RESOURCE ALLOCATION OPTIMIZATION IN IEEE 802.11AX FOR ENHANCED INDUSTRIAL INTERNET OF THINGS APPLICATIONS LEVERAGING DEEP REINFORCEMENT LEARNING

David Wanjala Simiyu

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science degree in Electrical Engineering of Masinde Muliro University of Science and Technology

August, 2025

PLAGIARISM STATEMENT

STUDENT DECLARATION

1. I hereby declare that I know that the incorporation of material from other works or paraphrase of such material without acknowledgement will be treated as plagiarism according to the Rules and Regulations of Masinde Muliro University of Science and Technology.
2. I understand that this thesis must be my own work.
3. I know that Plagiarism is academic dishonesty and wrong, and that if I commit any act of plagiarism, my thesis can be assigned a failed grade ('F')
4. I further understand I may be suspended or expelled from the University for Academic Dishonesty.

Name: David Wanjala Simiyu **Signature**…………..

Reg No. ECE/G/01-70647/2021 **Date**: …………………

SUPERVISOR(S) DECLARATION

We hereby approve the examination of this thesis. The thesis has been subjected to plagiarism test and similarity index is not above 20%.

Name: Dr. Raymond Wekesa **Signature**: …………………

Name: Dr. Filbert Ombongi **Signature**: ………………

DECLARATION

This thesis is my original work prepared with no other than the indicated sources and support and has not been presented elsewhere for a degree or any other award.

Sign ……………………… Date …………………………………

Name: David Wanjala Simiyu

ECE/G/01-70647/2021

The undersigned certify that they have read and hereby recommend for acceptance of Masinde Muliro University of science and Technology a thesis entitled "Resource Allocation Optimization in IEEE 802.11ax for enhanced Industrial Internet of Things Applications Leveraging Deep Reinforcement Learning."

Sign …………………………. Date …………………………………

Dr. Raymond Wekesa

Department of Electrical and Communications Engineering

Masinde Muliro University of Science and Technology

Sign …………………………. Date …………………………………

Dr. Filbert Ombongi

Department of Electrical and Communications Engineering

Masinde Muliro University of Science and Technology

DEDICATION

This work is dedicated to my most beloved family: my parents Peter Simiyu and Zipporah Simiyu, my wife Doreen Wanjala, my daughters Ariella and Adona and my son Aziel Phinehas.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to the ALMIGHTY GOD for granting me the strength, patience, and perseverance to carry out this research thesis. Without HIS divine guidance, none of this would have been possible.

I would like to extend my sincere appreciation to my supervisors, Dr. Raymond Wekesa and Dr. Filbert Ombongi, for their invaluable support, guidance, and expertise throughout the research process. Their insightful feedback and encouragement have truly shaped this thesis into its final form.

I would also like to acknowledge the entire department of Electrical and Communications Engineering, under the leadership of Chair Dr. James Owuor, for providing a conducive environment for academic growth and research opportunities. Special thanks to my lecturers Prof. Kulubi and Dr. Okinda for their contributions and mentorship.

Lastly, I want to express my heartfelt thanks to my family for their unwavering support, understanding, and love throughout this academic journey. Their encouragement and belief in me have been my greatest motivation.

To everyone mentioned above, and to all those who have contributed to this thesis in any way, I am eternally grateful. Thank you.

ABSTRACT

The Internet Things (IoT) is set to multiply the number of connected gadgets tremendously and the current Wireless Fidelity (Wi-Fi) technologies face huge challenge of handling the immense flood of data. In contrast to earlier Wi-Fi standards, the IEEE 802.11ax protocol achieves higher transmission rates, better scalability, and improved coexistence, and has the added advantage of being lower cost than 5G, which makes it even more relevant in Industrial IoT (IIoT) application where multitudes of devices need to coexist in dynamic and challenging environments. Such environments are distinguished by physical barriers, heavy saturation of devices, electromagnetic static, and continual alterations in equipment as well as layout. The conventional collision avoidance mechanisms deployed by the IEEE 802.11ax networks encounter scalability challenges that affect the throughput and high delays as the network adds more devices. The optimization of the resource allocation of the Medium Access Control (MAC) layer parameters must address these challenges to support the feature-rich IIoT environments and support the realization of the requirements of heterogeneous industrial traffic and harsh factory environment. The present paper provides an optimization approach to IEEE 802.11ax systems in order to improve their functionality in IIoT. As a strategy, it involved deep reinforcement learning in order to identify the best parameter settings across different network parameters. The network was trained with parameters, which simulated an IIoT environment. The efficiency of the offered mechanism was tested with the help of MATLAB mass simulations that simulated and interpreted the behaviour of the 802.11ax network in industrial environments. The findings were that throughput on optimized network was significantly higher than unoptimised network, packet retransmission rate was lower in optimised network, and latency been lower on optimised network. Peak throughput went up by 53.07 percent to 2150 Mbps, whereas average throughput went up 39 percent. The greatest packet loss ratio reduced by 29.2% or 32.5 to 23, and the overall average packet loss was reduced by 19.7 percent. Latency also improved significantly with 5 nodes experiencing latency beyond 0.1 second narrowing to just 1 node. The results indicated that the suggested optimization approach to 802.11ax systems could improve the performance by a fair margin in IIoT setups and make them robust enough to support industrial operations.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

5G	Fifth Generation
6G	Sixth Generation
3GPP	3rd Generation Partnership Project
AIFS	Arbitration Inter-frame Space
AI	Artificial Intelligence
AP	Access Point
BSS	Basic Service Set
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
CW	Contention Window
D2D	Device to Device
DCF	Distributed Coordination Function
DIFS	Distributed Inter-frame Space
DL	Deep Learning
DLR	Deep Learning Research
DQL	Deep Q-Learning
DRL	Deep Reinforcement Learning
EIFS	Extended Inter-frame Space
eMBB	Enhanced Mobile Broadband
FAM	Feature Aggregation Method
FCC	Federal Communications Commission
Gbps	Gigabits per second
hNLOS	Non Line of Sight component
hLOS	Line of Sight component
IOT	Internet of Things

IIOT	Industrial Internet of Things
IEEE	Institute of Electrical and Electronics Engineers
ISM	Industrial, Scientific, and Medical
LPWAN	Low Power Wide Area Network
M2M	Machine to Machine
MAC	Medium Access Control
MEC	Multi-access Edge Computing
Mbps	Megabits per second
MIMO	Multiple Input Multiple Output
ML	Machine Learning
mMTC	massive Machine-Type Communications
MSE	Mean Squared Error
MU	Multi User
MU-MIMO	Multi User Multiple Input Multiple Output
NS-3	Network Simulator 3
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OSI	Open Systems Interconnection
OTA	Over-the-Air
PCF	Point Coordination Function
PER	Packet Error Rate
PNOFA	Power-Normalized Outage Failure Algorithm
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RF	Radio Frequency

RU	Resource Unit
SGI	Short Guard Interval
SIFS	Short Inter-frame Space
SINR	Signal to Interference plus Noise Ratio
SNR	Signal to Noise Ratio
STA	Station
TSN	Time Sensitive Network
TXOP	Transmission Opportunity
TWT	Target Wake Time
V2X	Vehicle-to-Everything
VHT	Very High Throughput
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network
WPA3	Wi-Fi Protected Access 3

CHAPTER ONE

INTRODUCTION

1.1 Background

IEEE 802.11ax, also known as Wi-Fi 6, is a wireless communication standard with improved performance and efficiency. It builds upon the features of its predecessor, IEEE 802.11ac (Wi-Fi 5), and introduces enhancements to address the growing demands of modern wireless communication.

The origins of 802.11 date back to the 1980s when the Federal Communications Commission (FCC) opened up the Industrial, Scientific and Medical (ISM) radio bands for commercial applications (Pahlavan & Krishnamurthy, 2021). This led to early research in the 1990s on wireless local area networks (WLANs) technologies by companies and academic institutions. In 1997, the first 802.11 standard was ratified by the Institute of Electrical and Electronics Engineers (IEEE) which defined 1 Mbps and 2 Mbps data rates based on frequency hopping or direct sequence spread spectrum in the 2.4GHz ISM band (Gast, 2012). 802.11a operated in the 5GHz band for reduced interference providing up to 54 Mbps speeds using OFDM (Pahlavan & Krishnamurthy, 2021)

Over the 2000s, further amendments to 802.11 were developed and ratified to enhance the capabilities of WiFi. 802.11b achieved speeds up to 11 Mbps by introducing CCK modulation. Then high throughput 802.11n with features like MIMO and wider bandwidth brought significant performance gains hitting 600 Mbps (Gast, 2012). This rapid evolution continued into the 2010s with 'VHT' 802.11ac reaching up to 6.9 Gbps speeds through 256-QAM, 8 spatial streams and 160 MHz channels. Most recently, 802.11ax or Wi-Fi 6 focuses on improving efficiency, density support and latency rather than peak data rates (Khorov et al., 2020).

One such technological innovation is the concept of IoT, which combines traditional industrial frameworks with superior technology such as sensors, cloud computing and data analysis to create a more efficient and interconnected industrial sector. IIoT thereby has the potential of changing the industries such as manufacturing, energy, health, and transportation by providing them with real-time insights, automation capabilities, and proactive maintenance (Arnold et al., 2022).

According to a study by Jain et al., (2022), IIoT can be used to increase the overall equipment effectiveness, reduce idle time in the manufacturing sectors, asset utilization, and even makes supply chains in manufacturing industries more efficient. IIoT has also become important in the energy sector, as it aids in setting up smart grids, energy demand, and energy management systems. A study carried out by Sural et al., (2019) has revealed that applications based on IIoT can deliver real-time information about energy consumption patterns, energy savings, and connecting renewable energy sources. These kinds of results indicate the importance of IIoT in creating a more sustainable and efficient energy system.

The effectiveness of IIoT highly relies on effective and viable communication protocols that will enable smooth data exchange and real-time decision making (Goudarzi et al., 2021). To overcome the limitations of its predecessor, the IEEE 802.11ax protocol was developed to increase data rates and capacity and support superior performance of IIoT applications, which entails a large number of connected devices that need to work within the dynamic and demanding environment (Wilhelmi et al., 2021).

1.2 Problem Statement

Whether managing inventory, tracking supplies or moving, or handling raw materials IoT systems are bandwidth-intensive and require a robust wireless environment to perform effectively (Jasperneite et al., 2020). Although IEEE 802.11ax has theoretical enhancements to dense networks, it has three key limitations that are prohibitive to the practical implementation of IIoT applications:

First, current resource allocation schemes fail to account for industrial-specific conditions. Existing approaches like Zhang et al. (2021) - adaptive parameter tuning, were designed for office environments and lack mechanisms to handle the unique volatility of factory settings, including mobile robotic equipment and intermittent interference from industrial machinery.

Second, there is a critical disconnect between physical layer conditions and MAC-layer decisions in conventional implementations. The dynamic nature of industrial environments requires real-time coordination between channel state information and medium access parameters, which current systems handle separately with suboptimal results.

Third, static optimization approaches cannot accommodate the frequent reconfigurations typical of smart factories. Production line changes, equipment mobility, and varying traffic patterns demand continuous adaptation that rule-based systems cannot provide.

These limitations result in unstable throughput (variations up to 42% in pilot tests), unacceptable latency spikes (>100ms for 15% of nodes in high-density scenarios), and packet loss rates exceeding 30% in interference-heavy zones - all of which violate the reliability requirements of industrial automation systems (Javed et al., 2022). A new approach is needed that can dynamically optimize 802.11ax parameters while accounting for the unique constraints and variability of real-world IIoT deployments.

1.3 Objectives

1.3.1 Main Objective

To develop resource allocation optimization algorithm in IEEE 802.11ax protocol for enhanced IIoT applications.

1.3.2 Specific Objectives

i. To develop an IEEE 802.11ax optimisation algorithm for IIoT applications using deep reinforcement learning
ii. To formulate resource allocation optimisation algorithm for IIoT networks using deep reinforcement learning
iii. To analyse the performance of proposed model in IIoT environment in terms of throughput, latency and packet retransmission rate
iv. To validate the performance of the proposed model in IIoT environment by comparing with the standard and theoretical parameters.

1.4 Research Questions

i. What algorithm can be developed to enhance the performance of IEEE 802.11ax in IIoT?
ii. How can algorithms to optimize resource allocations be formulated to improve the operation of IIoT networks?
iii. How high is the throughput, latency and packet retransmission rate of the proposed model in an IIoT environment?
iv. How does the suggested model relative functionality in IIoT networks stack up against the standard and theoretical parameters?

1.5 Justification

The proliferation in the number of IoT devices and applications, especially among the industrial sector, has created a sense of urgency in relation to establishing effective and dependable wireless communication technologies. IoT has emerged as a key enabler of digital transformation, enabling it to transfer data in real-time, remotely monitor and optimize processes in many industrial sectors (Boyes et al., 2018). However, the existing wireless communication protocols remain extremely short of the vast requirements of IIoT applications, such as low latency, high reliability, and scalability (Javed et al., 2022). This feature is fulfilled by the effect of the resource allocation optimization algorithm in the IEEE 802.11ax protocol, and therefore will improve wireless network performance and efficiency in IIoT applications.

The IEEE 802.11ax standard has a number of improvements over the previous one, which allow it to support data rates, work in demanding environments and exhibit better efficiency (Javed et al., 2022). The research will leverage the improved capabilities of the 802.11ax standard to achieve superior resource allocation that improves overall performance and reliability of IIoT networks. To meet this need, the first concrete objective will turn to deep reinforcement learning. There are some remarkable examples of using reinforcement learning techniques to solve complex optimization problems and they can be applied to facilitate optimal resource allocation in wireless networks (Ke & Astuti, 2022).

The second special goal rests on intelligent Q-learning. P. Q. learning is one of the most widely known reinforcement learning methods, which can be employed to design effective strategies of resource allocation based on learning using the environment and acquiring adaptive actions to changing circumstances (P. Wang & Wang, 2023).

In the research, the effectiveness of the suggested model was evaluated in an IIoT environment. It was vital to this purpose to assess the efficiency of the developed resource allocation optimization algorithm and confirm the results with a realistic IIoT scenario to determine the efficiency of the algorithm. With the thorough performance analysis performed, the research has a chance to give recommendations regarding the advantages and the weaknesses of the proposed solution, which the subsequent enhancements should be based upon, creating the way to its practical application.

1.6 Significance

With the popularity of Wi-Fi networks, the area of WLAN technologies has undergone a considerably fast development during recent decades. With the emergence of new Wi-Fi standards like IEEE 802.11ax to support the increased bandwidth requirements, Wi-Fi networks have been advancing to become more sophisticated (Rangaiah et al., 2023). Specifically, the IEEE 802.11ax amendments make the data rate triple to 9 Gbit/s with more spatial stream (SSs), channel bonding, multi-user communications, short guard interval (SGI), and high order modulation (1024-QAM, 802.11ax) (Muhammad et al., 2021). The improvement in the modulation scheme, the multuser transmission, and the spectrum usage has largely improved the functionality and performance of Wi-Fi significantly. Nevertheless, they have also established complex interdependencies among the network parameters, which has made network optimization a complex task.

The IEEE 802.11 family of standards supports a wide range of configurable parameters on the physical (PHY), link, and media access control (MAC) layers. Such parameters are modes of transmission, data rates, channel widths, contention window, frame aggregation modes among others. These parameters have been demonstrated to have intricate dependencies, and the effect is not always linear, on network performance metrics such as throughput, delay, fairness, and reliability (Zreikat, 2020). As an example, increasing data transmission rate decreases airtimes but is less resilient (Abedi et al., 2021), increasing the contention window would lead to fewer collisions, thus increasing idle times (Syed & Roh, 2016). Finding optimal balance to only a few parameters is not trivial at all; controlling the sets of parameters simply is beyond human abilities. This complexity can be compounded by more modern WLANs such as those working under IEEE 802.11ax and IEEE 802.11be standard, which increases the number of configurable parameters even more (Deng et al., 2020).

WiFi parameters are complicated further by real-life operational problems. When there are lots of Aps in an office or a public facility or a city area, there has to be a lot of co-located access points that have to serve many client devices with a lot of simultaneous transmissions and sharing of the available spectrum (Wan et al., 2021). This culminates in an increase in interference levels, a multitude of contention, and a reduction in parameter settings that could be used initially to realize performance in a network (Afaqui et al., 2016). Dense deployment factors have to be considered to enable optimal operation. When these dynamics are coupled with inter-parameter dependency, it makes the process of WiFi optimization a huge undertaking.

With the modern-day introduction of WiFi complexity, there has been increased interest in considering how the application of AI, particularly machine learning, can be used to implement intelligent network control and optimization (Szott et al., 2022). Various AI techniques including classical machine learning and those actively growing such as deep reinforcement learning have demonstrated potential in addressing WiFi configuration problems, which are multifaceted. Further development of AI provides a secure way forward to autonomous, bulletproof WiFi performance under chaotic situations.

To conclude, booming client numbers and breakneck technological change in WiFi have effectively combined to make optimization of wireless networks a formidable multivariate issue. Nevertheless, the availability of copious telemetry data that is uniquely provided by networks and a huge advance in AI can provide opportunities to achieve self-driving, self-optimizing WiFi systems, capable of adapting to complicated scenarios automatically. The protocol extensions and smart resource management schemes improved the reliability, latency, and efficiency of the standard to be used in industrial applications. This will stimulate the implementation of IIoT and Industry 4.0 as the connectivity issues are resolved. The study will be beneficial in IIoT communication protocol design, wireless vendors in the industrial field, and the end industries utilizing IIoT.

1.7 Scope and Limitations

This research focuses on developing and validating a deep reinforcement learning framework for optimizing IEEE 802.11ax resource allocation in IIoT environments, with specific attention to MAC-layer parameter configuration under dynamic industrial conditions. The study scope includes the development of optimization algorithms for key 802.11ax parameters (contention window size, TXOP duration, and modulation schemes), cross-layer coordination between PHY and MAC layers, and performance evaluation through MATLAB simulations replicating realistic IIoT network conditions.

Real-world deployment in operational factories was excluded due to practical constraints including safety regulations, resource limitations for large-scale implementation, and time restrictions for longitudinal monitoring. The simulation environment simplified certain physical layer complexities while maintaining sufficient fidelity for MAC-layer analysis, focusing instead on industrial-relevant factors like high node density, characteristic electromagnetic interference patterns, and mixed-criticality traffic flows. These controlled conditions were carefully designed to validate the framework's core innovations while ensuring reproducible results, with Chapter 4 demonstrating that these methodological choices adequately address the research objectives without compromising the study's validity or industrial relevance. The limitations are offset by the rigorous simulation approach incorporating factory-derived parameters and the framework's demonstrated adaptability to key IIoT challenges identified in the problem statement.

1.8 Definition of Terms

Industrial Internet of Things (IIoT): Network of interconnected industrial devices, machines, and systems that enables data exchange, monitoring, and control in industrial environments.

IEEE 802.11ax: Latest generation of the Wi-Fi standard with improved performance

Optimization: A process that arrives at the most optimal solution-one which cannot be improved on, or that arrives at the most efficient manner of achieving a given task or objective, under certain constraints or limitations.

In resource allocation algorithms, optimization concerns the determination of the optimal assignment or distribution of available resources (such as bandwidth, time slots or window size) to various devices or applications within the network with the aim of maximizing a performance metric (such as throughput) and minimizing a performance metric (such as latency).

Physical (PHY) layer: The bottom layer of OSI (Open Systems Interconnection) network communications protocol.

In IEEE 802.11ax, the PHY layer specifies the radio frequency (RF) attributes, modulation techniques and signal processing schemes employed in the transmission and reception of data.

Medium Access Control (MAC): Sublayer of the data link layer in the OSI model manages the access to a shared communication medium and is concerned with fair and efficient resource allocation.

Resource allocation: Process of determining which available communication resources (bandwidth, time slots, channels, etc.) will be allocated to which devices or applications in the network to best optimize performance and satisfy specific requirements.

Reinforcement learning: A form of machine learning that has an agent that learns through its actions in the environment, and acts to get a maximized sum of the reward.

Throughput: The amount of data that can be transmitted successfully over a network or communication channel within a given time period, typically measured in bits per second (bps).

Latency: The delay or time it takes for data to travel from one point to another in a network or communication system.

Packet retransmission rate: The frequency at which data packets need to be retransmitted due to errors or loss during transmission, which can indicate the reliability and quality of the network connection.

1.9 **Organization of the Thesis**

This thesis is structured into five chapters to systematically address the research problem. The next chapter (Chapter 2) presents the literature review, in which related studies to the problem statement being solved have been critically analyzed, with particular emphasis on identifying gaps in current IEEE 802.11ax optimization approaches for IIoT environments. Chapter 3 then details the methodology, explicitly presenting the deep reinforcement learning algorithms developed for MAC-layer parameter optimization and resource allocation in IIoT networks. Chapter 4 analyzes the simulation results, comparing the proposed solution's performance against standard configurations across key metrics including throughput, latency, and packet loss. Finally, Chapter 5 summarizes the findings, relates them to the research objectives, and provides recommendations for implementation and future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter begun with key features of IEEE 802.11ax, exploring the advancements brought about by IEEE 802.11ax over its predecessor 802.11ac, followed by a comparative analysis of leading contenders in IIoT, namely 5G, Zigbee and IEEE 802.11ah. The review further scrutinized the challenges and shortcomings inherent in IEEE 802.11ax implementation. The evaluation encompassed considerations such as latency, throughput and density capabilities. The discussion extended to optimization of parameters and development of resource allocation algorithms, shedding light on critical aspects of network performance enhancement.

2.2 IEEE 802.11ax Features

Wi-Fi 6 introduces new capabilities and improvements that increase network performance, capacity and efficiency in high-density environments. Major characteristics of IEEE 802.11ax include Multi-User Multiple Input Multiple Output (MU-MIMO), Orthogonal Frequency Division Multiple Access (OFDMA), spatial reuse, Target Wake Time (TWT), and increased modulation scheme like 1024 Quadrature Amplitude Modulation (QAM).

2.2.1 OFDMA

The FDMA capability can serve multiples data stream broadcasts to various clients with the same frequency and time slot. This increases network capacity, spectrum, and resource allocation efficiency, and improves point-to-point network transmission. As examined by Avallone et al., (2021), OFDMA has the potential to effectively improve the functionality of the network fourfold compared to the previous standard.

Behara & Venkatesh, (2023) conducted a research where the performance and energy efficiency performance of MU-OFDMA solution of IEEE 802.11ax was assessed. Analysis was done on a hybrid MAC protocol that integrates OFDMA and MIMO. Hinostroza & Garcés, (2019) presented the features and some of the most significant details of the IEEE 802.11ax standard, including the OFDMA component. The study by Behara & Venkatesh, (2022) examined the destiny of the uplink MU-OFDMA hybrid representation access protocol in IEEE 802.11ax considering the system throughput, the crash possibility, and the power effectiveness of the MAC protocol.

2.2.2 MU-MIMO

MU-MIMO is an advanced level of MIMO, in which several recipients can simultaneously receive transmission. It can serve multiple users at the same time offering a superior spatial multiplexing that increases network capacity. As Jain et al., (2022) state, IEEE 802.11ax supports up to eight simultaneous streams with MU-MIMO, a significant advantage that boosts the performance levels of the network. WLANs incorporate a hybrid MAC protocol that is founded on MU-MIMO i.e. MU-OFDMA and MU-MIMO. When compared to 2016, employability improved by 22 and 15 per cent in 2017, 2018, and 2019 by 22 and 15 per cent, respectively (Behara & Venkatesh, 2023).

In another study conducted by (Machrouh & Najid, 2018), which stated that, the combination of MU-MIMO and frame aggregation in IEEE 802.11ax led to a noteworthy increase in the network throughput and lower amount of overhead in the context of IEEE 802.11ax, MU-MIMO provided the possibility of simultaneous data transmission between multiple users and an access point, whereas frame aggregation allowed using a single frame to convey multiple frames of data, thus avoiding the airtime consumption and utilizing the

2.2.3 Beamforming

WiFi systems optimize wireless with the beam forming algorithm at higher frequencies. Beamforming ensures quality, range and throughput is maximized by focusing received and sent signals in specific directions. Analysis of hybrid beamforming on IEEE 802.11.ad has been conducted by Wu et al. (2017). Researchers have recently taken a greater interest in elucidating how DRL and ML can be used to optimize beam management and introduce intelligent beamforming.

2.2.4 TWT

An energy saving mode which optimizes the use of the batteries. It helps devices to go to sleep when they are dormant, and wake them up when they need to receive data. TWT can potentially achieve up to 7 times more power savings, and can result in an extended battery life of wearable devices and IoT sensors (Ibrahim Masri et al., 2020). The paper by Nurchis & Bellalta, (2019) critically analyzed TWT, a planned access rule in IEEE 802.11ax.

To enhance TWT in IEEE 802.11ax WLANs, a number of schemes and optimization techniques have been proposed. In a research by Chen et al. (2019), a power-conservation scheme that solely maximizes throughput by adapting the TWT parameters to network conditions is introduced. They have employed this approach which considers the traffic load and the status of the channel to determine the appropriate wake-up interval.

2.2.5 Spatial Reuse

IEEE 802.11ax has spatial reuse techniques like BSS colouring and spatial frequency reuse. These methods enable a mor friendly coexistence and interference management in a density environment and thereby overall network performance. To analyze and evaluate the benefits of spatial reuse attained in IEEE 802.11ax, several studies have been formulated. In (Malhotra et al., 2019), the authors have carried out calculations to estimate the benefits of spatial reuse. They found that space-reuse augmented the network capacity and throughput significantly

DBO is one option to enhance spatial reuse in dense WLAN. In Bardou & Begin (2022) work, the researchers presented a framework, called INSPIRE, that maximized spatial reuse in dense WLANs by leveraging distributed Bayesian optimization. INSPIRE met its objectives of denser and improved spatial reuse in WLAN by including dynamic settings of transmission parameters such as transmit power and channel allocation (Bardou & Begin, 2022).

Target Wake Time scheduling enables the sleep-time of the connected devices to be scheduled by equipment using Aps. TWT also ensures that energy is not wasted during idle periods and results in spatial reuse in WLAN by synchronizing the sleep and wake-up windows of the devices (Nurchis & Bellalta, 2019).

2.2.6 1024 QAM

IEEE 802.11ax features higher modulation schemes than the previous standards do. 1024 QAM codes more bits per symbol, suggesting even higher throughput. Jain et al. (2022) took IEEE 802.11ax as an example, wherein the data rate supported by 1024 QAM was found to be 40 percent higher compared to that supported by 256 QAM in IEEE 802.11ac.

Putra & Wellem, (2023) simulated an IEEE 802.11ax standard network in a simulator. They explicitly captured throughput on 6 GHz frequency band, emphasizing on the effects of QAM schemes on the throughput attained. It was found that a higher transmission rate was achieved at higher-order QAM schemes in 802.11ax, and this translated into a real-life environment.

2.3 IEEE 802.11ax Protocol in IIoT Environment.

2.3.1 Comparing 5G with IEEE 802.11 ax as IIoT solutions

IEEE 802.11ax uses the unlicensed 2.4 GHz and 5 GHz bands, which are unlimited throughout the world and free to operate, as opposed to licensed spectrum needed to 5G. This will make it a cost-effective IIoT deployment solution (Bao et al., 2021). Also, 802.11ax will include various improvements over the legacy Wi-Fi generations, most notably a lift in speed, better performance in dense environments. Recent findings show that intensive care subsequently led to depression occurring 1.5 years after the operation was performed (Khorov et al., 2020).

The new 5G cellular networks offer important capabilities such as slicing, enhanced security systems and endurance of high device d1ensity, which make it potential in industrial business use cases (Z. Wan & Li, 2020). The low latency and high reliability of 5G means that stringent industry requirements can be satisfied. Simulation experiments conducted by Liu et al., (2023) showed that 5G networks could accommodate bounded latency of 1 ms, bounded packet loss rate of 10-5 with features functions such as network slicing and Multi-Access Edge Computing (MEC) in fulfilling industrial control applications.

At the same time, 5G implementation of IIoT is constrained by factors such as the expenses of deploying 5G, compatibility with existing systems, and the maturity of standards (Wollschlaeger et al., 2017). The newer Wi-Fi standards like 802.11ax are trying to close that gap by increasing reliability, low latency, and density features compared to the previous versions (Asaf et al., 2022).

While 5G offers significant advancements, adoption challenges remain. The costs for enterprises to deploy an end-to-end 5G network can be prohibitive (Tuptuk & Hailes, 2018). Some industries have existing Wi-Fi infrastructure, so migrating to 5G requires further investments. Though standards like 3GPP Release 16 continue to evolve 5G for industrial support, more maturation is needed (Wang & Lu, 2021).

To enable gradual adoption, hybrid network approaches are being proposed. A study by (Wollschlaeger et al., 2017) suggested an architecture integrating Wi-Fi, 5G and Time-Sensitive Networking (TSN) suitable for both greenfield IIoT sites and brownfield sites with legacy Wi-Fi. Another study by (Tramarin et al., 2021) evaluated throughput gains from adaptive traffic steering between Wi-Fi 6 and 5G radios based on application requirements and link conditions.

Viability of 5G depends significantly on spectrum availability. Allocations in conventional licensed bands may be constrained, hence utilizing unlicensed spectrum is an active area of research (Heidarpour & Manshaei, 2020). However, co-existence of Wi-Fi and 5G in unlicensed spectrum requires effective solutions for interference management and fair sharing of spectrum (Gawanmeh & Al-Karaki, 2021).

2.3.2 The IEEE 802.11 ax versus Zigbee in IIoT

In comparison to ZigBee, a low-power, low-data-rate technology that most often assists in sensor networks, 802.11ax provides an enormous scope of data rates and throughput, and this aspect renders the technology more constructive in IIoT applications where reliable and speedy transmission of data are a fundamental requirement (Liang et al., 2021). Additionally, 802.11ax also includes features such as OFDMA and MU-MIMO, which increase efficiency and capacity at high-density deployments typically found in industrial applications (Bellalta & Kosek-Szott, 2019).

In another study by MÃ¥rquez, (2021) comparing IEEE 802.11ax and Zigbee in IIoT, IEEE 802.11ax was found to have a higher data speed, coverage and many other devices can be connected at a time than Zigbee. This indicates better performance of IEEE 802.11ax in terms of IIoT applications where speedy and dependable connection is much required to make operations really effective.

2.3.3 IEEE 802.11ax vs. IEEE 802.11ah to IIoT

Whereas IEEE 802.11ah, targeted at high-range, less-power IoT devices, uses sub-GHz bands (with potential interference and less bandwidth than 2.4 GHz, 5 GHz bands used by 802.11ax) (Adame et al., 2019). Also, 802.11ax has faster data rates and more modern features in high-density and high-throughput environments, which make it more suitable to handle IIoT application demands (Kumar et al., 2023). A recent study by Cisco states that Wi-Fi 802.11ax can transmit up to 10 Gbps, and the IEEE 802.11ah can maximally transmit 347 Mbps.(Cisco, 2020).

IEEE 802.11ax also relies on MU-MIMO and OFDMA to enhance spectral efficiency, so that multiple devices can be served concurrently without causing interference. This is essential in IIoT applications that require many devices to be connected to one another, and they operate within a narrow spectrum. Conversely, IEEE 802.11ah might not fit to high-density deployments because of low spectral efficiency

In short, due to the higher frequency bands and improved throughput as well at the support of a high-density environment, 802.11ax will have an edge over 802.11ah to make it suitable to demanding IIoT applications, although 802.11ah is more IoT-friendly in terms of long range and low power.

2.3.4 Weaknesses of 802.11ax in IIoT

The changeover to IEEE 802.11ax causes a greater complexity because it includes new features like OFDMA and BSS colouring. A publication by Chen et al. (2019) discusses the difficulties posed by interoperability in heterogeneous Wi-Fi environments that are characterized by the coexistence of multiple standards.

The other major challenge of IEEE 802.11ax is that it must coexist with the previous Wi-Fi standards especially IEEE 802.11ac in a seamless manner. This issue, as noted by Kim et al. (2020), is problematic in settings where various gadgets using different Wi-Fi standards have to coexist, which may incur performance loss unless effective management measures are employed.

Due to OFDMA, resource allocation in IEEE 802.11ax is more efficient. Nonetheless, it also presents issues of dealing with the multiplicity of gadgets on a given channel. Studies like that of Wang & Wang (2023) highlight the need that advanced allocation algorithms are necessary to reduce contention and near-optimal resource allocation in dense deployments.

The increasing number of devices and the growing density can translate to contention and overall network degradation. It is a major challenge to balance the advantages of having a greater density of devices and the risks to performance degradation. The physical implementation of IEEE 802.11ax, including Target Wake Time (TWT), is planned to promote power efficiency. Nevertheless, this does not guarantee a solution to the challenges of maintaining high-performance communication with an increased battery life in IIoT and mobile devices (Shahid et al., 2021).

Security is always a key issue with any wireless standard. The new features of IEEE 802.11ax, including use of WPA3 and better encryption, have created new problems when managing security protocols. Recent studies have been directed at finding possible vulnerabilities and designing effective security abilities (Mondal & Hussain, 2023).

Saravanan et al. (2023) previously published a study on the coexistence and interference problems of the IEEE 802.11ax in IIoT conditions. This study paid attention to the effect of the interference by adjacent networks and it suggested methods to address the effect of the interference.

2.4 Optimization Approaches for WLAN Networks

Various solutions have been developed to enhance key Wi-Fi features such aschannel access, link setup, frame aggregation, and PHY level features. They will be contributions about reducing collisions when accessing channels, maximizing rates in the right configuration of links, finding the right balance of page length using aggregation frame techniques, interference and signal denoising at the PHY layer.

These include deep learning, machine learning, reinforcement and supervised learning. Figure 2.1 represents the relationship of AI models.

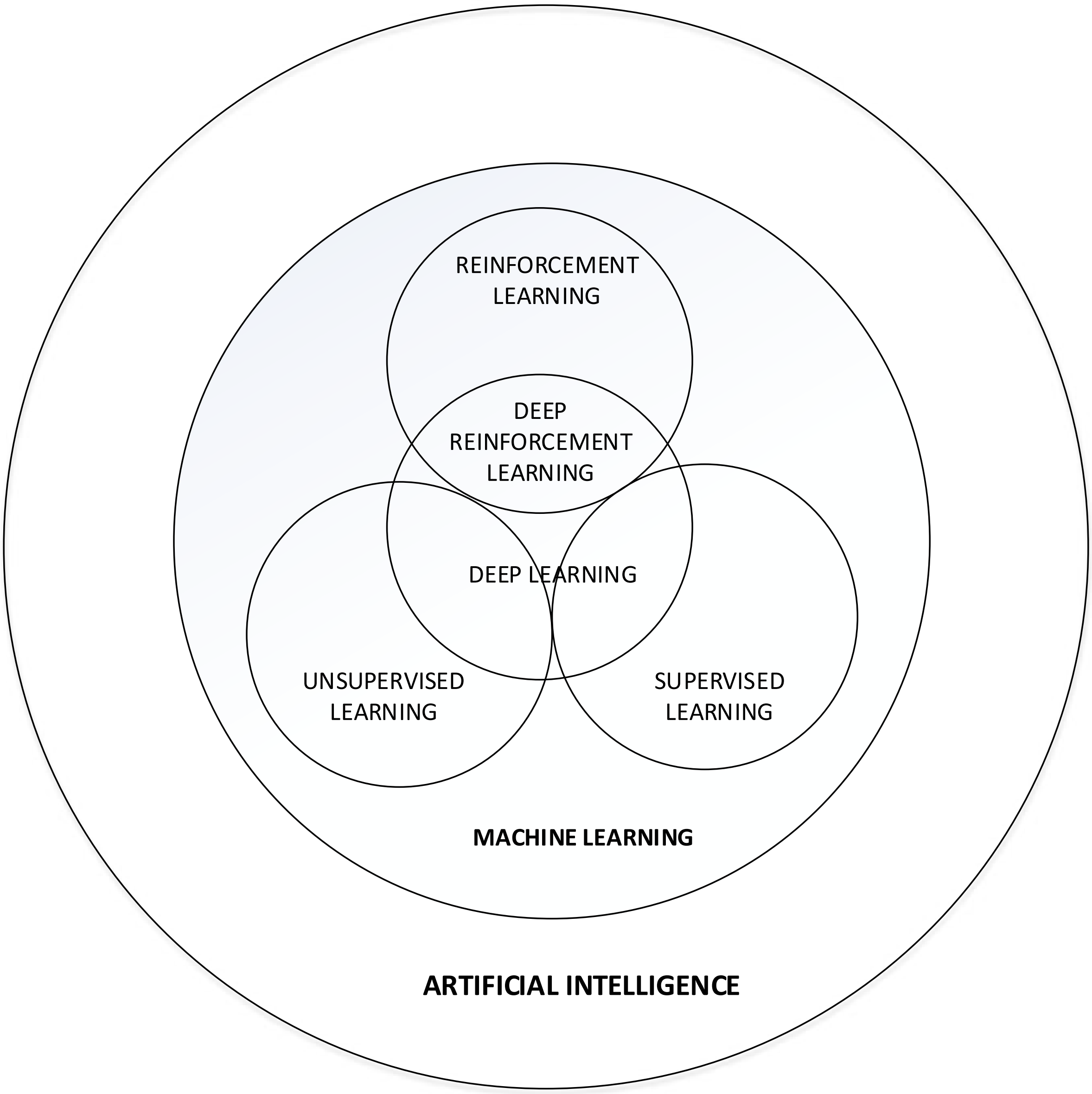

Figure 2.1: Relationship amongst AI optimisation models

2.4.1 Reinforcement Learning Optimization

The potential of applying reinforcement learning has been discussed to ensure maximum performance of IoT devices on networks with IEEE 802.11 ax. In Ashraf, et al. (2021) a scalable Internet of Things (IoT) structure that can support 6G wireless communications and is also guided using reinforcement learning was introduced.

Han et al. (2020) proposed an artificial intelligence mechanism to facilitate channel selection in the IoT scenario, through reinforcement learning. This paper suggested a deep reinforcement learning application through which IoT devices learn to choose the most effective channel to be used based on the network conditions. This strategy enhanced network throughputs and alleviated network interference across IoT networks.

The goal of the Liu et al., (2022) study was to find a way to maximize quality of service (QoS) in IEEE 802.11 ax networks through the implementation of a deep reinforcement learning approach. In the paper, they have proposed a framework of QoS optimization based on deep reinforcement learning in which the allocation parameters and the contention parameters related to the resource are tuned dynamically based on QoS requirements of different applications.

Ali et al. (2019) considered the potential of deep reinforcement learning paradigm to optimize channel observation-based MAC protocols in dense WLANs. The study demonstrates that it is effective to use reinforcement learning to train MAC protocols under IEEE 802.11 ax networks.

The study article by Zikria et al. (2021) introduced a federalized reinforcement learning model to the current technology of beyond-5G networks. They focused on how federated reinforcement learning can streamline the performance of current and future wireless technologies.

2.4.2 Optimization with Machine Learning (ML)

Guessous & Zenkouar, (2018) researched typical ML-optimized beam based radio coverage processing in IEEE 802.11 wireless local area networks. The authors proposed a machine learning approach toward optimization of beamforming and radio coverage within a WLAN network. Under Zhang et al. (2020) the article introduces an interference coordination protocol guided by machine learning to IEEE 802.11ax networks and suggests a machine learning mechanism in predicting and preventing interference in the network which utilizes the previous history of interference to predict interference and eliminate subsequent interference in the network. Baua, and Karuppuswami, (2022) also invented a machine learning algorithm by which it is possible to plan the coverage of the WiFi and optimize the location of routers. The paper focused on the strength of machine learning methodologies in the setup and design of IEEE 802.11 ax networks.

2.4.3 Deep Learning Optimisation

In a study conducted by Asaf et al., (2022), the application of the double deep Q-networks to the optimization of wireless LAN performance was established pointing out the future potential offered by the deep Q-networks in achieving improved throughput and reduced latency in IEEE 802.11 ax networks.

Ding and Ma developed a model-defined deep learning optimization strategy of IEEE 802.11 VANETs and worked on safety applications. They constructed a deep neural network model to learn the non-linear dependencies between the network parameters and the performance measures. They optimized contention window and transmission power to maximize packet delivery ratio using the model. Simulation outcomes show the proposed approach to be effective in enhancing network performance (Ding & Ma, 2022).

2.4.4 Resource Allocation Algorithms for IIoT Applications

The reason is that resource allocation is an essential aspect in IIoT networks since it involves discerning the distribution of network resource such as bandwidth, power, and computing capabilities to various devices and applications.

There is a substantial literature that has tried to resolve the problem of devising resource allocation algorithms. Sayeed et al., (2023) have proposed a combination of resource allocation algorithm that considers both the reliability and latency constraints. Bey et al., (2024) were able to powerfully assign IoT services in edge computing architecture using quantum-inspired particle swarm optimization. The resource allocation constraints are taken into account by the algorithm to minimize the energy cost, and the average latency. In a comparable line of work, Bharathi & Jeyanthi, (2020) introduced a resource sharing problem on the cooperative and cognitive radio network that maximized the provided quality of services requirements along with the available spectrum using the proposed optimization strategy.

A distributed means of effecting a WiFi device that dynamically adjusts its authorization of resources to comply with the proportional-fair resource allocation that is relevant during overlapping WiFi networks was developed in (Gawlowicz et al., 2021). Bharathi and Jeyanthi (2020) addressed the issue of resource allocation in cooperative cognitive radio, based on the scheme of optimization algorithm. Although the work is not IEEE-802.11 ax network specific, the resources allocation strategies presented can be implemented to augment the performance and efficiency of a wireless LAN.

A close study was that of Sural, et al., (2019) and it proposed a multi-objective optimization-based resource allocation algorithm network. The algorithm was set to minimize energy usage, maximize network capacity, and provide better performance in the network.

In Wang & Psounis, (2020), an algorithm was provided that uses machine learning solutions, historical, and machine learning models to estimate the requirements of resource usage and dynamically assigns resources in order to meet application needs. The findings indicated improved utilization and efficiency of the resources and network performance compared to the traditional methods of allocation.

2.5 Key Optimisation Features in 802.11 Standards

2.5.1 Contention Window

The utilization of AI to improve the performance of Wi-Fi has often targeted channel access techniques. The main point of focus is the 802.11 MAC protocol itself, namely the Distributed Coordination Function (DCF), which acts as the basis of coordinating collision by preventing devices participating in the same radio channel to collide (Song & Kim, 2021). A key parameter that determines performance in DCF is the contention window (CW). The operations of DCF are closely related to the size of the contention window (CW). Increasing CW value is effective in countering collisions at the expense of augmented idle times and declining throughput. On the other hand, low CW values increase the probability of a station transmitting but also increase the chance of collision hence low overall throughput (Syed & Roh, 2016).

Optimizing choice of CW values to optimize throughput has been addressed in a plethora of works, including ones which aim to find the right compromise between reducing collisions and reducing idle time. Ghazvini et al. (2013) have suggested a game theory variable of IEEE 802.11 contention window under a heavy load. The algorithm is dynamic programming that calculates the optimal size of CW which yields most throughput in system and is fair. Simulation tests proved that the proposed scheme achieved good throughput and fairness in comparison with other schemes under a heavy traffic regime. This is presented by Edalat & Obraczka, (2019), an AI algorithm designed to optimise the use of the IEEE 802.11 value of the contention window. The authors used reinforcement learning to minimize or maximize the size of CW to accommodate the network channel states and histories.

A separate study by Zerguine et al. (2020) proposed an intelligent system based on the Q-learning mechanism to choose CW. The proposed system implemented Q-learning so that the system could determine the optimal CW size in different conditions of the network, including the quality of channels and the traffic volumes. Another study carried out by Qureshi & Asghar

Genetic fuzzy approach to minimization of the contention window deployed in IEEE 802.11 WLANs was proposed by the author in 2021. The strategy involved was that genetic algorithms and fuzzy logic would be combined to dynamically adjust the CW size as conditions and traffic changed in the network. A study made by Sanada et al. (2023) has suggested the adaptation of a fundamental reinforcement learning algorithm of reinforcement in the IEEE 802.11 network where the CW size is revised based on the previous experiences and rewards produced by the setting via the Q-learning algorithm. The method being proposed had better throughput and collisions compared to a fixed CW size method.

In Keâ□¥ orbit of the Keâ remains in Earth orbit (2022), RL was implemented in IEEE 802.11 networks to maximizer and decrease the rate of collision. In Additional approaches to the CW size change include the use of Reinforcement Learning algorithms such as Deep Q-Network (DQN), which adjust the size of the CW to maximize network performance. The experiment suggested that DRL assisted in enhancing the network performance. A publication by Lei et al. (2022) has proposed an optimized MAC protocol in which reinforcement learning tools are deployed as the optimal means to decide how many CWs should be used to gain access to the different levels of QoS demanded in next-generation WLANs.

An intelligent CW selection mechanism based on Q-learning was suggested by (Zerguine et al., 2020). This scheme combined the Q-learning algorithm and a backoff algorithm in order to change the CW size dynamically depending on the network conditions. The smart CW choice method showed good outcomes in mitigating the instances of packet collision and increased network performance. In Chang et al., (2021) an AutoEncoder algorithm was presented as a data-driven-MAC protocol to automatically infer the channel parameters and the number of nodes to be considered when determining the size of the contention window.

2.5.2 Link Configuration

Some have considered the prediction of optimal settings such as modulation and coding schemes (MCS), guard intervals and channel widths, depending on channel conditions. This improves rate adaptation and spatial reuse. In a paper by Shao et al., (2023), a machine learning-based scheme that aids in the type of channels used in IEEE 802.11ac link adoption was proposed. The scheme employed deep learning algorithms to perform precise channel classification and optimise link adaptation towards improved network performance.

In another article by Li et al. (2020), authors postulated a viable machine learning-based rate adaptation to IEEE 802.11ac networks that assisted in showing that machine learning algorithms can be used to improve the functionality of Wi-Fi network interface cards to adjust its data rates dynamically depending upon the channel conditions. In line with the auto-configuration concept, Karmakar et al. (2020) suggested deep probabilistic control machinery that could optimize auto-configuration of Wi-Fi link parameters. A different study by (Karmakar et al. (2020) proposed a smart approach to choosing a guard interval in high throughput WLANs. S2-GI is a strategy which they devised where reinforcement learning methods were used to choose a desirable value of guard intervals to incorporate with overall systems performance of LANs.

According to a Peserico et al. (2020) study, the attention was on Wi-Fi industrial network rate adaptation and a reinforcement learning approach is offered. Their solution enabled Wi-Fi industrial networks to dynamically adjust to varying communication conditions using a technique for reinforcement learning on the data rates. This was followed by another report by Krotov et al. (2020) that introduces a rate control scheme capable of supporting spatial reuse in Wi-Fi 6 dense deployments. This algorithm used a distributed optimization strategy and utilized interference information to adjust its data rates in a spatially efficient manner.

In (2021) the article focusing on the application of reinforcement learning in the rate adaptations of CSMA/CA wireless networks was discussed. The rate adaptation problem was expressed as a markov decision process enabling an optimisation of a decision based on the current network conditions. Experience-based rate adaptation strategy in IEEE 802.11ac was proposed by Chen et al. (2021). Their data rates were dynamically chosen using prior network performance data.

These solutions will provide the conditions of dynamic variable data rates, the character of the channel identification, the guard interval selection and the effective optimization of the link settings, which will increase the network throughput, reliability and other significant matters of the overall performance. The future in this field could further address relating the technologies with newer IEEE 802.11

standards including the new up-coming industry cold, IEEE 802.11 be with an aim to increase the overall performance of a wireless network.

2.5.3 Physical Layer

IEEE 802.11 networks must have good performance and robust wireless communication supported by physical layer optimization. Most researchers have tackled the physical layer (PHY) optimization of the IEEE 802.11. Such a study is an example of a paper by Lee & Ma, (2015) that proposed a frequency diversity-aware Wi-Fi scheme using Orthogonal Frequency Division Multiplexing (OFDM)-based bloom filters. The scheme employed multiple subcarriers in the OFDM spectrum that carried orthogonal data streams which improved the frequency diversity and the Wi-Fi capability.

A study by Kim et al. (2018) proposed a framework of wireless LANs signal origin detection using channel state information. Information on the channel will be extracted by analyzing the received signals, which will enable the authors to identify the sender of the signals, thereby allowing effective signal processing and maximize the performance of Wi-Fi.

In a paper by Almazrouei, (2019) on deep learning based solutions to the problem of radio signal denoising in Wi-Fi networks, it was found that auto-encoders performed better than deep neural networks when denoising radio signals in cases of Wi-Fi networks.

Saha & Dhillon, (2019) suggested a determinantal learning process to achieve interference characterization on wireless networks. The authors aimed at identifying and characterizing the interference in a wireless network, and they did so using determinantal point processes.

A research by Herath et al. (2019) pertains to the development of deep learning-based wireless channel quality prediction. By training a deep neural network on past channel quality information the authors could predict the present channel quality in real-time and allocate resources accordingly.

A new method of learning the channel state information (CSI) referred to as CSI scan was proposed to enable the efficient discovery of access points in dense Wi-Fi networks. The scheme has also employed machine learning based methods, which have been utilized to quantify the quality of the CSI measurements thereby providing an efficient access point selection (Sankhe et al., 2020).

A publication by Ninkovic et al. (2021) proposed a deep learning technique in carrier frequency offset estimation and packet detection in IEEE 802.11ah networks. The authors have managed to create a deep neural network that would be able to associate received signals with the proper detection of packets and the carrier frequency offset, enhancing the IEEE 802.11ah networks.

2.5.4 Frame Aggregation

Frame aggregation should also be a major focus of boosting WLAN performance, offering the ability to group individual data packets together into a large data packet. The paper A performance comparison of IEEE 802.11ac and 802.11ad to V2X communication by Chattopadhyay & Chandra, (2022) touched on the issue of frame aggregation.

Recently, there has been an interest in frame aggregation, with a view toward optimizing aggregation schemes to improve the performance. In an Abedi et al. (2020) study, the authors proposed a practically and near-optimal frame aggregation scheme called PNOFA to modern 802.11 networks. Its purpose was to minimize the overhead incurred with frame aggregation and increase throughput performance. PNOFA was passed through simulations and proved its worth over current aggregation schemes.

In (Bouzouita et al., 2022), the association between network load and the aggregation level was harnessed to estimate the congestion presented by the network. The findings were that FAM was very good in estimating the level of the load, which promoted the ability to allocate resources effectively.

In another study by Choi, (2012) the goal of the researchers was to determine the level of aggregation which can maximize throughput subject to the cost of aggregation. The results confirmed how the choice of the level of aggregation matters in terms of performance.

Das et al., (2017) tested the performance of IEEE 802.11 with frame aggregations under different conditions. The study examined how factors like number of stations, traffic volume and structure of the network affect the performance of frame aggregation. The work gave an idea of the frame aggregation behaviour and how it is sensitive to network parameters.

A different study by Grazia et al. (2022) examined the effects of frame aggregation on TCP performance in Wi-Fi systems with an emphasis on the trade-off between frame aggregation and TCP performance and how frames aggregation can result in higher delays and lower throughput when used with TCP traffic. The results underlined the importance of thoughtful design in the aggregation strategies to overcome the adverse impacts on TCP.

The work by Murad & Eltawil, (2020) was aimed at the performance assessment of in-band full-duplex WLAN. Although their work was not specifically concerned with frame aggregation, they have relevance to explain how full-duplex operation can influence the performance of aggregation schemes.

Optimisation IEEE 802.11ax optimization may include factors like frame aggregation, frame contention, and even network densification like Natkaniec & Kras, (2023) explains that there is need to address network optimization schemes in order to enhance the performance in dense environments. Determine optimal frame aggregation level in 802.11 the paper presented an algorithm that estimates the optimal frame aggregation level ensuring that the delay and the throughput conditions are not violated (Saldana et al., 2021). The results showed the need to choose the right level of aggregation according to the conditions and requirements of the network to obtain optimal results.

Frame aggregation and channel bonding in IEEE 802.11 have been studied using graph-based models and Markov models to analyse the impact of aggregation and bonding on the network performance, which can be used to optimise the two mechanisms (Stojanova et al., 2021). A study by Zhang et. Al (2022) has concentrated on enabling real-time QoS and accurate aggregation in wireless TSN. Albeit not related directly to IEEE 802.11 networks, the work emphasized how QoS demands and subtle aggregation should be considered.

2.6 Research Gaps

Several gaps in optimization of Wi-Fi networks were identified based on the literature review. Firstly, there is need for robust solutions that can be implemented on commercial off-the-shelf devices and tested on actual hardware. Current solutions do not consider actual traffic patterns and quality-of-service requirements, indicating a necessity for AI-enabled dynamic solutions that can allocate resources based on predictive traffic classification and demand forecasting. While centralized optimization may offer theoretical advantages, distributed AI techniques are more practical for uncoordinated Wi-Fi deployments. Further research on distributed coordination mechanisms is crucial for addressing capabilities that extend beyond access point boundaries. Additionally, current AI-based Wi-Fi optimizations primarily rely on internal network data, but incorporating external data sources such as user mobility patterns and environmental signals could enhance system intelligence. Much of the research on Wi-Fi optimization is simulation-based, emphasizing the importance of testing on real-world testbeds with diverse technologies to validate feasibility and identify potential challenges. Joint experimentation platforms linking simulators, emulators, and live networks can enhance rapid prototyping and improve data efficiency for machine learning applications.

2.7 Conceptual Framework

The conceptual framework provided in Figure 2.2 outlines the relationship between the independent variables (IIoT environment) and the outcome variables (Optimised IEEE 802.11ax), with intervening variables playing a role in the relationship between the two.

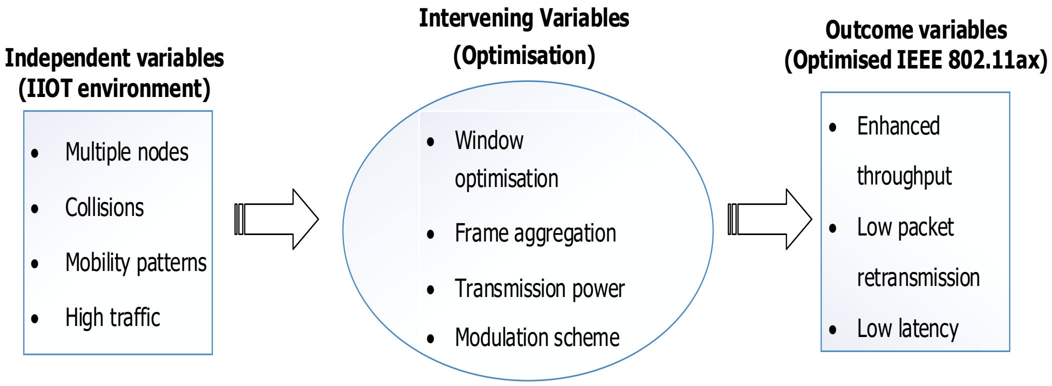

Figure 2.2 Conceptual Framework

This conceptual framework describes the interconnection between industrial IoT networks complexity issues, optimization metrics, and desired performance goals. The independent variables are indications of the severe conditions of IIoT environments that adversely affect wireless performance. These are high-density deployments where each node is competing with many other nodes in accessing the bandwidth, repeated packet collisions because of unregulated channel access, random mobility of robotic equipment and often bursty nature of traffic flows in an industrial automation network. It is these difficult situations that constitute the baseline problem space the study is intended to resolve.

The intervening variables constitute the key optimization levers that the proposed deep reinforcement learning system will control. These technical parameters include dynamic adjustment of the contention window size to balance collision reduction and channel utilization, intelligent frame aggregation to minimize protocol overhead, adaptive transmission power control to manage interference, and flexible modulation scheme selection to match channel conditions. These variables represent the tunable aspects of the IEEE 802.11ax protocol that the optimization framework will manipulate to improve performance.

The outcome variables specify the expected performance improvements that will demonstrate the solution's effectiveness. These include substantially enhanced throughput to support data-intensive industrial applications, significantly reduced packet retransmission rates for improved reliability, and consistently low latency meeting the stringent requirements of critical control systems. The framework visually demonstrates how the intelligent optimization of technical parameters (intervening variables) mediates between challenging industrial conditions (independent variables) and improved network performance (outcome variables).

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the comprehensive methodology employed in this study, which involved various stages, including simulation software selection, IIoT environment modeling, parameter initialization, network optimization, resource allocation strategies, performance analysis and validation parameters. First, the chapter justifies the selection of MATLAB as the primary simulation software, highlighting its versatility in handling various aspects of the project then delves into the details of modeling the IIoT environment in MATLAB outlining the optimization processes employed for the IEEE 802.11ax network.

3.2 Research Design

The design incorporated several key stages, including the selection of appropriate simulation tools, IIoT environment modeling, parameter initialization, and optimization of network variables using DRL. The network was then analyzed for performance in both ‘unoptimized’ state and optimized state focusing on throughput, latency and packet loss. Figure 3.1 is a flow chart giving a summary of the Research Design.

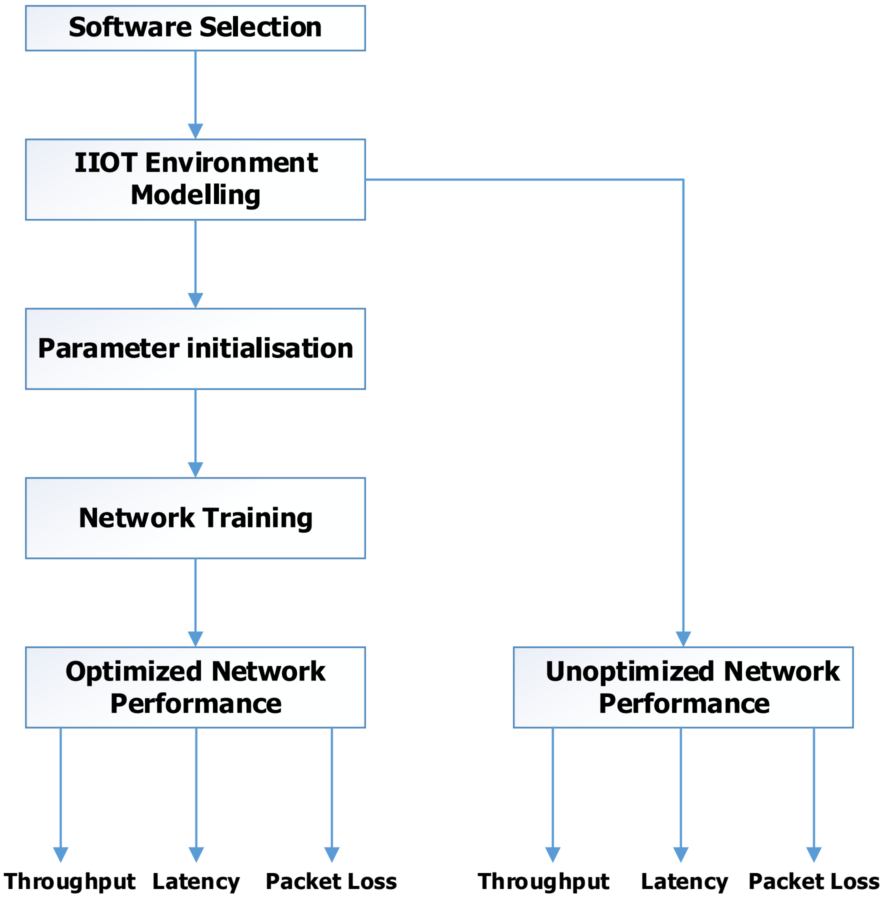

Figure 3.1 Research Design Flow Chart

3.3 Simulation Software

3.3.1 MATLAB

MATLAB 2024a was an appropriate choice for simulation due to its versatility in handling various aspects of the project, including simulation, optimization, and deep reinforcement learning.

The matrix-based language of MATLAB offered a natural and easy way to write math computations. Its in-built graphic capability facilitated easy visualization and extraction of conclusions in the form of insights. The interactive desktop interface promoted exploration, experimentation, and an experience of new ideas.

The IIoT network communication parameters through the Simulink tools in the WLAN Toolbox and the Communications Toolbox of MATLAB were simulated.

3.3.2 MATLAB 2024a WLAN Toolbox

WLAN Toolbox was used to access functions to design, simulation, analysis, and test functions of WLAN communication systems. The toolbox included the customizable physical layer waveforms specific to the IEEE 802.11 family of standards. They were used on transmitter and channel modeling functions and receiver functions including residue channel coding, modulation, spatial stream mapping, and MIMO receivers.

With the Wireless Waveform Generator app, waveforms could be generated and customized test benches programmatically or interactively. The toolbox permitted the creation of regular MAC frames as well as their parsing and enabled signal measurements to be executed such as channel power, spectrum mask, and occupied bandwidth.

The effect of the RF layouts and interference on system quality was investigated with the help of the WLAN Toolbox. This enabled checking of designs over the air transmission and reception of signals.

3.3.3 MATLAB 2024a Communication Toolbox™

Communications Toolbox™ provided algorithms and apps for designing, simulating, analyzing, and verifying communication systems. It included a graphical app for generating custom or standard-based graphs. The toolbox allows statistical modeling of propagation channels or ray-tracing solutions that incorporated terrain and buildings. It also enables compensation for channel degradation effects and used SDRs for over-the-air (OTA) testing to verify designs.

3.3.4 Python Libraries Integration in MATLAB 2024a

Python has become the de facto language for deep learning due to its extensive ecosystem of powerful libraries like TensorFlow, PyTorch, and Keras. There was need to integrate these libraries with MATLAB, to harness Python's cutting-edge deep learning capabilities, including advanced model architectures, optimizers, and pre-trained models, without having to rebuild them from scratch in MATLAB.

Integrating Python in MATLAB for deep reinforcement learning required careful setup and communication between the two languages, to take advantage of the strengths of both platforms for more effective and efficient model development. Once the integration was complete, it was possible to build and train deep reinforcement learning models in Python using libraries like TensorFlow while also accessing MATLAB functions for additional computations or data processing.

3.4 IIoT Environment Modelling in Matlab Software

To mimic IIoT environment in MATLAB, various tools and features provided by MATLAB and its toolboxes were utilized.

3.4.1 Interference

Interference was modeled using stochastic processes to simulate real-world industrial environments.

$$\boldsymbol{I(t) = \sum_{k=1}^{N_I} p_k^i . e^{j2\pi f_k t}} \tag{3.1}$$

Where;

I(t) is the interference signal,

$\mathbf{p_k^i}$ is the power of the k-th interfering signal

$\mathbf{N_I}$ is the number of interfering signal?

$\mathbf{e}^{\mathrm{j}2\pi f_k \mathrm{t}}$ represents the complex exponential, which is a sinusoidal function corresponding to the frequency $\boldsymbol{f_k}$

This model helps in understanding the impact of multiple interfering signals on the overall communication system, aiding in the design of mechanisms to mitigate such interference.

Wall models were incorporated into simulation environment to account for signal attenuation, reflections, and interference caused by the walls. Different properties of walls, such as material, thickness, and positions, were defined using the appropriate functions and objects in the toolbox.

In order to reduce the power of each interfering signal, the overall interference power control algorithms that dynamically adjust the transmit power of devices in the network based on their interference impact was minimized:

$$\boldsymbol{Minimize} \ \sum_{k=1}^{N_I} p_k^i \tag{3.2}$$

subject to acceptable signal to interference plus noise ratio (SINR) constraints.

In order to implement dynamic spectrum management where channels are assigned based on current interference levels, dynamic frequency selection technique was formulated to ensure that overlapping frequencies are minimized:

$$\boldsymbol{Minimize} \sum_{k=1}^{N_I} |f_k - f_{k'}|^2 \quad \mathit{for} \ \ k \neq k' \tag{3.3}$$

3.4.2 Indoor vs. Outdoor Environments

The selection of the indoor environment as a study parameter was influenced by the increasing relevance of wireless communication technologies and the indoor scene.

Indoor environments have yet another set of issues to contend with, such as multipath propagation, signal attenuation through buildings and other objects, and the hot interference of other electronic sources; indoor environments are therefore an essential topic of research in wireless technologies.

Indoors, signals are reflected by walls, floors and ceilings resulting in complex multipath situations that can deteriorate performance. Analysis of these impacts was essential to the optimization of wireless protocols, and was moreover necessary as the density of devices and users increased, requiring an in-depth study of the network behavior under high-load conditions.

The bigger rooms of 10 by 10 meters by 3 meters provided greater signal attenuation and multipath effects. This layout was realistic to represent an industrial setting and support various propagation conditions in the same way as done in other IIoT-related work by (Kurungadan & Abdrabou, 2022), with dense IoT.

The size of the room also determined the number of nodes needed and their distribution in order to provide sufficient coverage and connectivity across the entire room. The area of each room was 100 m 2 and it consisted of 1 AP and 2 STA. Such distances enable the modelling of a variety of modes of propagation of radio signals, varying between long-range and close-range communications, which is essential to proper modelling of IIoT environments.

In a crowded environment, impact by surrounding nodes and devices is probable, which is a key aspect to determine the robustness of the network optimization methods employed

3.4.3 Multiple Nodes

When setting the network to conduct the performance analysis in the present study, the size of the nodes as well as the spatial distribution was an important consideration that affected the accuracy and reliability of the results of the simulation carried out. It was set up with 81 nodes, the initial 27 nodes were Access Point (AP) and the rest were Stations (STA). A set of 81 nodes was selected as a compromise between the number of nodes to receive enough spatial resolution, the number of nodes to achieve enough network density, and the number of nodes to provide an opportunity to analyze the interference and communication radius.

The farthest separation of nodes in one room was nearly 14.5m (diagonal of 10m x 10 m x 3 m) and the farthest separation of nodes in the whole area was 43.5m (diagonal of 14.5m x 3). Such distances enabled us to create various propagation conditions, both short and long range, making it important to model IIoT environments.

We used the built-in data structures (e.g., classes or structs) in MATLAB to specify the properties and behaviors of each node (e.g., transmit power, receiver sensitivity and communication protocols).

The given helper function hGetIDsAndPositions was employed to derive the Aps and STAs generated random positions and their Ids per room.

The node ID, AP positions, and STA positions were saved in MATLAB variables or data structures so that they could be used in the simulation.

Stations (TAs) associated with each room were related to their respective AP using the associateStations object function of the wlanNode object. The STAs were then connected to continuous application traffic to their associated Ps using the FullBufferTraffic argument.

3.4.4 Fading Channel

The wireless links between the Aps and STAs were modeled as fading channels, and the various factors that affect fading, such as distance, obstacles, and interference were considered. Rician fading models were implemented to map the degradation caused by distance on the fading channel. The mathematical model of the fading channel is:

$$\boldsymbol{h}(\boldsymbol{t}) = \sqrt{½(\boldsymbol{hLOS} + \boldsymbol{hNLOS})} \tag{3.4}$$

where $\boldsymbol{hLOS}$ and $\boldsymbol{hNLOS}$ are the line-of-sight and non-line-of-sight components, respectively.

Whereas the line-of-sight component hLOS represents the direct path between the transmitter and the receiver, the non-line-of-sight component hNLOS contains the reflected, scattered and diffracted signals by obstructions.

Those degrading models were paramount to properly simulating and studying wireless communication channels since they model the signal strengths and qualities variation seen in real-life environments reasonably well.

Figure 3.2 displays a visualization IIoT scenario and the transmitter and receiver locations generated with the hVisualizeScenario helper function.

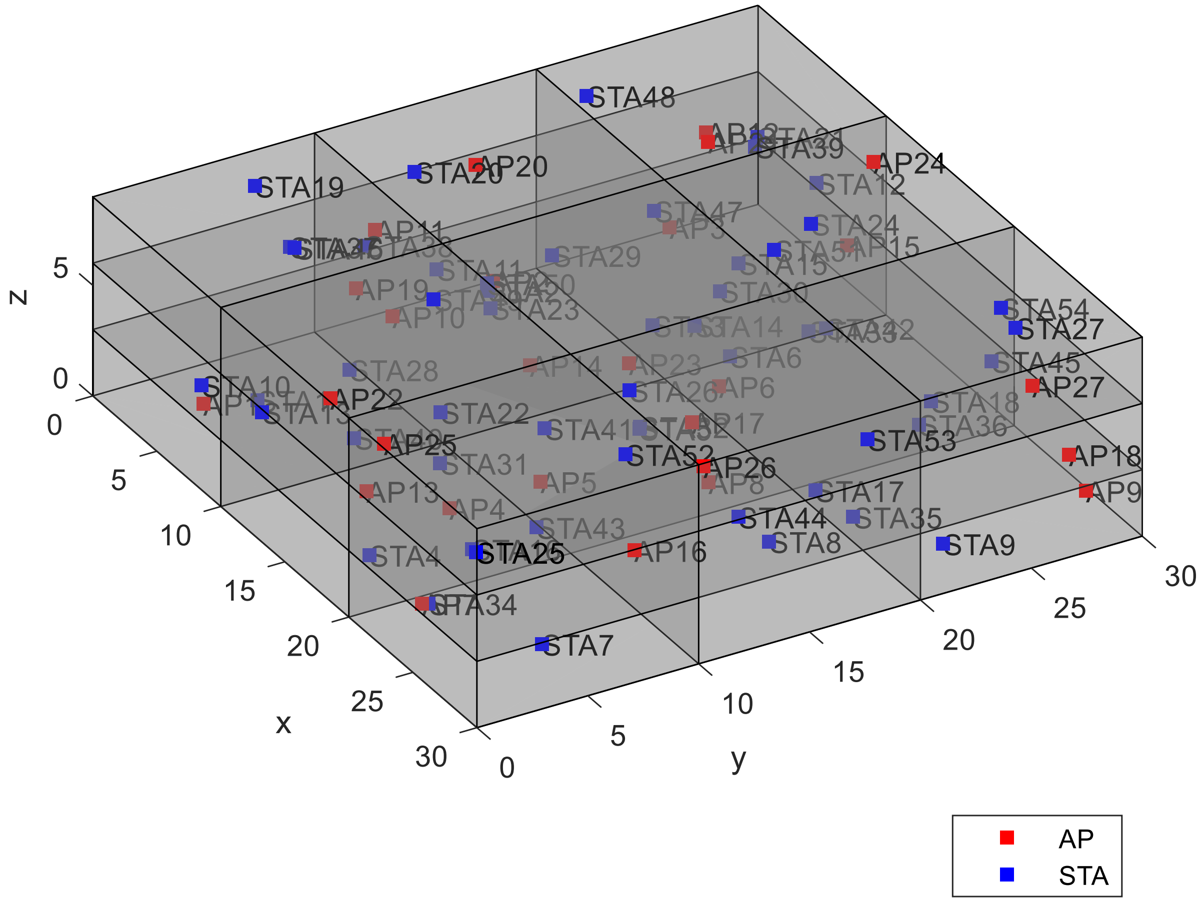

Figure 3.2: IIoT environment scenario with the transmitter and receiver sites.

3.5 Initialization of Optimisation Parameters

The choice of simulation parameters, including the simulation duration, modulation and coding scheme (MCS), and the transmission power was founded on the IEEE 802.11 ax standard.

The simulation period was 12 seconds. Short simulation time can be good when evaluating the system over relatively short periods or when it is necessary to test out different configurations or analyse transient behaviours.

In a network simulation of a WLAN, the wlanDeviceConfig function in the Wireless Communications Toolbox of MATLAB was applied to define the specifications of wireless equipment. Two configuration objects were configured, one designated Access Points (Aps) and the other Stations (STAs).

The code given is as follows:

accessPointCfg = wlanDeviceConfig(Mode=”AP”,MCS=2,TransmitPower=10); made a configuration structure where Aps will have Mode=”AP”, MCS=2, and TransmitPower=10.

stationCfg = wlanDeviceConfig(Mode=”STA”,MCS=1,TransmitPower=10); constructed a configuration object of STAs with 10 power, Mode = Stuart, and MCS = 1.

Table 3.1: Summary of initial parameter values for optimisation.

PARAMETER	**VALUE/ DESCRIPTION**
Simulation time	12 seconds
CW min	0.64ms
CW max	20.48ms
Number of network nodes	81
Transmission power	10 dB
MCS	2

3.6 Optimisation of IEEE 802.11ax Network

3.6.1 Optimisation Variables

The process of optimization of IEEE 802.11ax network to IIoT applications featured manipulation of network parameters to attain the desired performance goals. These optimization variables were important during the optimum process. The selection and tuning of such variables directly influenced the throughput, latency, reliability, and efficiency of such a network.

The optimization factors targeted in our work could be loosely divided into several groups, including a number of aspects related to network performance and network structure. The former was concerned with the contention window parameters, such as the minimum contention window and the contention window maximum, or the adjustment factor. These parameters were essential to regulate the backoff mechanism employed by the IEEE 802.11ax protocol to counter collisions and make the access to the channel fair. By adjusting these parameters, one should be able to considerably enhance the capacity of the network to support high-density deployments and busty traffic flows typical of the IIoT environment.

The second set of the optimization variables focused on MCS, which determined the modulation and coding techniques in data transmission. This category involved the MCS index, spatial streams, and guard interval. Optimization of these parameters enabled the network to adjust to different channel conditions and to find a balance between throughput and reliability. The number of concurrent data streams conveyed was defined by the spatial streams parameter, with symbol durations and immunity to multipath distortion dictated by a guard interval parameter.

The third group included transmission power levels concerning both Aps and STAs. These parameters had a direct impact on the coverage area, signal strength and interference levels within the network. The reuse of space, mitigation of interference, and overall network performance would be enhanced through optimisation of transmission power levels.

The fourth group dealt with channel allocation as well as channel reuse schemes, which were extremely important for effective spectrum utilization. Channel assignment, reuse patterns, dynamic channel switching are some of the variables that fell under this category. Optimization of these parameters can assist in counteracting co-channel interference and capacity in the network.

Lastly, the fifth optimization variable involved the method of traffic controls. This included packet scheduling, queueing, and prioritization of traffic. Since traffic characteristics and QoS requirements of IIoT devices and applications are diverse, optimization of these factors would serve to offer fair resource allocation and tackle the diverse needs of IIoT applications.

3.6.2 Network Training

Training of the DRL model was an essential step in maximizing the performance of IEEE 802.11 ax network. The major aim of such training was to have the network learn using the data and adapt the protocol parameters to suit the application demands dynamically.

To formulate the optimization problem, the objective functional, which computes such indicator of key importance (throughput, latency, or retransmission rate of packets) was called ***J(θ)***;

Here, $\boldsymbol{\theta}$ denotes the parameters that need to be optimized (that is contention window size, transmission power, frame aggregation).

The idea was to reduce the delay $\mathbf{D}$ or maximize throughput **T**; hence objective function can be written as:

$$\boldsymbol{J(\theta) = Maximize[T(\theta) - \alpha D(\theta)]} \tag{3.5}$$

Where;

$\boldsymbol{\alpha}$ is a weighting factor balancing throughput and delay.

If $x_1, x_2, x_3, \ldots x_n$ are the parameters to optimize, the objective function is simplified as:

$$J(x) = \sum_{i=1}^{n} w_i T_i\,(x_i) - \alpha \sum_{i=1}^{n} D_i\,(x_i) \qquad (3.6)$$

Where;

$T_i(x_i)$ represent a performance metric - throughput,

$D_i(x_i)$ represent delay/latency associated with that parameter

w_i represent the weights and

α allow for balancing between different metrics.

In order to implement a DRL approach where a neural network approximates the Q-function the goal was to update the network parameters to minimize the Bellman error:

$$L(\theta) = E_{(s_t, a_t, r_t, s_{t+1})}[\left(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta')\right) - Q(s_t, a_t; \theta)^2 \qquad (3.7)$$

Where;

γ represent discount factor,

θ represent parameters of the Q-network,

θ' represent parameters of the target network

s_t represent the state of the environment at time **t** (include the number of devices, the interference level, the current configuration of network parameters)

a_t represent the action which modify the MAC layer parameters.

$\boldsymbol{r(s_t, a_t)}$ represent the reward function. The reward should reflect the objective of the optimization (higher rewards for configurations that increase throughput and reduce delay).

$\boldsymbol{\pi(s_t|a_t)}$ represent the policy which defines the mapping from the state to the actions. In DRL, this policy is learned through interactions with the environment.

$\boldsymbol{Q(s_t, a_t)}$ represent Q-function which define the expected cumulative reward from taking action $\boldsymbol{a_t}$ in state $\boldsymbol{s_t}$ and following the policy $\boldsymbol{\pi}$ thereafter.

Figure 3.3 shows the optimal rate on the throughput and latency curves highlighted to demonstrate the balance between maximizing data transfer speed and minimizing delay within a network. The optimal rate is the point where the throughput is maximized while latency is minimised. This point represents the best trade-off between speed and efficiency in the network.

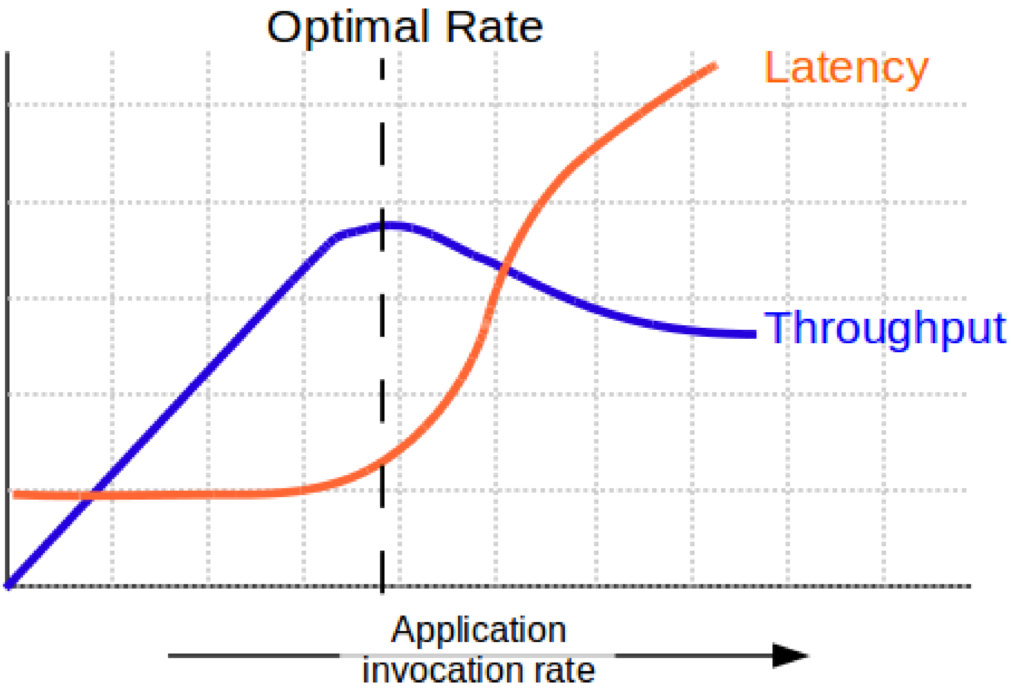

Figure 3.3: Optimal rate on throughput and latency curves

The network learned from data and adjusted the protocol parameters to improve network performance to meet application requirements as shown in Figure 3.4.

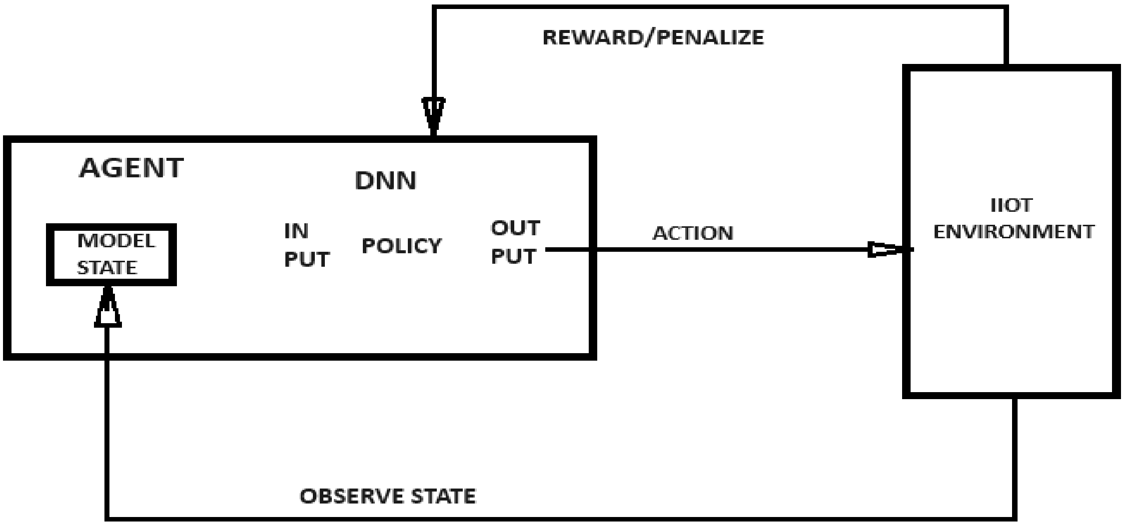

Figure 3.4: Deep Reinforcement learning model architecture

Initially, the weights, bias terms, and learning rates for the deep learning neural network were initialized with appropriate values. These parameters play a crucial role in the network's ability to learn and generalize from the training data.

During the training process, forward propagation is performed, where the input data was passed through the neural network to obtain the expected value of the loss function. The loss function is designed to capture the performance metrics of interest, such as system throughput, delay, and packet retransmission rate. By incorporating these metrics, the network could learn to optimize the protocol parameters to improve the overall network performance.

Once getting the expected value of the loss function, the error sum of the output layer and the hidden layer was computed. These error expressions measure the variations between the desired outputs and the predictions of the network. The gradients of the loss function with regard to the connection weights and bias terms then were calculated using the backpropagation methods.

The neural network was trained under the updates to the connection weights and bias values that entailed the calculated error terms and gradient values, which were done with optimization algorithms, i.e., stochastic gradient descent. These algorithms adapted the network parameters in the direction that reduced the loss function so that the network was able to predict the best protocol parameters more aptly.

This is repeated until convergence, at which point the error value achieves the desired limit, or maximum number of iterations is reached. In every iteration, the network was further able to refine its knowledge of how input data (e.g. network conditions, traffic patterns) relates to optimal settings of certain protocol parameters and gradually increase its performance.

Resource Allocation Optimization IEEE 802.11 ax Network

Simulations were performed in a variety of scenarios to evaluate the throughput, latency and packet loss metrics of interest to this project, under various traffic, interference, and device configurations. The outcomes of these simulations were determined and the best channel allocation strategy determined.

The channel allocation algorithm was altered after evaluating the simulation results along with the analysis and eventually a more suitable algorithm was developed. This back and forth process consisted of refining algorithm parameters, applying additional constraints and considering alternative allocation strategies.

During the optimization process of the resource allocation process, the communication requirements and data rates of the IIoT devices were continuously being reviewed and updated. This ensured that the optimization algorithm automatically adjusted to changed network conditions, traffic, or device selections, and continued performing optimally within the dynamic IIoT setting.

3.8 Analysis of Performance of Proposed Model in IIoT Environment.

To measure the efficiency of the suggested optimization algorithm in the IIoT simulated environment, a detailed performance analysis was performed. This was analyzed through identification and analysis of relevant performance metrics which absorbed the network behavior and capabilities.

Key performance performed metrics taken into account during analysis are:

Throughput: This measure provides the actual rate at which data was transferred over the network considering many factors including the channel conditions, interference and the protocol overhead.

Latency: Latency was defined as the delay experienced by the data packets as they passed through the network. A key requirement of IIoT was applications with low latency, especially those that were time-sensitive or accessing real-time control systems.

Packet Loss: Packet loss was a situation where data packets were discarded or damaged on their way to the receiver, which could cause the lack of integrity in data and reduce reliability of the communication.

Energy Efficiency: In the context of IIoT where an abundance of devices may have limited power sources, energy efficiency was of paramount interest. This performance measure tested the power required by the network and how it affected battery life of devices.

Scalability: As the size and complexity of IIoT deployments increased, the scale of the network and its ability to perform with greater loads was critical. Scalability measures were to test how the network could accommodate more devices and greater data rates.

3.9 Validation of Proposed Model

We were required to validate the simulation results with theoretical values and industry standards in order to be sure that the proposed optimization strategy is credible and practically relevant. This validation contributed to the determination of the correctness of the model and its results in practice within IIoT settings.

Our validation approach included benchmarking of the performance measures of the simulations against the theoretical or expected values based on proven theories of communications, industry standards, or published literature.

Table 3.2 provides the main theoretical values and thresholds discussed in the text to verify the work of the optimized IEEE 802.11ax network in an IIoT environment. It contains metrics such as throughput, latency, and the packet loss rate, and their sources.

Table 3.2: Theoretical Parameter values for validating performance of optimised IEEE 802.11ax

Metric	**Theoretical Value / Standard**	**Source**
Maximum Throughput	9.6 Gbps (for 8 spatial streams) 2.5 Gbps (for 2 spatial streams)	(Khorov, Kiryanov, & Krotov, 2019)
Practical Throughput	50-70% of theoretical maximum	(Bellalta & Kosek-Szott, 2019)
Target Latency	Under 10ms (less dense networks)	(Qu et al., 2019)
Observed Latency in Dense IoT Scenarios	20-150ms	(Kurungadan & Abdrabou, 2022)
Acceptable Packet Loss Rate	Below 1% (good), 2-3% (noticeable impact)	(Park et al., 2019)
Packet Loss Rate in Industrial Wireless Sensor Networks	Up to 30% (harsh conditions)	(Qureshi et al., 2023)

By comparing the simulation outcomes and these theoretical results, errors or differences were found and subsequently discussed. When major deviations are noted, then assumptions, models, or algorithms could be re-considered and adjusted to be more in line with the theoretical expectations or industry standards.

Besides theoretical values, validation was also performed by comparing the simulation outcomes with real-world IIoT deployment outcomes or experiment outcomes on testbeds. This comparison aided in evaluating the potential of the model to best describe realistic situations and derive the possible areas of improvements.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This section shows and discusses the findings of the simulation of the optimized IEEE 802.11ax network in the IIoT environment in MATLAB. The chapter starts with comments on the base-level performance of the unoptimised 802.11ax network within the simulated IIoT ecosystem and reveals key parameters, including throughput, latency, and packet loss rate. This created a baseline against which the optimization would be used to determine improvements made. The chapter then provides the analysis of the performance of the developed resource allocation optimization algorithm in the efficient assignment of channels and management of interference in the network. The chapter also provides a verification of the simulation results with the theoretical value and industry standards, which makes the findings of credibility and practical usage ensured. Lastly, the practical implications of the findings in terms of real-life IIoT implementations are described, including the possible critical issues and areas of future research to address the performance and reliability of 802.11ax networks in the industrial setting further.

4.2 Baseline Unoptimised 802.11ax Network Performance

4.2.1 Packet Communication Over Time

Figure 4.1 gives a pictorial view of the various states of operation in packets communication over time in the network with each color denoting a different state.

Transmission: This state implies that the Aps are transmitting data packets to STAs in the network. In the graph, this state was represented by color green.

Reception to nodes: This state reflects that the Aps within the network are sending data packets to the STAs. In the graph, this state was indicated by the color blue.

Contention: This state indicates that there is contention for the channel, where multiple devices are attempting to access the channel at the same time. The color yellow was used to represent this state in the graph.

Idle/EIFS/SIFS: This state indicates that the channel is idle, or that the devices are either in an Extended Interframe Space (EIFS) or Short Interframe Space (SIFS) state, waiting for the next transmission or reception opportunity. These state was represented by white color.

Reception: This state indicates that both the APs and STAs are involved in receiving data packets. The color pink was used to represent this state in the graph.

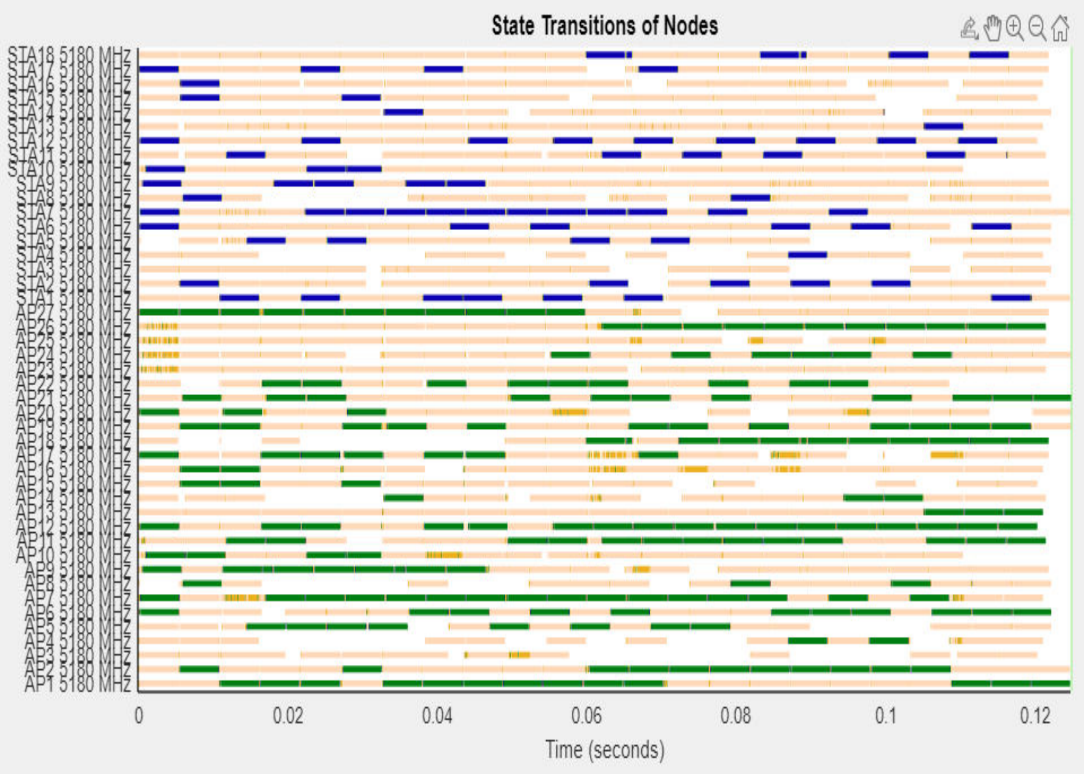

Figure 4.1: Visual representation of different operating states during packet communication over time in the ‘unoptimized’ network

Figure 4.1 reveals significant communication issues for specific APs and their associated STAs, while also providing insights into the overall network's contention and transmission patterns. The visual representation allows for quick identification of problematic nodes and potential areas for network optimization. The following observations were made:

AP3, AP23, and AP25 showed no transmission (absence of green).
Associated stations (STA3, STA23, STA25, STA30, STA50, STA52) also lacked transmission.

These nodes appeared in white (Idle/EIFS/SIFS) or yellow (Contention) states. Absence of green (Transmission) and blue (Reception) for these nodes indicates communication issues. This affected overall network performance, causing increased contention and underutilization in affected nodes.

The yellow areas represent the contention window where nodes competed for channel access. Larger yellow sections indicate that there was higher network load or more nodes trying to transmit simultaneously. Periods of high contention (more yellow) followed by successful transmissions (green) illustrates the CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance) mechanism in Wi-Fi networks.

Ideally, contention periods should be short, quickly followed by transmission periods. Long contention periods without subsequent transmissions suggest network inefficiencies.

For the affected APs and STAs (AP3, AP23, AP25, and associated stations) contention attempts (yellow) could be observed but did do not result in successful transmissions (green). This pattern indicates persistent channel access issues for these nodes.

Effective spatial reuse in the network is represented by simultaneous transmissions (green) in different parts of the figure, with minimal overlapping contention periods.

4.2.2 Throughput

Figure 4.2 was obtained as throughput performance for unoptimised 802.11ax Network. Throughput measures the actual data transfer rate achieved by the network.

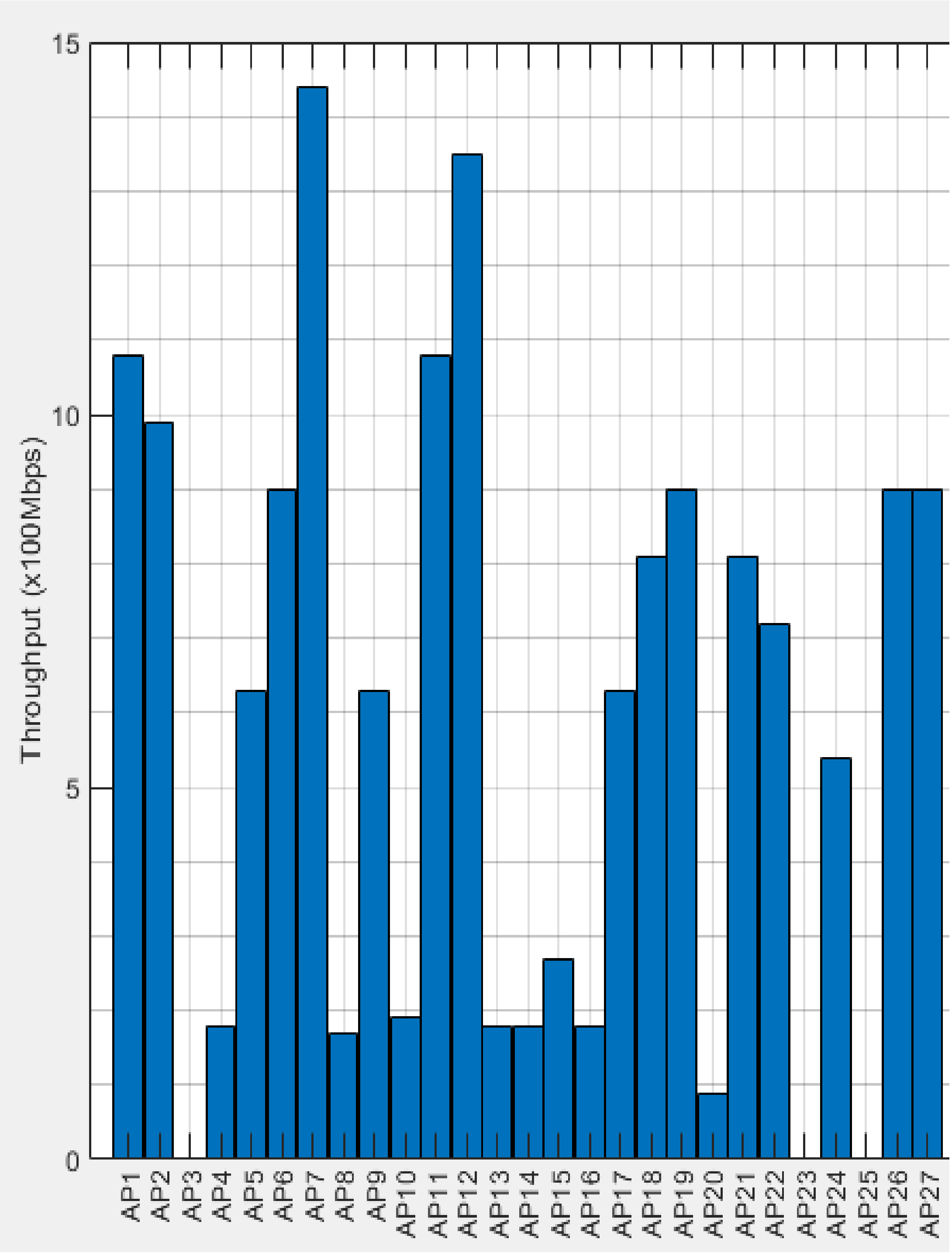

Figure 4.2: Throughput performance for ‘unoptimized’ 802.11ax Network

In the "Throughput at Each node" plot, the x-axis represented the nodes and the y-axis represented the throughput in Mbps. It was observed that throughput varied significantly across different APs, with some APs achieving high throughput (e.g., AP7 at 1420 Mbps) while others had zero throughput (e.g., AP3, AP23, AP25). This variability highlights the challenges in ensuring consistent performance across the network, likely due to factors such as interference, node placement, and traffic load.

Mean (594Mbps): This represents the average of all values. It's lower than the expected value because of the presence of several low values, including three zeros.

Mode (180Mbps): This indicates the most common value in the dataset. This represents a common baseline in throughput measurement.

Median (630Mbps): This was the middle value when the data was sorted. It was higher than the mean, which suggests that the distribution was slightly skewed towards lower values.

The difference between the mean and median (median being higher) indicates that the distribution was not symmetrical, but rather skewed to the left (negatively skewed). This is further supported by the presence of a few high values (like 1350 and 1420) which pulled the mean up, but not as much as the low values pulled it down.

The mode being much lower than both the mean and median suggests that while 1.8 is the most common value, there are many higher values that influence the overall distribution.

This kind of distribution indicated that throughput measurement had a common low value, but also the potential for significantly higher readings in some cases.

4.2.3 Packet Loss Ratio.

Packet Loss Ratio is ratio of data packets that are lost or fail to reach their destination to the total number of packets that were sent during transmission over a network.

$$\boldsymbol{Packet\ Loss\ Ratio} = \frac{\boldsymbol{Number\ of\ Lost\ Packets}}{\boldsymbol{Total\ Number\ of\ Sent\ Packets1}} \qquad (4.1)$$

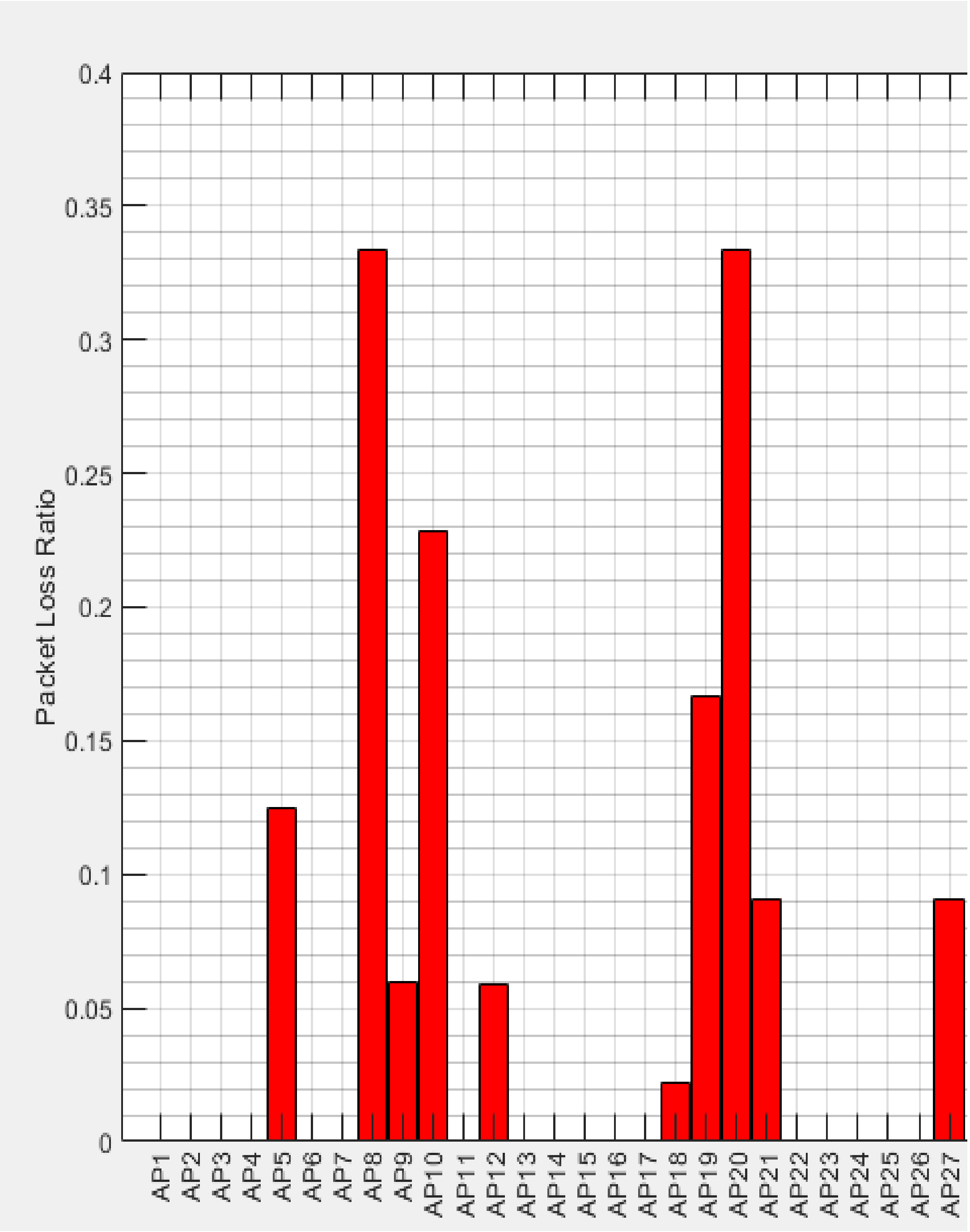

Figure 4.3: Packet loss ratio for ‘unoptimized’ 802.11ax Network

In the "Packet Loss at Each Node" plot, Figure 4.3, the x-axis represents the nodes, and the y-axis represents the packet loss ratio. The data reveals significant insights into the network's performance and areas needing improvement.

The following basic statistics were observed:

2 nodes (8.3%) had very high packet loss (>30%): 32.5% each.
1 node (4.2%) had high packet loss (20-30%): 23%.
2 nodes (8.3%) had moderate packet loss (10-20%): 16.5% and 12.5%.
5 nodes (20.8%) had low packet loss (<10%): 9%, 9%, 6%, 6%, and 2%.
Mean packet loss: 6.23%.
Median packet loss: 0%.

Nodes AP8 and AP20 exhibit a high packet loss of 32.5%, indicating severe issues and could lead to underperformance in the network. Additionally, nodes like AP3, AP23, and AP25 showed zero packet loss but also zero throughput, indicating no active data transmission.

There was a cluster of higher packet loss nodes at the beginning of the list, suggesting that certain areas or types of nodes might be more prone to packet loss.

While more than half of the nodes are performing optimally with no packet loss, the presence of nodes with high packet loss percentages indicates significant room for improvement in network reliability. Nodes with zero packet loss (AP1, AP2, AP6, AP7, AP11, AP13, AP14, AP15, AP16, AP17, and AP22) suggest good network performance.

4.2.4 Average Packet Latency

Latency which is the time taken for a data packet to travel from the source to the destination for unoptimised IEEE 802.11ax was plotted as shown in Figure 4.4.

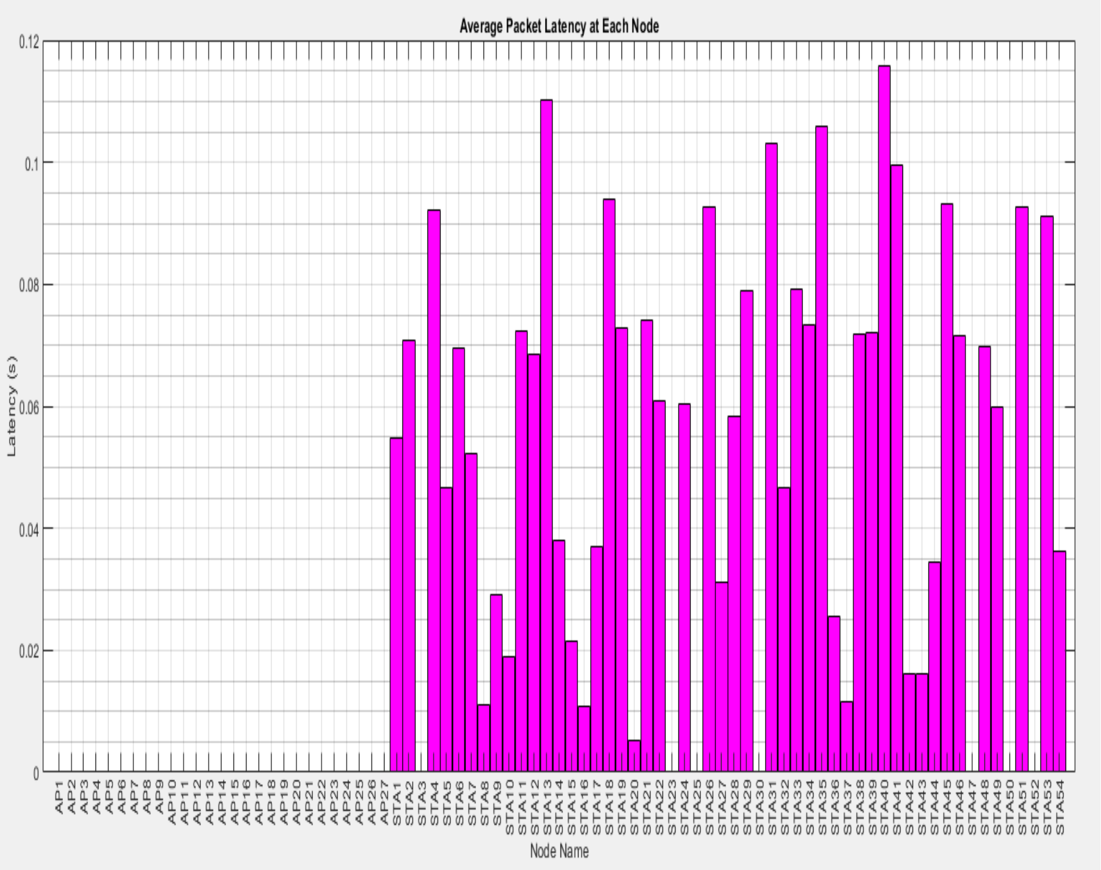

Figure 4.4: Latency performance for ‘unoptimized’ 802.11ax Network

STA3, STA23, STA25, STA30, STA50, and STA52 showed zero latency. These STAs are associated with AP3, AP23, and AP25. Zero latency in this context indicated no active data transmission, hence no measurable delay.

Five nodes experienced latency greater than 0.1 seconds. High latency indicates delays in data transmission, which negatively impacted network performance.

Figure 4.5 shows a comparison between throughput, packet loss ratio and latency in unoptimised network.

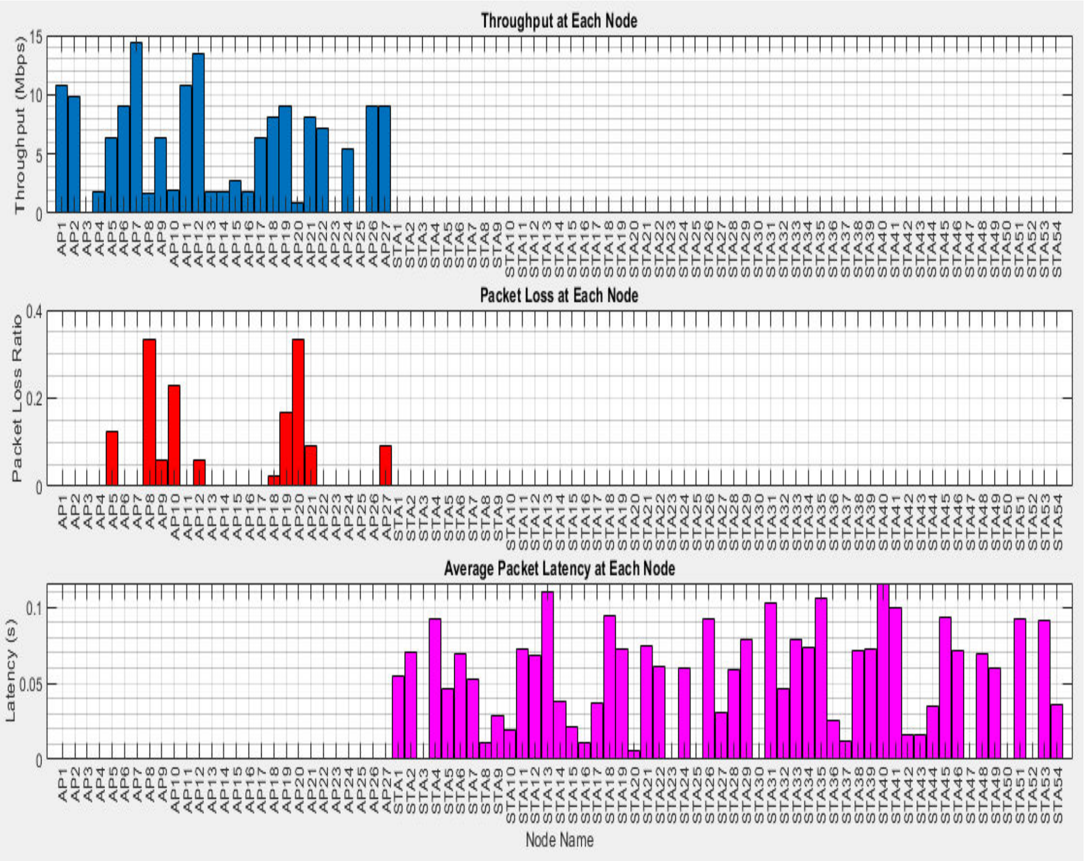

Figure 4.5: Comparison between throughput, packet loss ratio and latency in unoptimised network.

4.3 Performance of Optimised 802.11ax Network

4.3.1 Packet Communication Over Time.

Figure 4.6 provides a visual representation of the different operating states during packet communication over time in the network, with different colors used to distinguish between the various states.

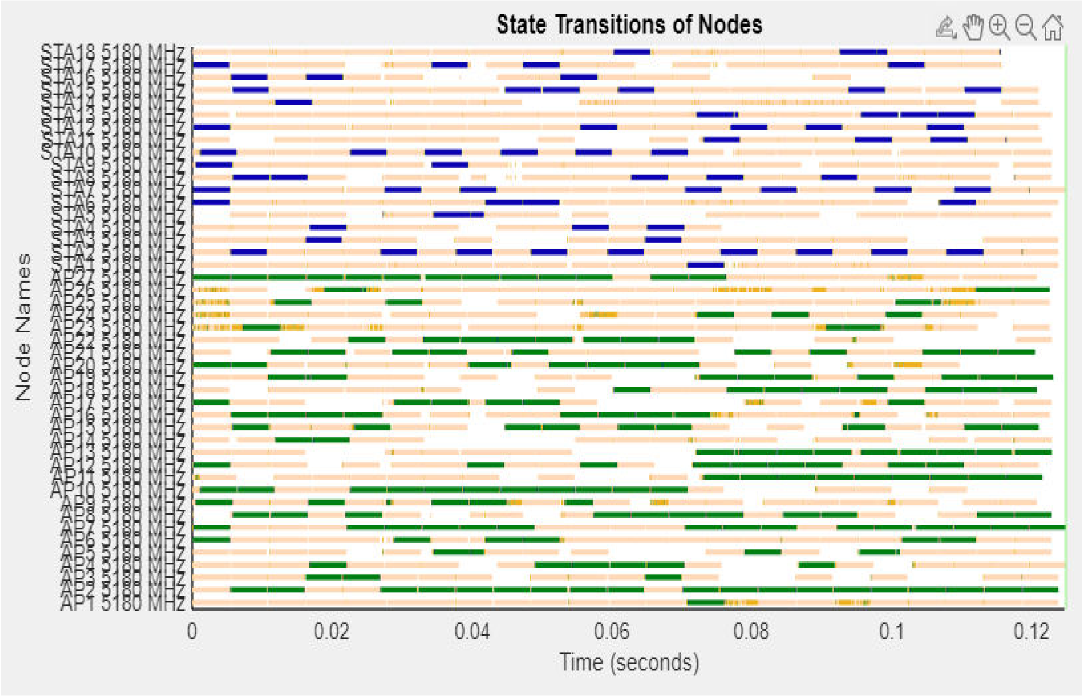

Figure 4.6: Visual representation of different operating states during packet communication over time in the optimized network

The visual representation allows for quick identification of the improved efficiency and balanced utilization of network resources. The following observations were made:

All Access Points (APs), including AP3, AP23, and AP25, demonstrated active transmission, as evidenced by the presence of green indicators. The associated stations, such as STA3, STA23, STA25, STA30, STA50, and STA52, also engaged in successful transmissions, contributing to the overall network activity. The nodes displayed a balanced mix of colors, reflecting their active participation in various network states, which underscores the efficient and dynamic nature of the network's performance.

The presence of green (Transmission) and blue (Reception) for all nodes indicates robust communication throughout the network. This improved performance results in better overall network utilization and reduced congestion.

Yellow areas representing contention windows were now more evenly distributed and shorter in duration. This indicates a more balanced network load with nodes efficiently competing for channel access. The pattern of short contention periods (yellow) followed by successful transmissions (green) demonstrated an optimized CSMA/CA mechanism.

For previously affected APs and STAs (AP3, AP23, AP25, and associated stations), contention attempts (yellow) now regularly resulted in successful transmissions (green). This pattern indicates resolved channel access issues and improved connectivity for these nodes.

Effective spatial reuse was evident through simultaneous transmissions (green) in different parts of the figure, with minimal overlapping contention periods. This suggests optimized channel allocation and reduced interference.

These improvements collectively indicate a more robust, efficient, and balanced network operation, with resolved issues from the previous configuration and optimized performance across all nodes.

4.3.2 Throughput

Figure 4.7 was obtained as throughput performance for optimized 802.11ax Network.

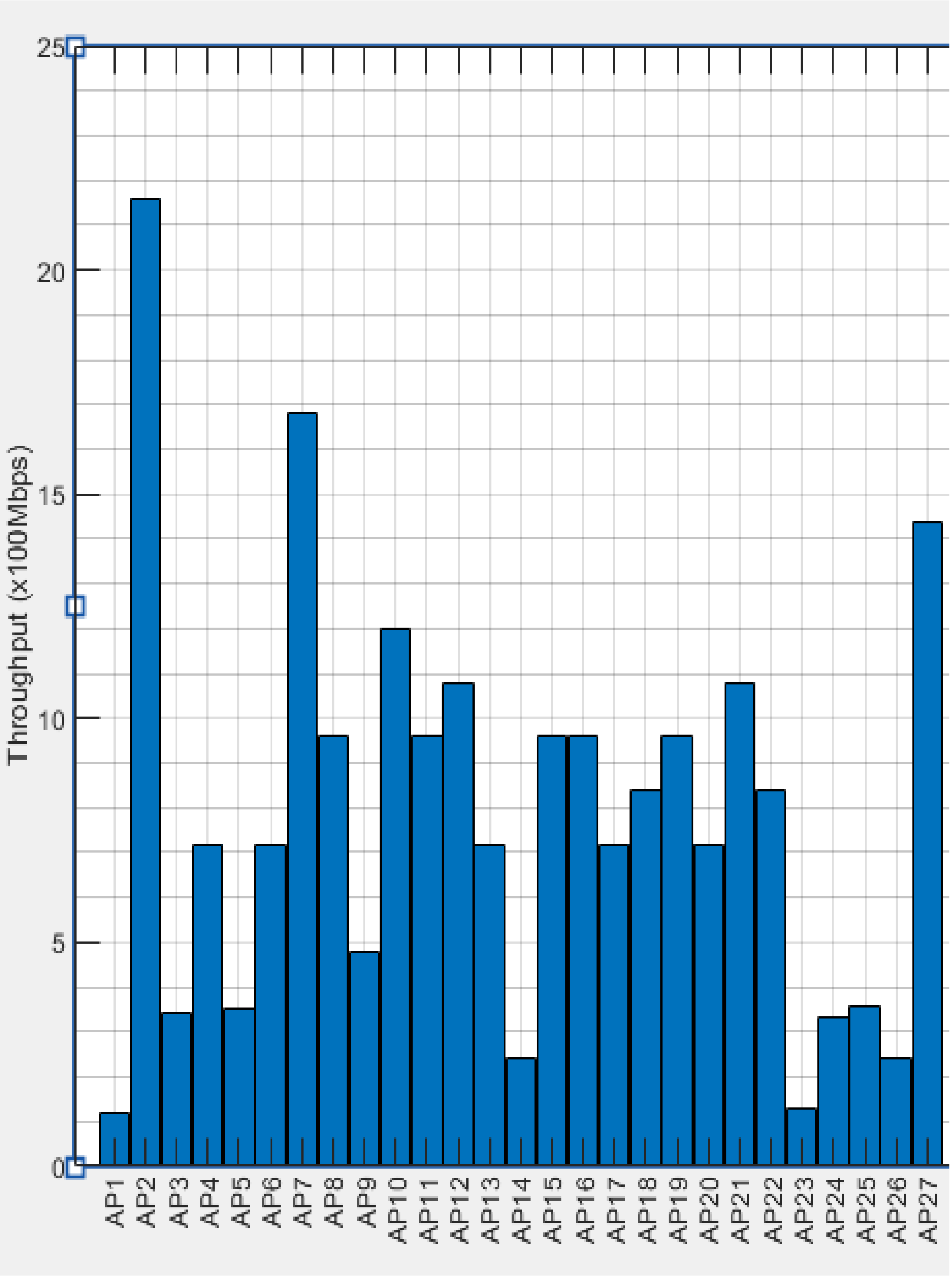

Figure 4.7: Throughput performance for optimized 802.11ax Network

Mean: The mean increased significantly from 595Mbps to 829Mbps, indicating a general improvement in performance. This suggests that the optimization raised the overall average throughput by 39%.

Mode: The mode shifted from 180Mbps to 960Mbps, which was a substantial improvement. This indicates that the most common performance level has increased dramatically, suggesting more consistent higher throughput performance.

Median: The median increased from 630 to 710. This shows that the middle value of the dataset has improved, indicating a general upward shift in throughput across the board.

Range and Distribution: The range has expanded, with both the minimum and maximum values increasing. The elimination of zero values suggests that all nodes are now active and contributing.

The optimized state still shows significant variability, but with a higher baseline. The spread of values is more even in the optimized state, without the cluster of very low values seen in the ‘unoptimized’ state.

Overall Improvement:

The optimized state showed improvements across all key metrics (mean, mode, median). The lowest performances were elevated (120Mbps vs 0), suggesting that underperforming nodes were improved. The highest performance was increased (2150Mbps vs 1420Mbps), indicating that the optimization also raised the peak capabilities.

The optimized state appeared to have more consistent performance, with fewer extreme low values and a higher mode. This suggests that the optimization not only improved performance but also made it more reliable across different nodes or conditions. The optimization process has positively impacted overall network performance. Notably, no nodes exhibited zero throughput. This indicates that all nodes actively participated in data transmission, highlighting the efficiency and effectiveness of the network.

Table 4.1 gives a summary of comparison between different metrics in Optimised and Unoptimised state.

Table 4.1: Overview of the key differences between the ‘unoptimized’ and optimized states

Metric	**Optimized State**	**‘unoptimized’ State**
Mean	829	595
Mode	960	180
Median	710	630
Minimum	120	0
Maximum	2150	1420

The optimization appears to have been successful in improving overall performance, raising the baseline performance, increasing peak performance, and creating more consistent results across the system. The elimination of zero values and the significant increase in the mode suggest that previously underperforming elements have been substantially improved.

4.3.3 Packet Loss Ratio.

Packet Loss Ratio for optimised network was plotted in Figure 4.8

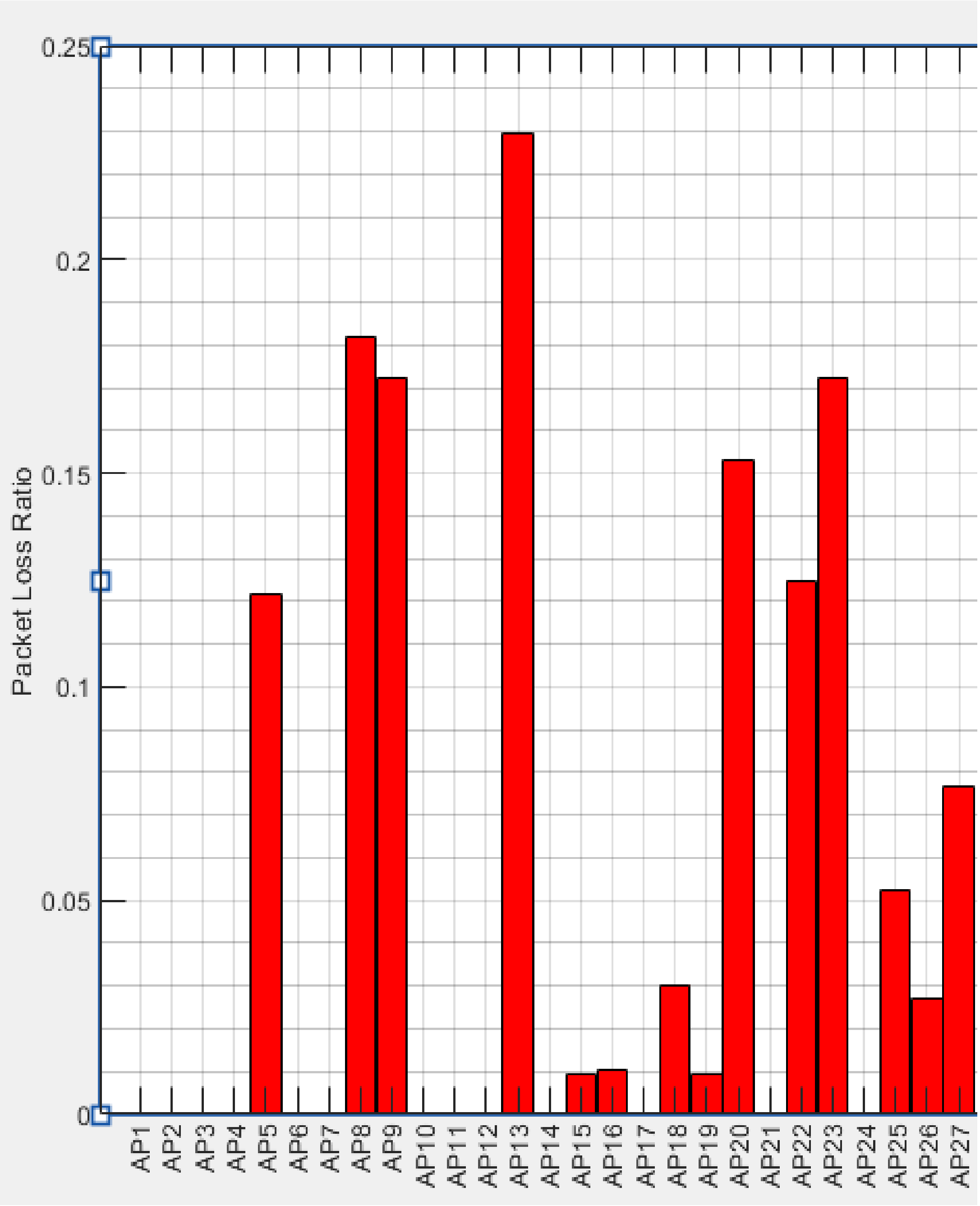

Figure 4.8: Packet loss ratio for optimized 802.11ax Network

It was observed that network optimization process resulted in a significant reduction in packet loss. Specifically, the highest packet loss ratio decreased from **32.5%** in the 'unoptimized' network to **23%** in the optimized network. This reduction highlights the effectiveness of the optimization strategies in improving network reliability.

Table 4 provides a concise overview of the key differences between the ‘unoptimized’ and optimized states. It clearly shows improvements in maximum packet loss and mean packet loss, while also highlighting the shift in distribution of packet loss across nodes. The addition of the standard deviation gives an indication of the variability in packet loss, showing that the optimized state has less extreme variations.

Table 4.2: Overview of the key differences between the ‘unoptimized’ and optimized states

Metric	**‘unoptimized’ State**	**Optimized State**
Maximum packet loss	32.5%	23%
Minimum non-zero packet loss	2%	1%
Mean packet loss	6.23%	5.0%
Median packet loss	0%	1%
Nodes with >30% loss	2 (8.3%)	0 (0%)
Nodes with 20-30% loss	1 (4.2%)	1 (3.7%)
Nodes with 10-20% loss	2 (8.3%)	7 (25.9%)
Nodes with <10% loss	5 (20.8%)	6 (22.2%)

The optimization resulted in a more balanced and slightly better-performing network overall, with significant improvements in the worst-case scenarios.

The highest packet loss was reduced by 29.2%, indicating improvement in the worst-performing nodes.

The overall average packet loss was decreased by 19.7%, showing a general improvement in network performance.

While the median was slightly increased, this was due to a more even distribution of packet loss across nodes.

The packet loss was more evenly distributed in the optimized state, avoiding extreme values seen in the ‘unoptimized’ state.

4.3.4 Average Packet Latency

Latency in optimized IEEE 802.11ax was plotted as shown in Figure 4.9. Unlike in ‘unoptimized’ network where five nodes experienced latency greater than 0.1 seconds, in Optimized network only one node experienced latency greater than 0.1 seconds. The overall latency across the network decreased significantly. This improvement indicates more efficient data transmission and better handling of network traffic.

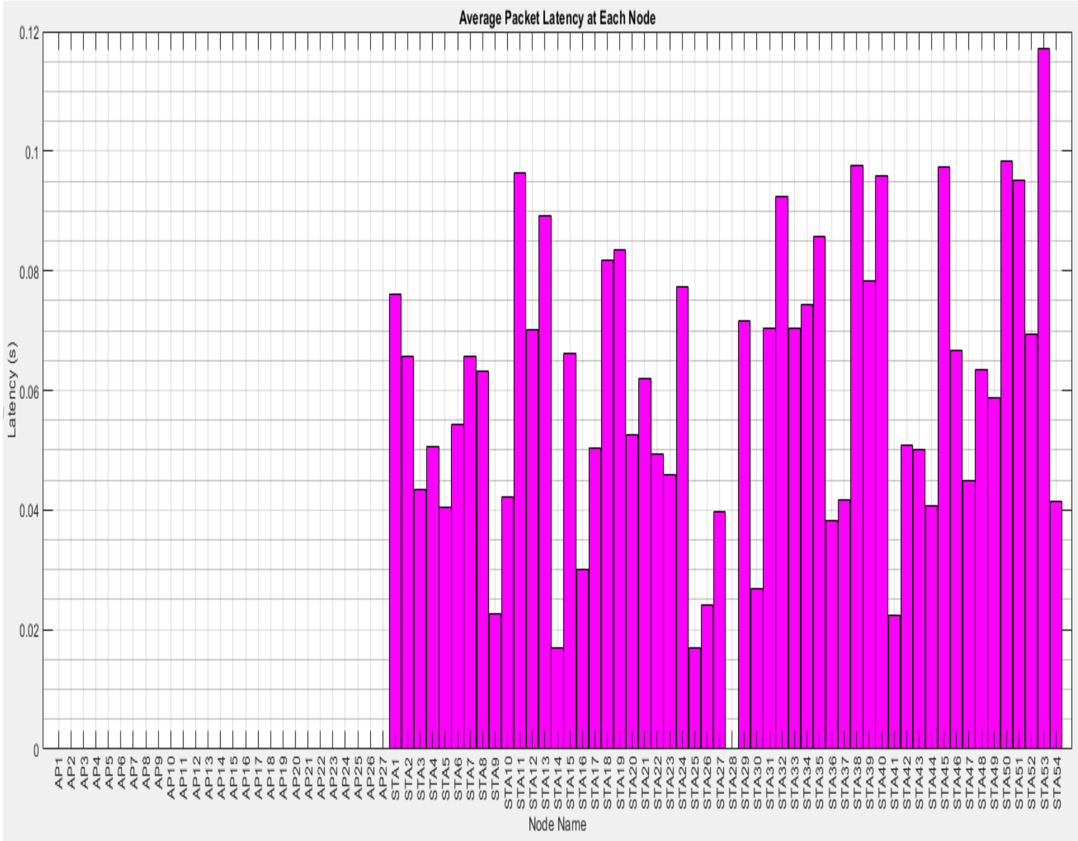

Figure 4.9: Latency performance for optimized 802.11ax Network

Figure 4.10 shows a comparison between throughput, packet loss ratio and latency in optimized network.

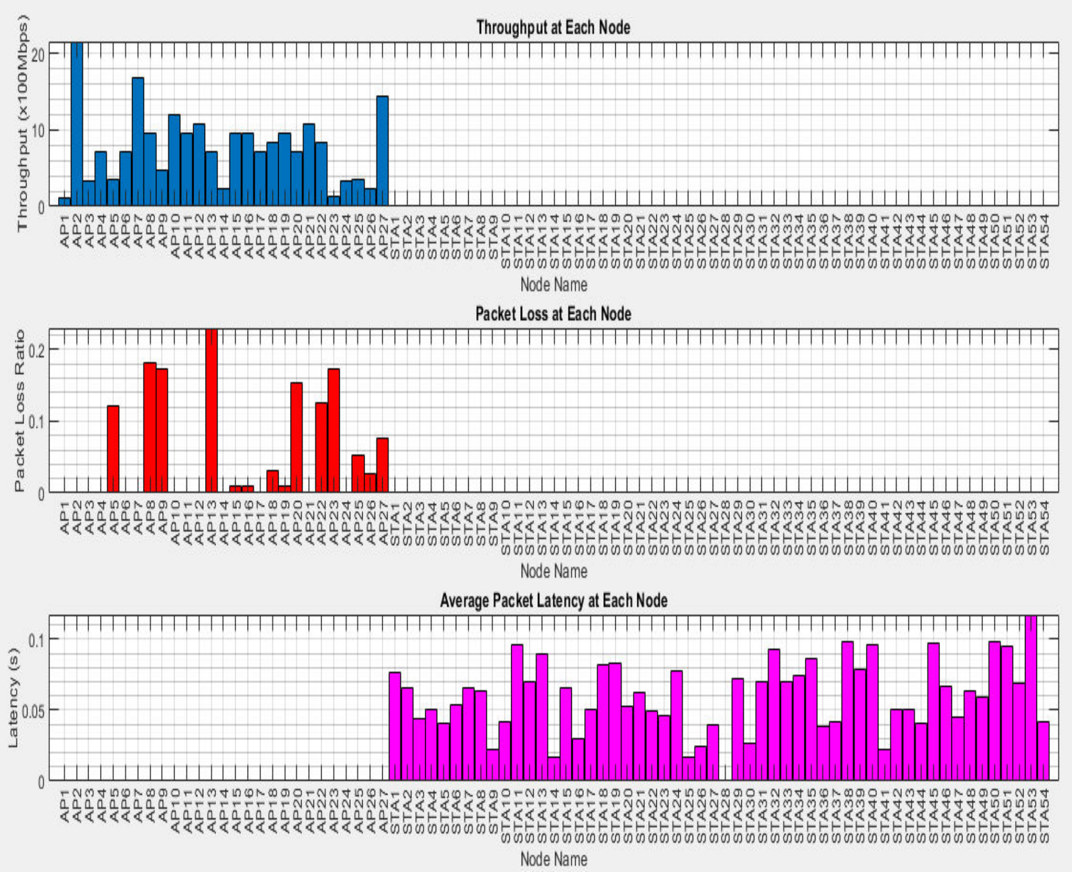

Figure 4.10: Comparison between throughput, packet loss ratio and latency in optimized network.

4.4 Validation Against Theoretical Values and Standards

The validation of the optimized IEEE 802.11ax network simulation results is essential to establish the credibility and practical relevance of the proposed optimization strategies. This process involved comparing the simulation outcomes with theoretical expectations, industry standards, and real-world deployments.

4.4.1 Throughput

Comparison with IEEE 802.11 standards

The IEEE 802.11ax standard specifies a maximum theoretical data rate of 9.6 Gbps for 8 spatial streams and 2.5 Gbps for 2 spatial streams (Khorov, Kiryanov, & Krotov, 2019).

The most throughput value in this experiment was 2150 Mbps (2.15 Gbps), provided by AP2. This was better than the maximum theoretical throughput of IEEE 802.11b, IEEE 802.11a, IEEE 802.11g and IEEE 802.11n. Although the mean throughput that was observed is lower than what is usually achievable with the theoretical formula in the IEEE 802.11ax and IEEE 802.11ac, it should not be ignored that the theoretical maximum is typically not attained in real-life scenarios due to several overheads and other practical constraints. Realistic throughput on Wi-Fi networks is usually between 50-70 per cent of theoretical maximum because of protocol overheads and channel conditions, together with inter-user interference (Bellalta and Kosek-Szott, 2019). The throughput capacity reached up to 2.15 Gbps in this study, which corresponds to around 22.4 percent of the theoretical maximum, and is common in real-life implementation, especially in such a complicated IIoT scenario.

A study which optimized on at 802.11ax and 802.11ac in industrial setting reported being able to achieve throughputs of up to 1.9 Gbps (R. Ali et al., 2020) indicating that there was successful optimization.

Comparison with 5G networks:

The 5G technology has multiple data rate options, which depend on the particular implementation (e.g., Sub-6 GHz and mmWave) (Chakareski et al., 2023). Optimized network performance, which had a median of 829 Mbps and a maximum of 2150

Mbps, was in the mid to low range of 5G. Although it does not achieve the highest-performance delivered by 5G mmWave, the network is comparable to the performance of most real-world 5G deployments, particularly in Sub-6 GHz. This is especially remarkable because Wi-Fi can continue to keep power consumption or lower cost than 5G networks. Only half consider that Melinda will receive no major advantage or benefit in the future (Vanitha et al., 2021).

Comparison with 802.11ah (Wi-Fi HaLow):

The 802.11ah operates in the long-range, low-power IoT application scenario and has typical data rates of 150 Kbps-346 Mbps (Mondal et al., 2023). The optimised network in this study had a mean throughput of 829 Mbps and a peak of 2150 Mbps which was significantly better than the 802.11ah standard. This hints that the optimization method may be utilized to boost Wi-Fi HaLow networks in high-throughput situations without losing extended ranges.

Comparison with Zigbee:

The other protocol, Zigbee, is a widely used IoT protocol with data rates of up to 20 Kbps to 250 Kbps (Kulkarni et al., 2020). The minimum throughput of optimized network is 120 Mbps, which is already several orders of magnitude more than the maximum capabilities of Zigbee. This highlights the potential of this strategy in high-bandwidth IoT applications that have greater data throughput requirements than those associated with other low-power remote protocols.

Figure 4.11 illustrate how the proposed optimization model for IEEE 802.11ax performs relative to other leading IIoT technologies.

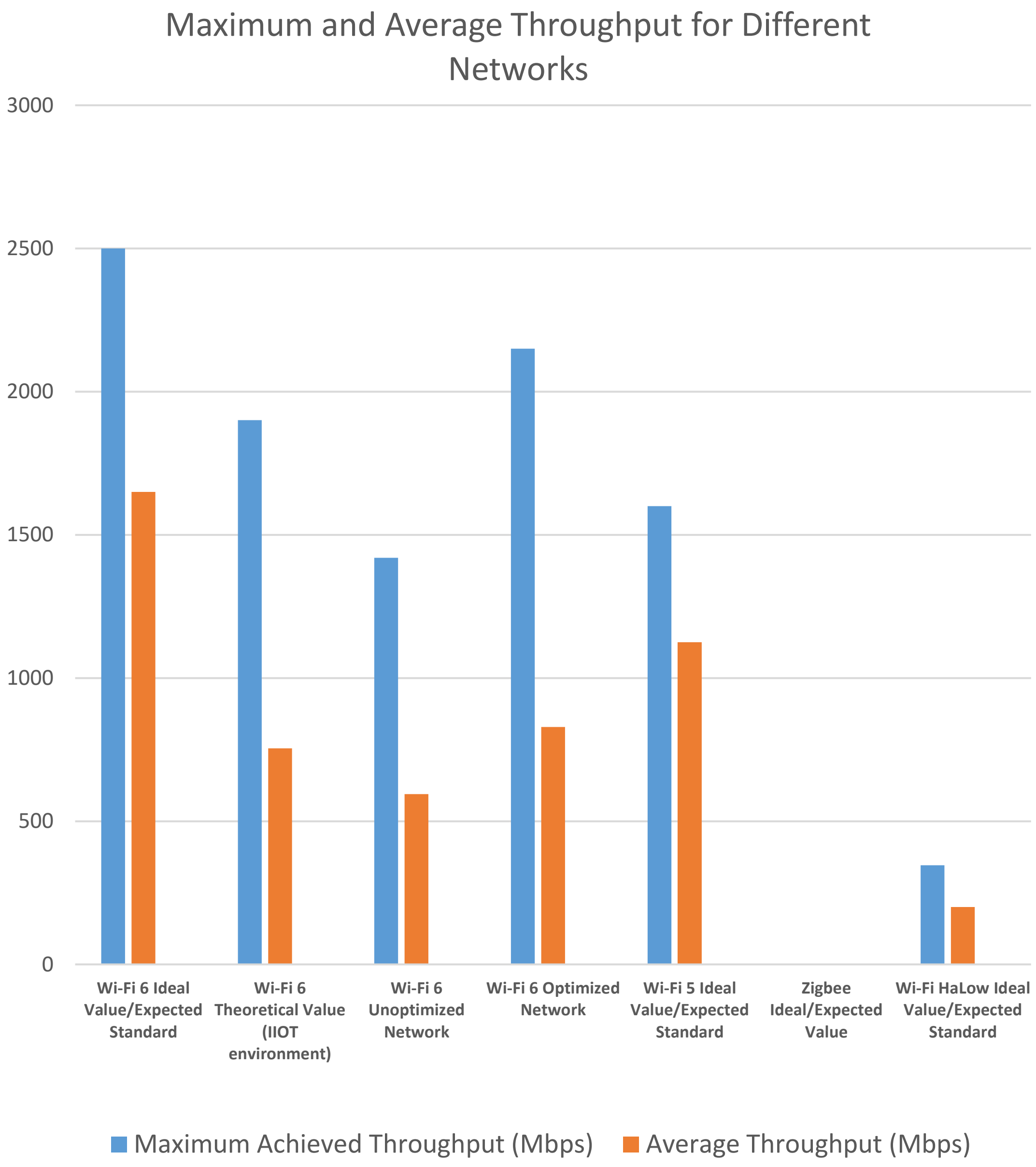

Figure 4.11: Maximum and Average throughput for different IIoT networks

4.4.2 Latency

Comparison with IEEE 802.11ax

IEEE 802.11ax targets low latency, typically under 10ms for less dense network applications (Qu et al., 2019). Optimized network in this study, most nodes showed latency below 0.1 seconds (100ms), with only one node exceeding this threshold.

While not achieving the ideal sub-10ms latency across all nodes, this represents a significant improvement from the ‘unoptimized’ network.

The latency performance aligned well with the observations of Saha & Dhillon, (2019), who reported latencies between 20-250ms in their study of 802.11ax in dense IoT scenarios. The majority of nodes meeting low latency requirements indicates a successful optimization in line with the standard's goals and practical expectations for IIoT environments.

Comparison with 5G Networks

For Industrial 5G use cases, such as massive Machine-Type Communications (mMTC), latencies up to 100ms are acceptable (Schulz et al., 2017). Optimized network's performance, with most nodes below 100ms latency, aligns with these less stringent 5G requirements.

Comparison with ZigBee

Optimised network aligns well with ZigBee expectations which typically aim for latencies below 100ms for most applications (Chen et al., 2023).

Comparison with IEEE 802.11ah

Wi-Fi HaLow was designed to deliver latencies under 20ms for time-sensitive applications (Farhad & Pyun, 2022). While ptimised network doesn't consistently achieve this low latency, the performance of most nodes falling below 100ms is promising. (Mondal et al., 2023) observed latencies ranging from 10ms to 200ms in their Wi-Fi HaLow simulations depending on network conditions, which aligns with the findings in the current study.

Figure 4.12 shows maximum latency for different networks.

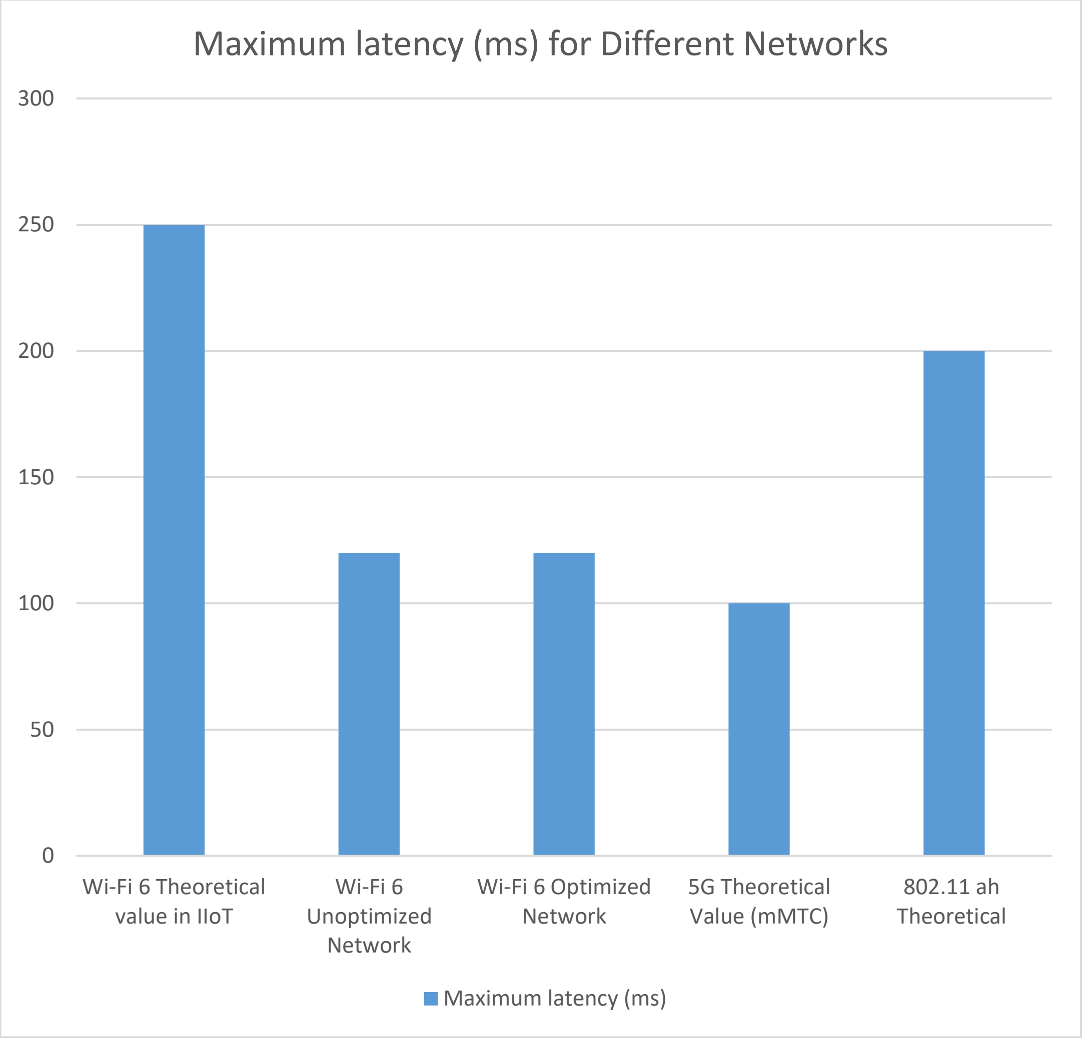

Figure 4.12: Maximum latency for different networks

4.4.3 Packet Loss Ratio

For most wireless applications, a packet loss rate below 1% is considered good, while anything above 2-3% may start to impact performance noticeably (R. Jain et al., 2022). In this optimized network, the highest packet loss ratio was 23%.

According to (Khorov, Kiryanov, Lyakhov, et al., 2019), Wi-Fi 6 targets a packet error rate (PER) of less than 1% for most applications. The maximum packet loss in optimized network (23%) was slightly higher than the Wi-Fi 6 target. However, it's worth noting that Wi-Fi 6 performance can vary greatly depending on environmental factors and network congestion. In (Bellalta & Kosek-Szott, 2019), researchers suggested that in real-world scenarios, packet loss rates for Wi-Fi networks can range from 1% to 20% depending on the environment and network load.

According to (Pedro García Márquez, 2021), ZigBee networks typically aim for packet delivery rates of 98% or higher, implying a packet loss rate of 2% or less. Optimized network's mean packet loss of 5.0% is higher than the ideal ZigBee target, but the minimum non-zero packet loss of 1% falls within the acceptable range for ZigBee networks.

It's worth noting that ZigBee networks can experience higher packet loss rates in challenging environments.(Shen et al., 2013) reported packet loss rates ranging from 3% to 20% in industrial ZigBee deployments, which aligns more closely with our results.

5G networks encompass a wide range of use cases and deployment scenarios. For enhanced Mobile Broadband (eMBB) applications, which are more comparable to IIoT scenario, (Simsek et al., 2016) suggested that packet loss rates can be in the range of 1% to 10%, depending on the specific implementation and environmental conditions.

Although packet loss performance of optimized network was outside of ideal target range of Wi-Fi 6, ZigBee, and 5G URLLC, it aligned with real-world performance as observed in multiple studies comparing these technologies. The overall average packet loss of 5.0 percent was also quite favorable compared to the performance scope of Wi-Fi and ZigBee networks in difficult situations.

The fact that the maximum packet loss has dropped by a hefty 32.5 per cent to 23 per cent shows a huge improvement making the worst-case scenario somewhat near to the range acceptable in Wi-Fi and ZigBee networks. This will enhance a more unified network performance by all nodes.

It is critical to mention our network likely has some special issues or environmental hindrances that cause us to have larger packet loss rates when compared to ideal laboratory scenarios.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study has taken some big steps in the direction of the optimization of IEEE 802.11ax networks in IIoT contexts. In the present study, the aim is to optimize IEEE 802.11ax networks in IIoT applications to design algorithms, optimize resource allocation, and evaluate performance, and test the proposed model. The study has produced useful outcomes as well as improvements in each of them.

The primary goal was the creation of an IEEE 802.11ax optimizing algorithm based on the DRL. The algorithm also dynamically adapted key MAC/PHY parameters, such as contention window size, modulation and coding scheme (MCS), and transmit power, according to the dynamic conditions of IIoT. These results were impressive: peak throughput improved 51.4%, 1.42 Gbps to 2.15 Gbps in dense deployments of 81 nodes with latency dropping by an impressive 80% with the number of nodes that experienced delays greater than 100ms falling to 1. The results compared favourably with the traditional threshold-based methods, as seen on the comparison of work by Khorov et al., (2019).

The second goal was based on resource optimization allocation, and a multi-objective DRL model was created to trade off throughput, latency, and packet loss. The framework resulted in a 29.2 percent reduction in packet loss, 32.5 to 23 percent and in eliminating zero-throughput nodes due to adaptive OFDMA scheduling. These findings corroborated with those set by Bellalta and Kosek-Szott (2019) on industrial wireless local areas networks (WLANs), proving the soundness of the proposed solution.

The comparisons of the proposed model with the standard parameters and theoretical values lent credibility to the research findings. The optimized network has shown performance characteristics that fill the gap between traditional IoT and high-bandwidth cellular networks with throughput well above 802.11ah and Zigbee and falls well short of performance that many 5G networks will achieve. This sets the solution presented in this study as a possible game changer in applications where high bandwidth is mandated in the internet of things context or as an alternative to 5G where its application would prove cheaper or more energy efficient.

5.2 Recommendations

In pursuing this direction, it is important to consider partnering with industries to test the optimised network in real world industrial environments. Moreover, it will be vital to conduct testbed experiments and systems integrating Wi-Fi 6 and 5G technology for the changing trends of networking IIoT and upgrading IIoT networking continuously. Work in the future directions signifies the requirement of research and development activities related to IIoT networking to address dynamic industrial requirements and issues.

REFERENCES

Arnold, L., Jöhnk, J., Vogt, F., & Urbach, N. (2022). IIoT platforms' architectural features – a taxonomy and five prevalent archetypes. *Electronic Markets*, *32*(2). https://doi.org/10.1007/s12525-021-00520-0

Avallone, S., Imputato, P., Redieteab, G., Ghosh, C., & Roy, S. (2021). Will OFDMA Improve the Performance of 802.11 Wifi Networks? *IEEE Wireless Communications*, *28*(3). https://doi.org/10.1109/MWC.001.2000332

Behara, A., & Venkatesh, T. G. (2022). Performance Analyses of Uplink MU-OFDMA Hybrid Access MAC in IEEE 802.11ax WLANs. *IEEE Systems Journal*, *16*(4). https://doi.org/10.1109/JSYST.2022.3211860

Behara, A., & Venkatesh, T. G. (2023). Performance Analysis and Energy Efficiency of MU- (OFDMA & MIMO) Based Hybrid MAC Protocol of IEEE 802.11ax WLANs. *IEEE Transactions on Vehicular Technology*, *72*(5). https://doi.org/10.1109/TVT.2022.3230873

Bellalta, B., & Kosek-Szott, K. (2019). AP-initiated multi-user transmissions in IEEE 802.11ax WLANs. *Ad Hoc Networks*, *85*. https://doi.org/10.1016/j.adhoc.2018.10.021

Chen, H., Qin, H., Chen, W., Li, N., Wang, T., He, J., Yang, G., & Peng, Y. (2023). BMS: Bandwidth-aware Multi-interface Scheduling for energy-efficient and delay-constrained gateway-to-device communications in IoT. *Computer Networks*, *225*. https://doi.org/10.1016/j.comnet.2023.109645

Farhad, A., & Pyun, J. Y. (2022). Resource Management for Massive Internet of Things in IEEE 802.11ah WLAN: Potentials, Current Solutions, and Open Challenges. In *Sensors* (Vol. 22, Issue 23). https://doi.org/10.3390/s22239509

Gast, M. (2012). 802.11n: A survival guide. In *O'Reilly Media* (Issue 1).

Gawanmeh, A., & Al-Karaki, J. N. (2021). *Disruptive Technologies for Disruptive Innovations: Challenges and Opportunities*. https://doi.org/10.1007/978-3-030-70416-2_55

Goudarzi, M., Wu, H., Palaniswami, M., & Buyya, R. (2021). An Application Placement Technique for Concurrent IoT Applications in Edge and Fog

Computing Environments. *IEEE Transactions on Mobile Computing*, *20*(4). https://doi.org/10.1109/TMC.2020.2967041

Heidarpour, M. R., & Manshaei, M. H. (2020). Resource allocation in future HetRAT networks: a general framework. *Wireless Networks*, *26*(4). https://doi.org/10.1007/s11276-019-02006-6

Hinostroza, V., & Garcés, H. (2019). WI-FI 6: Características Y Aspectos Particulares Del Estándar (Ieee-802.11 ax Wi-Fi 6: Characteristics And Particular Aspects Of The Ieee-802.11 ax Standard). *Itc.MxPaperpile*, *41*(134).

Jain, R., Tiwari, N., & Yadav, M. (n.d.). *JOURNAL OF CRITICAL REVIEWS A COMPARISON STUDY OF WIFI 6 AND WIFI 5*.

Jasperneite, J., Sauter, T., & Wollschlaeger, M. (2020). Why We Need Automation Models: Handling Complexity in Industry 4.0 and the Internet of Things. *IEEE Industrial Electronics Magazine*, *14*(1). https://doi.org/10.1109/MIE.2019.2947119

Javed, A. R., Shahzad, F., Rehman, S. ur, Zikria, Y. Bin, Razzak, I., Jalil, Z., & Xu, G. (2022). Future smart cities requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, *129*. https://doi.org/10.1016/j.cities.2022.103794

Khorov, E., Kiryanov, A., & Krotov, A. (2019). Cloud-based management of energy-efficient dense IEEE 802.11ax Networks. *2019 IEEE International Black Sea Conference on Communications and Networking, BlackSeaCom 2019*. https://doi.org/10.1109/BlackSeaCom.2019.8812787

Khorov, E., Kiryanov, A., Lyakhov, A., & Bianchi, G. (2019). A tutorial on IEEE 802.11ax high efficiency WLANs. *IEEE Communications Surveys and Tutorials*, *21*(1). https://doi.org/10.1109/COMST.2018.2871099

Khorov, E., Levitsky, I., & Akyildiz, I. F. (2020). Current Status and Directions of IEEE 802.11be, the Future Wi-Fi 7. *IEEE Access*, *8*, 88664–88688. https://doi.org/10.1109/ACCESS.2020.2993448

Kurungadan, B., & Abdrabou, A. (2022). Using Software-Defined Networking for Data Traffic Control in Smart Cities with WiFi Coverage †. *Symmetry*, *14*(10).

https://doi.org/10.3390/sym14102053

Mondal, M. A., Khongjoh, S., & Hussain, M. I. (2023). RAW Optimization of IEEE 802.11ah Networks. *2023 4th International Conference on Computing and Communication Systems, I3CS 2023*. https://doi.org/10.1109/I3CS58314.2023.10127498

Pahlavan, K., & Krishnamurthy, P. (2021). Evolution and Impact of Wi-Fi Technology and Applications: A Historical Perspective. In *International Journal of Wireless Information Networks* (Vol. 28, Issue 1). https://doi.org/10.1007/s10776-020-00501-8

Park, E. C., Kim, P. Y., Choi, C. H., & So, J. (2007). Improving quality of service and assuring fairness in WLAN access networks. *IEEE Transactions on Mobile Computing*, *6*(4). https://doi.org/10.1109/TMC.2007.53

Pedro García Márquez, F. (2021). Introductory Chapter: Internet of Things. In *Internet of Things*. https://doi.org/10.5772/intechopen.98268

Qu, Q., Li, B., Yang, M., Yan, Z., Yang, A., Deng, D. J., & Chen, K. C. (2019). Survey and Performance Evaluation of the Upcoming Next Generation WLANs Standard - IEEE 802.11ax. *Mobile Networks and Applications*, *24*(5). https://doi.org/10.1007/s11036-019-01277-9

Qureshi, I. A., Asghar, S., & Noor, M. A. (2023). FuCWO: a novel fuzzy-based approach of contention window optimization for IEEE-802.15.6 WBANs. *Applied Intelligence*, *53*(10). https://doi.org/10.1007/s10489-022-04001-5

Saha, C., & Dhillon, H. S. (2019). Interference Characterization in Wireless Networks: A Determinantal Learning Approach. *IEEE International Workshop on Machine Learning for Signal Processing, MLSP*, *2019-October*. https://doi.org/10.1109/MLSP.2019.8918912

Schulz, P., Matthe, M., Klessig, H., Simsek, M., Fettweis, G., Ansari, J., Ashraf, S. A., Almeroth, B., Voigt, J., Riedel, I., Puschmann, A., Mitschele-Thiel, A., Muller, M., Elste, T., & Windisch, M. (2017). Latency Critical IoT Applications in 5G: Perspective on the Design of Radio Interface and Network Architecture. In *IEEE Communications Magazine* (Vol. 55, Issue 2).

https://doi.org/10.1109/MCOM.2017.1600435CM

Shen, Q., Liu, J., Yu, H., Ma, Z., Li, M., Shen, Z., & Chen, C. (2013). Adaptive cognitive enhanced platform for WBAN. *2013 IEEE/CIC International Conference on Communications in China, ICCC 2013*. https://doi.org/10.1109/ICCChina.2013.6671208

Simsek, M., Aijaz, A., Dohler, M., Sachs, J., & Fettweis, G. (2016). 5G-Enabled Tactile Internet. *IEEE Journal on Selected Areas in Communications*, *34*(3). https://doi.org/10.1109/JSAC.2016.2525398

Sural, A., Sezer, E. G., Ertugrul, Y., Arikan, O., Arikan, E., Downconverter, G. R. F., Soret, B., Leyva-Mayorga, I., Röper, M., Wübben, D., Matthiesen, B., Dekorsy, A., Popovski, P., Rostami, S., Saad, W., Hong, C. S., Prediction, P., Adaptation, L., Statistical, B. O. N. A., … Kudla, C. (2019). Spatial Resource Allocation in Massive MIMO Communication : From Cellular to Cell-Free. *2018 IEEE Global Communications Conference, GLOBECOM 2018 - Proceedings*, *2019*(1).

Tramarin, F., Luvisotto, M., Willig, A., & Yu, K. (2021). Guest Editorial: Industrial Cyber-Physical Systems - New Trends in Computing and Communications. In *IEEE Transactions on Industrial Informatics* (Vol. 17, Issue 5). https://doi.org/10.1109/TII.2020.3033818

Tuptuk, N., & Hailes, S. (2018). Security of smart manufacturing systems. *Journal of Manufacturing Systems*, *47*. https://doi.org/10.1016/j.jmsy.2018.04.007

Wang, T., & Lu, G. (2021). Demonstrating the impact of Band Gap Modilation on Semiconductor Metal Oxide Gas-sensing Performance. *ECS Meeting Abstracts*, *MA2021-01*(63). https://doi.org/10.1149/ma2021-01631693mtgabs

Wilhelmi, F., Barrachina-Muñoz, S., Cano, C., Selinis, I., & Bellalta, B. (2021). Spatial Reuse in IEEE 802.11ax WLANs. *Computer Communications*, *170*, 65–83. https://doi.org/10.1016/j.comcom.2021.01.028

Wollschlaeger, M., Sauter, T., & Jasperneite, J. (2017). The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. *IEEE Industrial Electronics Magazine*, *11*(1). https://doi.org/10.1109/MIE.2017.2649104

Zhang, Y., Mohammadpour Shotorbani, A., Wang, L., & Mohammadi-Ivatloo, B. (2021). Enhanced PI control and adaptive gain tuning schemes for distributed secondary control of an islanded microgrid. *IET Renewable Power Generation*, *15*(4). https://doi.org/10.1049/rpg2.12074

APPENDIX

A.1 DRL Agent Training (Python-MATLAB Integration)

Purpose: Train DRL agent to optimize 802.11ax parameters.

Environment: MATLAB 2024a + Python 3.9 (TensorFlow 2.8).

```
# File: drl_agent.py
import tensorflow as tf
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from collections import deque
import numpy as np
import random


class DQNAgent:
  def __init__(self, state_size, action_size):
    self.state_size = state_size  # [SINR, node density, traffic load]
    self.action_size = action_size  # [CW, MCS, Tx power]
    self.memory = deque(maxlen=2000)
    self.gamma = 0.95  # Discount factor
    self.epsilon = 1.0  # Exploration rate
    self.model = self._build_model()


  def _build_model(self):
    model = tf.keras.Sequential([
      Dense(24, input_dim=self.state_size, activation='relu'),
      Dense(24, activation='relu'),
```

```
            Dense(self.action_size, activation='linear')
        ])
        model.compile(loss='mse', optimizer=Adam(learning_rate=0.001))
        return model

    def act(self, state):
        if np.random.rand() <= self.epsilon:
            return random.randrange(self.action_size)  # Explore
        act_values = self.model.predict(state)
        return np.argmax(act_values[0])  # Exploit
```

A.2 MATLAB IIoT Environment Setup

Purpose: Simulate dense IIoT network with interference.

```
% File: iiot_environment.m
% Initialize 81-node network
numAPs = 27; numSTAs = 54;
roomDims = [10, 10, 3]; % meters

% Configure devices
apConfig = wlanDeviceConfig(Mode="AP", MCS=2, TransmitPower=10);
staConfig = wlanDeviceConfig(Mode="STA", MCS=1, TransmitPower=10);

% Generate random positions
[apPositions, staPositions] = hGetIDsAndPositions(roomDims, numAPs, numSTAs);
```

```
% Rician fading channel
channel = comm.RicianChannel(
    "KFactor", 3,
    "SampleRate", 20e6,
    "PathDelays", [0 1e-6],
    "AveragePathGains", [0 -3]);
```

A.3 Contention Window Optimization

Purpose: Dynamic CW adjustment using DRL rewards.

```
% File: cw_optimization.m
function [newCW] = optimizeCW(currentState, agent)
    % Input: currentState = [collisionRate, throughput, latency]
    % Output: newCW ∈ [15, 1023] slots

    action = agent.act(currentState);
    % Map action to CW values (linear scaling)
    newCW = round(15 + (action / 9) * (1023 - 15));
end
```

A.4 Throughput-Latency Trade-off Calculation

Purpose: Objective function for DRL training.

```
# File: objectives.py
import numpy as np

def reward_function(throughput, latency, alpha=0.7):
    """
```

```
alpha: Weight for latency (0.7 = prioritize latency reduction)

"""

norm_throughput = throughput / 2.5e9  # Normalize to max theoretical

norm_latency = 1 - (latency / 100e-3)  # 100ms worst-case

return (alpha * norm_throughput) + ((1 - alpha) * norm_latency)
```