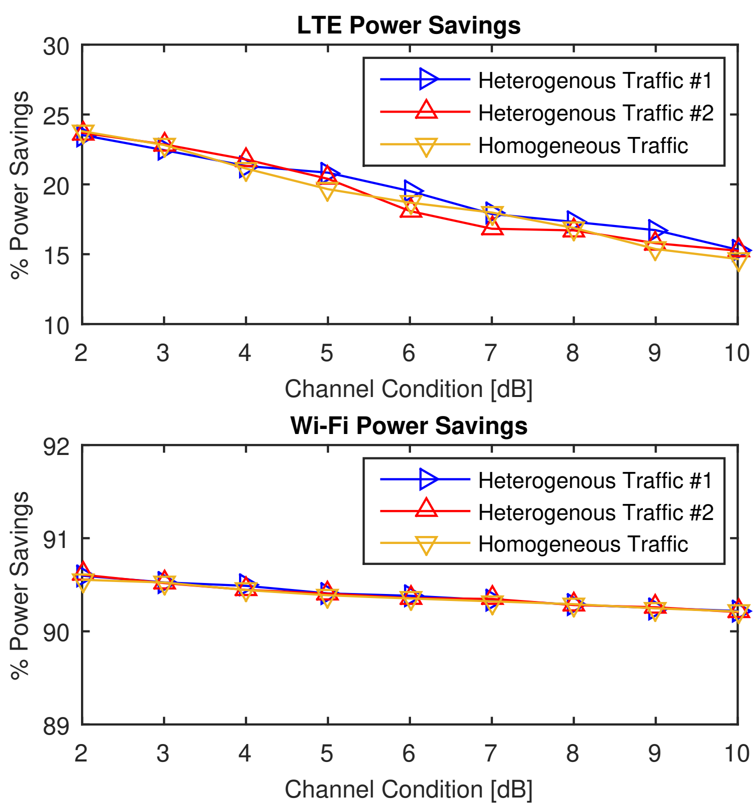


Figure 2.9: Percent Power Savings for different traffic cases

Fig. 2.9 shows the power savings in three traffic cases. Heterogeneous traffic case 1 contains LTE users having higher minimum rate requirement than Wi-Fi users, and case 2 simulates the Wi-Fi users to have higher minimum rate requirement than LTE users. The results show very similar results for each case because the throughput was maximized first, and then the power savings was minimized; therefore, there are no changes in power savings in different traffic cases.

2.8 Conclusion

In this paper, a framework for power-aware resource allocation in the LTE downlink coexisting with the Wi-Fi network in the unlicensed band is proposed. First, a MINLP problem was formulated to solve the coexistence of the LTE and Wi-Fi network. Due to the NP-hardness of the problem, the problem was divided into four sub-problems using the Lagrangian dual decomposition method. These sub-problems address LTE and Wi-Fi throughput and power allocation. The sub-problems involving maximizing the aggregated throughput and the results of the throughput of each LTE and Wi-Fi user was previously solved [28], while minimizing the transmission power was solved in this paper.

Additionally, the heuristic algorithms were developed to solve the resource allocation problem for LTE as well as the power allocation for LTE and Wi-Fi. Through the simulation, the results was shown that the proposed approach has an average power savings of 19% for LTE users, and up to 90% for Wi-Fi users and there is an improvement of power savings using WRV, with significant increase in Wi-Fi users. Also, the results show that there is a minimal difference between each traffic case due to maximizing the data rate, which has little to no effect on the power savings.

Note that this paper focuses on the coexistence of Wi-Fi and LTE using wireless resource virtualization, this work can be extended to improve user experience such as Quality of Service (QoS). Further, while this paper includes data rate and power, QoS also conforms to the delay constraints which is a much needed attention in the future work for the coexistence of LTE and Wi-Fi. Also, this paper uses a fixed coexistence configuration for scheduling of each technology, which should be extended to determine the dynamic scheduling.

Chapter 3

QoS-Aware Coexistence in Unlicensed 5G New Radio Based on Time-Domain Virtualization

3.1 Introduction

There has not been any indication the exponential growth of mobile applications and services is slowing down. Cisco has predicted in the Annual Internet Report White Paper that over 70% of the global population will have mobile connectivity by 2023, and that 5G devices and connections will be over 10% of the global mobile devices and connections by 2023 [3]. Data traffic and network capacity growth is still an increasing key issue in the limited licensed spectrum. Some mobile operators have considered and implemented the communication over the unlicensed spectrum as it offers a larger amount of resources, resolving the spectrum scarcity related issues. This will provide new opportunities for the operators to increase the efficiency of the licensed networks [61].

Focusing on the cellular radio, the unlicensed spectrum is partially utilized by technologies such as Wi-Fi. Either the cellular networks are working alternatively or cooperatively with these technologies. There is a need for a coexistence mechanism between such technologies as they utilize the same frequency band. In particular, recent studies have shown that without any coordination or coexistence between technologies, mobile cellular communication such as LTE or 5G NR-U significantly interferes with Wi-Fi communication [18, 19, 62, 63]. In addition, more regulatory voiced opposition expressed their fears from the use of cellular spectrum to the ISM bands as it might degrade the performance for the users' Wi-Fi devices [64].

The third generation partnership project (3GPP) standards (Rel 13 - Rel 16) introduced several architectures to address this critical problem [30, 65, 31, 32, 33]. Following the release of these standards, many researchers studied the coexistence in their work. For example, researchers focused on the time-domain approach where the scheduler determines when each technology would share the spectrum, by implementing Listen-Before-Talk (LBT) protocol in LAA and 5G New Radio-Unlicensed (5G NR-U) and the Carrier Sensing Adaptive Transmission (CSAT) protocol in LTE-U [34, 35, 36, 37, 62]. Other time-domain approaches include time-partitioning through duty cycle and sending almost blank subframes to allow Wi-Fi to communicate while LTE maintains its channel state information (CSI) data [19, 40, 41, 42, 43].

In addition to the concerns over the performance degradation of ISM technologies, the added requirements of 5G applications/use cases is another challenge to consider. This mobile network generation focuses on high-speed connections, ultra-high reliability and low latency communications, higher connectivity density and higher mobility range [9, 10]. Many of these attributes are the characteristics of high Quality of Service (QoS), which require a vast work on MIMO antennas, Cloud RAN and the NFV core network. Due to propagation and transmission through the radio access network, the queuing delay of the packets needs to be as low as possible.

To meet the 5G QoS requirements, Wireless Resource Virtualization (WRV) represents a promising and viable solution to improve the spectrum efficiency as the demand for data traffic continues to grow. WRV allows for available resources to be shared across service providers (SPs) using the same hardware and software. By sharing resources, SPs can support higher peak rates through resource aggregation, and allows for the initial investment and maintenance costs to be shared among SPs. In turn, this decreases both the Capital and Operational Expenditures [20]. Additionally, deploying WRV introduces a multi-provider multiplexing gain to allow for more users to access the network [21].

To that end, this work proposes the time-domain virtualization of 5G NR-U and Wi-Fi in the unlicensed spectrum. More specifically, it considers the practical scheduling of Wi-Fi and downlink NR-U transmission by assigning packets into the scheduler with QoS constraints rather than determining the available throughput for each user.

Therefore, this paper proposes a downlink QoS-aware coexistence scheduler for Wi-Fi and 5G technologies using WRV. This scheduler will maximize the available throughput while maintaining the physical layer constraints and QoS requirements. Thus, this paper focuses on the future trends by proposing the coexistence between 5G and Wi-Fi. The proposed approach will include a real-time simulation of a scheduler to guarantee QoS constraints. These demands will result in a significant increase of data transmission, power consumption and potentially spectrum inefficiency. Accessing the unlicensed spectrum will improve the spectral efficiency as well as potential savings. Moreover, while we are formulating the optimization problem describing the coexistence, we are also developing a low complexity heuristic that is suitable for real-time deployment.

The rest of the paper is organized as follows: Section 3.2 provides a background information about the coexistence, WRV and QoS requirements. Section 3.3 explains the coexistence system model which includes information about the channel access and the delay analysis. Section 3.4 outlines the problem formulation of the optimization model. Section 3.5 proposes the heuristic algorithms. Section 3.6 reports the results of the simulation as well as the discussion. Finally, Section 3.7 concludes this work with recommendations for the future directions.

3.2 Background and Related Works

3.2.1 Background

Due to the increasing demands of various performance requirements, 5G standard was proposed as a next generation wireless network standard [9]. Subsequently, the 3GPP developed 5G New Radio (5G NR) to meet the continuously growing demand for mobile network [10]. The International Telecommunication Union (ITU) recommended three use cases for 5G network, which are enhanced mobile broadband (eMBB), ultra-reliable and low latency communication (URLLC), and massive machine-type communication (mMTC) [66]. Although these three use cases have different requirements, they all need more network capacity. Currently, 3GPP has focused on the use case of eMBB and has also been working on a new radio access technology, called 5G NR Unlicensed (5G NR-U) aiming to extend 5G NR to unlicensed bands.

Licensed Assisted Access (LAA) is a 3GPP R13 standard released in 2015 that allows LTE systems to offload data traffic onto unlicensed 5GHz band. LTE offers better coverage and resource allocation than Wi-Fi, and LAA allows mobile devices to seamlessly connect to licensed and unlicensed spectrum in a single core network. Through carrier aggregation in LAA, the primary carrier provides reliable control signaling and meets LTE's QoS requirements, while the secondary carrier delivers data speed bursts. LAA implements Listen-Before-Talk (LBT) which allows the Wi-Fi systems to communicate on the same spectrum. However, there still needs an improvement for spectrum sharing. Further, LAA implements scheduled channel access whereas Wi-Fi implements random channel access. For further reading, Ali *et al.* outlines different deployment scenarios for 5G systems using LTE-U and Wi-Fi in heterogeneous networks [67].

Although we are working on 5G, there is extensive work on LTE technology that will play a role for 5G [68]. There are proposed 5G technologies that use LTE-based variants such as LTE-M (for machine type communication). For example, Bell is deploying an LTE-M based solution as part of its 5G rollout [69]. 3GPP is initially focused on Unlicensed National Information Infrastructure (U-NII) bands at 5 GHz and 6 GHz. While mobile operators can operate on unlicensed band, they are required to comply with the wireless regulation and therefore must coexist with other wireless technologies. Furthermore, 5G systems should not impact the existing Wi-Fi systems any more than the other Wi-Fi systems to ensure fairness on channel access.

To evaluate the impact of coexistence, QoS is a useful metric. QoS provides stability and performance to the network service, which will improve the user experience [70]. Some parameters in QoS are latency, packet loss, and jitter [71]. To guarantee a network's performance, QoS assigns priority to packets to maximize the available bandwidth required over a short period of time. Accordingly, two main radio bearer categories are typically considered: 1) Guaranteed Bit Rate (GBR) and 2) Non-GBR (NGBR). Real-time applications such as voice and video call require GBR, otherwise applications such as buffered streaming use NGBR [72]. The default bearers of LTE-LAA in the unlicensed band are the Non-GBR bearers since it cannot guarantee channel access [72]. However, if the quality of the channel meets the standard, LTE-LAA is capable of servicing GBR bearers. In our case, to offer some type of GBR bearers, we are guaranteeing the 5G a dedicated time-slot as we are adopting a time-based sharing scheme between 5G and Wi-Fi. In this paper, to ensure QoS requirements are satisfied, the packet scheduler will meet the delay constraints of each class by assigning the number of packets required per subframe.

3.2.2 Related Works

The concept of WRV has been proposed in multiple works from the literature in various systems and scenarios with the goal of improving the spectrum efficiency. This is because WRV can be implemented with varying cell sizes. For example, LTE users at both macro-cell and micro-cell level can share the available resources [47]. Kalil *et al.* proposed a WRV framework in an LTE system [20]. In this framework, the SPs aggregated the available spectrum and allowed their users to share the resources while simultaneously allowing each SP to maintain its own inter-user scheduling policy. As a result, it was shown that all users experienced an increase in the average throughput. As a further extension, the authors proposed an efficient low-complexity scheduler that also ensures that the different SPs have a fair and proportional access to the spectrum [48]. Using a system-level simulation, the results showed that WRV again allowed for higher user throughput when compared with the static sharing case. Moreover, it was shown that access fairness between the SPs was ensured due to the proposed scheme.

In a similar fashion, Moubayed *et al.* proposed combining WRV in LTE systems with Device-to-Device (D2D) communication as an underlay network [21]. More specifically, the authors proposed a framework in which D2D users can share the resources with LTE users as long as the interference caused does not negatively impact the LTE users. Simulation results showed that combining WRV and D2D communication had a positive impact by helping combat the degrading channel conditions and improving the user throughput. The author further extended their work by proposing a power-aware sharing mechanism with the goal of maintaining the throughput increase while simultaneously decreasing the transmission power [26]. Simulation results again showed that WRV helped reduce the overall transmission power for both LTE and D2D users since they had access to better channels and thus needed less power to achieve the same throughput performance.

Zimmo *et al.* also proposed WRV as part of a coexistence framework for LTE and Wi-Fi in the unlicensed spectrum [28]. More specifically, the authors developed a coexistence mechanism involving virtualization in the time-domain between LTE and Wi-Fi to improve the spectrum efficiency further. A further extension by the authors considered the power consumption in the optimization problem. Additionally, the authors developed a power-aware heuristic algorithm to solve the power-aware optimization problem formulated [73]. Simulation results again illustrated the benefit of adopting WRV as the throughput was improved and the transmission power was reduced for both technologies. It is worth mentioning that WRV is used for practical purposes. This is particularly important given the emergence of virtual SPs since it allows different technologies to co-exist and utilize the spectrum more efficiently.

3.2.3 Limitations of Current Work

El-Shal *et al.* proposed the intelligent monitoring scheme to manage the scheduling and resource allocation at each LTE base station [74]. Xiao *et al.* considered the channel access problem in the LTE-U and Wi-Fi coexistence by developing a hybrid adaptive channel access mechanism [75]. Cui *et al.* demonstrated the value of using clustering machine learning for network management [76]. Nui *et al.* used the max-k-cut approach for the user association problem on the millimeter wave (mmWave) transmission while satisfying the QoS requirements for each user [77].

The coexistence mechanism can improve the resource availability for 5G NR-U on the unlicensed spectrum, however these work do not discuss the QoS requirements for both Wi-Fi and NR-U systems. These work also do not consider the resource efficiency such as wireless resource virtualization. Also, our work focuses on the updated system, such as Wi-Fi 6 and 5G NR-U as opposed to Wi-Fi 5 and LTE-LAA or LTE-U. While our paper lacks the machine learning, we simulate traffic using the Discrete Event Simulation.

3.2.4 Contributions

In this research problem, considering the Wi-Fi and NR-U coexistence scenario, we will focus on optimizing the user's throughput while maintaining acceptable QoS levels. As such, this work makes the following contributions:

- Propose a time domain-based WRV coordinated coexistence mechanism for 5G and Wi-Fi.

- Formulate an optimal formulation of QoS-aware resource allocation that maximizes the throughput while meeting the QoS constraints as a Integer Linear Programming Problem

(ILP).

- Decompose, using the Lagrangian dual decomposition method, the formulated ILP problem into a pair of Binary Integer Programming (BIP) problems.

- Propose two low-complexity heuristic greedy-based algorithms to solve each of the formulated optimization sub-problems.

To the best of our knowledge, the concept of WRV in the context of 5G has not been previously proposed in the literature.

3.3 System Model

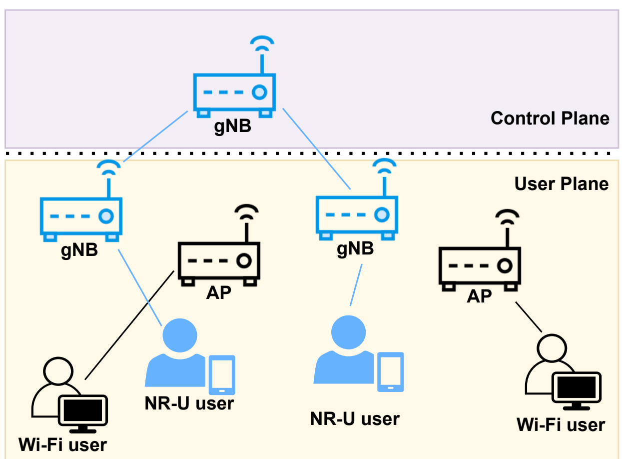


Figure 3.1: An architecture showing how users coexist with 5G NR-U gNBs and Wi-Fi AP using a centralized scheduler that local gNBs have access to.

The proposed approach in this work is a QoS-aware time domain-based WRV framework for 5G NR-U and Wi-Fi coexistence. The time domain-based coexistence is accomplished by dedicating subframes to each technology, with the virtualization allowing for the resources to be shared between two technologies. Therefore, the scheduler involves leaving almost blank subframes (ABS) for the Wi-Fi system to access the channel and reduce co-channel interference. The scheduler provides ABS to allow Wi-Fi systems to access the spectrum as Wi-Fi runs on contention-based MAC protocol. This scheduler is in a centralized gNB in the control plane that communicates with the core as well as the gNBs in the user plane such that the scheduling process can be done at the local gNB, as shown in Fig. 3.1. Furthermore, once the cellular resources stop using the channel, the Wi-Fi systems senses that the channel is free and starts transmitting during the almost blank subframes based on CSMA/CA.

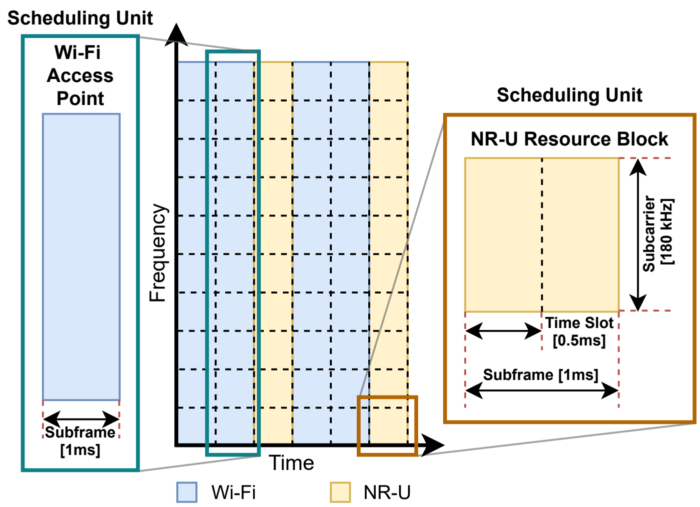


Figure 3.2: How users access the spectrum, where the proposed scheduler will assign each technology to its dedicated subframe

Fig. 3.2 is the proposed scheduler that demonstrates a time frame over 10ms, where the scheduler assigns four subframes to Wi-Fi and one subframe to 5G. In the previous work [28], the 4-by-1 configuration was chosen in such a manner that there is time-sharing fairness between LTE and Wi-Fi. This was done to avoid the LTE access overpowering the Wi-Fi access. However, LTE has different channel access methods than 5G. Therefore, in this paper, several different configurations are tested. Also, Wi-Fi users will access the spectrum by occupying all of the frequency in its unlicensed band per subframe, whereas the 5G NR-U will access a resource block that is a unit of frequency and time.

In addition to the coexistence mechanism adopted, the QoS-aware framework requires the scheduler to consider the delay constraints for each user and for each class. Accordingly, this paper considers three different traffic types, each belonging to a different QoS class: VoIP, video streaming and FTP. These QoS class types represent the most commonly used and expected traffic classes in 5G networks.

3.3.1 Problem Definition

This study aims to maximize the throughput/data rate for each user for 5G NR-U or Wi-Fi, while maintaining the QoS performance by meeting both the rate and delay constraints for each user.

3.3.2 Channel Access

We consider an indoor office setting where NR-U operates in the unlicensed spectrum for downlink communication. Three gNBs are deployed by the NR-U operator that share a 20 MHz channel at 5 GHz with three other Wi-Fi access points (APs). The corresponding evaluation topology as per the 3GPP indoor scenario for NR-U/Wi-Fi coexistence is shown in Fig. 3.3 [8].

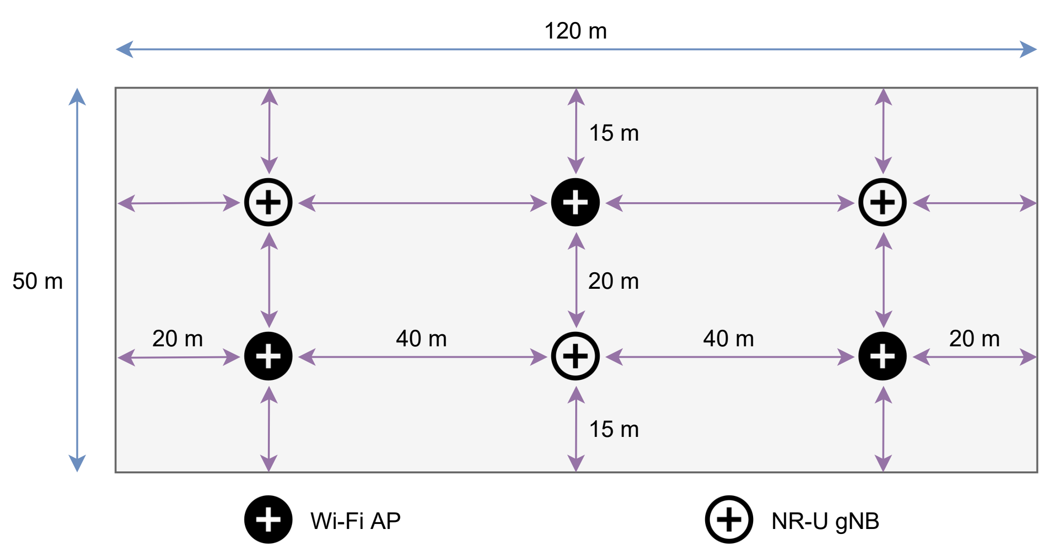


Figure 3.3: Indoor topology for Wi-Fi APs and 5G NR-U gNB coexistence

Fig. 3.4 demonstrates three cases of resource allocation. In the figure, the first column in the RB allocation box shows the number of resource blocks available for that frequency, which currently do not have any resource allocated yet. The second column shows the resource blocks being allocated. The first SP's two users are allocated to the first six RBs, while the second SP's two users are allocated to the last four RBs. Finally, the last column implements WRV, which enables virtualization by sharing the resources among users across all SPs. WRV allows a user to potentially access a better channel by maximizing the available RB pool for a user.

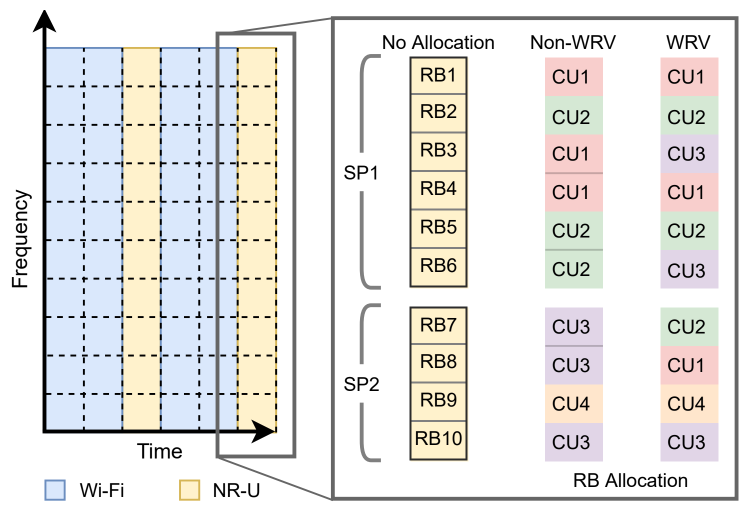


Figure 3.4: How resources are shared in Wireless Resource Virtualization in the proposed scheduler

Each gNB serves a set of cellular users and each AP serves a set of Wi-Fi users in a 120 m by 50 m area. The association is based on the channel condition, which can be nearest neighbour-based association, however not always the case due to the distance and microscopic path fading. Furthermore, the channel model includes both macroscopic and microscopic path loss components, where the macroscopic portion depends on the distance, and the microscopic portion is randomized including fading effects.

An indoor model can capture an office environment or shopping malls where a base station (BS) can be within 3m on the wall or on the ceiling from the end-user. 5G NR-U macroscopic path loss is as follows [78]:

$$L_{dB}^{N}(d) = 17.30 + 38.3 \log_{10}(d) + 24.9 \log_{10}(f_c) \tag{3.1}$$

where the distance d ranges between 1 m to 150 m.

In contrast, to characterize the Wi-Fi's macroscopic shadow fading path loss component between the AP and the user at distance d, the path loss model is defined as [79]:

$$
\begin{aligned}
L_{dB}^{W}(d) &= 40.05 + 20\log_{10}(f_c/2.4) \\
&\quad + 20\log_{10}(min(d,10)) + 35\log_{10}(d/10)
\end{aligned}
\tag{3.2}
$$

A Gaussian distribution with zero mean and standard deviation is used to characterize the long-term (log-normal) fading in the logarithmic scale around the mean path loss PL (dB). Thus, the microscopic path loss is the log-normal shadow fading path loss X_j of user j; the path loss component for Wi-Fi has a Gaussian distribution, a zero mean and standard deviations of 5 dB. NR-U distribution of shadow fading is log-normal, and its standard deviation is 8.03 dB for the indoor-office model [79, 78]. Although both technologies operate on the same frequency and the same scenario, the path loss equation is different due to its physical properties such as the transmission power, receiver sensitivity, antenna and cell size. It is important to note that the Wi-Fi model is for all traffic, including uplink or downlink due to random access between all Wi-Fi network interface card.

Therefore, by combining the macroscopic and microscopic path loss components, the total path loss for between a transmitter i (whether it is a 5G NR-U gNB or a Wi-Fi AP) and a receiver j (either a NR-U or a Wi-Fi user) is:

$$
PL_{dB,(i,j)}(d) = L_{dB}(d) + \log_{10}(X_j) \tag{3.3}
$$

Based on the aforementioned total path loss model in dB, the corresponding linear gain between the transmitter and receiver is:

$$
G_{(i,j)} = 10^{-PL_{dB,(i,j)}/10} \tag{3.4}
$$

3.3.3 Queuing Delay Analysis

To determine the queuing delay, we require information from the previous time iteration. Therefore, the queuing delay is extracted from the queue size, which is calculated as follows:

$$q_k[t+1] = q_k[t] + a_k[t] - T_k[t] \tag{3.5}$$

where $q_k[t]$ is the number of queuing packets at the start of TTI t, $a_k[t]$ is the number of arriving packets and $T_k[t]$ is the transmitted packets of user k at TTI t.

The arrival time of the packets is assumed to follow the Poisson distribution. As a result, the number of arriving packets, $a_k[t]$, also follows a non-linear pattern. Note that due to the fine-grained granularity of the scheduling process (in the order of 1ms), it treats the scenario as static. To implement the channel communication, we need a sliding-average window of length F for variable q_k:

$$W(q_k[t], F) = \frac{1}{F} \sum_{T=t}^{t+F} q_k[T], \tag{3.6}$$

Note that this sliding window average of the queue length is used to ensure that the average delay is bounded.

The current time is t and the length of one window is F TTIs. Therefore, the observation interval is $[t, t+F]$.

Once the channel access is implemented, the number of packets needed to be transmitted T_k can be calculated using the available throughput from the channel access algorithm and the packet size required for each QoS class.

3.4 Problem Formulation

The objective function aims to maximize the aggregate user throughput while maintaining QoS constraints. Therefore, using the notations defined in Table 3.1, the problem can be formulated

Table 3.1: Parameters used in the model

Parameters	
β_i	Binary indicator of assigning NR-U or Wi-Fi to a subframe i
N_0	Noise Figure and Thermal Density at Receiver
Q^n_{max}	Maximum queuing delay for QoS class n
NR-U Resource Allocation and Power Allocation	
S	Set of Base Stations (gNBs)
M	Set of service providers (SPs)
C	Set of NR-U cellular users
L	Set of resource blocks (RBs)
m	Index number in the set of M SPs
c	Index number in the set of C NR-U users
l	Index number in the set of L RBs
$x^{m,l}_{s,c}$	Binary decision variable to assign NR-U user to an RB
$P^m_{BS,c}$	Transmitted power from the gNB to each NR-U user belonging to each SP
$G^{m,l}_{(BS,c)}$	Linear gain between each NR-U user and the gNB
$r_{min,c}$	Minimum rate required for each NR-U cellular user
$r^m_{c,ach}$	Achieved rate for the NR-U user after RB allocation
ρ^m_{min}	Minimum number of RBs per SP
$P^m_{eq(BS,c)}$	Equal power distribution of gNB for each NR-U users
Wi-Fi Throughput Allocation and Power Allocation	
A	Set of access points (APs)
W	Set of Wi-Fi users
a	Index number in the set of A APs
w	Index number in the set of W Wi-Fi users
α	Wi-Fi bandwidth efficiency
$x_{w,a}$	Binary decision variable to assign Wi-Fi user to an AP
$P_{a,w}$	Transmitted power from the APs to each Wi-Fi user
$G_{(a,w)}$	Linear gain between each Wi-Fi user and the APs
$r_{min,w}$	Minimum rate required for each Wi-Fi user
$r_{w,ach}$	Achieved rate for the Wi-Fi user after AP allocation
$P_{eq(a,w)}$	Equal power distribution of AP for each Wi-Fi users

as follows:

$$\max_x \sum_{T=t}^{t+F} \left[\beta_i \sum_{s=1}^{S} \sum_{m=1}^{M} \sum_{c=1}^{|C_m|} \sum_{l=1}^{|L|} B\, x^{m,l}_{s,c} \log_2 \left(1 + \frac{P^m_{S,c} G^{m,l}_{(s,c)}[T]}{N_0} \right) \right. \\ \left. +(1-\beta_i) \sum_{a=1}^{A} \sum_{w=1}^{W} \frac{\alpha}{W+1} x_{w,a} B \log_2 \left(1 + \frac{P_{A,w} G_{(a,w)}[T]}{N_0} \right) \right] \tag{3.7}$$

subject to

$$W(q_k[t], F) \leq Q^n_{max}; \forall w \in W; c \in C_m; \forall m \in M \tag{3.8}$$

$$\sum_{m=1}^{M} \sum_{c=1}^{|C_m|} x^{m,l}_{s,c} = 1; \forall l \in L; \forall s \in S \tag{3.9}$$

$$\sum_{l=1}^{|L|} \sum_{c=1}^{|C_m|} x^{m,l}_{s,c} \geq \rho^m_{min}|L|; \forall m \in M \tag{3.10}$$

$$\sum_{l=1}^{|L|} B\, x^{m,l}_{s,c} \log_2\left(1 + \frac{P^m_{S,c} G^{m,l}_{(s,c)}}{N_0}\right) \geq r_{min,c};$$

$$\forall c \in C_m; \forall m \in M \tag{3.11}$$

$$\sum_{a=1}^{A} x_{w,a} = 1; \forall w \in W; \forall m \in M \tag{3.12}$$

$$\sum_{a=1}^{A} \frac{\alpha}{W+1} x_{w,a} B \log_2\left(1 + \frac{P_{A,w} G_{(a,w)}}{N_0}\right) \geq r_{min,w};$$

$$\forall w \in W; \forall m \in M \tag{3.13}$$

Constraint (3.8) ensures the queuing delay in each subframe does not exceed the maximum delay for each QoS class n by ensuring that the average queue length does not exceed the threshold queue length. Constraint (3.9) is the RB allocation constraint. It ensures that an RB can only be allocated to one user. Constraint (3.10) is the service-level agreement (SLA) constraint that ensures that a minimum number of RBs is allocated to each SP. Constraint (3.11) defines the 5G NR-U user's minimum rate while constraint (3.13) defines the Wi-Fi user's minimum rate. Finally, Constraint (3.12) is the AP association constraint that forces each Wi-Fi user to only be connected to one AP.

Since the original problem formulation uses information over a time window $(t, t+F)$, we cannot solve it to optimality since it needs future information. Thus, we solve each sub-problem for each time instance rather than over the window. Additionally, this problem is decomposed further into two sub-problems as the formulated optimization problem cannot be solved for both technologies simultaneously (due to the time-based WRV mechanism proposed).

The first sub-problem for NR-U is the RB allocation for each user. Likewise, the second sub-problem for Wi-Fi is the users' access point allocation problem. Based on the time-sharing mechanism, each technology will solve the RB or AP allocation problem. Moreover, each of the two sub-problems is considered to be a linear integer programming problem. The objective for the first sub-problem is to maximize the NR-U users' throughput through effective RB allocation. Similarly, the objective of the second sub-problem is to maximize the Wi-Fi users' throughput through proper AP allocation. Therefore, these sub-problems are solved to optimality after decomposition. The scheduler takes results of these algorithms as an input.

3.4.1 NR-U Users' RB Allocation Problem

The NR-U Users' RB Allocation optimization problem the aims at allocating the available RBs to the NR-U users in such a manner that it maximizes the aggregate throughput is formulated as follows:

$$\max \sum_{s=1}^{S} \sum_{m=1}^{M} \sum_{c=1}^{|C_m|} \sum_{l=1}^{|L|} B\, x_{s,c}^{m,l} \log_2\left(1 + \frac{P_{S,c}^{m} G_{s,c}^{m,l}}{N_0}\right) \tag{3.14}$$

subject to

$$\sum_{l=1}^{|L|} B\, x_{s,c}^{m,l} \log_2\left(1 + \frac{P_{S,c}^{m} G_{s,c}^{m,l}}{N_0}\right) \geq r_{min,c};$$

$$\forall\ c \in C_m;\ \forall\ m \in M \tag{3.15}$$

$$W(q_k^c[t], F) \leq Q_{max}^{n}; \forall c \in C_m; \forall m \in M \tag{3.16}$$

$$\sum_{m=1}^{M} \sum_{c=1}^{|C_m|} x_{s,c}^{m,l} = 1;\ \forall\ l \in L; \forall s \in S \tag{3.17}$$

$$\sum_{l=1}^{|L|} \sum_{c=1}^{|C_m|} x_{s,c}^{m,l} \geq \rho_{min}^{m}|L|;\ \forall\ m \in M \tag{3.18}$$

B is the bandwidth of an RB. $x_{s,c}^{m,l}$ is a binary decision variable which is equal to 1 if user c is assigned an RB l and 0 otherwise. ρ_{min}^{m} is the pre-agreed access ratio for each SP as per the SLA agreement. Constraints (3.15) and (3.16) represent the QoS requirements constraints.

More specifically, constraint (3.15) guarantees that each user's throughput is higher than its minimum required rate. On the other hand, constraint (3.16) ensures that the delay constraint is met. Constraint (3.17) again is the RB allocation constraint. It ensures that an RB can only be allocated to one user. Lastly, constraint (3.18) is the SLA constraint that ensures that a minimum number of RBs is allocated to each SP.

The search space for this sub-problem is $2^{|SMLC_m|}-1$. For each user, the problem considers L different possible resource allocation combinations, with the no allocation combination omitted as it is not a possible combination (due to the minimum rate constraint). For example, assume there are $S = 2$ gNBs, $M = 2$ SPs, $L = 12$ RBs, and $M \times C_m = 10$ cellular users, (i.e., 5 cellular user per SP). In this scenario, the worst case search space is 1.767×10^{72}. This implies that the estimated complexity has exponential relationship with the decision variable size. Accordingly, this would be prohibitively complex for real world scenarios.

3.4.2 Wi-Fi Throughput Allocation Problem

The Wi-Fi channel efficiency α is assumed to be 50% [52, 59, 42]. This is to account for the impact of the DCF mechanism for CSMA/CA with binary exponential backoff rules and the Wi-Fi transmission interruption caused by NR-U [52, 59, 42]. Inspired by Sagari's model which is characterized using the Markov chain analysis given in Bianchi's model [44, 52], and accounting for the interference of NR-U coming on when Wi-Fi is communicating, the Wi-Fi throughput maximization problem is formulated as follows:

$$\max \sum_{a=1}^{|A|} \sum_{w=1}^{|W|} \frac{\alpha}{W+1} x_{w,a} B \log_2\left(1 + \frac{P_{A,w} G_{a,w}}{N_0}\right) \tag{3.19}$$

subject to

$$\sum_{a=1}^{|A|} \frac{\alpha}{W+1} x_{w,a} B \log_2 \left(1 + \frac{P_{A,w} G_{a,w}}{N_0}\right) \geq r_{min,w};$$

$$\forall w \in W; \forall m \in M \tag{3.20}$$

$$W(q_k^w[t], F) \leq Q_{max}^n; \forall w \in W \tag{3.21}$$

$$\sum_{a=1}^{|A|} x_{w,a} = 1; \forall w \in W; \forall m \in M \tag{3.22}$$

Similar to the NR-U case, B is the system bandwidth while $r_{min,w}$ is the Wi-Fi user's minimum throughput. $x_{w,a}$ is a binary decision variable that is set to 1 if user w is connected to AP a and 0 otherwise. Constraints (3.20) and (3.21) represent the QoS requirements constraints for the Wi-Fi users. More specifically, constraint (3.20) guarantees each user has the minimum rate requirement, while constraint (3.21) ensures the delay constraint is met. Finally, constraint (3.22) is the AP association constraint that forces each Wi-Fi user to only be connected to one AP.

For this sub-problem, the search space is $2^{|AW|} - 1$. This is because the sub-problem only considers two possible AP allocation options for each user. Additionally, the no allocation possibility is omitted since this would violate the minimum rate requirement of the users. Assuming $|A| = 2$ and $|W| = 10$, the worse case search space is 1.049×10^6.

The search space for NR-U allocation problem prompts the need for an heuristic algorithm as it is in the order of 72, whereas the search space for Wi-Fi allocation is 12 times less of the order of search space of NR-U. This illustrates the need for low-complexity heuristics that can solve these problems in a manner suitable for real-world deployment. The optimization problem considers RA allocation and QoS constraints simultaneously for each technology whereas for the heuristic algorithm, we are iteratively making the allocation decisions based on the channel conditions and delay constraints of the users to ensure that the QoS requirements are met.

3.5 Heuristic Algorithm

Since the search space is high, there needs a more computationally efficient heuristic algorithm for both 5G and Wi-Fi sub-problems to allow for real-world solution deployment.

The heuristic algorithm involves three phases for each technology. The first phase is a greedy-based algorithm to determine the resource allocation in 5G NR-U or AP association in Wi-Fi and ensures the minimum rate is met. The simplicity of greedy-based algorithm in a fine-grained granularity allows for SP to deploy locally at the gNB and AP. The second phase ensures the SLA is met and the throughput is maximized according to the best channel. The last phase allocates the packets into the scheduler based on the throughput calculated from phase one and two while meeting the QoS requirements.

Before running the simulation, a traffic matrix is developed for each Wi-Fi and NR-U user, which describes the arrival time for each packet, which will be used in phase three. Keeping track of each packet belonging to which user, the traffic vectors for each user are concatenated and sorted to create a queuing packet vector to simulate the packets arriving to the queue before being assigned to the subframe in the scheduler. Furthermore, the matrix is sorted, such that for each subframe, the user with the highest delay is served first, to ensure the delay-aware process. After a traffic matrix is generated, for each scheduling window, which is set to 10 subframes, simulate the channel access as shown in Algorithms 5 and 6 for each technology. For each subframe, the available throughput is calculated from the previous two algorithms to be able to schedule each packet in the current subframe.The functionality is illustrated in Fig. 3.5.

Note that the delay is implicitly considered when we sort the users based on their delay before performing the resource allocation procedure. Based on the available throughput for each user, the scheduler will determine how many packets are needed for each subframe, and allocate which technology will occupy that subframe. Each packet has an arrival time, determined by the Discrete-Event Simulation (DES). DES is developed for each user to have an array of arrival times for each packet. Based on the exponential distribution, the arrival times

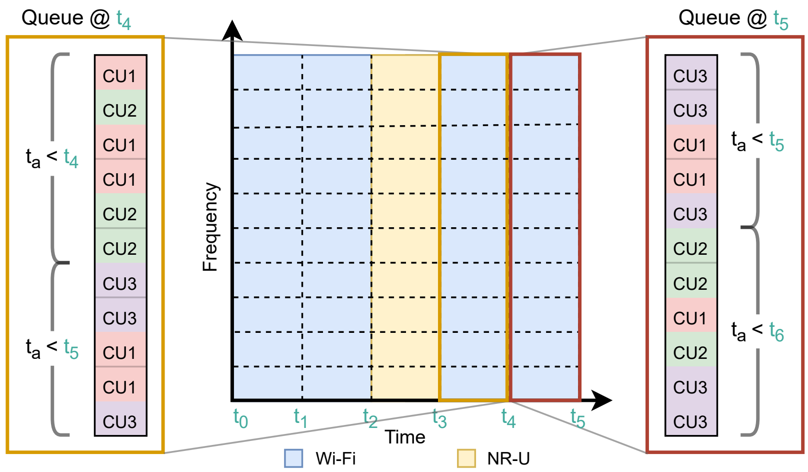


Figure 3.5: The packet queue before and after t_4 is allocated, where each packet is labelled for each Wi-Fi user at this time instance.

generated from DES are verified using the histogram of the exponential probability density function (pdf).

The resource allocation algorithm shown in Algorithm 5 is a QoS-aware greedy-based algorithm to allocate the RBs to meet minimum rate requirement for each 5G NR-U user. Once the minimum rate constraint is met, the remaining RBs are allocated in such a manner to meet the SLA agreement. Lines 1-18 represent the first phase. In this phase, RBs are allocated with the goal of meeting the minimum rate requirement or until there is no more packets in the queue. More specifically, the algorithm sorts users based on their delay. Then, for each user, it searches for the best channel condition in $G^{m,l}_{S,c}$ and assign the RB the user. This is done by setting the corresponding decision variable $x^{m}_{c,l}$ to 1. This is repeated until the user's rate requirement is met. To determine the second phase (represented in lines 19-27), the number of assigned RBs is calculated, denoted as N^{m}_{c}. This phase focuses on meeting the SLA constraint. More specifically, the remaining RBs L^{m} to m SPs are allocated according to the SLA constraint. The SP with the highest access ratio is given priority since it will provide more chance to improve the aggregate users' throughput. Therefore, for each unallocated RB, the algorithm searches for the best channel condition in the remaining $G^{m,l}_{BS,c}$. It then allocates the RB to the user with the best channel by setting the corresponding decision variable $x^{m}_{c,l}$ value to 1. The algorithm has a linear complexity. More specifically, its order of complexity is $O(|S \times L \times C|)$ where $|S|$ is the number of gNBs, L is the number of RBs, and $|C|$ is the total number of users in the system, $|C| = \sum_{m=1}^{M} |C_m|$. This is because we search among a list of L possible RBs in each iteration for each user.

Algorithm 5 Heuristic Algorithm for NR-U Users' Resource Allocation

$S_L = \{1, 2, .., S\}$
$M_{sp} = \{1, 2, .., M\}$
$L_{tot} = \{1, 2, .., L\}$
for $s \in S_L$ **do**
  for $m \in M_{sp}$ **do**
    sort $q_k^c[t]$
    for $c \in C_s^m$ **do**
      while $r_{c,ach}^m < r_{min}^{NR-U}$ OR $q_k^c[t] \neq 0$ **do**
        find $g_{c,l}^{m,s} = \max_{l \in L_{tot}}(G_{S,c}^{m,l})$
        set $x_{s,c}^{m,l} = 1$
        calculate $r_{c,ach}^m$
        allocate q_k^c
        update $L_{tot} = L_{tot} \backslash l$
      end while
    end for
    calculate $N_c^m = \sum_{c=1}^{|C_s^m|} x_{s,c}^{m,l}$
  end for
end for
for $m \in M_{sp}$ **do**
  calculate $L^m = \rho_{min}^m |L_{tot}| - N_c^m$
  for $l \in L^m$ **do**
    find $g_{c,l}^{m,s} = \max_{l \in L_{tot}}(G_{s,c}^{m,l})$
    set $x_{s,c}^{m,l} = 1$
    allocate q_k^c
    update $L_{tot} = L_{tot} \backslash l$
  end for
end for

Similarly, for Wi-Fi systems, the AP association shown in Algorithm 6 is also a greedy-based algorithm. The first phase of associating AP to each user to ensure minimum required rate is shown in lines 1-10, by finding the best channel condition in G_w^a for each user (sorted based on their head of queue packet delay) and associating the user with the AP for by setting the decision variable x_w^a to 1. This is repeated until the user's rate requirement is guaranteed

Algorithm 6 Heuristic Algorithm for Wi-Fi Users' AP Association

$A_{tot} = \{1, 2, .., A\}$
for $a \in A_{tot}$ **do**
  sort $q_k^w[t]$
  for $w \in W$ **do**
    while $r_{w,ach}^a < r_{min}^{Wi-Fi}$ OR $q_k^w[t] \neq 0$ **do**
      find $g_w^a = \max(G_w^a)$
      set $x_w^a = 1$
      allocate q_k^w
      calculate $r_{w,ach}^a$
    end while
  end for
  calculate $N_w = \sum_{w=1}^{|W|} x_w^a$
end for

or there are no more packets in the queue. There is no SLA requirement for Wi-Fi, due to number of users typically being larger than the number of APs.The order of complexity of this algorithm is $O(|A \times W|)$ where A is the number of APs and $|W|$ is the total number of Wi-Fi users in the system. This is because we search among a list of A possible APs in each iteration for each user.

Thus, it can be seen that both heuristic algorithms have a linear order of complexity. This makes them suitable for deployment in real-world scenarios.

3.6 Simulation Results & Discussion

The system model is simulated using MATLAB on an Intel(R) Core(TM) i7-9700 CPU @ 3.00GHz, 32.0 GB RAM computer on Windows 10 Home. The elapsed time for the optimization problems and heuristic algorithms are provided for comparison. However, they do not represent the actual time needed to find a solution in a real-world scenario as this is a simulation completed on a desktop computer.

In the simulation, we assume 15 users divided equally among each application. The packet rate requirement for video streaming ranges from 64 kbps to 384 kbps, and for FTP range from 36 kbps to 128 kbps. The VoIP requires the delay constraint to be met, therefore the delay

Table 3.2: Simulation Parameters

Common Parameters	
Channel Model	Downlink Indoor Office model
Layout	120 m x 50 m x 3 m
gNB Height h_{BS}	3 m (ceiling)
User Height h_{UT}	1 m
Carrier Frequency	5 GHz
Carrier Channel Bandwidth	20MHz baseline
Parameters in NR-U	
Number of gNBs	3
Number of SPs	2
Number of RBs/gNB	100
Number of users/gNB	5
BS Tx Power	23dBm (total across all TX antennas)
UE Tx Power	18dBm (total across all TX antennas)
BS Noise Figure	5dB
UE Receiver Noise Figure	9dB
SLA Access Ratio	[0.6 0.4]
Standard Deviation of Log-normal Shadowing	8.03 dB
Parameters in Wi-Fi	
Number of APs	3
Data Preamble Type	11ac
STA Tx Power	15 dBm per antenna
AP Tx Power	20 dBm per antenna
Noise Figure	7 dB
Channel Efficiency	50%
Standard Deviation of Log-normal Shadowing	5 dB

must be less than 100ms. The parameters used for the simulation are shown in Table 3.2. The parameters for 5G NR-U and Wi-Fi were obtained from [80, 78, 8] and [79, 81] respectively.

Table 3.3: Different Coexistence Configurations

	Subframe Number									
Coexistence	0	1	2	3	4	5	6	7	8	9
LTE Only	L	L	L	L	L	L	L	L	L	L
1 by 4	W	L	L	L	L	W	L	L	L	L
1 by 2	W	L	L	W	L	L	W	L	L	W
1 by 1	W	L	W	L	W	L	W	L	W	L
2 by 1	W	W	L	W	W	L	W	W	L	W
4 by 1	W	W	W	W	L	W	W	W	W	L
Wi-Fi Only	W	W	W	W	W	W	W	W	W	W

Fig. 3.6 shows the normalized throughput for 5G NR-U and Wi-Fi communication, according to Table 3.3 where the number of Wi-Fi subframes is assigned before the number of 5G NR-U. The first observation is that the throughput of NR-U or Wi-Fi is at its highest when the no coexistence configuration is adopted. This is expected since the no coexistence configuration represents the case where the technology has access to the full spectrum band in all time

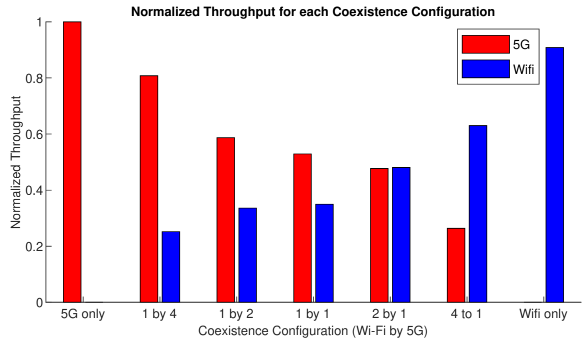


Figure 3.6: Normalized Available Throughput for each technology

slots. In this case, NR-U has a higher throughput than Wi-Fi. This is because NR-U is more reliable when it comes to scheduling its resources. The second observation is that the Wi-Fi throughput increases as the number of subframes allocated to it increases, while that of NR-U decreases. This again is expected since more time is given to Wi-Fi transmission at the expense of NR-U. The preferred configuration is 2 by 1 where 2 subframes are assigned to Wi-Fi and 1 subframe is assigned to NR-U. It is important to note that at 2 by 1 configuration, NR-U and Wi-Fi suffers about 47% and 48% compared with no coexistence, respectively. Although the 5G NR-U technology loses about 50% of throughput through this coexistence, it is important to note that the unlicensed band is primarily used for Wi-Fi users and each user's minimum rate requirement is still met in this configuration.

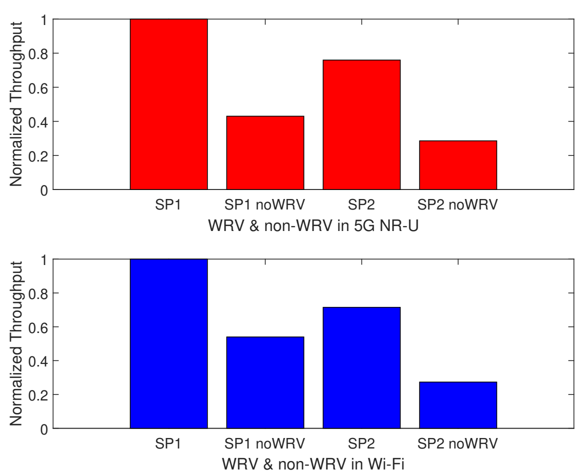


Figure 3.7: A normalized throughput for each SP in each technology with and without WRV

Fig. 3.7 shows the throughput improvement of utilizing WRV for each SP. As per the SLA in this scenario, the first SP (SP1) has 60% of the RBs and the second SP (SP2) has the remaining RBs, which is consistent with the results shown in Fig. 3.7. The results with no WRV represent the no resource sharing scenario between SPs. Furthermore, with WRV active, the 5G NR-U users have the freedom to utilize RBs from a combined larger pool, thus higher probability of accessing better channels. Likewise, the APs are shared across SPs, therefore there is also a higher chance of Wi-Fi users to get better channels. The benefits of using WRV is visible, where the throughput increased by 57% and 62% in SP1 and SP2, respectively for 5G NR-U users, and by 46% and 62% in SP1 and SP2 for Wi-Fi users.

For Figures 3.8 and 3.10, two different solutions are solved for resource allocation while maintaining the delay constraints: the optimization-based programming (OP) and the heuristic algorithm (HA). It is expected that the optimization-based programming solution has better results, although heuristic algorithm may solve the problem 50% faster. The heuristic algorithm solved the problem in 1.38 seconds, whereas the optimization-based programming was solved in 2.78 seconds. This is based on 15 trial runs per channel condition from 2 to 10 dB, totalling 135 trial ones. This is done to ensure the average results mimic the real-world application better. Fig. 3.8 shows the available throughput of each technology as the channel condition

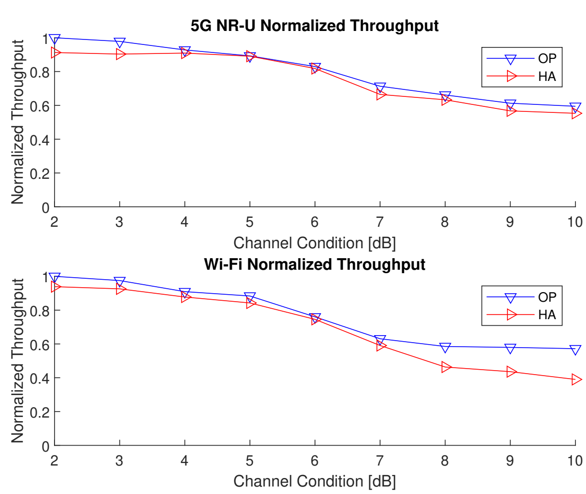


Figure 3.8: Normalized Available Throughput for each technology

worsens. The term available was used in this case is that although users may be assigned l RBs, the scheduler assigns packets based on the availability of the RBs for each user. As the channel condition gets worse, the quality of the RBs is less, therefore the throughput is worse. Another observation is that the heuristic solution achieves close-to-optimal performance. This further highlights its effectiveness and efficiency in finding a suitable solution for both the resource allocation and AP association sub-problems. For a more insightful study, the simulation is conducted with increased number of gNBs and APs to six each in the same area, which resulted in a similar trend and rate as shown in Fig. 3.9.

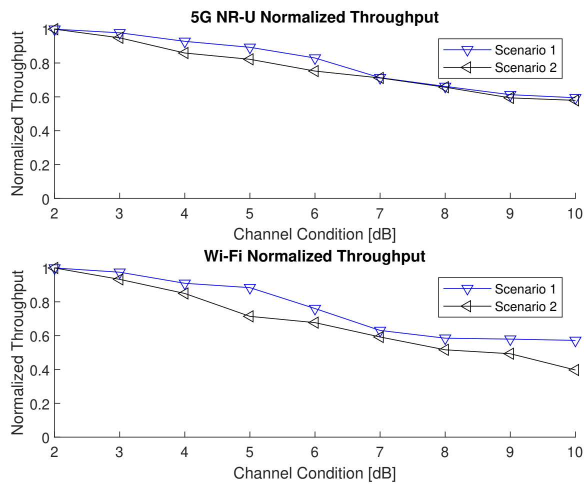


Figure 3.9: Different topology produces a similar trend for each technology

Fig. 3.10 plots the average delay per user for each technology as the channel gets worse. It is expected to see that as the channel condition gets worse, the delay is longer. However, for the optimization problem, it has maintained its delay throughout. This can be attributed to the fact that the system is still able to meet the minimum rate requirement and thus send the packets with the most delay. It is also expected to see that NR-U has a higher delay for heuristic algorithm than the Wi-Fi. This is due to the coexistence configuration, where NR-U has to wait its turn to access the channel every two milliseconds.

Fig. 3.11 shows different QoS classes used in this simulation over one frame (10 ms). The delay is higher for 5G NR-U due to the configuration, where NR-U is unable to access the

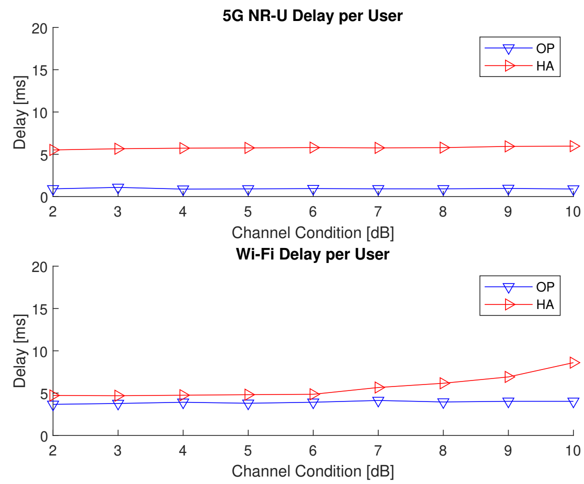


Figure 3.10: Average Delay per User for each technology

channel for 2 ms when Wi-Fi is communicating. Although 5G NR-U delay is almost twice as much as the Wi-Fi, the QoS requirement is satisfied.

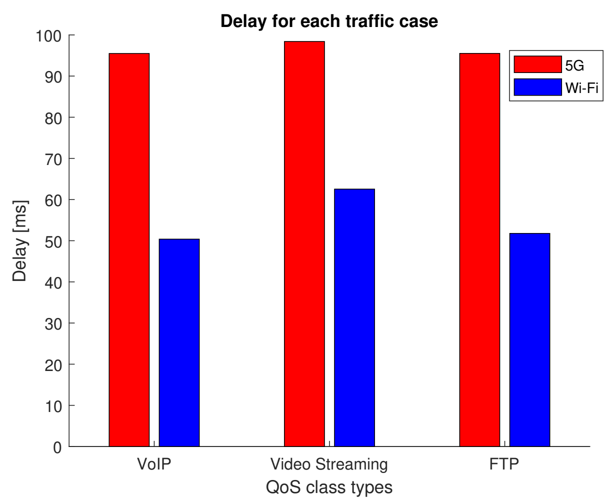


Figure 3.11: Sum of delays over one frame per traffic case

3.7 Conclusion & Future Directions

This paper proposed a mechanism for QoS-aware resource allocation in the downlink 5G NR-U and Wi-Fi coexistence using wireless resource virtualization and time-domain virtualization. The BIP was solved using Lagriangian dual decomposition method to solve the coexistence by dividing it into two sub-problems, which addressed the resource allocation for each technology over each subframe while maintaining the QoS requirements of its users. Additionally, heuristic algorithms were developed to mimic the optimization problem solution performance while having a significantly lower complexity space.

This paper used a fixed configuration to have similar throughput for each technology. Thus, considering a dynamic coexistence configuration can improve the throughput and the delay performance. This is due to dealing with data at the packet level. For example, choosing a 4 by 1 configuration (4 Wi-Fi and 1 NR-U subframe) will have on average a higher delay for NR-U when compared to a 2 by 1 configuration. This is due to the fact that NR-U users need to wait longer to be able to send their data. A potential solution is to consider the throughput of each technology in the previous subframes and assign whichever technology to ensure fairness in the throughput. Finally, this work assumed that the user to gNB association in 5G NR-U is known apriori. Therefore, the user to gNB association problem can be considered as a future direction.

Chapter 4

B5G: Intelligent Coexistence Model for Edge Network

4.1 Introduction

Internet of Things (IoT) is a promising technology that continues to ignite innovations in the future. IoT is a system of connected devices which is not limited in the distance as these smart devices can communicate seamlessly over the Internet. The surging growth of IoT is driven by a strong return of investment (ROI), with industrial as the top global share of enterprise IoT projects [82]. The fifth-generation (5G) wireless network standard focuses on high-speed connections, ultra-high reliability and low latency communications, higher connectivity density, and higher mobility range [66, 10]. Beyond 5G (B5G) is currently under development which inherits the 5G specifications and supports IoT devices and edge computing. Hence these benefits of 5G, as well as B5G, have allowed IoT to advance in microelectronic circuits and device technologies to improve cellular operations and smart services.

IoT devices connect to the 5G base stations (BS) via the IoT gateways which then send information to the cloud to finally utilize the end-user applications. 5G networks can also be accessed on the unlicensed band, called 5G New Radio-Unlicensed (5G NR-U). Although much research focuses on utilizing the spectrum more efficiently using virtualization [20, 21, 48, 28, 73], unlocking more spectrum for 5G expands the network capacity to solve the spectrum scarcity in the current licensed spectrum. 5G is focused on Unlicensed National Information Infrastructure (U-NII) bands at 5 GHz and 6 GHz, which is dominated by Wi-Fi. While mobile operators can operate on the unlicensed band, they are required to comply with the wireless regulation and therefore must coexist with other wireless technologies, such as Wi-Fi, Bluetooth and Zigbee to ensure the fairness of channel access.

Edge computing takes place at the edge of the network, such as end devices, access points and base stations. Sensors in the end devices collect so much data that the sheer volume requires larger and more expensive connections to data centres and the cloud. Edge devices can collect, sort, and perform a preliminary analysis of data before transmitting the analyzed data, therefore the volume of traffic can be reduced [83]. For example, an IoT device with a sensor detecting dangerously high pressure in the pipes requires immediate reaction to shut down the valve for safety reasons to minimize catastrophic events [84]. Without edge computing in the IoT devices, the detection is instead triggered in the cloud, and the response to shut down may be too late. Therefore, processing power is located in the end devices, hence the term ”edge” to minimize the latency and round-trip time. In this paper, the BS is a network edge server.

While demands have dramatically increased for faster rates and lower delays, energy consumption has increased. The telecom sector made efforts to follow the 2015 Paris Agreements to achieve net-zero emissions by 2050. Also, many operators have made efforts to increase efficiency to combat rising network costs. Over 90% of network costs are spent on energy including fuel and power [12], where more than 70% of the energy is consumed in BS [13, 12]. Wu *et al.* have surveyed and classified five categories for energy efficiency, and have shown that BS has the highest energy consumption in the cellular work. Guo *et al.* investigated the trade-off between energy efficiency and quality of service (QoS) using three BS sleeping strategies [13] and found up to about 35% energy consumption savings. Sesto-Castilla *et al.* implemented the use of machine learning to analyse traffic patterns and derive predictive models to improve energy efficiency and reduce the energy cost [85]. Mahdy *et al.* have applied machine language algorithms by clustering the base stations and forecasting the traffic load to decrease energy consumption in 5G networks [86]. Many works of literature applied the prediction on the load of the BS to address the energy consumption[87, 88, 89].

In this paper, we propose a new scheme for prediction, while considering the practical scenario by including communication and computing overhead needed to have the edge server back fully functional. To the best of our knowledge, there has been limited research on the wake-up operation of BS to decrease energy consumption while maintaining the QoS. The proposed algorithm is to use forecasting prediction on a data set of traffic data. Guo *et al.* analyzed the effect of energy savings using wake-up policies with setup time and sniffing cost [13]. Our contribution is to consider the wake-up and association time and determine the threshold time to keep it awake while maintaining the QoS and increasing the energy efficiency.

The rest of the paper is organized as follows: Section 4.2 describes the dataset used in this paper and outlines data preprocessing to extract useful information. Section 4.3 forecasts the traffic load by investigating different prediction methods and reporting the accuracy of each method. Section 4.4 introduces the concept of BS wake-up policy. Finally, section 4.5 concludes this work with recommendations for future directions.

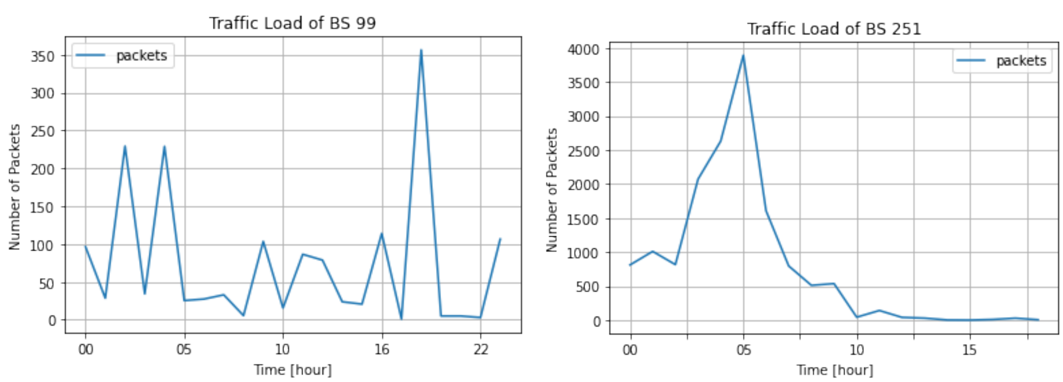
4.2 Data Preprocessing

Typically the real-world data is incomplete, inconsistent and contains outliers. The data require preprocessing such as data cleaning, imputation and specific attributes that need to be derived. This section focuses on preparing the data to ensure the success of any ML models.

In general, dataset needs to be inspected to determine what are the preprocessing steps such as data cleaning, transformation, imputation, normalization, balancing, feature generating and feature selection. For this paper, data cleaning and imputations was sufficient to not overly manipulate the data but to remove extreme outliers. The obtained dataset is a public dataset and was originally in a CRAWDAD repository from Dartmouth and can be obtained from github [90].

The dataset used is week-long traffic generated by a large population of people in a median-size city of China, taken for 192 hours in the cellular area of 50 km $\times$ 60 km. The dataset is a trace file identifying the base station ID, the timestamp of each hour, the number of users associated with the BS ID and the hour, and the number of packets and bytes associated with the BS ID and the hour.

This dataset is a time-series, which is a set of data points indexed in time order. A time-series have different components to make up a pattern, including trend, seasonality, and residuals. A trend shows an increase or decrease over time and a seasonality shows similar peak patterns that happen periodically over time. A residual is a random noise that has no pattern over time. To visualize the traffic load, Fig. 4.1 was generated to show the average load on an eight-day period on two different BS. In other words, the traffic is averaged at the same hour for the eight days. Fig. 4.1 (a) is an example of a BS with a very low traffic load, which further emphasize the need of a wake-up policy to reduce energy consumption, thus effectively reducing operating expenditures.



(a) (b)

Figure 4.1: The average weekly load on (a) BS 99 and (b) BS 251

Before the time-series prediction techniques is applied to this dataset, the data needs to be stationary to ensure the statistical properties remain constant over time. To verify, the rolling

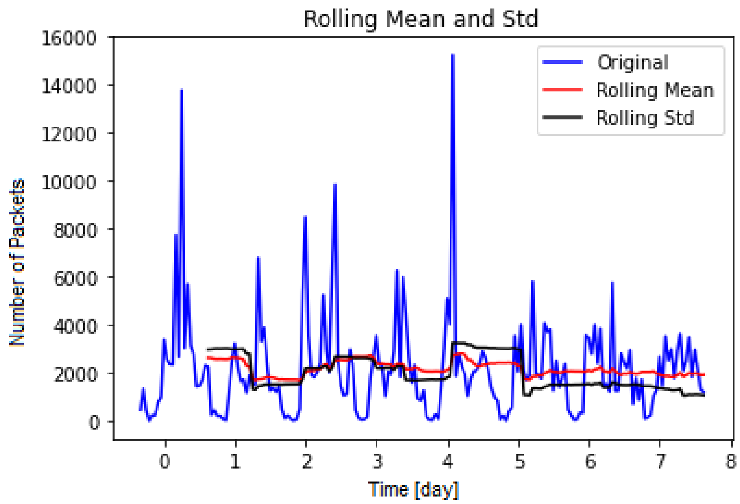


Figure 4.2: Traffic load vs. the rolling mean and standard deviation

average and standard deviation are applied and shown in Fig. 4.2, which therefore is shown as not constant over time and is non-stationary. Also, the time-series is decomposed into trend, seasonality and residuals as shown in Fig. 4.3. Since there is a pattern that is not constant for each of the decomposed components, it is confirmed that the time-series is not stationary.

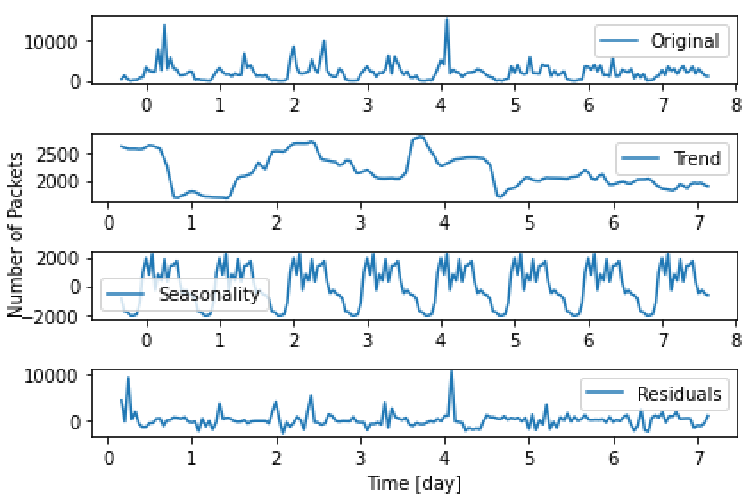


Figure 4.3: Decomposition of traffic time-series of one base station

After inspecting the dataset with the number of hourly records, it is noted that some BSs do not have sufficient information. Data on a total of 13,269 BSs were collected over 8 days, therefore any data collected less than a total of 3 days worth of information are removed to maintain consistency. Furthermore, the cutoff for each BS is 24 hours $\times$ 3 days, which is any BS with less than 72 records are removed. As a result, 3466 records were removed to ensure that the dataset does not include any BS with no record for more than 5 days of 8 days.

Any BS with extreme instances are also removed from the dataset to preserve a predictable behaviour. Fig. 4.4 visualizes the outliers in a box plot. The outliers are determined using Z-score, such that if it is three times the standard deviation, it will be removed from the dataset. Furthermore, the three standard deviation from the mean contain 99.7% of the data according to the empirical rule [91]. It is important to note that some outliers may be important to indicate specific events to be included in the traffic prediction, however for this research, these outliers are removed to improve the prediction about what the true value would be in this population as the outliers may skew the results. Extension of this work should investigate in using different methods to remove unnecessary outliers in a non-normal distribution or time-series data.

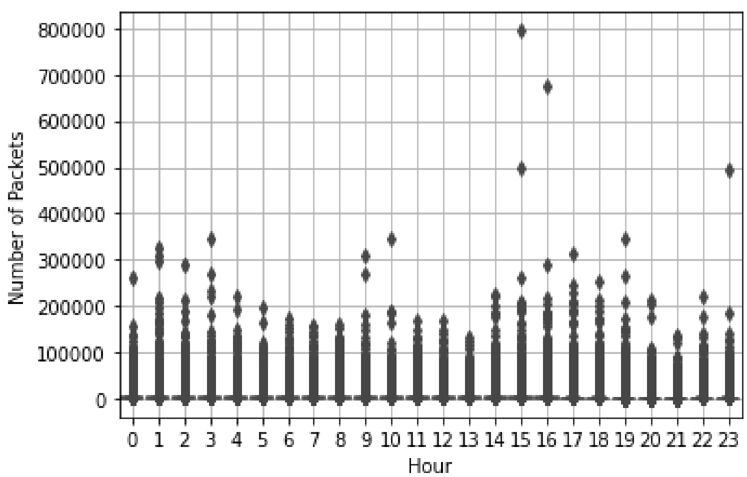


Figure 4.4: Box plot of the traffic load of all BS with outliers

After cleaning, formatting and organizing the raw data, the boxes are now visible in Fig. 4.5. A time-series is an ordered sequence, therefore any BSs with missing hourly records are imputed using the neighbouring values and averaging them to avoid wasting any corresponding data. The average values are imputed to not significantly affect the performance.

Finally, the data undergoes the Augmented Dickey-Fuller (ADF) test, where the null hypothesis is that the time-series is stationary, the p-value resulted in less than 0.005. This test indicates strong evidence against the null hypothesis, therefore the data is stationary and can be used for time-series prediction.

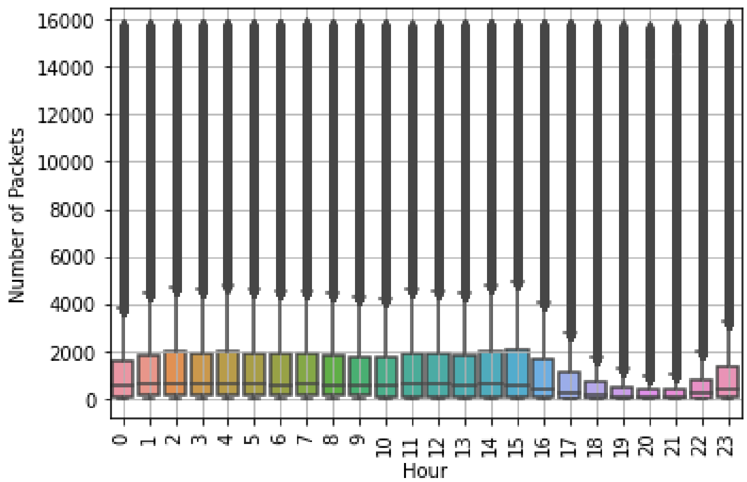


Figure 4.5: Box plot of the preprocessed traffic load of all BS

4.3 Traffic Prediction

Traffic flow fluctuates over time, causing the base stations to be underutilized. Therefore, the operation of BS needs to determine when the traffic flow may be low in order to switch between operation modes. Mobile operators can utilize traffic prediction by learning historical traffic data to accurately plan their networks to optimize resource utilization and energy consumption. In this section, we will use different algorithms to determine the best traffic forecasting performance to use for a wake-up policy in the next section. Root mean square error (RMSE) is used to quantify the performance of each technique, where the smaller these values are, the more accurate the traffic prediction. RMSE is chosen as it calculates the square error before averaging, therefore accounts for negative values as well as penalizing large errors. Rooting of this mean square error allows the error to be observed in the same units as the result making it easier to understand the magnitude of the error. For all traffic prediction techniques, the data will be split into train and test sets. Naive forecast is used as a baseline to compare the RMSE

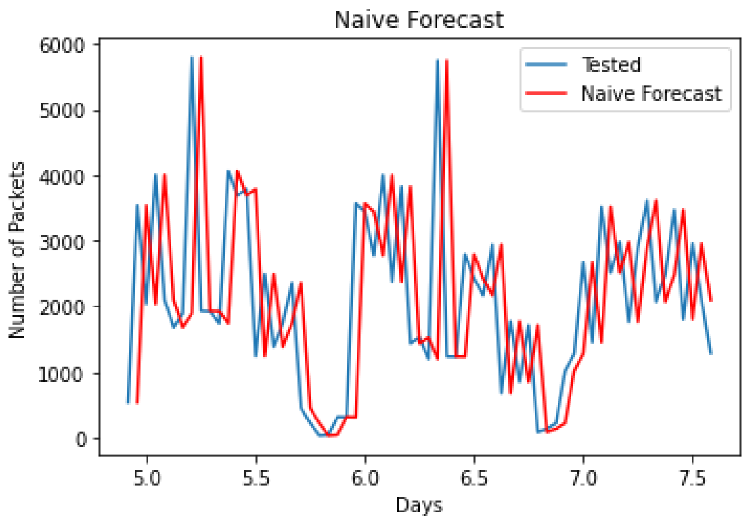


Figure 4.6: Real vs predicted number of packets using Naive Forecasting

between models. Naive forecasting, also known as persistence forecasting, is using the test sets and shift one time step, and is shown in Fig. 4.6.

4.3.1 Statistical Prediction Method

The first prediction is a statistical method called Autoregressive Integrated Moving Averages (ARIMA) model [92]. First, the autocorrelation function (ACF) and partial ACF (PACF) are performed to determine the parameters for the ARIMA model, results shown in Fig 4.7. The prediction obtained from the ARIMA model is shown in Fig 4.8. It shows that there is a delay between the expected and predicted value, and there is an indication if there is an increase or decrease, however does not specify how much the change is. The test RMSE is 1383.33.

As seen in Fig. 4.3, there is a periodic pattern for seasonality, therefore seasonal ARIMA (SARIMA) is also utilized for traffic prediction to support seasonal data that ARIMA does not offer [92]. The results are shown in Fig. 4.9, and the RMSE is 1342.77 which is a small improvement. It is important to note in the figures that ARIMA visually report better prediction, but have worse RMSE because RMSE measures the difference between the actual data vs the predicted data at a point of time, not accounting for the horizontal shift in the plot. However, there needs a better traffic prediction, therefore machine learning methods are investigated.

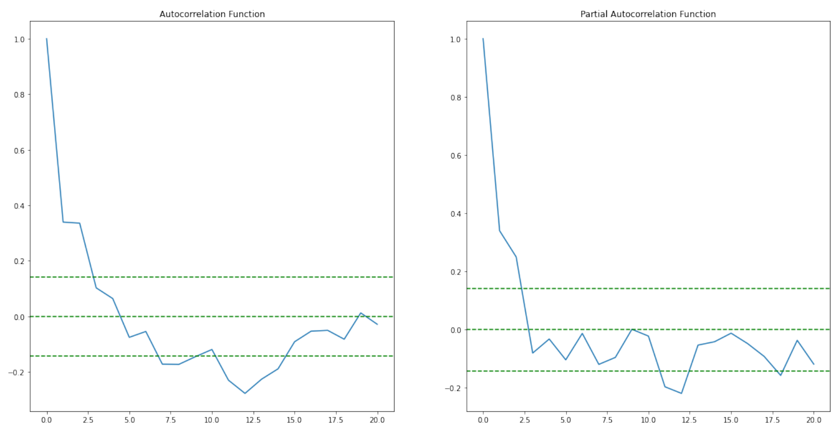


Figure 4.7: Plotting ACF and PACF to find the parameter values for ARIMA model

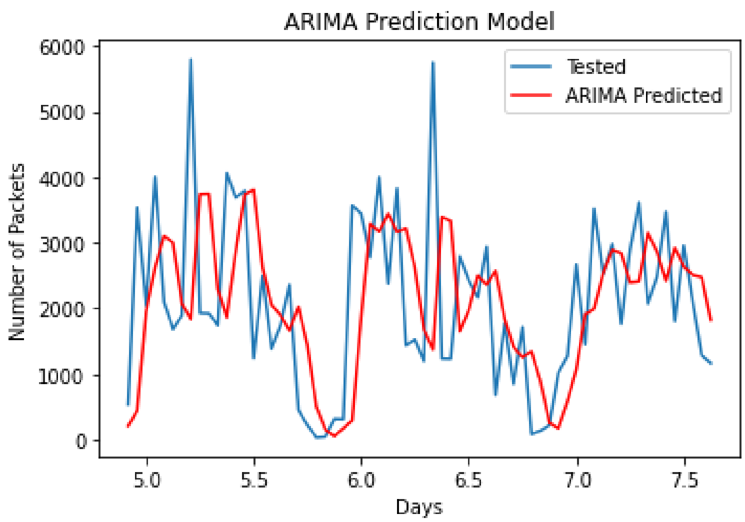


Figure 4.8: Expected vs predicted number of packets over time using ARIMA model

4.3.2 Machine Learning Method

Before applying Machine Learning (ML), the time-series model needs to be restructured as a supervised learning problem. The traffic pattern data is a time-series data, it is univariate as we have the number of transmitted packets for each hour in one BS. To transform univariate time-series data, the data needs to be transformed into inputs and outputs for each time period. In this case, the transformation involves splitting the data into train set as inputs and test sets as output. Supervised machine learning methods include Support Vector Machines (SVM) and Multi-layer Perception (MLP).

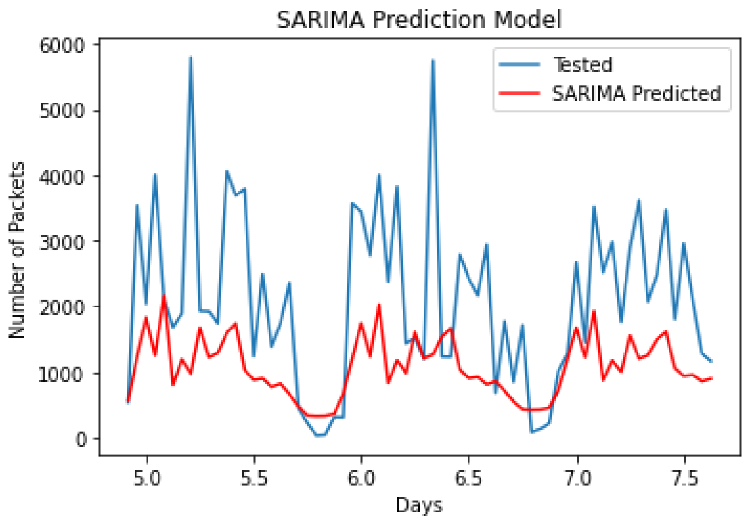


Figure 4.9: Expected vs predicted number of packets over time using SARIMA model

Support Vector Machines utilizes a kernel function to systematically find the support vector classifier to classify the observations in higher dimensions [93]. The support vector classifier is a decision boundary, in the case of traffic prediction, to dictate if a data point belongs higher or lower number of packets at a time instance. Fig. 4.10 shows the traffic prediction using SVM, with an RMSE of 1510.67.

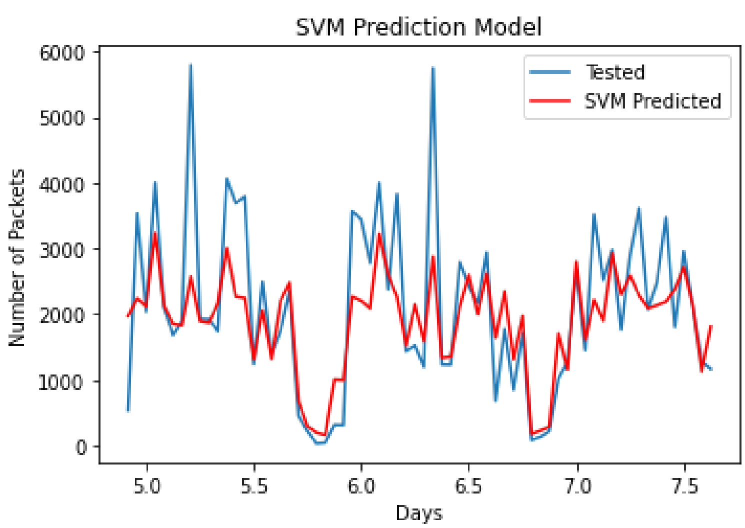


Figure 4.10: Expected vs predicted number of packets over time using SVM model

Multi-layer Perception (MLP) is a supervised learning algorithm and an artificial neural network (ANN) [94]. MLP accepts one or more inputs but has one output. Applying MLP on

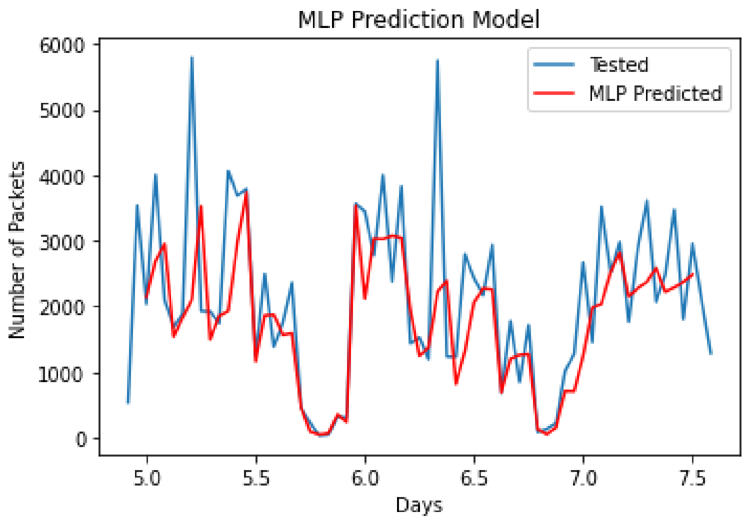


Figure 4.11: Expected vs predicted number of packets over time using MLP model

a time-series will perform a feed-forward network where the input layer feeds a hidden layer that maps the output layer. Each time this feed-forward step occurs, the mean squared error loss function is utilized to adjust the hidden layer by comparing the test and predicted outputs. MLP determines the output by the hidden layer where the weighted value for each input is adjusted with the bias. MLP algorithm repeats until the maximum number of iteration is hit or the loss function approaches zero. The input is an hourly sequence of a number of packets. The result of the MLP prediction is shown in Fig. 4.11 with test RMSE of 1328.50.

Model	RMSE
Baseline (Naive)	1609.89
ARIMA	1383.33
SARIMA	1342.77
SVM	1510.67
MLP	959.79

4.4 Wake-Up Policy

Although the traffic prediction done in this paper is for the cellular network, the same method can be done for the Wi-Fi network, and incorporating the spectrum sharing as proposed in [73], the wake up policy still apply for both BS in cellular network and access point in Wi-Fi system.

The wake-up policy inherits the N policy where the BS wakes up when there are N users waiting in the queue. The proposed methodology of the wake-up policy is as follows: 1) Predict the traffic and flag if traffic is low under the threshold. 2) Determine the duration of low traffic, and if this duration is longer than overhead time, then put BS to sleep. 3) When N customer is at the queue, wake-up the BS.

The operation of BS can be divided into the busy period, the close-down period, the sleep period, and the setup period. Therefore the time for each period is denoted as T_{bs}, T_{cd}, T_{sl}, and T_{st}, respectively. The T_{st} is the fixed wake-up time for the BS to come back in service, where as the T_{cd} is the fixed preparation time to go into sleep mode. The duration of T_{bs} is variable and depends on the traffic flow, where it is active until the threshold of low packet rate is passed to activate sleep mode. The duration of T_{sl} is also variable and depend on the wake-up policy. The power consumption over time can be visualized in Fig. 4.12. Some of relative values of power and period were obtained from [95].

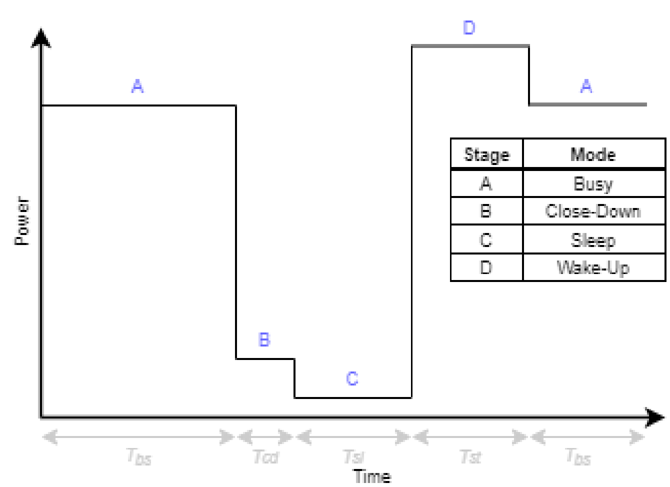


Figure 4.12: Base Station Power consumption over different operation modes

Based on the prediction from Section 4.3, the best method was the MLP prediction as it had the lowest RMSE. Therefore, the threshold to classify low traffic is chosen as a constant at 10% of the maximum number of packets, and the duration that the BS experiences less than this threshold is about 20% of the cycle. It is important to note that although this BS is put into sleep mode and will be inactive for any incoming traffic for a short period, there are neighbouring BSs that accept incoming traffic and utilize the resources needed to satisfy the user's requests. Many literature focus on which and when BS should be selected to sleep and should be investigated in future works [96, 97, 98]. The threshold is an empirical value and should be investigated in the future works to determine the threshold to minimize the power consumption while maintaining the QoS.

4.5 Discussion and Conclusion

In this paper, the traffic dataset includes hourly records which is a limitation of this work. Finer granularity is needed to work with minutes or seconds, however, there are limited data sets available for traffic predictions. One BS was investigated to determine the traffic prediction as well as the wake-up policy. The concept of determining the wake-up time is still the same and is relative to what the prediction reports for any other BS. This paper presents many opportunities for future works. For example, contributions should involve clustering technique to group the BSs with similar traffic behaviour. This will improve the accuracy of the traffic prediction and further improve the wake-up policy, which will affect the energy efficiency and the QoS of the users. As seen in Fig. 4.3, the trend line of one BS traffic is not consistent, thus classification of the traffic flow should remove odd traffic patterns and produce more accurate prediction results. However, the mechanism of wake-up policy does not change regardless of the prediction results as it still considers the duration of sleep time vs the wake-up time.

Currently, the threshold to determine low traffic is constant. Future works should include this threshold to be a design parameter and test on changing to see its impact on power savings be made. Also, the sleeping mechanism can be implemented to focus on traffic-aware, where if the BS has low traffic altogether, sleep so other neighbouring BS can handle the traffic. The wake-up policy can be extended to include a single vacation policy, where the BS wakes up after a fixed time, or a multiple vacation policy, where if there is no queue after a fixed time, sleep again. This paper introduces the idea of a BS wake-up policy that can improve the QoS while keeping the energy consumption low. This work can be extended to determine the performance of QoS and energy efficiency by comparing different wake-up policy times versus no policy.

Chapter 5

Conclusion

5G and Wi-Fi technologies are pitted against each other and while one may have benefits over the other, both technologies are needed and offer complementary functionalities. Wi-Fi technology may offer greater capacity and lower cost to deploy that is more suitable for home and enterprise networks, while 5G cellular network offer longer connection range and mobility.

Cellular network operates on licensed spectrum but with billions utilizing the licensed spectrum, the spectrum is running out of space. Instead, the unlicensed spectrum can be utilized, which has an immense capacity as compared to the licensed counterpart. As a result, mobile networks have explored the idea of utilizing the vast unlicensed spectrum in which Wi-Fi is prominently operated on. Adopting this coexistence between the cellular and Wi-Fi network poses several challenges.

One challenge is the spectrum sharing that affects the network capacity and the spectrum efficiency by properly allocating the available resources for each technology. A second challenge is to maintain the quality of service (QoS) in the coexistence while maximizing the aggregated throughput. Finally, the last challenge is to reduce the power consumption of cellular base station as network capacity increases to reduce the capital and operating expenses.

Accordingly, this thesis suggested various optimization modeling for the coexistence mechanism in the unlicensed spectrum; it also proposed machine learning techniques to manage the increasing power consumption with increasing usage. First, this thesis introduced optimization modeling techniques to allow the Wi-Fi and cellular networks to coexist in the same spectrum by improving the aggregate throughput, while satisfying the minimum required power consumption. Next, the thesis tested the coexistence mechanism using traffic simulation to maximize the aggregate throughput, while satisfying the quality of service for each user. Finally, the thesis proposed the use of machine learning techniques to be integrated into base stations to minimize the power consumption while maintaining the quality of service for each cellular user.

The remainder of this chapter summarizes the work and contributions completed in this thesis. Moreover, future research directions are presented to conclude this chapter.

5.1 Summary of Contributions

Chapter 2 formulated the problem of wireless resource virtualization with a coexistence mechanism between cellular and Wi-Fi network. The problem is a Mixed-Integer Non-Linear Programming (MINLP) problem to maximize the throughput and minimize the transmission power. This problem was decomposed into a pair of Binary Integer Programming (BIP) problem using the Lagrangian dual decomposition method for each technology. Each of these linear integer programming problems was solved to optimality. Additionally, two lower complexity heuristic algorithms, each solving one of the subproblems were introduced. Results showed that setting different coexistence configuration affected the throughput for each technology and to achieve similar throughput for each technology, a preferred configuration was used throughout the research. Wireless resource virtualization was proven to increase the system throughput. Moreover, the heuristic algorithm achieved close to optimal performance while having a much lower computational complexity.

Chapter 3 extended the previous work by formulating the problem of QoS-aware wireless resource virtualization and implemented the traffic simulation to determine the delay constraints. Due to requiring future information from the traffic simulation, it was not possible to solve to optimality, therefore the problem is broken into sub-problems to be solved for each time instance rather than over a period. Therefore, for each technology, the sub-problems are integer linear programming to solve resource or access point allocation to maximize the throughput for each user. Each of these linear integer programming problems was solved to optimality. Moreover, two lower complexity heuristic greedy-based algorithms were introduced that solve the QoS-aware allocation problems. Results show that with the delay constraints for each QoS class, the QoS requirements is satisfied. Moreover, the heuristic algorithms achieved similar results to the optimization problem, proving their efficiency.

Chapter 4 proposed using different machine learning techniques to predict the traffic for each of the base station in the cellular network. The best prediction model with the lowest error is used to determine the communication and computing times of the base station to return to service after it has been put to sleep-mode. This is done to minimize the energy consumption as well as to maintain the QoS for each user. Due to the prediction model, traffic data can be used as a predictor of the wake-up policy for base stations to improve the energy efficiency and reduce the operating expenses.

5.2 Future Research Directions

This thesis focused on making the systems more efficient and intelligent by utilizing the optimization modeling and machine learning algorithms. While this thesis presented novel approaches to address many challenges of an efficient and intelligent system, there are many opportunities to improve this system to tackle technical and economical challenges.

5.2.1 Technical Challenges

Technology is always evolving. At the start of this PhD journey, the cellular network used in the second chapter was the fourth generation, LTE. Currently, 5G is being deployed (focus of chapter three) and many researchers have focused on beyond 5G and Internet of Things (IoT) (focus of chapter four). Meanwhile, Wi-Fi standard have improved to Wi-Fi 6 as the latest standard, which was used in chapter three. However, optimization modeling can still be utilized once the channel model is known for whichever technology it is used for. Chapter 2 and 3 uses a fixed coexistence configuration which should be dynamic to account for different throughput for different time of day and user requirements. Especially for Chapter 3 when dealing with delay constraints, a dynamic coexistence configuration can be considered to increase the throughput and delay performance. Chapter 3 adopted the newer cellular network standard which required more base station and therefore the user to base station association can be considered as a future direction. Chapter 4 presents many different directions such as creating a design parameters for the threshold to determine low traffic for the base station for the wake-up policy. Clustering technique should be utilized to group the traffic behaviour to increase the accuracy of the prediction to improve the wake-up policy.

5.2.2 Economical Challenges

Operators continue to maximize the revenue while presenting an affordable plan to users. Many aspects can be reviewed to address the economical challenges, such as power consumption, resource sharing, spectrum efficiency and operating expenses. Chapter 2 minimizes the power consumption for mobile users with portable devices to maintain untethered powered connection. Chapter 3 implements the traffic simulation with delay constraints. However, both chapters can further improve on power efficiency as a main constraint to reduce the operating costs. Wireless resource virtualization should further evolve as resource sharing helps with the capital expenses between service providers. Chapter 4 focuses on minimizing the energy consumption as base stations continue to contribute most of the operating expenses. This chapter should include the implementation of IoT devices to allow business reap the benefits of higher return of investment.

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