Automated Management of Radio Spectrum and Transmission Power in Heterogeneous Shared Spectrum Networks

PhD Thesis

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Abstract

The huge benefits of internet connectivity and the impact of communication on human existence make connectivity extremely important in today's world. Digitization has impacted education, health, commerce, and governance and recently ignited the fourth industrial revolution. Increased demand for wireless communication services has driven the need for cheaper wireless telecommunication infrastructures and affordable connectivity, which are some of the benefits of dynamic spectrum access (DSA) technologies.

DSA technologies' spectral maximization uses the spectrum-sharing paradigm that allows a timed or space shared use of spectrum. This permits a central spectrum coordination of vertical (unequal priority) access fixed nodes and a device-based (distributed) coexistence management of equal priority (horizontal) sharers. A detailed study of distributed coexistence management techniques/protocols revealed that flexible spectrum access is achieved when devices use similar techniques/protocols (homogeneous networks) and when this is not the case (heterogeneous networks) there is a huge contention for limited spectrum. Furthermore, homogeneous and heterogeneous networks suffer contention when the number of available resources is fewer than the number of requesting radios.

This thesis investigates the coexistence management of unequal priority of typical DSA systems in two countries and highlights spectral availability in the two nations. It quantifies the impact of government policy on spectral availability. It also bolstered the huge information overload necessary for existing central coordination systems and the challenge of coexistence management of dynamically located radios.

This work further addresses the high contention among dynamically located radios (nodes/base stations/access points), operating as equal priority users, for limited available spectrum and the huge information overload in central coordination by framing a central artificial intelligence (AI) algorithm for optimal resource assignment to dynamically located nodes. Its Artificial Intelligence models (trained Reinforcement learning algorithms) are designed to optimize the reuse of spectrum at different transmitter power levels among such nodes while simultaneously limiting interference among them. These minimize inter-device interference and maximize their signal-to-noise plus interference ratio (SINR), enabling spectral overlay, underlay, and reducing information overhead. Thus permitting more equal access devices to share resources without harmful interference.

Two AI models, a two-stage optimization RL algorithm (TSA) and a joint optimization RL algorithm (JOA), are designed to solve the optimization problem and learn to assign spectrum and power resources to devices. The TSA used two reward functions, while the JOA used a single reward function to arrive at optimal solutions. These were compared with DSA's random and recursive resource assignment. Two indices assessed the number of nodes with good SINR experience (assignment performance) when two to four available channels were assigned to 3 to 8 radios or nodes. The TSA and random assignment were inconsistent in providing nodes with good quality of service (fair assignment) and a reasonable request performance (assigning resources to requesting nodes). The JOA model resulted in a close to exclusive (ideal) resource assignment in its assignment performance and was at par with device requests with the two staged and random assignments in most scenarios examined. JOA, therefore, resulted in an average of 20% increase in request assignments as against exclusive assignments and an above 20% in assignment performance compared with other techniques in all network scenarios examined.

These performance outcomes are helpful in shared spectrum technologies that adopt a random or recursive approach in resource assignment. An AI algorithm can improve the quality of service and number of nodes using limited available resources at the request instance. It is also valuable for regulators, as intelligent resource sharing can increase the number of nodes that share resources. In these scenarios, the node's properties provided individualistic resource assignment, while the predictive algorithm provided an instantaneous search for optimal resource sharing. Thus taking advantage of nodes' ability to accommodate a level of interference. Future works include improving the state space RL optimization formulation and training episodes. Also, advancements in deep Q-learning may solve increased state space dimensions, reducing the effect of state space approximation.

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Chapter 1

Introduction

According to the United Nations (UN), over one-third of the world's population is unconnected to the internet. Global connectivity remains a priority in its Vision 2030, accelerating digital inclusive connectivity that facilitates nations to profit from the economic, social, industrial, and medical benefits of digitization [1]. At the heart of the action plan of the UN is the need for affordable connectivity, and wireless technologies will play a key role in achieving this. Continued improvement in wireless technologies makes connectivity of rural and hard-to-reach areas cost-effective, especially when high-performing technologies are extended to lower bands [2]. Automating spectrum coordination in such bands promotes affordable wireless communication by excluding the high cost of physical wires and managing timely access to frequency [3].

This thesis designs an automated spectrum coordination system for such bands using artificial intelligence algorithms and quantifies the resulting improvement. This is done to improve resource sharing in Dynamic Spectrum Access (DSA) technologies that have been used for rural connectivity and provide new licensing and spectrum coordination opportunities for future shared spectrum systems. DSA systems have been recommended [4] and used at lower bands to provide affordable connectivity to hard-to-reach areas [5]. It has also been used in the 1G to 7GHz band to provide instantaneous access to the internet for broadcast and other low-latency IoT applications. [6]

Automated spectrum coordination has become imminent with increased use cases for shared spectrum by IoT devices in the 4th industrial revolution [7] and 5G standalone or private networks (pop-up networks). The growing demand is evident in using 5G pop-up networks for event broadcasting since 2021 when the first successful trial was conducted at MotoGP (Silverstone, UK) for a bike race. It was subsequently tried in 2022, at the Premiership Rugby matches (at the StoneX stadium, UK), Fleadh Cheoil Traditional Music Festival in Mullingar, and National Ploughing Championships in Ratheniska, Ireland, the Pitlochry Highland Games, Perthshire, and the Queen's departure in Scotland, and at the Danish General Elections, Copenhagen, Denmark [6]. This was further explored at the King's Coronation in London, UK in 2023 [8] and the first full-scale deployment of 21 cells at 5 sites at the 2024 Olympics in France [9]. These use cases established the potential for shared spectrum to support broadcasting at large events, supplementing public wireless networks and connecting hard-to-reach locations. These use cases are anticipated to continue to grow, with an increased need for spectrum management (licensing) of shared spectrum.

1.1 Research Background

Advancements in wireless communication have facilitated the efficient use of radio spectrum for various services. Spectral resources are coordinated among services in different nations internationally by the International Telecommunication Union (ITU) to prevent inter-service and inter-nation interference. Services such as air traffic communication, radio and television broadcasting, naval navigation, etc, are allocated different operating frequencies in nations. This is generally known as fixed or exclusive resource/spectrum sharing [10].

Growth in these services resulted in a high demand for spectrum/Channels/Frequencies. Therefore, Spectrum became a commodity sold by government regulatory bodies to service providers as spectrum licenses for spectrum use in specific areas and periods. These spectral resources are underutilized in countries where ITU's allotted services for predefined spectra are non-existent or are scarcely used. Similarly, this fixed allocation of spectrum for long periods stifles the use of better spectrum-efficient technologies and dynamic reuse of spectrum [11]. Finally, licensed service providers in predefined areas sometimes never deploy these services, rendering their licensed spectrum spatially unused [10]. A solution that enables flexible or shared use of spectral resources is proffered by the Dynamic Spectrum Access (DSA) framework in low and high bands [12–17].

The DSA framework enables licensed owners or Primary Users (PUs) of spectrum for specific services to share this resource with other Secondary Users (SUs). This spectrum-sharing attribute permits multiple services to share spectrum at the same space and time, allowing the opportunistic use and reuse of spectrum, thus maximizing spectral resources [18]. This non-exclusive access to spectrum/channel by SUs results in a loss of spectral certainty, which most service providers require for continuous services supply [19,20]. However, it can be argued that other services, such as pop-up private 5G networks (used for live broadcasts at public events), unmanned aerial vehicles (UAVs), and IoT networks, can use spectrum temporarily for their services. Thus, permitting the use of fixed spectrum and shared spectrum to serve a wide range of services. This was adopted by the United Kingdom's Shared Access License (SAL), which permits the shared use of spectrum with licensed operators in locations where licensed users are not deployed [17, 21]. This enabled the support of more service vendors and maximized spectral usage [22].

Spectrum licensing strategies have, therefore, evolved to suit technological and service evolution. This evolution has triggered a need for a change in SUs licensing structure. As the long-timed auctioning and delayed licensing scheme for fixed-located PUs service providers will not suit temporarily located SUs. These long licensing periods and processes suit PUs who need exclusive access and are a bottleneck for some SUs in need of instantaneous spectral access [19]. Satisfying these varied SUs' diverse spectral demands by regulators is increasingly challenging, as old techniques adopted for static PUs are ineffective for dynamic SUs. Coexistence management strategies adopted in shared spectrum technologies can, therefore, be extended to regulatory policies and vice versa.

The shared spectrum paradigm has been adopted in technologies such as Television White Space (TVWS), Citizen Broadband Radio Service (CBRS) in the United States of America, and WiFi 6e and by regulators (in the UK) for spectrum coordination and licensing. Although TVWS and CBRS use shared spectrum concepts, they operate at different frequencies and possess similar architecture shown in Fig. 1.1. A common feature is their spectrum management system, adopted as a Geolocation database in TVWS, extended in CBRS as a Spectrum Access System (SAS), and Automatic Frequency Coordination (AFC) in WiFi 6e. The spectrum management system is responsible for spectrum coordination among coexisting PUs and SUs. It uses a central database approach for PU-to-SU interference mitigation and a central and distributed approach for SU-to-SU interference management. Thus, PUs maintain their exclusive access to channels and share unused licensed spectrum with SUs safely [23]. The temporary use of spectrum by SUs is not protected from interference by other devices.

The lack of SU protection is worsened by the explosive demand for wireless connectivity in the fourth industrial revolution and the increased need to connect devices and machines to the internet. This leads to a more significant contention among SUs for limited available shared spectrum, thus accentuating the need to better manage scarce spectrum among SUs [24]. There have been various suggestions on minimizing interference effects while maximizing resources, especially among SUs in share spectrum networks. These include increasing the distance between such devices, coding the signals from each device (hardware dependent), reducing the transmission power, fixed/exclusive frequency sharing, or timed frequency sharing approach [10]. Irrespective of the approach adopted, the need to optimize spectral resource reuse while managing other constraints is pertinent in the coexistence management of many unique SUs.

Also, deploying heterogeneous and homogeneous networks is necessary to support a wide range of applications. Future networks deploy different sizes of networks and utilize different devices with dissimilar protocols (heterogeneous networks) [25]. These futuristic heterogeneous networks consist of many wireless radios having exclusive and non-exclusive spectral needs that change over time and, as such, require unique coordination for sharing limited available spectrum. The dynamic nature of shared spectrum networks, in terms of evolving spectral resources and dynamic SUs' specifications and locations, means that conventional resource management techniques may fail in such networks.

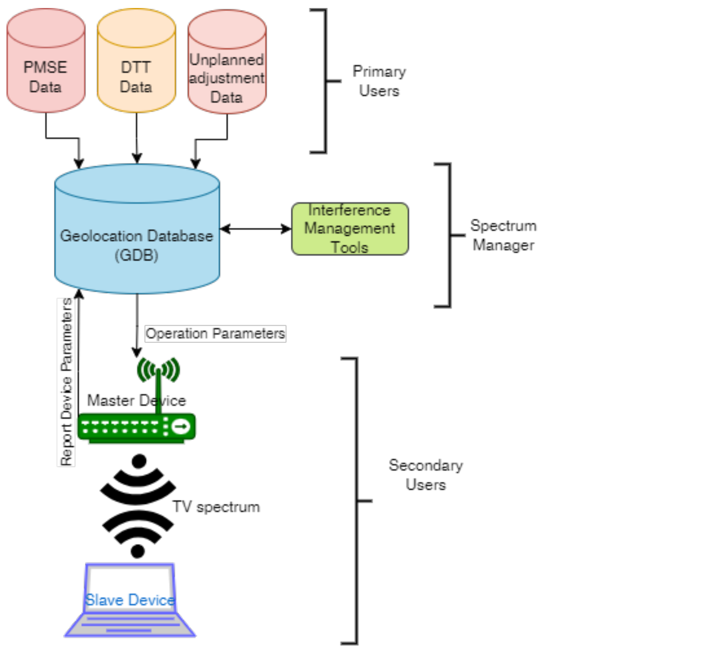
Conventional spectrum-sharing management schemes require strict avoidance of harmful interference to PUs, as stipulated by most regulations [13]. However, coexistence management entities leave SUs to coordinate their coexistence among themselves while reporting their actions to a central database. Therefore, there is a pressing need to protect SUs who share spectrum with PUs by providing a close to exclusive resource availability, as this increases their performance and temporal spectral certainty. The existing TVWS architectures do not proffer exclusive protection or frameworks for SUs' protection [13, 26, 27]. The CBRS architecture provides a three-tiered protection comprising Incumbent (PUs), Priority Access Licensed (PAL) SUs, and General Authorized Access (GAA) SUs as shown in Fig. 1.1 [28]. Incumbent users, like PUs in TVWS, are protected by the database system, giving them exclusive spectral access. PAL, paying SUs, are given a priority level with a higher degree of spectral certainty and protection by SAS from GAAs. In contrast, GAAs, with the least priority, are not protected [29–31]. Therefore, CBRS' GAA and TVWS SUs suffer from high spectral uncertainty and interference in both CBRS and TVWS systems.

Internal interference management techniques or protocols accomplish coexistence management among SUs in TVWS and GAA users in CBRS [14, 31]. In these protocols, devices or radios are configured to listen to other users in a channel before accessing it. These protocols include beacon frames adopted in Wireless Regional Area Network devices, Wireless Local Area Networks, and Wireless Personal Area Networks. Beacons use carrier sensing and multiple access (CSMA) mechanisms similar to the listen-before-talk mechanism. These mechanisms prevent the collision of SUs when sharing a channel simultaneously. These protocols are hardware-dependent, and adaptive radios can be designed with different interference-limiting protocols [32]. When radios/nodes/base stations use different protocols (heterogeneous networks), internal spectrum coordination becomes challenging.

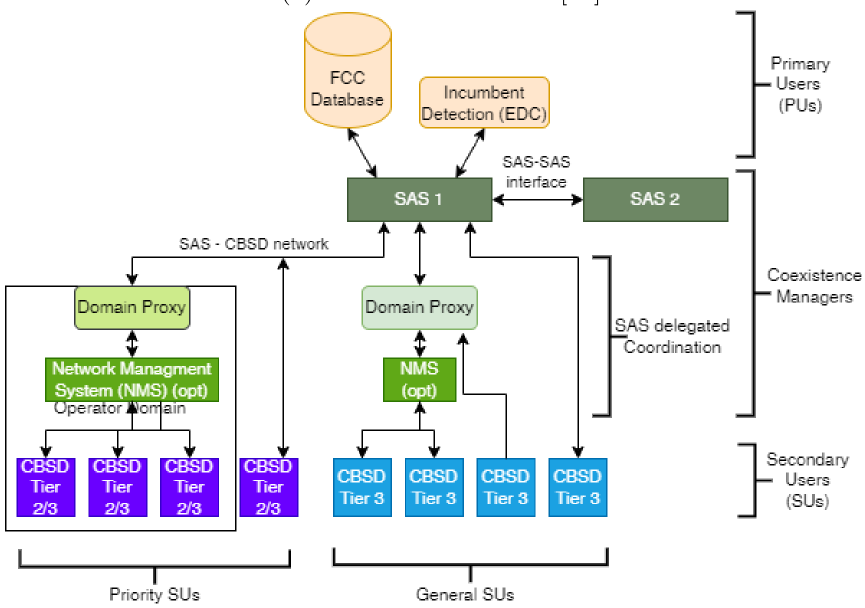
A method to improve shared spectrum coordination is a database and real-time monitoring/sensing for PUs protection [33, 34]. Some suggestions for heterogeneous shared spectrum management systems have been studied in [35–37]. A coexistence management entity was proposed for shared spectrum networks (DSA systems), and guidelines for designing communication protocols and spectrum management algorithms were proposed for CBRS and TVWS networks in IEEE 802.19 documentation [38]. The CBRS architecture incorporates a coexistence manager entity within the SAS framework [31], providing a detailed role of managing spectral resources to SAS registered and non-registered CBRS devices (CBSDs).

However, the IEEE 802.19 documentation's guidelines were algorithms not implemented, and similar to other suggested works, are restricted to timed spectrum sharing amongst radios (known as spectrum overlay). This guideline should have considered scenarios with many SUs demanding few available spectrum. Also, it does not account for the unique demand of SU's nodes/radios or their ability to coexist with other SUs, accommodating a level of interference (called spectrum underlay). Such unique use cases of SUs requiring temporary or non-exclusive spectrum and interference resilience are not catered to. Their suggestions, however, lay the foundation for improving the capabilities of the coexistence manager entity to intelligently optimize spectral resources for all SUs. This is especially important as shared spectrum technologies become an alternative to connecting the projected high number of wireless devices.

Spectrum allocation techniques can be improved to make real-time spectrum and power allocation, allowing multiple radios to use the same spectrum, in different locations at the same time. Thus, SUs reuse available PU spectral gaps in real time using overlay and underlay spectrum techniques. The effectiveness of spectrum management becomes critical as several SUs with different quality of service requirements try to access the limited spectrum from diverse locations. Learned algorithms, therefore, provide close to real-time adjustments, making them a plausible coordination option [39]. Machine learning algorithms have been explored in improving shared spectrum coexistence manager's responsiveness to real-time demands of its DSA network [40–42], and learn from datasets to make decisions on future data. They are generally categorized into supervised, unsupervised, and reinforcement learning algorithms. Each category has been explored in improving dynamic spectrum access systems [43–45]. However, decision-making reinforcement learning algorithms are better suited for DSA intelligent



(a) TVWS architecture [13]



(b) CBRS architecture

Figure 1.1: High-level architecture of CBRS systems and TVWS

coexistence management tasks.

Reinforcement Learning (RL) algorithms can learn from a network's changing states and decide on specific actions. Distributed spectrum coordination studies on maximizing spectrum allocation using reinforcement learning have shown that models can be built to adapt to real-time changes in a network [39,46–48]. These studies evaluated the optimization algorithms based on their ability to arrive at convergence and improved throughput. It is evident that when deployed, there lies a high probability that, irrespective of the changing size of the network, a learnable resource allocation algorithm capable of optimal assignment is possible.

Adaptable algorithms capable of learning have been developed to optimize spectrum allocation in cellular systems [47,49–51], cognitive networks [52,53], DSA cellular systems [25,54,55] and DSA networks [56]. These algorithms focused on protecting PUs from SUs and improving the distributed allocation of resources by SUs. Other spectrum allocation and power optimization RL algorithms were investigated in controlled environments where limited or fixed power limits, few SUs, and fixed available spectrum were assumed. Others explored cell, channel, and modulation selection, and limited studies explored spectrum reuse [57] or joint optimization of spectrum and power for optimal spectral reuse.

RL algorithms have been explored mainly in cellular systems that operate at high frequencies. However, the deployment at lower bands where terrain parameters alter the overall interference status of networks has yet to be explored. Current research in spectrum management in DSA has focused on distributed/decentralized or autonomous coexistence management among static or mobile SUs. It assumed that RL algorithm agents were in these UEs, influence parameters used in designing the RL algorithms environment. These parameters were not available to the central RL coordinating resources for shared spectrum networks. Also, previous central studies examined only equal-priority homogeneous networks. This thesis provides an in-depth understanding of the structure of decisions made in these existing research and identifies that the location of an RL agent redefines its possible Markov Decision Problem (MDP). To address spectrum and power allocation to equal priority users (SUs) at lower bands;

Assign resources to SUs/nodes that are not mobile or static but need access to spectrum instantaneously and intelligently; and contribute to intelligent central coordination; this thesis designs an intelligent resource management system that optimally shares resources among continuously location-changing heterogeneous nodes.

The unique contribution of this thesis is the development of a central RL-trained model that is implemented in a representative DSA system. To the best of the author's knowledge, learning algorithms that mitigate SU-to-SU interference in a dense heterogeneous DSA network have not been modeled or implemented at lower bands. It established the quantitative impact of adopting intelligent spectrum management techniques in increasing the number of SUs while reducing their contention for limited spectral resources. This thesis seeks to establish the protection of PUs from SUs using a designed database system and develops a central intelligent coexistence manager for SUs in a DSA heterogeneous network, a principle that can be extended to higher bands.

1.2 Research Aims and Objectives

This thesis aims to expand the coexistence manager's capabilities in intelligently optimizing spectrum and transmission power allocation and reuse among competing equal-priority heterogeneous radios. Thus creating adaptive spectrum management in a dense DSA network and increasing the number of supported devices or radios. The existing DSA management schemes, such as TVWS's first come first serve (random) and CBRS recursive approaches, do not support intelligent optimal channel re-use, but instead support rationing of the spectrum [31, 38, 58]. Similarly, SU nodes do not have fixed locations as PUs, hence existing algorithms for static PU management are not suitable for SU coexistence management.

This thesis, therefore, proposes two novel RL coexistence management reward functions that are adaptable to changes in a DSA network. It presents a novel model that learns from a DSA network's SUs locations to optimize spectrum and power resource assignment. Thereby maximizing the number of operating SUs' nodes while minimizing their interference. The specific objectives of the project are:

1. To design and evaluate the end-to-end implementation of a Dynamic Spectrum Access (DSA), assessing its performance in spectrum utilization and optimization. The purpose of this was to understand the database and other resource coexistence management techniques and to assess and identify areas in which its performance can be improved.

2. To build a simulated Dynamic Spectrum Access (DSA) network that serves as a neutral test bed for comparing the performance of existing iterative random and recursive coexistence management techniques with intelligent models.

3. To develop an intelligent model capable of real-time learning of a wireless communication network's architecture and adapting its weights to optimize spectrum utilization amid constraints of interference and transmitter power limits in a dense heterogeneous DSA network.

4. To justify the need for intelligent networks by quantifying and comparing the performance of the designed intelligent model with existing models in assigning resources to SUs of a heterogeneous DSA network.

5. To establish use cases for adopting intelligent spectrum management.

1.3 Original Contributions

1. A detailed review of the literature on coexistence management approaches in DSA networks is presented in Chapter 2. This review differs from previous literature reviews, as it identifies industries' perceptions of the challenges of adopting DSA/share spectrum frameworks. An up-to-date RL and non-RL approaches to resolving these issues are also addressed, showing the limited central RL approaches in Chapter 3. Thus identifying gaps in the implementation of intelligent coexistence coordination approaches. This contributes to understanding other coexistence management methods in specific objective 1 of section 1.2.

2. In Chapter 4, an end-to-end DSA system is designed for two locations to ascertain its spectrum utilization and optimization in a developed and a developing

country. An examination of the level of protection given to PUs in the developed country's design was published in [59] (section 1.3.1 research output). The details of the design for a location in a developing country highlight the methodology adopted and the impact of the country's policy on spectrum utilization; this was published in [60] (section 1.3.1 research output). These peer-reviewed publications contribute to achieving specific objective 1 in section 1.2.

3. In Chapter 5, an illustrative heterogeneous DSA network comprising IEEE 802.11 and IEEE 802.22 base stations and access points (nodes) is designed and simulated. The nodes had different specifications and were assumed to use different protocols for interference control. This served as a testbed for random, recursive, and novel models' resource allocation, contributing to specific objective 2 in section 1.2.

4. Also, in Chapter 5, a novel two-staged Q-learning optimization allocation algorithm and deep Q-learning algorithm are designed for power and spectrum allocation. The intelligent model is designed to optimize two cost functions: maximize the spectrum reuse and minimize interference between SUs. The outcome and performance of the first novel Q-learning algorithm are published in [61], and a comparison of designed coexistence methods' (random and recursive algorithms) performance was presented in [62]. These contribute to specific objective 3 in section 1.2.

5. In chapter 6, a summary of the designed intelligent algorithms' performance is presented and assessed based on the number of devices allocated resources and SUs' quality of service. The assignment algorithms are all compared based on their convergence, quality of service, consistency, and scalability. Four metrics assessed the scalability of the intelligent and other resource allocation algorithms, quantifying the impact of adopting intelligent coexistence management techniques in DSA systems. Thus, it contributes to specific objective 4 in section 1.2.

6. The final application and use cases of the model in DSA and shared spectrum networks are discussed in Chapter 7, contributing to specific objective 5 in section

1.2.

1.3.1 Research Outputs

The research was disseminated in the following publications and conferences:

Peer-Reviewed Publications

1. E. Atimati, D. Crawford and R. Stewart "Intelligent Joint Resource Management of Shared Spectrum HetNets", IEEE Future Networks World Forum, Dubai, Oct. 2024. Presented.

2. E. Atimati, D. Crawford, R. Stewart, I. Achumba, L. Ezema, and U. Diala, "An Interference Management System for a Shared Spectrum Access Network," Proceedings of 2022 IEEE Niger 4th Int Conf Disruptive Technol Sustain Dev NIGERCON 2022, doi: 10.1109/NIGERCON54645.2022.9803165.

3. Louise H. Crockett (Editor), David Northcote (Editor), Robert Stewart (Editor), Douglas Allan, Ehinomen Atimati, Kenny W. Barlee, Lewis J. Brown, James Craig, Graeme Fitzpatrick, Joshua Goldsmith, Andrew Maclellan, Lewis D. McLaughlin, Blair McTaggart, Tawachi Nyasulu, Marius Šiaučiulis, David Crawford, "Software Defined Radio with Zynq Ultrascale+ RFSoC". (Book), Strathclyde Academic Media, January 2023,https://www.rfsocbook.com/.

4. E. Atimati, David Crawford and Robert Stewart, "Intelligent Shared Spectrum Coordination in Heterogeneous Networks", IEEE Virtual Conference on Communication, Nov 2023, doi:10.1109/VCC60689.2023.10474686.

Poster Presentation

1. E. Atimati, D. Crawford, and R. Stewart, "Shared Spectrum Coordination in a heterogeneous IoT network," in IEEE Communication Theory Workshop, 2022.

Abstract Submission

1. E. Atimati, D. Crawford, and R. Stewart, "Towards an Automated Spectrum Access Management Scheme for Improved Rural Connectivity.," in Doctorial School Multidisciplinary Symposium (DSMS) 2020 Proceedings, June 2020.

1.4 Thesis Organization

A summary of the organization of this thesis is provided in the Fig. Chapter 2 discusses, in detail, the concept of Dynamic Spectrum Access, its architecture, and the framework for the coexistence management of SUs under different lower band standards. It also reviews existing resource management challenges and the proposed solutions from the research community. This sets the scene for the design of an end-to-end DSA system in Chapter 4 as described in Fig. 1.2. It also highlights the unique device-dependent protocol for SU-to-SU coordination and its limitation in managing heterogeneous networks.

Chapter 3 introduces different arms of machine learning (ML), its applications, and challenges in DSA systems. It launches a detailed review of reinforcement learning algorithms' (RL) approaches to resolving the DSA issues. It classifies RL spectrum management automation suggestions based on their suitability in solving industry concerns of adopting DSA frameworks. It thus establishes the research gap in implementing central RL-based coordination in DSA systems. This informs the designs of the DSA optimization problem in Chapter 5 as shown in Fig. 1.2.

Chapter 4 explores the process for designing and simulating a representative DSA system to study spectrum coordination and interference prevention among PUs and SUs. It measures spectrum availability and quantifies the impact of policy on spectral utilization in developed and developing countries. Understanding PU-to-SU coexistence management reveals the unique challenge of heterogeneous SUs' coordination. Thus, it establishes the importance of coexistence managers' assignments when implementing overlay and underlay spectrum sharing.

Chapter 5 describes the design and simulation of an illustrative heterogeneous DSA network that examines the performance of different resource allocation schemes. It also details the design of coexistence management algorithms adopted in existing DSA systems and two novel reinforcement learning algorithms. The central coexistence management approach of SU-to-SU coexistence management in existing DSA systems is mimicked in a typical heterogeneous DSA network, and its flaws are quantified. So,

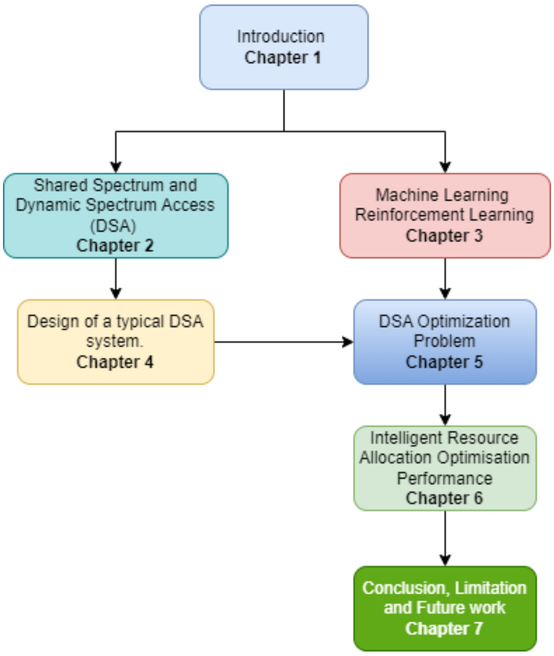


Figure 1.2: Thesis Organization

it is essential to know how important it is to use existing database information for improved DSA coexistence management.

Chapter 6 evaluates the novel resource assigning models' convergence and consistency in adapting to changing networks while maintaining good SUs' quality of service. Two metrics, assignment performance and requests performance, assess all designed algorithms' scalability in resource assignment as the network size and available resources change. Based on the thesis objective, they measured each resource allocation algorithm's assignment of safe reuse of resources to satisfy many requesting nodes.

Chapter 7. A conclusion on intelligent coexistence management's contribution to maximizing spectrum reuse and improving DSA capacity is discussed. This showcases the measured impact of adopting artificial intelligence in DSA central coexistence management and its implications for future shared spectrum policies and deployments.

Chapter 2

Dynamic Spectrum Access Systems' Architecture

2.1 Introduction

This chapter discusses Dynamic Spectrum Access systems and their architecture in detail. The DSA architecture and structure permit multiple secondary users (SUs) radios within a network to exist in the same space and time as primary users (PUs). The Two DSA technologies discussed assign the role of spectrum management to a central database or spectrum management system. However, interference avoidance or control among SUs is achieved through the use of SU radios (distributed spectrum management).

A study of the radios' Media Access Control (MAC) protocols provides an understanding of the limitations of this coexisting management strategy. The coexistence strategies of MAC protocols in different standards investigated varied, showing its inability to coordinate Interference avoidance in heterogeneous networks.

This chapter reviews existing DSA studies on shared spectrum and takes a deep dive into challenges faced by the industry in deploying such networks. It, therefore, identifies gaps in the literature that address industry-related challenges of DSA systems.

2.2 Dynamic Spectrum Access (DSA) System Concepts and Terminologies

IEEE defines DSA as "the real-time adjustment of spectral resources to changing circumstances or objectives, such as changes in energy conservation, radio's state, interference-avoidance, environment, policies, quality of service, and operating conditions" [18]. This definition suggests a tailored allocation of resources to a network of nodes satisfying their required quality of service. The network's nodes can change in location, quality of service requirement, and operational conditions and be provided with spectral resources through interference avoidance techniques. This can be achieved by a resource coordination system that is responsive to real-time wireless network scenarios, which improves the reuse of spectrum among nodes improving spectral utilization while maintaining nodes' quality of service.

DSA is also defined as the re-use of a spectral band at a specific time and region when it is unused by another in [63]. Dynamic spectrum access can, therefore, be seen as the flexible use of spectrum by radios. It differs from the fixed spectrum access philosophy, where frequency bands are exclusively allocated for specific services in certain locations (regions). DSA was born out of advanced radio designs and the programmability of chips. This influenced the development of Software Defined Radios (SDRs)/cognitive radios [18], which were capable of changing their operating frequencies.

A fundamental property of DSA systems is their ability to adapt. This is useful in maximizing scarce spectral resources, minimizing cost, and enabling affordable connectivity. The definition in [63] provides an insight into the pragmatic resource sharing adopted by management systems in deployed DSA technologies. In these technologies, resources are shared and reused within a specific place and time between licensed/Primary Users (PUs) and secondary users (SUs). The PUs had fixed spectrum access (licensed users) in these systems, while the SUs were opportunistic users, sharers, or unlicensed users. The shared use of resources in these systems required a coordinating management system. The need for dynamic access to spectrum facilitated the shared use of spectrum and initiated the concept of shared infrastructures in the

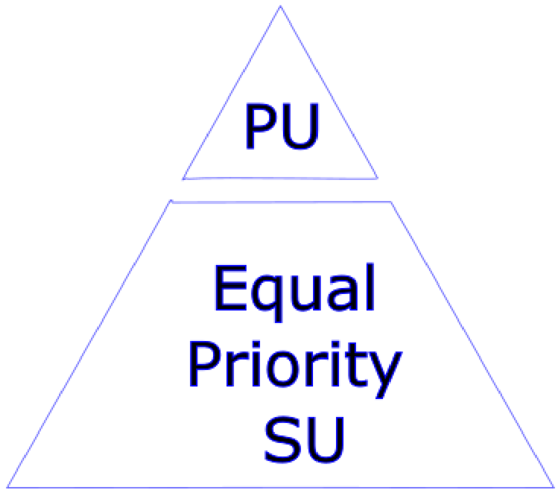


Figure 2.1: TVWS Two Tiered Resource Sharing.

telecommunication systems [10].

Deployed DSA systems can have two or three tiers. The TVWS architecture had two tiers, the licensed PUs and the unlicensed SUs, as shown in Fig. 2.1. A two-tier system shares the spectrum between licensed users and other opportunistic or secondary users (SUs), such as TVWS devices. All secondary users usually have equal access to available channels; this is termed horizontal access. They, however, have a lower priority than PUs in the use of channels; this unequal priority access to spectrum is termed vertical access [10]. In vertical access, lower-priority devices vacate the spectrum when a higher-priority device needs it.

In the CBRS architecture, there are three tiers: Incumbent (licensed users), Priority Access Licensed (PAL) users, and General Authorized Access Users (unlicensed users). Unlike the two-tier structure that had only one priority user, the three-tier structure has two priority users: the incumbent and PAL. The incumbent has the highest priority, similar to the PU in TVWS. The CBRS three-tiered structure extends the TVWS second tier of equal priority, as shown in Fig. 2.1, to include licensed SUs (PAL) with greater priority than other SUs (GAAs). It, therefore, combines vertical and horizontal access SUs, as illustrated in Fig. 2.2 [10].

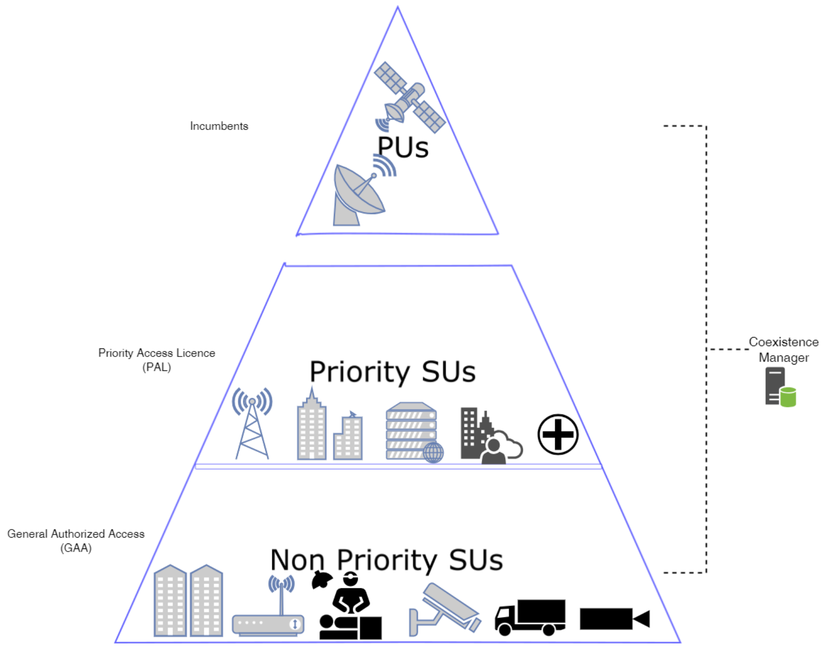


Figure 2.2: Three Tiered Resource Sharing.

2.2.1 Shared Spectrum Paradigm

The shared spectrum paradigm encompasses DSA systems and other shared spectrum concepts. Other shared spectrum concepts include the use of licensed and license-exempt spectrum. The Licensed Shared Access (LSA) of Long Term Evolution-Unlimited (LTE-U) and Wifi in the 2.4 and 5Ghz band [3] use license-exempt spectrum for communication. Each of these technologies, with equal priority, shares license-exempt bands with other technologies (horizontal access). They operate as secondary users attempting to share the license-exempt spectrum at a specific time. It can be argued that these are not typical DSA systems, as they do not necessarily need cognitive or software-defined radios and share a fixed license-exempt spectrum band. However, they are technologies that support shared spectra and have coexistence management schemes relevant to this study. This work, therefore, considers both DSA and shared spectrum techniques in studying coexistence management.

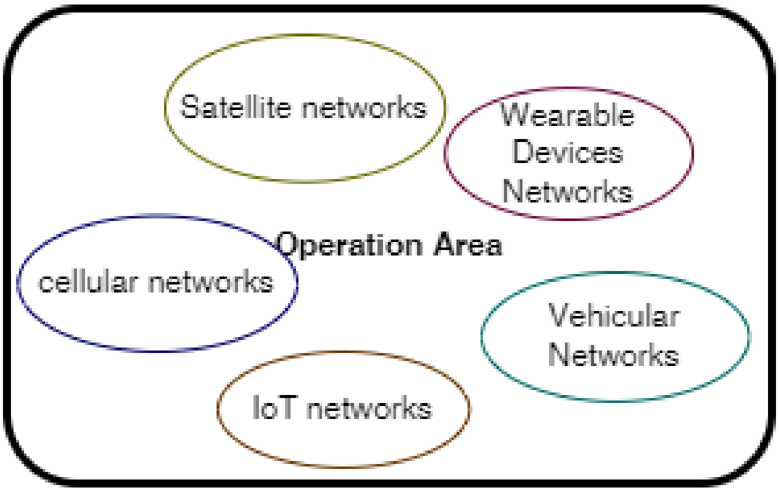


Figure 2.3: Independent Heterogeneous Networks

2.2.2 Heterogeneous and Homogeneous networks

Heterogeneous networks (HetNets) can be defined as a composition of different network standards such as cellular, satellite, and Vehicle-to-vehicle communication networks. These may use different or similar spectral bands and coexist in the same location for improved system capacity. Various Technologies can create wireless access to a communication network or specific radio technology [18]. Examples include Wireless Local Area Networks (WLAN), Long-Term Evolution (LTE), Universal Mobile Telecommunications Systems (UMTS) Terrestrial Radio Access (UTRA).

These network standards can operate independently, as in the exclusive or fixed spectrum for specific services or regions, shown in figure 2.3. They can also rely on each other for different sections of their communication links; for example, an IoT network can depend on a cellular network for back-end connection to the internet (figure 2.4). To support these diverse future communication links, spectrum coordination becomes significantly crucial in HetNets, thus needing innovative and progressive spectrum coordination solutions [25].

Homogeneous nodes that make up a homogeneous network, have media access con-

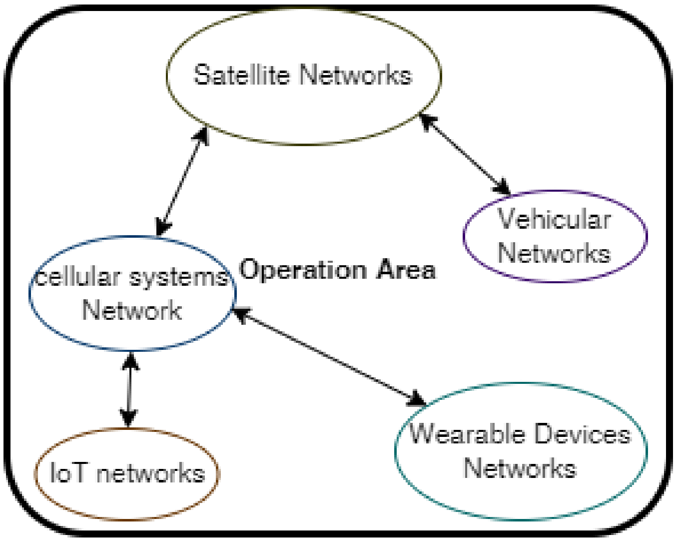


Figure 2.4: Dependent Heterogeneous Networks

trol protocols that are similar; spectrum management can, therefore, be left to devices to manage resources guided by available resources (like in TVWS). However, in heterogeneous networks with different MAC protocols, this communication is absent; as such, resource coordination needs a form of communication among these devices.

2.2.3 Fixed or Static Spectrum Allocation

Fixed or Static spectrum allocation means a fixed channel is assigned exclusively to a network's node. It also refers to the exclusive or traditional allocation of spectrum licenses to services or service providers to cover extensive areas such as states and nations for a fixed period. The issue with this method of spectrum allocation is the under-utilization of these resources in some places where the services are not used (usage exclusivity), licensed operators owning spectrum in regions they do not operate (geographical exclusivity), and obsolete licensed allocation [10]. This, however, means that licensed PUs or incumbents have exclusive access and use of the spectrum and have uninterrupted, secure, and consistent spectrum assurance for their services [64]. A typical example is in the UK, where the 87.5 to 108 MHz are assigned exclusively to broadcast (multimedia) service providers. However, the bands 470MHz to 694 MHz are shared between Broadcast, Programme Making, and Special Events (fixed site) and internet service providers [65]. This is a first step towards the Dynamic Spectrum Allocation concept, which is when licensed spectrum are allocated based on the real-time needs of service providers in a location rather than a predefined band allocation.

2.2.4 Dynamic allocation

In dynamic allocation, channel assignment/allocation varies with need, location, and network situations [20]. There is no exclusive spectrum assignment to nodes; this level of flexibility permits more SUs to utilize scarce spectral resources. Thus, making it suitable for spontaneous network scenarios. However, it trades off the resource certainty for improved spectral utilization. A hybrid form of fixed and dynamic assignment is adopted in CBRS multi-tiered architecture where PALs have exclusive access to specific available resources when an incumbent is absent [16]. Dynamically accessing the available spectrum while exclusively using it maintains a level of spectral certainty and assurance for PAL users.

2.2.5 Spectrum Sharing

Spectrum sharing is the application of technical methods or operational procedures to permit many users to coexist in a spectral space [18]. It has also been described as the cooperative use of fixed radio frequency resources by several independent entities within a specific geographical area [64]. In this work, shared spectrum pertains to technical, operational, and structural methods that support multiple smart radios' spectrum use. It encapsulates DSA technologies that leverage shared spectral space and provide coexistence techniques for similar or dissimilar priority users [63].

2.2.6 Spectrum/Resource Manager

The ability for PUs and SUs or just SUs to share spectral resources in the same space can be termed "coexistence". It has been defined as "the state of two or more radio devices or networks existing at the same time and place in a shared spectrum space" [66].

Coexistence is made possible by coexistence managers or spectrum/resource managers in DSA systems.

A spectrum or resource manager is a system administrator that specifies the coexistence policy within a wireless network; this can be a regulator or regulatory policy [18]. The spectrum/resource manager represents the role of a regulator in the network and has been adopted in TVWS as the database or SAS in CBRS systems. In other shared spectrum systems, it is performed by coexistence protocols. They can perform their spectrum coordinating role centrally, distributed, or autonomously [16, 38].

Coexistence management techniques were categorized into two broad areas, channel/spectrum coordination and MAC-dependent protocols coordination, in [67] based on coexistence approaches. However, this work categorizes coordination based on the coordinator's location in a network.

Central Spectrum Coordination

In central spectrum coordination, the decision maker is a central entity or node with access to a global information pool, with which it makes strategic channel assignment actions. An example is an intra-coexistence manager in a CBRS architecture. This can be a server, base station, access point, database, or spectrum management system, disseminating its instructions to various nodes or links on a network [16, 68].

Its access to global information achieves an optimal channel assignment, resulting in maximal network rates, fair allocations, and priority access [69]. An advantage of central optimization coordination systems is the ease of implementation in center-based networks and the fact that the PHY/MAC of users does not require enormous modifications for deployment [70].

Its drawback is the reliability of the central coordinating entity, as a failure will lead to a complete network failure. Other disadvantages include the size of information flow overhead, database access congestion from multiple requests, information pool storage, request-response speed, the accuracy of propagation models used in computation, and their complexity [69, 70]. However, the central computations can be improved with real-time measurements and identification [71]. The coordination structure can have multiple central coordinators, reducing the risk of a central failure.

The central coordination, therefore, has a higher propensity to achieve efficient resource management because of its access to global information and decisions made by all or most neighboring SUs. However, it has more overheads as it shares this large information pool with all nodes/APs.

Decentralize/distributed Spectrum Coordination

In decentralized/distributed spectrum coordination, the decision-makers can be master or slave SU that decides on channel assignment/usage based on local information. Local information use results in the sub-optimal channel utilization [68]. In a CBRS system, this is defined as an entity that decides on resources and cooperates with other decision-makers in its resource scheduling [16,38]. This has been implemented by nodes deciding on resources while having limited knowledge of other nodes' decisions through CSMA/CS protocols. In other implementations, coexistence information among nodes has a separate information link among nodes [71].

Distributed/decentralized optimization structures require limited information exchange (local information pool) from nodes in a network, reducing signal exchanges and resulting in lower overhead. It uses this limited information and MAC protocols to make optimal resource-sharing decisions [69, 72]. It, therefore, supports simultaneous spectrum access, faster discovery of available channels, and can be easily implemented [72]. However, the limited information pool in distributed optimization structures results in local optimal solutions; they also have fairness challenges as their decisions are slightly independent [69]. SUs in distributed systems' decisions can be influenced by global information; this is termed a hybrid system in this thesis.

Autonomous Spectrum Coordination

In autonomous coordination, the decision maker is an entity or node with no information or prior knowledge of other existing requesting nodes. It has been implemented as SUs taking autonomous decisions on available channels without knowing the choices of other SUs [16, 38, 73].

Hybrid Network Coordination

In a layered network, a hybrid assignment approach can be adopted. A central node, aware of all its links to other nodes, makes channel assignment decisions based on this knowledge and disseminates resources to its master devices. Slave devices can then choose resources using distributed or autonomous coordination and, as such, manage less resource contention. This is the structure adopted by SAS in CBRS and Database systems, as these use different coordination methods for resource sharing among priority users.

2.2.7 Spectrum Overlay and Underlay

Spectrum overlay is the timely and opportunistic use of spectrum when not used by other licensed/unlicensed users. It is defined as when DSA secondary users exploit spectral opportunities that do not cause interference with PU/other users [18]. It is sometimes called interweave, the time-based sharing of a channel by multiple users supported by their MAC protocols [19]. In this work, spectrum overlay is defined as when no interference exists between PUs and SUs or between SUs, such that they exclusively use an available spectrum as shown in figure 5.1.

Spectrum underlay allows for the reuse of spectrum by multiple users simultaneously, as they all operate at power levels that do not result in harmful interference. As defined in [18], spectrum underlay occurs when interference experienced by an incumbent/PU from an SU results in unharmful/non-disruptive interference.

2.2.8 Vertical and Horizontal Spectrum Sharing

Vertical spectrum sharing/access is spectrum sharing between users with unequal priority [18]. This is usually when there are multiple tiers of nodes or users with different levels of priority to spectrum. Typically, between PUs and SUs, PUs have higher priority, and SUs have less priority. Resource coordination in these systems differs from horizontal spectrum access.

Horizontal spectrum access is spectrum sharing among equal priority users. The spectral access among SUs in TVWS, is equal; that is, every SU has equal priority and access to spectrum; this is termed horizontal spectrum access. Typically, devices on the same level of priority have horizontal access, while those with unequal priority have vertical access.

2.3 DSA Architectures

The general framework for a DSA system is shared access to a spectrum by equal or unequal priority users. In DSA systems with unequal priority users, the framework usually has priority users' (PUs) transmission parameters stored in a database. This information is used to conduct real-time environment analysis around the lower priority users (SUs), enabling the shared use of PU's resources without interference. Figure 1.1 shows the framework for a TVWS and CBRS, which are specific examples of a DSA system. Although these two technologies have different tiers, as discussed in section 2.2, their coexistence management architecture is similar, and these are studied in this section.

The coexistence management strategies of these technologies are centrally managed among unequal priority users (PUs and SUs) and a distributed mechanism is adopted for equal priority users. The coexistence/spectrum managers (TVWS database) protect the static TV transmitters from SUs' interference Fig. 1.1a while CBRS' Spectrum Access System (SAS) protects Fixed Satellite Services and other incumbents from SUs interference Fig. 1.1b. The DSA framework ensures licensed PU protection and national policies expect SUs to protect themselves from PU and SU-to-SU interference [3]. Although this approach allows for the discoveries of new coexistence methods, it limits resource assurance among SUs, and becomes more challenging in heterogeneous shared spectrum networks.

In unequal priority (vertical access) central coexistence management, the TVWS and CBRS spectrum managers use the PUs parameters in computing and predicting interference levels that PUs encounter. These prediction methodologies differ based on the country's policy on such technologies. Still, they can be categorized into two strategies: calculating the distance covered by PU signals or the minimum signal strength needed at PU's receivers. There may be an argument on the efficacy of these methodologies and a dilemma of the choice of methods in shielding PUs from interference (interference discovery approaches). A general opening for further research is the absence of central spectrum coordination among SUs. However, CBRS provides a more detailed protection plan for priority SUs in their three-tiered system than TVWS's two-tiered system.

Distributed/autonomous coexistence mechanisms among equal priority users (Horizontal access) are MAC protocols and standards for sharing resources in TVWS, Licensed Assisted Access (LAA), and CBRS systems. These MAC protocols adopt CDMA/CA or listen-before-talk (LBT) protocols, allowing radios to wait for their turn to access bandwidth. Thus, it enables multiple nodes to reuse the same channel and permits timed access to the band. Other mechanisms, spatial separation and timed spectral reuse adopted in CBRS systems, are termed spectral overlay. When this is combined with transmit power consideration to improve spectral utilization, it is termed spectral overlay and underlay.

2.3.1 Television White Space Technology

The TVWS communication paradigm allows the opportunistic use of spectrum unused by licensed Television stations. These spectrum gaps exist due to the non-operation of the stations in a specific location/time or protection gaps that prevent interference between TV stations. Deployment of this technology in various countries has proved that the technology can support a reasonable data rate at affordable rates [3]. Different regulatory bodies have provided the standard architecture for the system's deployment in [14, 26, 74, 75].

TVWS architecture

The TVWS operates at the 400 to 700 MHz lower bands in most countries. The TVWS architecture comprises a master white space device (WSD), a Geolocation Database (GLD), and optional slave WSDs as shown in Fig. 1.1a. The master WSD requests

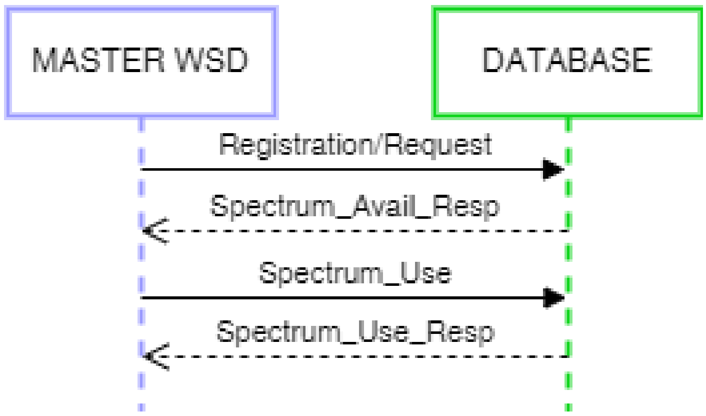


Figure 2.5: TVWS architecture.

transmission information from GLD on the available spectrum, and the database takes a log of the location of the device and informs it of operation parameters (spectrum and power limits) Fig. 2.5 [75]. The master device acknowledges receipt of this information and chooses available channels or shares them with its slave devices. It then updates the database with the channels it or its slave devices use. The master devices use these operating parameters to gain access to the internet through an existing TVWS network or by creating the network. A TVWS base station, for example, becomes the base station through which other master or slave White space devices can connect to it as shown in Fig. 1.1a. The database entity is an external system coordinator, serving as an information entity to guide telecommunication activities [76].

Coexistence Management in TVWS

The database is populated by PU and SU information obtained from registration information that regulators stipulate. A specialized protocol for this communication is known as the Protocol for Access to White Space (PAWS) [77]. This central entity then supports the coordination of spectrum and power at which the devices can safely operate without interference. A geolocation database is used to identify the free spectrum and then allocate it to SUs, thus preventing PU-to-SU interference. The role of the database, as stipulated in [14, 26], is to provide SU devices with available channels and safe power limits to coexist with PUs. It also maintains a log of requests and spectrum used by SUs [3]. It, therefore, serves as the administrator for the two-tiered system with licensed PUs and license-exempt sharers (SUs).

The TVWS system databases assume that PUs' available channels can be safely shared by SUs [26]. This assumption is correct when SUs in a specific location use a particular standard (Homogeneous networks). However, when the number of requesting homogeneous SU devices is high, there is a higher level of contention for available resources. This inhibits the MAC protocol's coordination and leads to many devices waiting to access the available spectrum.

The infusion of spectrum sharing into the IEEE 802.11, 802.15, and 802.22 standards (radio access technologies (RAT)) at TV frequency complicates resource coordination. Each RAT adopts different coordination MAC protocols for the coexistence of their devices in TV bands. Thus, a heterogeneous network is created when multiple radios compliant with different RATs are deployed in a network. To minimize contention among similar or dissimilar RATs for available resources, a central coexistence framework is necessary to share available channels safely.

2.3.2 Citizens Broadcast Radio Service (CBRS)

The CBRS is operational in the United States of America and provides 5G cellular connectivity. The UK government coordinates a similar operating frequency [17,19] to enable the shared use of the band for private (pop-up) 5G cellular networks used in broadcasting [6]. This section focuses on understanding the CBRS architecture and its coexistence management structure.

CBRS Architecture

The CBRS system operates at a 3.55 – 3.7GHz band in the United States. It enables the sharing of spectral resources with the incumbent (PU) grandfathered wireless broadband licensee, operating at 3.650 – 3.7GHz, federal radio location service operating at 3.5 – 3.7 GHz, and Fixed Satellite Service (FSS) operating at 3.600 – 3.7GHz [78]. These incumbents are protected and allowed to share spectrum with Long Term Evolution 4 or 5G cellular CBRS devices (CBSDs). CBRS supports private 5G cellular or LTE networks for standalone business connectivity. It's popularly known as the OnGo initiative. The private network provides exclusive applications for hospitals, IoT-enabled facilities, and remote locations where access may be limited. The CBRS system, unlike the TVWS, is a three-tiered system consisting of a licensed incumbent or PU operating at 3.55 to 3.7GHz, Priority Access Licensee (PAL) operating at 3.55 – 3.650 GHz, and General Authority Access users (GAAs) operating at 3.55 – 3.7GHz [78].

Coexistence Management in CBRS

An external entity or database, like the GLD called Spectrum Access System (SAS), coordinates spectrum access in CBRS systems. It ensures that the incumbents suffer no interference from SUs (PAL or GAA) by using an interference discovery methodology (path-loss algorithms) together with its Environmental Sensing System (ESS). The PALs, however, are protected from GAAs, and GAAs are allowed to endure a degree of interference from PALs and GAAs. In the United States, a 150MHz band is available for sharing within a location. Each CBSD operating as a PAL or GAA can have a maximum of 10MHz each, and in any area, only 15 CBSDs can be supported. However, the maximum number of PALs in such a location is limited to 7 to restrict PALs from usurping all available resources.

The incumbent has the highest priority; available resources are only used when the incumbent is not using a band or is absent in the region. This means that when resources are available, the PAL users have higher spectrum access to a stipulated portion of the available bands, and these resources are only available to GAA users when PALs are not using the portion of bands. Should a PAL user appear in a band being used by a GAA user, the GAA user vacates the band; similarly, should an incumbent user appear on a band in use by a PAL user, the PAL vacates the band. GAAs can opportunistically utilize available PAL bands in locations with few PAL users.

SAS, through its higher tier protection function in Fig. 2.6a, ensures incumbent and PAL interference are within baseline standard [31]. Its repository function keeps a log of incumbent, PAL, and GAA information, which is used to update spectrum availability regularly. Inter-block communication uses SAS-SAS and SAS-CBSD protocols or other non-standard means. An easier protocol for SAS-to-CBSD communication, was suggested in an end-to-end design of a CBRS system in [79].

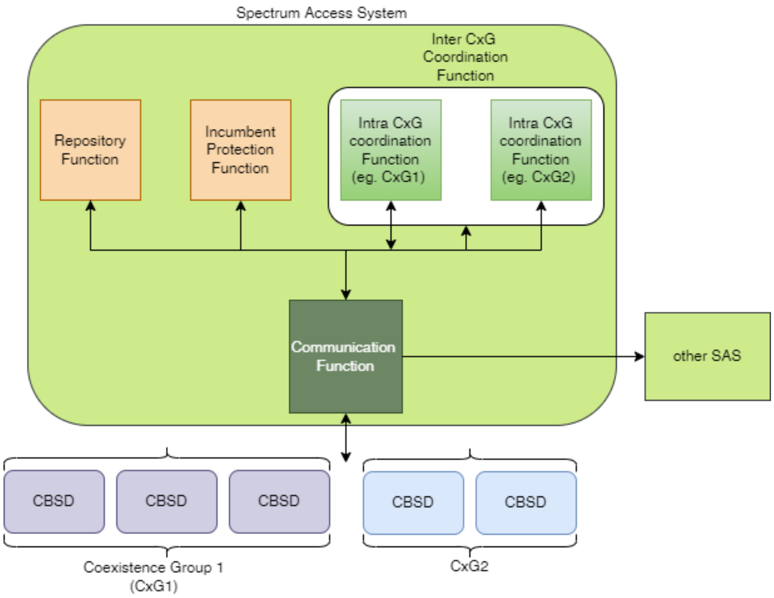
SAS inter and intra coexistence groups (CxG) coordination function manages coexistence among GAAs. It can function solely as an inter-CxG manager or as both inter and intra-CxG manager, as illustrated in Fig. 2.6a and Fig. 2.6b. In the former, it collaborates with the CBSDs intra-CxG coordinator to perform its tasks. SAS decision-making topology can be independent of other SAS (autonomous). It can negotiate with other SAS in resource sharing (Distributed), or it can make unilateral decisions, as a master SAS, on resource sharing among other slave SAS (central) [31]. The responsibilities of SAS intra and inter-coordination include:

1. identification of potential interference between CBSDs (interference discovery).
2. mitigating this potential interference.
3. creating channel information to be relayed to others.
4. resolving interference when it occurs.

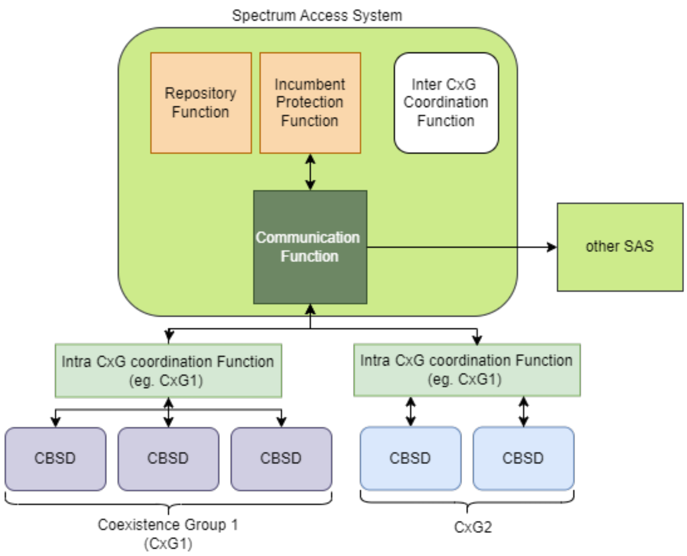
Unlike SUs in TVWS, SAS provides GAAs with a level of coordination. SAS's inter or intra-coexistence management scheme adopts a recursive approach in limiting interference among GAA groups [31]. However, the GAA users within a group are expected to perform a form of internal spectrum coordination. This assumes that a coordinating system among the GAAs prevents interference, which may not be the case in a heterogeneous network.

2.4 Coexistence Techniques in Standards

DSA systems rely on interference mitigation schemes of WSDs' Media Access Control (MAC) protocols. Radios achieve coexistence through coordinated time use of spectrum, geographical separation, frequency separation, and orthogonal modulation [67]. However, improved ways of coexistence use multiple methods in real-time, thus improving coexistence, especially in heterogeneous networks (HetNet) [18]. A typical HetNet



(a) SAS inter and intra-coordination



(b) SAS coordinator (Intra CxG coordinator)[15]

Figure 2.6: SAS architecture

example is a network consisting of portable devices (IEEE 802.15 standard), Wireless Fidelity (WiFi) devices (IEEE 802.11af), and consumer premise equipment (IEEE 802.22). These standards or RAT discussed in this section, use opportunistic spectrum sharing but differ in structure and coexistence management protocols, thus limiting optimal coordination.

2.4.1 Personal Area Networks/Portable Low Power Devices (IoT)

The IEEE 802.15 documentation [80] details the physical (PHY) and MAC specifications for the interoperability of low-power portable devices operating at low data rates among fixed, portable, and moving devices. These devices range from Internet of Things (IoT) devices to very low-power radios for device-to-device communication or Internet access. Unlike mobile devices, these portable devices only transmit data at different fixed locations, while mobile devices transmit in motion [80].

Personal Area Networks (PAN) can be deployed as wireless sensors for industrial control and monitoring (wireless sensor networks) or for intelligent agricultural monitoring. They have two main topologies: star and mesh or peer-to-peer network, shown in figure 2.7. Its TVWS multichannel cluster tree PAN (TMCTP) consists of Full Function Devices (FFDs) and Reduced Function Devices (RFDs). Its Super PAN coordinator (SPC) manages and synchronizes services (master device) to other PAN coordinators as shown in the cluster Figure 2.7 [80]. The RFDs may have some or none of the coexistence protocols, hence the need for the SPC. Therefore, TMCTP and PANs can support central or distributed spectrum coordination as shown in figure 2.8.

To facilitate coexistence amongst themselves while preventing interference, they use beacon frames, ALOHA, and carrier sense multiple access, collision avoidance (CSMA/CA) protocols. However, adopted protocols can be based on regulators' requirements as devices may choose to adopt all, any, or none of these protocols [80]. These can operate on 25, 50, and 100 KHz bandwidths [81] at Ultra High Frequency (UHF), 433-780MHz bands or below 1GHz, and 2.4GHz.

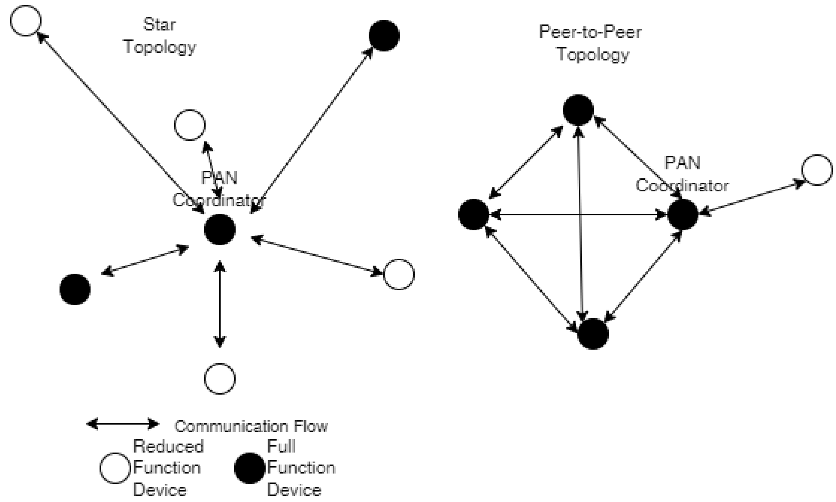


Figure 2.7: star and peer- to- peer

2.4.2 Local Area Networks (LAN)

IEEE 802.11af standard on Local Area Networks (LAN) allows for local interconnection of access points (APs) that cover a small region. They are usually used to provide internet to devices within their coverage area. A wide range of devices use this standard, which provides a single MAC for multiple physical layers specification, to support wireless connectivity of fixed, portable, and mobile stations (STAs) within a local area. The significant difference between these devices and the IEEE 802.15 standard is the low coverage area provided by the latter. Wireless Fidelity (WiFi) access points and user equipment are popular devices that use this standard.

The typical architecture is that a WiFi access point or station (which may be fixed – e.g., a fixed WiFi router in a shop, or portable or mobile – a mobile phone's hotspot) has dependent stations or users that get connected through the access point [82]. Figure 2.9 shows a sketch of the LAN architecture that enables stations (STA) or devices or WSDs' UEs to depend on a basic service set (BSS), a form of master device or Access Point (WSD). Based on its operating channel, the BSS establishes a distributed communication system (DS) for device-to-device communication and possible connection to the Internet.

The standard's wide operating frequency range enables the interoperability of de-

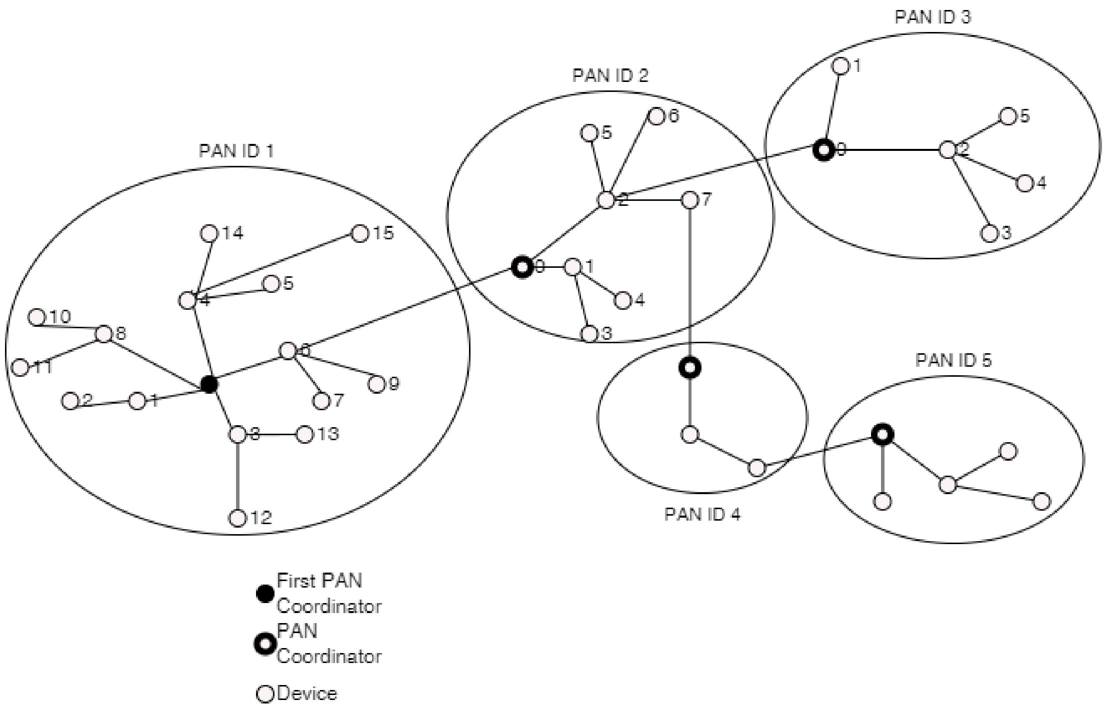


Figure 2.8: TVWS multichannel cluster tree PAN

vices in different countries. They can operate in TV, 2.4GHz, 6GHz and 7GHz bands. Their contention-resolving mechanisms are CSMA-CA and beacons. The MAC layer inputs beacons into frames to announce the presence of a device within a channel [82].

2.4.3 Regional Area Network

The IEEE 802.22 [32] provides guidelines for the air interface, Media Access Control (MAC), and physical layers of point-to-multiple-point and backhaul communication links of Wireless Regional Area Networks (WRAN). Operating in bands that support the opportunistic use of spectrum. It generally consists of a fixed-based station that makes a back-haul connection to the internet and a front-haul connection to fixed or portable access points called Customer Premise Equipment (CPEs) [32]. A typical base-station's wider coverage and many dependent CPEs are shown in Figure 2.10.

Coexistence in regional area networks is more challenging due to their wide coverage areas that easily intersect and cause interference. In managing this, a Coexistence

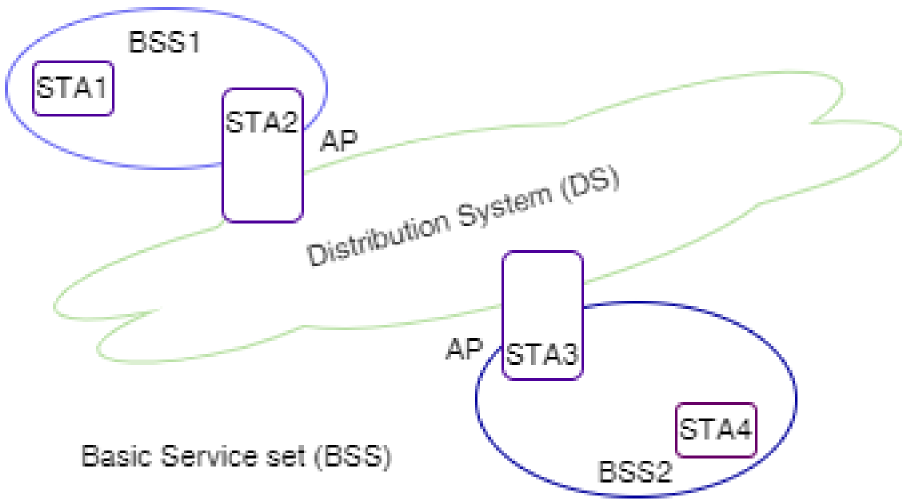


Figure 2.9: Topologies of 802.11 standard devices

Beacon Protocol (CBP) is adopted. CBP appends packet frame structure and can coordinate spectral resources centrally, distributively, or both, figure 2.6 [32].

The coexistence management technique in this standard can determine the occupancy of a channel based on information from:

1. A geolocation database (an external entity)
2. Sensing the presence of PUs (MAC sensing abilities of CPEs)
3. Beacon signals for SUs collision prevention.

This allows base stations or central CPEs to use a channel exclusively or coexist with other radios (BS or CPEs) in the same location. This standard utilizes a Time Division Duplex (TDD), as each frame consists of the uplink and downlink data information. A self-coexistence Window (SCW) is established in its uplink frame for beacon signals from the reference BS and other dependent CPEs.

2.4.4 IEEE 802.19 Coexistence Management

The IEEE 802.19 unifies SAS and databases' function in the coexistence management of Base Stations (BS), access points (APs), or nodes, thus providing the foundation for framing a coexistence problem for DSA systems [38]. A Coexistence Manager's

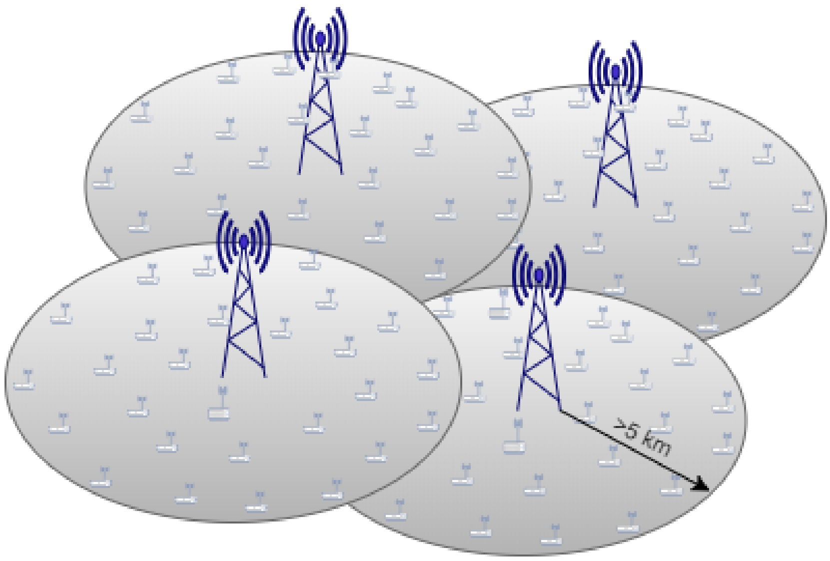


Figure 2.10: Regional Area Network deployment Setup

(CMs) role is to determine how radio resources are shared among interfering nodes, radios, or devices called white space/geolocation-capable objects (WSOs/GCO). [38]. In the CBRS architecture, the CM is the Intra CxG coordination function coordinating resource management among WSO/GCOs. It enables the reuse of spectrum, spectrum overlay, and underlay, increasing network capacity. Its overall objective [38] similar to SAS is to:

1. Ensure no overlapping WSO/GCO allocation of operating channels
2. If 1 is impossible, group similar WSO/GCO together in the frequency domain.
3. If 2 is impossible, split operating channels for WSOs/GCOs in time, code, or frequency domain.

CMs' Decision-making topology, similar to the CBRS structure, can be autonomous, distributed, or centralized. The decision topology assumed in this thesis is the centralized topology, where the CM makes decisions for WSOs/GCOs. A central CM can be an intra-SAS in CBRS systems and communicate with the inter-SAS or a database in TVWS [83]. The WSOs/GCOs choose their channels and inform CM through their coexistence enabler, as shown in Figure 2.11 [38].

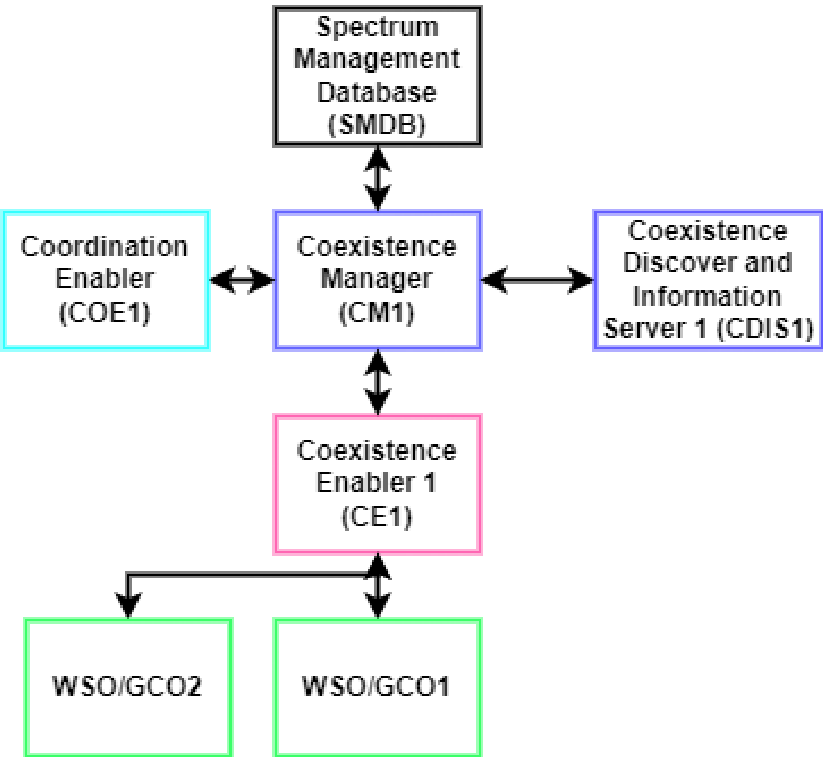


Figure 2.11: DSA coexistence management system

2.5 Medium Access Control (MAC) Coexistence Management Techniques

2.5.1 Beacon

Beacons are used by all standards discussed; however, their frame structure, purpose, and mode of operation vary with the deployed standard. In the standard for personal/portable area network (PAN), IEEE 802.15, beacons are used to synchronize attached devices (FFD & RFD), identify PANs, and describe the structure of superframes. The period between two beacons is called the contention access period (CAP). Thus, devices compete to access the channel during CAP using the CSMA-CS or ALOHA mechanism randomly [80, 81].

In the TMCTP (an extended PAN), the beacon frame structure contains allocation time slots and interference management information, such as a Contention Access Period (CAP) that communicates commands/data, a contention-free period (CFP) containing guaranteed time slots (GTS), and Beacon Only Period (BOP). In LANs, the directional multi-gigabit (DMG) beacon frame within its distributed coordination function (DCF) has an additional feature called the beacon report. The beacon report keeps track of other device's beacon activities. RAN's beacon frame consists of a synchronized self-co-existence window (SCW) that allows multiple base stations to compete for access. It also permits various CPEs to share a spectrum in time. The internal component of the beacon frame of each of these standards is unique, as shown in figures 2.12, 2.13, 2.14. However, the CSMA-CA mechanism is deployed in all RATs studied and used to access channels during contention access periods (CAPs) [32, 80–82, 84].

Despite using the exact coordinating mechanism (CSMA-CA) by the three standards discussed, the beacon size, purpose, and frame structure differ. Thus, synchronization among homogeneous networks and redesigning heterogeneous networks is sometimes required. A similar conclusion was arrived at by Chen et al.'s analysis of other radio access technologies' MAC protocols operating at higher bands [85].

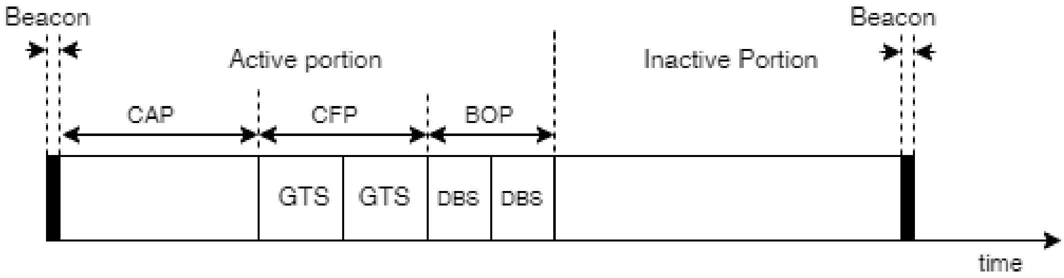


Figure 2.12: TMCTP PAN superframe extension

FRAME CONTROL	DURATION	BSSID	FRAME BODY	FCS

Figure 2.13: Directional Multi-gigabit frame format

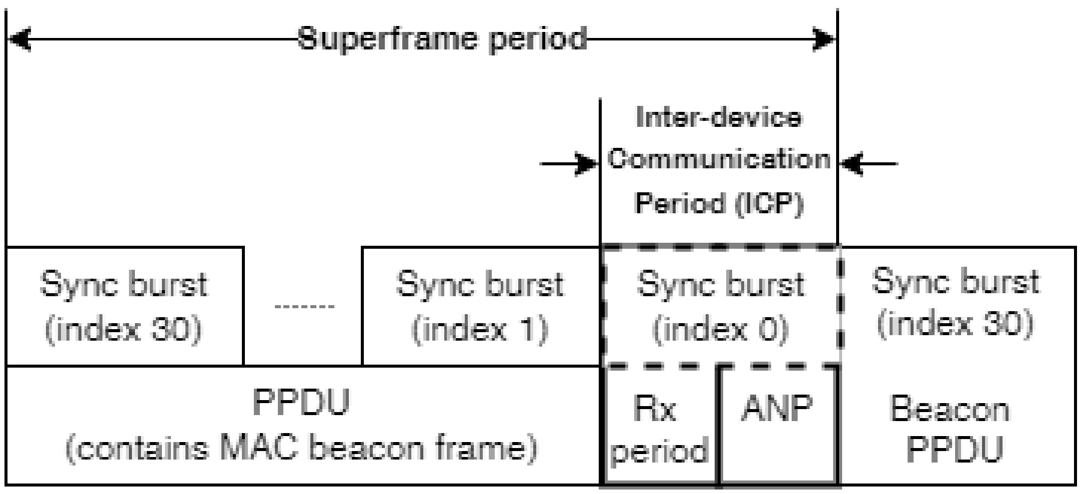


Figure 2.14: WRAN beacon superframe structure

2.5.2 Carrier Sensing Multiple Access with Collision Avoidance

Carrier Sense Multiple Access with Collision Avoidance (CSMA-CA) is an interference prevention mechanism that allows overlapping coverage areas to coexist. It is deployed in 802.11 distributed coordination function (DCF) and beacon functions in IEEE 802.15 and IEEE 802.22 standards. By effectively communicating, the protocol enables multiple devices to schedule access to a channel. Thus reducing the probability of collision of transmitted data from multiple radios sharing a channel/medium at points when a collision is most likely to occur (Contention Window -CW). It uses a random backoff CW size procedure at the CW point, thus minimizing contention [82].

The mechanism requires that all requesting devices sense the medium for other transmitting devices. The sensing mechanism uses physical signal measurement of the medium/channel and predicted future traffic of a medium (Virtual Carrier Sensor) containing CSMA transmission information. A perceived vacant medium is accessed by a request to send (RTS) frame. The receipt of a clear-to-send (CTS) frame permits a device to transmit its data on a medium/channel; a successful transmission is preceded by a CTS (containing acknowledgment information) frame [82]. If a device does not receive a CTS, it waits for an appropriate transmission time (back off CW size) to resend an RTS frame. The random backoff time is a random multiple of the CW size that counts down before another attempt, as shown in figure 2.15. RTS/CTS frames are used for large data frames due to their high overhead. In virtual carrier sensing(V-SC), shared reservation information, such as request to send (RTS) and Clear to Send (CTS) frames, before transmission informs medium/channel status. Deploying different CSMA/CA mechanisms versions in similar devices may impact MAC-dependent coexistence management.

Challenges of CSMA/CA coexistence mechanism.

1. Delayed access to spectrum, resulting in poor quality of service when many devices request access.

2. Hidden devices with obstructed beacons may never gain access to shared medium.

3. Failed transmission is only detected after an entire contention period and trans-

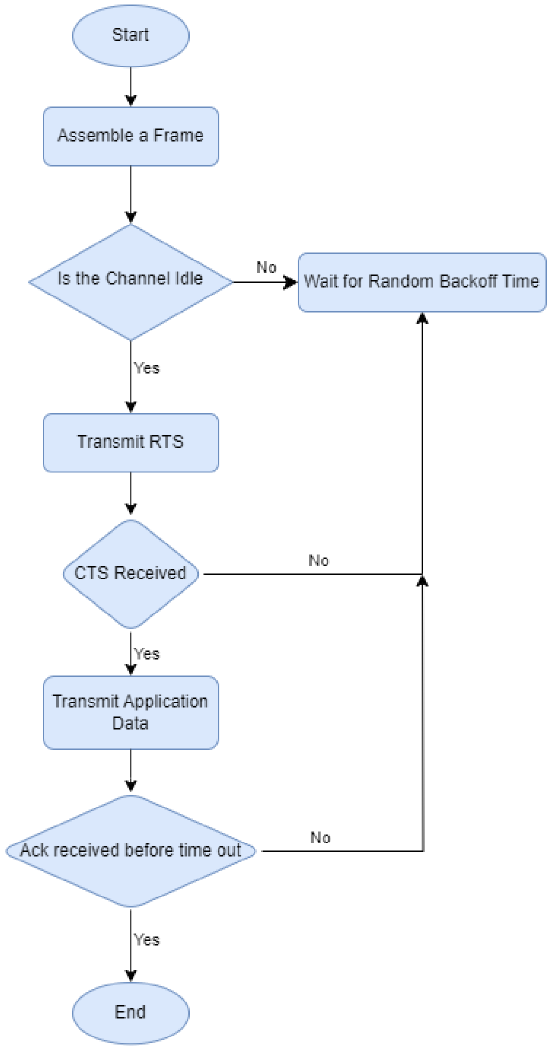


Figure 2.15: CSMA/CA flow chart

mission period have elapsed.

4. The protocol highly depends on the standard and MAC protocols adopted.

5. Beacon control header overhead

2.5.3 Listen Before Talk

Listen Before Talk (LBT) is a mechanism similar to CDMA/CS, where transmitters sense the channel/medium before attempting to transmit by performing a clear channel assessment (CCA) [86]. It is the coexistence coordination protocol adopted in License Assisted Access (LAA). As stipulated by the 3rd Generation Partnership Project (3GPP), it enables the equal priority coexistence of cellular and WiFi networks in licensed and unlicensed 2.4 and 3.5 GHz bands. A significant benefit of LAA in LTE Release 13 by 3GPP is the ability for cellular networks to use fixed bands and share other bands (top-up) when necessary [86, 87].

LBT uses a fixed CW which is about 20 mico-seconds and is termed a CCA period. In its CCA period, a requesting LAA/WiFi device uses energy detection to sense the presence of other devices in the medium/channel (physical sensing). Below a required threshold, the requesting device assumes the medium is empty and transmits, during its Maximum Channel Occupancy Time (COT). Otherwise, the medium is occupied and an extended CCA check is conducted. Extended CCA involves sensing the presence of other users in a channel, for a random N multiple of CCA observation time (back off time). This counts down to zero, at an idle CCA slot before a requesting device can transmit, as shown in figure 2.16 [86].

2.6 Practical Coexistence Issues

LBT and CSMA/CS mechanisms have similar structures and, as such, experience similar challenges. Therefore, most practical challenges and solutions raised in subsection 2.6.2 can be extended to self-coordination at lower bands.

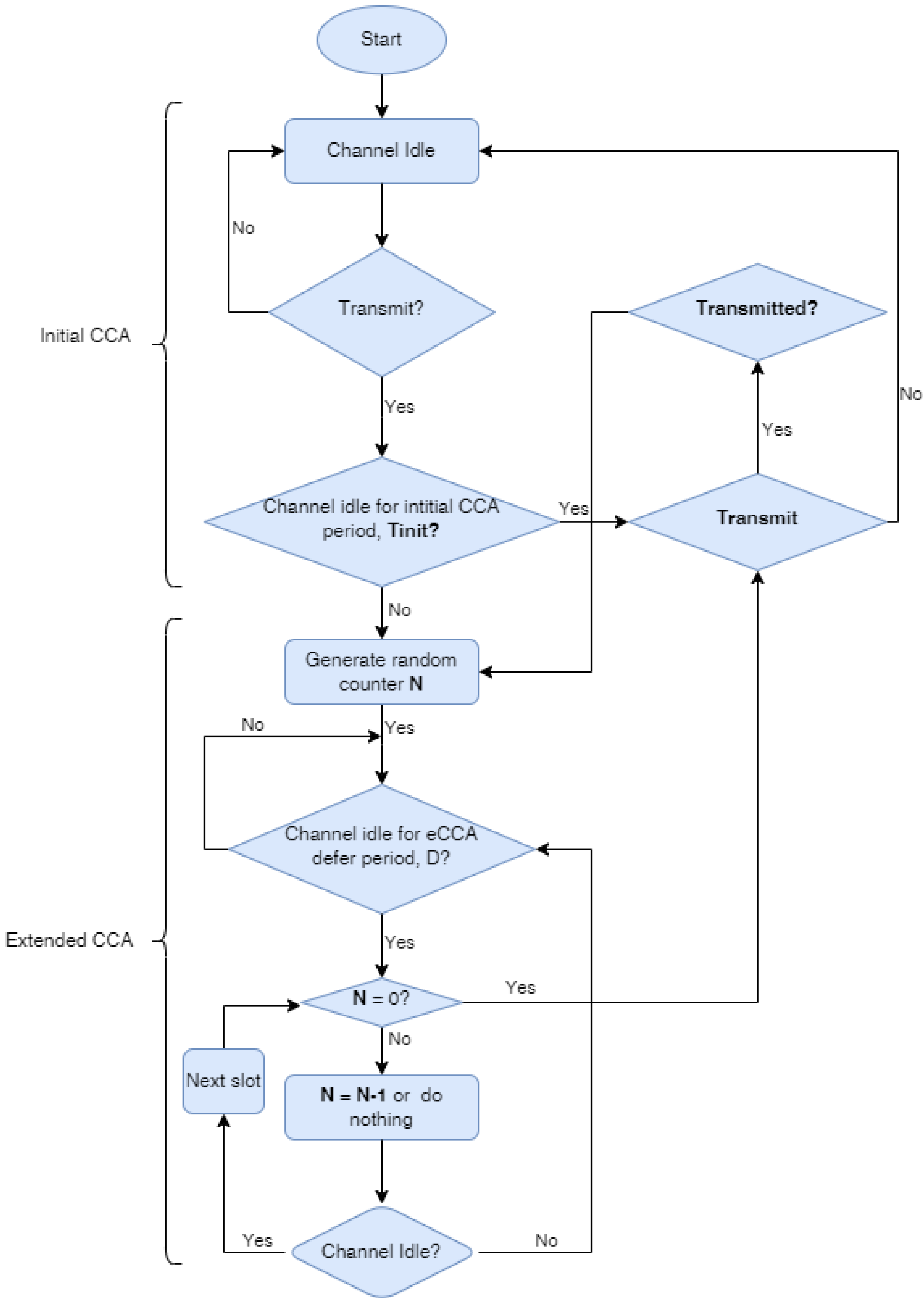


Figure 2.16: LBT procedure by 3GPP

2.6.1 WRAN and WLAN

Irrespective of the band examined (TV, 3.5, or 5GHz bands), the coexistence of devices of different standards in the same frequency space needs a form of coordination. The MAC-dependent protocols are primarily effective in managing homogeneous devices, although issues highlighted in subsection 2.5.2 must be checked. In heterogeneous networks, additional problems, such as devices with different MAC protocols and beacon frame structures, synchronization of radios/base stations, and varied coverage sizes and end-user sensitivity, must be overcome [83]. Thus, available resource allocation to dissimilar standards in a network will result in interference that individual device MAC coexistence mechanisms may not resolve [88].

2.6.2 LTE and WiFi

Long Term Evolution-Unlicensed was introduced to increase bandwidth allotted to Mobile Network Operators (MNO) to match the increased demand for their cellular services [89]. Sagari et al. discovered that the WiFi devices were prone to more significant interference than the LTE device in their single Cellular base station and WiFi device coexistence on a 5GHz band investigation. A further investigation into more devices revealed a similar outcome, establishing the need for better coexistence mitigation techniques [90]. This was attributed to the different versions of MAC protocols adopted by the LAA framework. A WiFi device constantly sensed the presence of LAA devices, preventing it from having sufficient contention window spaces to transmit in [91]. The impact of this interference was significantly reduced when cellular nodes adopted an LBT protocol in 3GPPs LAA architecture [91].

A wide range of studies have suggested improvement in MAC protocols. A redesign of the MAC protocol-based LBT mechanism to improve throughput was suggested in [92] by including CSMA's CW and DCF components to LTE unlicensed (LTE-U) devices to aid coexistence. To improve the fairness of LBT methods adopted in LTE/LAA devices, an improved algorithm that included the WLAN network's fairness index and statistical profile was proposed. It improved WLAN network throughput in [93, 94]. A similar improvement satisfied the devices' quality of service requirements of small cell users by creating an adjustable COT and idle time or back-off scheme identical to the CSMA/CS system [95, 96]. An adaptable duty cycle coexistence LBT mechanism's performance was evaluated in an LAA/WiFi 5GHz band in [67]. A joint optimization of licensed and unlicensed bands for LTE scheduling and allocation algorithm was developed in [97] to achieve fairness in spectrum sharing between LTE and WLAN networks. Better performance was achieved than conventional fixed and sequential allocation schemes in femto and WiFi networks.

Most of these solutions did not address co-existence management in heterogeneous networks (HetNets), as LAA-compliant nodes use similar MAC protocols at 2.4 GHz. MAC protocols (at higher bands) were sometimes redesigned to create a coexistence mechanism for heterogeneous networks. MAC-dependent coordination does not explore optimal resource sharing among nodes. This thesis proposes an intelligent central coexistence manager to reduce the contention managed by MAC protocols in Hetnets. Intelligent systems learn from past experiences and are achieved with machine learning algorithms.

2.7 Shared Spectrum Reviews and DSA Coexistence Management Challenges

A comprehensive study of existing reviews on resource management highlights the focus of previous reviews and identifies gaps in their approach. The authors justify the need for central coordination of SUs in heterogeneous DSA networks, as this supports existing regulatory frameworks.

Contributing to the wealth of research on resource allocation reviews, Table 2.1 summarizes these studies. This review differs from previous works as it provides an up-to-date review of existing literature and focuses on pragmatic shared spectrum issues and DSA resource allocation challenges.

2.7.1 Shared Spectrum Reviews

A review of algorithms and mathematical optimization of Shared resource allocation in future cellular networks is presented in [98]. Han et al. examined shared spectrum challenges based on their network type and size and adopted DSA architectures in [72]. Others have explored coexistence issues based on the network structures and problem formulations. It was observed that some assumptions made in these formulations to ease computation were most times impractical, resulting in theoretical concepts that do not address real DSA challenges [99]. Pragmatic DSA challenges by stakeholders on DSA deployment in [29] buttress Tragos et al.'s view of the impracticability of some DSA resource allocation solutions.

Pertinent issues with DSA networks identified and reviewed in [64] were network selection, sensing, channel allocation, power optimization, and security challenges. Addressing one of these problems, channel allocation or assignment, Tanab et al. identified some theories, such as colored graph theory, game theory, and heuristic solutions, that have addressed it [100]. A review of fair joint resource allocation schemes for unequal priority SUs in tiered CBRS architecture and solutions to their security challenges are presented in [101]. These reviews' investigation of coexistence issues validates the need for optimal resource allocation among secondary users in DSA networks.

Resource allocation and assignment solutions in literature were categorized based on the central or distributed location of coordinating agents. Maloku in [102], highlights drawbacks to centralized coordination, such as the amount of overhead and complexity of central coexistence managers structure. Arguably, if a network already has an existing central coordinating system, the global information can be leveraged for optimal coexistence management. In agreement with this, an overreaching universal framework for international central spectrum coordination was proposed in [103].

Fujii et al. proposed a four-staged architectural control system comprising innovative measurements, spectrum modeling, intelligent databases, and smart spectrum management that extract intelligence from a central pool of information. Their design merged AP sensing and communication capabilities. Sensed data built a pool of information from which coordination information was mined to determine PUs' usage and SUs demand patterns for a tailored spectral experience [103]. However, their idea of intelligent sensing and spectrum management systems can be adopted locally to minimize such risks.

Table 2.1: Literature reviews on Resource Allocation in Dynamic Spectrum Access systems.

Publication	Review summary/focus
[98]	Address resource allocation techniques and algorithms that address heterogeneous cellular and non-cellular networks.
[102]	A review of inter and intra coexistence issues in heterogeneous networks and a comparative analysis of coexistence management mechanisms in TVWS systems
[99]	An overview of issues with spectrum assignment in cognitive radio networks, and analysis of techniques used to solve spectrum assignment problems and pending open issues.
[68]	A thematic review of spectrum assignment algorithms' strengths, weaknesses, similarities, differences, and pending issues.
[64]	An exhaustive survey of spectrum sensing, network selection, channel allocation, power optimization and security challenges in shared spectrum future generation networks.
[100]	A survey of some resource allocation methods in underlay cognitive radio networks.

2.7.2 Dynamic Spectrum Management Challenges

A recurring challenge in DSA systems, addressed by various methods, is resource management among dynamic network components (fixed or mobile PUs and SUs). This problem is exacerbated in all types of heterogeneous networks and reiterated by Tripathi's choice of a machine learning algorithm in resource optimization, as typical optimization equations were insufficient in capturing heterogeneous networks and channel options dependencies [55].

Another challenge in DSA resource management is spectrum reuse, which in fixed allocation systems is implemented in cell reuse (cellular systems). However, in the DSA system, with no predefined cells or varying cell sites, real-time spectrum reuse becomes necessary, especially among equal-priority heterogeneous networks. It, therefore, becomes the responsibility of the DSA resource coordinator to know the needs of individual nodes and their interference limits and re-use or reallocate the used spectrum. This improves the overall spectral efficiency and enables the support of more nodes within a specific location.

A typical dynamic spectrum management system includes interference discovery and resource management features. Previously analyzed issues identified in the literature and pragmatic industry-based DSA challenges to designing these features are studied.

SUs protection and spectrum assurance

As in any typical DSA system, the CBRS spectrum manager consists of Dynamic Frequency Assignment (DFA) and Interference Management (IM) features. The DFA (resource manager) manages available PUs' channels, which vary with time, providing SUs with unassured access to spectrum. Thus, questioning the viability of such a tiered system in supporting cellular services that require assured/exclusive spectrum access [29]. The concern on spectrum assurance and protection to SU cellular operators was also highlighted in GSMA's view of future shared spectrum prospects in cellular systems [20].

A possible suggested solution is adopting shared spectrum, as an added resource (top-up) to assigned fixed/exclusive cellular bands, similar to the Licensed Assisted Access structure [19]. However, SU protection or spectral assurance issues for SUs have yet to be addressed extensively in the literature.

Spectrum Allocation/Assignment Structure

Resource sharing among dissimilar Physical and MAC properties (HetNets) needs an efficient coordination scheme [72], and especially among SUs [99]. This is due to the distributive resource sharing assumed in existing DSA technologies where SUs choose resources and coordinate their coexistence based on individual MAC protocols. However, these choices are vetoed by a central management system.

Flexible spectrum and power allocation that suits specific scenarios and licensees' distribution were proposed by stakeholders in [29], as CBRS' spectrum management structure was highly central. The central stringent rules on power and out-of-bound emission restrictions in the CBRS system stifle prospects of SUs meeting the required QoS of individual CBSDs. However, this shift to SUs (distributed access) is sustained when interference among diverse coexisting SUs can be effectively managed. It Reiterates the need for radio-specific spectrum and power allocation.

Interference detection and coordination

Interference is a significant challenge in maximizing channel assignment performance, as it increases the noise floor experienced by receivers, thereby reducing their signal-to-noise plus interference ratio. This increases the frame loss ratio, decreases the transmission rate of links, and lowers the receiver's throughput [68]. Interference around PUs or SUs transmitters has been computed based on their distance or contour coverage areas. This interference detection mechanism, adopted in CBRS, was contested based on its relatively fixed contours assignment and smaller cells' non-inclusiveness. Stakeholders recommended real-world or real-time interference measurements, as these were adaptable to the transmitter's actual interference experience [29].

However, real-time interference measurements lead to questions on how interference levels are measured, collated, decided, and disseminated. Dissemination of control information among heterogeneous networks can be distributed or centralized. Acquiring and disseminating real-time interference measurement of PUs or SUs (spectrum sensing) becomes fundamental for shared spectrum management [69]. Resource coordination and reuse of resources based on informed decisions improves spectral efficiency, as more access points are supported [99]. ‘ Despite these benefits, real-time interference detection and coordination have significantly focused on PUs. However, studies on interference threshold and coordination of SUs are required, as these differ from PUs since SUs can be fluid in characteristics and have non-fixed locations. Thus, regulators and stakeholders should know spectrum assurance risks and permissible trade-offs when maximizing spectrum reuse in SUs' coexistence coordination.

Spectrum Sensing/Measurement

Several sensing techniques, such as energy-based sensing, cyclo-stationary feature-based sensing, compressed sensing, matched filtering-based sensing, pilot sensing, pattern recognition-based sensing, waveform-based sensing, and radio identification-based sensing [64,70] provide a real-time measure of signals. However, these techniques have varied accuracy, computational complexity, cost, and measurement specifications [103].

Some issues still being investigated are the processing speed and hardware requirement for accurate spectrum measurement. Also, intelligent sensing that distinguishes PU and SU signals and categorizes their priority levels [72] enables informed sharing of spectral resources and helps identify neighbouring nodes. Thus, sensing and node identification can improve equal (horizontal access) and unequal (vertical access) coexistence in DSA networks.

Spectrum Handover and Resource uncertainty

The evacuation of a channel when an incumbent or higher-priority user needs it remains a challenge [69]. Existing solutions to this have been regular check-ins with the spectrum manager (SM) to ascertain updated available channels in TVWS and the transmission of stop transmission signals to the SUs in CBRS systems. In both systems, the SUs are re-assigned to another available channel where feasible. This reassignment can result in more APs struggling for depleted resources or reshuffling resources to suit real-time available channels. CBRS systems still lack an established way of achieving CBSD mobility or how these can be interfaced with existing mobile cellular systems [104].

Some other issues with DSA that industry stakeholders did not mention include fairness and priority access. Fairness among equal-priority SUs needs to be clearly defined in the literature. Tanab and Basnet integrate fairness into their coexistence problem formulation and establish fairness indices such as min-max fairness, proportional fairness, and Jain's index [100, 105].

Similarly, coexistence problem formulation, which captures and identifies the wide range of a coexistence system's properties and objective functions, is challenging. A formulated problem may tackle time, frequency, space, or code domain issues [72]. Shared spectrum management scenarios formulated in studies make assumptions to achieve solutions. Therefore, there is a great need to investigate further coexistence management solutions suitable for real-life DSA systems.

2.8 Chapter Summary

This chapter presented an overview of DSA's implementation of shared spectrum, architecture, and resource management coexistence strategies. The Central database/SAS systems for unequal priority users coordination and MAC distributed for equal priority users coordination are two coexistence strategies studied. A review of MAC protocols' architecture and structure revealed their drawbacks in resource coordination of heterogeneous devices in DSA networks. The complexity of the resource coordinator of equal priority users is worsened as heterogeneous networks do not have a standard means of communicating among themselves. This has necessitated a central approach to managing the spectrum among such networks, such that heterogeneous network communicates with a central spectrum manager, who coordinates spectrum allocation and reuse.

Industry perspectives on DSA issues were highlighted, and approaches to solving such problems in the literature were enumerated. Thus, pragmatic research gaps in coexistence management were identified. A primary challenge in DSA deployment, as identified by the industry, is the nonexclusive access to bandwidth (measured by throughput, latency, data rates, spectrum certainty/assurance, spectral efficiency, and duty cycle) and an appropriate coordination mechanism (measured by interference experience, time of dynamic frequency selection, transmit power allocation, quality of service, resource allocation efficiency, spectrum reuse, and probability of faulty assignment) [18]. These are of great importance to industry experts as such an investigation into the coordination mechanism of unequal priority users is done in chapter 4. Machine learning algorithms are also investigated in the next chapter to study how these have addressed resource assurance, coordination, and other DSA challenges.

Chapter 3

Reinforcement Learning in Shared Spectrum Management

In a shared spectrum network, unlike an exclusive spectrum network with fixed power and spectrum available to access points, the spectrum, power, and devices are dynamic. A brief introduction to artificial intelligence and machine learning algorithms is presented. This chapter provides an up-to-date review of an arm of machine learning, reinforcement learning's (RL) resource management approaches. It reviews suggestions on intelligently augmenting central or decentralized resource coordination. It also examines various optimization approaches (Non-RL based and RL based) to challenges highlighted in Chapter Two.

Different machine-learning algorithms have improved DSA networks' spectrum detection, access, and allocation. In resource coordination, these algorithms either use central mechanisms (Fig. 3.4), where the RL agent is centrally located, or decentralized autonomous mechanisms (Fig. 3.5), where RL agents are located in individual SUs, to coordinate other devices.

Emphasis is on RL's contribution to lasting solutions to such challenges. This chapter, therefore, presents an overview of reinforcement learning approaches to shared spectrum management in DSA systems and establishes a gap in its pragmatic implementation.

3.1 Introduction to Machine Learning

Artificial learning is made possible by machine learning algorithms. Machine learning uses algorithms to make sense of or extract knowledge from data. It provides great predictions of future events based on learned patterns. According to Samuel, machine learning 'is the field of study that allows computers to learn without explicit programming' [106]. Thus, a machine or device with a learning algorithm can learn from structured data to carry out some task without being explicitly programmed to do so. It extracts sequences, trends, and patterns from data and makes informed decisions on similar data patterns in the future. Unlike iterative or prescriptive algorithms, which are explicitly programmed to act a certain way and, as such, need to capture all possible scenarios. Learning algorithms are flexible [107].

Learning algorithms are, therefore, beneficial for optimization problems with ample search space, as prescriptive solutions spend long search times to arrive at optimal solutions (convergence), which is sometimes missed. Traditional and heuristic solutions to optimization resource allocation problems sometimes do not arrive at global solutions because of assumptions made to simplify their computation [108]. They also do not consider real-time changes in networks and, as such, may need to recompute network parameters each time there is a change in the network structure or components.

This complicates shared spectrum licensing, resource assignment, and node fluidity in a network. On the other hand, Learned networks are adaptable to real-time network changes, as their trained models can be regularly updated to capture such changes. The machine learning approach to optimization problems uses dynamic programming and trial and error search for solutions, thus reducing search times and increasing chances of arriving at optimal solutions [107].

Machine learning has been extensively explored in facial recognition, text completion, image classification, gaming, and robotics. Each of these broad applications uses different kinds of learning algorithms to achieve its purpose. Generally, machine learning algorithms are categorized into three broad sections: Supervised, Unsupervised, and Reinforcement Learning.

3.1.1 Supervised Learning algorithms

Supervised learning algorithms are trained from large data sets with expected outcomes; their observed features have known expected outcomes. The trained models contain weights that can be used to predict the outcomes of new observed features. This is termed 'supervised,' as the input data's patterns with their labeled expected results guide the model (model's weights) in making future predictions.

A multiple-layered artificial neural network was trained to recognize two LTE SU's spectrum usage patterns. They observed that a simple single node ANN showed the best predictions of SUs success rate in accessing available spectrum at specific periods, as PUs randomly reappear in a channel [41]. A typical supervised learning pipeline in figure 3.1 shows images of specific modulation signals labeled as respective modulation schemes. It comprises of a dataset of an equal number of spectrograms of four modulation schemes (QPSK, BPSK, 16QAM, and 64QAM).

These were split into 80:20 of training and test datasets. The training dataset is cleaned, and features are extracted. These features define some of the artificial neural network's (ANN) weights. The trained ANN is then validated with the test dataset, so its ability to predict the modulation scheme of images (spectrograms) in the test dataset is measured. For example, as shown in the figure, a single test spectrogram is predicted to be most likely QPSK modulated signal, with a 70% degree of certainty.

This can be applied in a DSA network where PU's spectrograms are correctly classified and used to train an algorithm; the trained model successfully predicts the modulation scheme of a new spectrogram. A similar supervised learning pipeline has been used for PU signal identification in [71, 109].

The algorithm extracts signal features automatically (with deep learning) or manually (using mathematical tools) from the training data subsets. It uses this to generate an error function to tune its weights until its output is like the training data subset's results. The trained model's prediction performance is evaluated with a subset of the training dataset called the testing subset (containing ground truth). Overall, the performance of a model is judged by its ability to generalize effectively (i.e the algorithm is adaptable to predicting new and unseen data). Supervised Learning Algorithms include

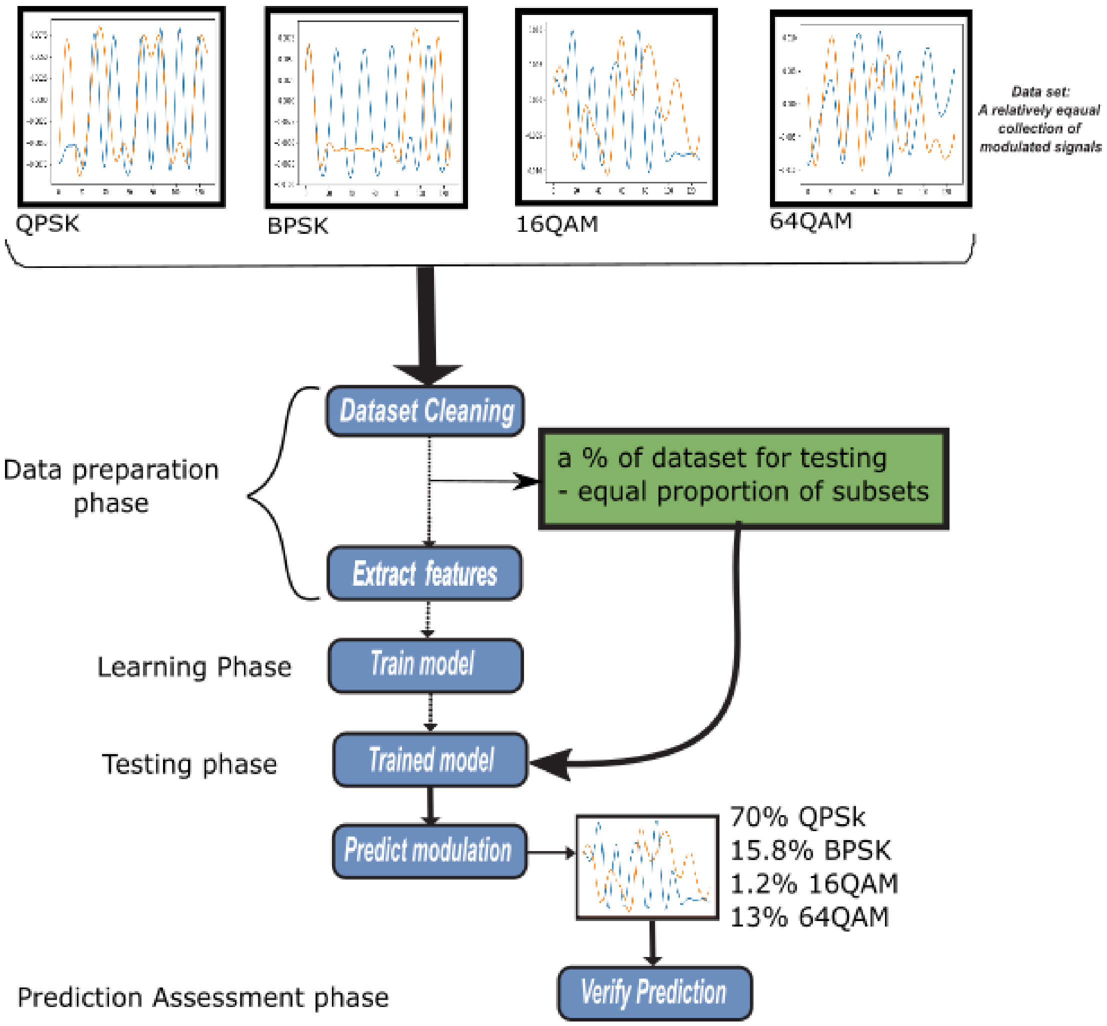


Figure 3.1: Supervised Learning Pipeline for PU modulation detection

Machine learning algorithms (k-Nearest Neighbour, Linear Regression, Logistic Regression, Support Vector Machines (SVM), Decision Trees, and Random Forests,) and deep learning algorithms (Neural Networks (Artificial, Convolution, and Recurrent).

3.1.2 Unsupervised Learning

Unsupervised learning has no prior knowledge of its outcomes. There are no results or ground truths for the dataset, as in the case of supervised learning. Unsupervised learning creates its outcome based on the perceived structure in the dataset. An unsupervised learning algorithm extracts data patterns without prior knowledge of the expected result. It, therefore, searches for similarities in the features of the input data and categorizes them into clusters.

Clustering involves grouping unarranged data into sets (clusters) based on some similarity indices with dissimilar features from other clusters [110]. Clustering has been used in DSA systems to group network nodes based on specific criteria such as distance from a transmitter [109]. In analyzing measured spectrum data for mapping, a Lloyd's K-means algorithm was used to cluster measured spectra's mean and covariance features. These assisted in defining a pattern between spectrum usage and human activities within a locality for one year [111]. It was also used for dimension reduction of state space in reinforcement learning algorithms.

These learning algorithms are necessary for reducing large datasets or grouping datasets that were not labeled, thus labeling unlabelled training data sets. However, evaluating the correctness of these classifications becomes an issue because of the absence of ground truth in the unstructured dataset. Techniques that measure the closeness of cluster elements have been developed to assess the performance of such algorithms. Examples of unsupervised learning algorithms are Clustering: k Means, Hierarchical Cluster Analysis, Expectation Maximisation, Dimension reduction algorithms: Principal Component Analysis (PCA), and Kernel PCA. Locally Linear Embedding (LLE), t-distributed Stochastic Neighbour Embedding (t SNE).

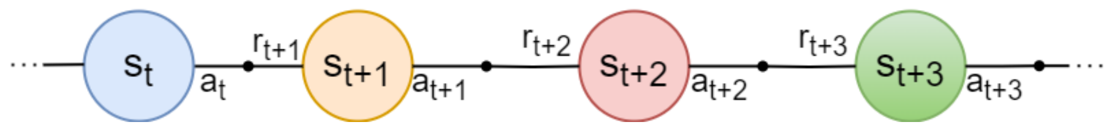


Figure 3.2: Alternating sequence of RL state action pairs.

3.1.3 Reinforcement Learning

Reinforcement Learning (RL) is a type of learning that seeks to find a set of optimal decision policies. Labeled or unlabelled data train supervised and unsupervised learning algorithms for classification, pattern recognition, and data reduction. RL, on the other hand, is trained for decision-making actions. An RL algorithm decides on a timed sequence of data sets, which makes it suitable for a Dynamic Spectrum Access network. The RL algorithm is structured to have an agent that learns to make decisions in an RL environment based on a trained policy to obtain the best cumulative reward by maximizing the expected returns.

An RL environment can be defined by a sequence of states $(s_t, s_{t+1}, s_{t+2}....s_T)$, on which an agent can take a sequence of actions $(a_t, a_{t+1}, a_{t+2}...)$ and receives a sequence of rewards $(r_{t+1}, r_{t+2}, r_{t+3}, ..)$. These form a transition of state action pairs within a time step of an environment and agent interactions, $s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1}, r_{t+2}, s_{t+2}, ...$ as shown in Fig. 3.2 [107]. The RL environment is framed as a Markov Decision Problem (MDP), which an agent guided by an appropriate policy, solves by finding the best sequence of actions that results in the best cumulative reward or maximizes the expected rewards in equation (3.1).

This cumulative reward is the sum of the sequence of the agent's rewards from interacting with its environment at each time step (t). It is defined as:

$$G_t \doteq r_{t+1} + r_{t+2} + ... + r_T. \tag{3.1}$$

where T is the final time step in a single episode of an assumed episodic RL environment. A reward function, therefore, measures an agent's actions' effect on the environment, generates reward feedback to the agent, and triggers a change in the environment's state (observation), as shown in figure 3.3.

Figure 3.3: Reinforcement learning algorithm flow chart

In training an RL algorithm a Bellman's equation is a mathematical MDP optimization solution for quick convergence. It quantifies the value (V(s)) an agent obtains by being at a specific state (s). The value of an agent starting a state and taking action is defined by an action-value function called Q-value. A tabular representation of these Q-values and state action pairs is termed a Q-table. An ideal set of Q-values (Q_π) forms the policy that guides an agent in a state to continuously take actions to arrive at the best expected future rewards (G_t) in equation 3.1. There are different approaches to guide a random set of Q-values in a Q-table to arrive at an optimal policy (Q_π); these include Temporary Difference (TD) and State-Action-Reward-State-Action (SARSA) methods, Monte Carlo, Dynamic Programming (DP), [107].

The temporary difference theorem uses Bellman's equation to arrive at convergence without full information on state transition in an environment (off policy).To arrive at the optimal policy (Q_π) from a random set of Q(s,a) values in a Q-table, each Q(s,a) value is updated in every time step, using the quick convergence bellman equation. Thus, at each time step the Q-table values are updated as:

$$Q(s,a) \text{ value estimate} = \text{old } Q(s,a) \text{ estimate} + \text{ step size}(target - \text{old } Q(s,a) \text{ estimate}). \tag{3.2}$$

The target in temporary difference (equation 3.1.3) is a function of the reward r_{t+1} from the environment when at a state, s_t, and an agent takes an action, a_t, and the maximum predicted future reward on all actions ($\max_a Q_{(s_{t+1},a)}$) after transiting to a next state, s_{t+1}. Its old $Q(s,a)$ estimate is the previous Q-value ($Q_{(s_t,a_t)}$) prior to the update. The objective, therefore, is to minimize the error estimate between the Q-value estimate and the target to arrive at the optimal policy which correctly defines the correct sequence of actions each time an agent is in an environment's state.

The temporary difference equation for updating Q-values is:

$$\underbrace{Q_{(s_t,a_t)}}_{\text{Q-Value update}} \leftarrow Q_{(s_t,a_t)} + \underbrace{\alpha}_{\text{learning rate}} [\underbrace{r_{t+1}}_{\text{Reward}} + \underbrace{\gamma}_{\text{Discount rate}} \overbrace{\max_a Q_{(s_{t+1},a)}}^{\substack{\text{max predicted reward,} \\ \text{in next state and all actions}}} - Q_{(s_t,a_t)}]$$

Consequently, the RL training occurs in two phases: the trial-and-error phase, or exploration, and the optimization phase, or exploitation [107]. In the RL algorithms' trial-and-error phase, different actions are tried/explored in the environment, which is usually formulated as a Markov Decision Problem (MDP). Trials are assessed by a reward system that measures how good or bad the trial was. These are used to frame the optimal policy exploited. An RL agent's action can explore its environment or exploit its policy.

In exploration, different actions are tested on the entire environment to keep track of all possible reactions or rewards from the entire environment for various actions. At the same time, if the agent constantly explores, it would never take advantage of the best-optimized sequence of actions it has discovered. On the other hand, if it performs more exploitation and is fixed on its discovered locally optimized solution. It eludes the possibility of searching for a better optimal solution and possibly never achieves a globally optimal solution or a better-accumulated reward. The RL algorithm's agent, therefore, learns to balance exploring for new solutions and exploiting found solutions to achieve global optimal solutions [107, 110].

The environment's state and reward are Markov Decision Problems that can vary from a simple control system to complex systems. In different levels of the DSA system, several problems can be framed and solved using RL algorithms, as discussed in subsequent sections. Decision-making applications in wireless networks have employed RL algorithms such as Q-learning, Deep Q-learning, and Double Duel Deep Q-learning algorithms.

3.1.4 Machine Learning in DSA and Shared Spectrum Access

Machine learning techniques (supervised and unsupervised) have previously been explored in smart signal sensing and the detection of PUs and SUs in DSA or cognitive networks [40] and IoT-based networks [45]. These models conducted feature extraction from available spectrum spectrograms (or sensors), estimated and predicted the future availability of channels [40], and identified PUs for security [112]. A similar approach has been explored for network resource allocation in narrow-band IoT systems [45] and in cellular networks [41].

A summary of future directions for AI in wireless communication networks in spectrum sharing, interference estimation, wireless coexistence, network association, and other wireless communication challenges was discussed in Wang et al.'s [44, 113] review of ML's thirty years evolution.

ML techniques have also addressed duty cycle, resource allocation, and interference management in cellular IoT, low power IoT, and NOMA networks in [108]. It proffers solutions to personalize resource allocation to unique SUs' needs. Despite the challenges discussed on machine learning challenges, supervised and unsupervised learning algorithms were adopted in maximizing DSA, cognitive radio networks, IoT, NOMA, and cellular networks. Thus, addressing their spectrum sensing, allocation, coexistence management and spectrum/network selection challenges.

Another core branch of AI algorithms that explored resource allocation is Reinforcement Learning (RL) algorithms in wireless and IoT networks [55, 114, 115]. Luong et al. reviewed RL formulation of dynamic network access, data rate control, wireless caching, and other wireless communication issues as an MDP to improve connectivity and resource maximization of wireless networks. In their study, few works were observed to centrally coordinate spectrum, power, and interference monitoring of SUs [114]. Similarly, Song et al. addressed IoT's sporadic and unique random spectrum access, sharing, and sensing requirement using AI frameworks [115].

Key shared spectrum issues AI algorithms address include spectrum sensing/detection, allocation, resource, interference management, and network access/selection in several networks as summarized in Table 3.1. Some benefits of adopting AI algorithms in distributed/decentralized resource allocations were identified as achieving:

1. non-global optimal solutions in non-convex resource allocation problems.
2. Realtime solutions from real-time resource allocation problems.
3. Individualistic or tailored resource assignment to SUs.
4. Optimal transmission schedules amid incomplete network information [114].

3.2 Challenges of Machine Learning in Network Management

Identified challenges that affect ML deployment in network management, which intersect with general ML issues, include:

3.2.1 Data collection and cleaning

Predicting PU patterns requires large datasets, usually pictures with many picture elements (pixels), to train a supervised learning algorithm. The storage space for such data or any other data type poses a considerable challenge in training neural networks. Labeling such massive data sets and incomplete data poses another challenge to learning algorithms. Solutions such as compressed images, reduced dimensionality, autolabelled cluster learning, and dataset modification techniques have been proposed. These all impact the accuracy and performance of the trained model [91].

3.2.2 Computational Power and Time

Machine learning algorithms, mainly neural networks (NN), have high computational needs for computing changing weight values as the system learns from its data set. The backward propagation, for example, updates the weights of each of the many neurons in the hidden layers of a deep neural network, thus requiring long training time to arrive at good predictions. Cloud and edge computing solutions may not be feasible for all wireless networks. Specialized NN computing systems such as Graphical Process Units (GPUs) and tensor processing units (TPUs) have been suggested, but these trade-offs have less computing time for more computing power.

3.2.3 Convergence Issues

Convergence issues emanate when reinforcement learning is applied to a problem with a large set of actions or observations (states). Careful formulation of the RL environment becomes critical when the optimization search space continuously increases. This typically occurs where the state is defined by a growing quantity, for example, if the state of an environment is determined or influenced by the number of Access Points in the network. There is a tendency for the algorithm to struggle with achieving optimization or convergence when there are many APs. Deep RL offers a possible solution but requires high computational power (a typical issue with Neural networks) and trades off accuracy in its state's approximations.

3.2.4 Realtime updates

Machine learning algorithms generally use trained models to make predictions. Models are trained with datasets; if the dataset is relatively static, such models can be used without updates. However, that is not the case for constantly changing DSA networks; therefore, machine learning models solving various DSA challenges need to be updated for continued correct prediction [116]. The frequency of model update schedules, online or offline updates, are critical decisions to be made before adopting an ML solution [71].

Table 3.1: Literature reviews on Machine Learning (ML) and Reinforcement Learning (RL) approaches.

Categories	Publication	Review summary/focus
ML approaches	[40]	An overview on how feature extraction and clustering techniques (supervised and unsupervised machine learning) improve spectrums sensing in cognitive radio networks.
	[45]	Machine learning tools for optimal performance in Narrowband IoT networks.
	[44]	Machine learning algorithms (supervised, unsupervised, reinforcement, and deep learning) in various wireless heterogeneous communication networks.
	[108]	A survey of machine learning tools that address resource allocation tasks in wireless HetNets, cellular, V2V, and NOMA networks.
	[113]	Machine learning parameters and approaches in solving spectrum sensing, allocation and selection in CRNs.
	[101]	Presents a detailed review on dynamic spectrum access proffers a framework for a smart spectrum management system combined with a smart database
RL approaches	[72]	An Investigation of Spectrum Sharing in varied radio frequency coexistence scenarios of similar and dissimilar standard communication networks.
	[114]	The application of deep reinforcement learning in addressing dynamic network challenges and resource sharing issues in large-scale networks.
	[115]	Artificial intelligent frameworks to resolve IoT random access and spectrum sharing challenges.
	[69]	Advanced resource allocation techniques,CR network design architectures, resource allocation problem formulations addressing spectrum aggregation, and frequency mobility.

3.3 Non-RL Based Coexistence Management

Non-reinforcement learning algorithms have approached optimal resource sharing. A review of mathematical and non-RL solutions (heuristic and game theory) provides a holistic view of problem formulation. Non-RL-based coexistence management systems in DSA can be prescriptive; this requires the complete capture of all resource allocation scenarios, which can be hard to define and are usually non-optimal. Nonlearning optimization approaches like game theory and heuristic methods search for global optimal resource allocation solutions, as such take a longer time, hence the choice of RL algorithms for approximate optimal solutions, which is sufficient for the purpose.

It also addresses the equal priority (horizontal) and unequal priority (vertical) resource management approaches. This highlights various DSA challenges and the limited use of central optimization solutions.

3.3.1 PU to SU interference mitigation

A Bayesian algorithm for rapid convergence and adaptable threshold learning of PU's presence, limited false alarms, and missed detection of PU's available channels. Mobile SU's learned to change their interference threshold for detecting spectral availability at low and high bands [117]. It showed that the SNR threshold can be adaptive to different scenarios. Fair assignment of channels by SAS was addressed in [118] for unequal priority SUs. They propose vertical and horizontal spectrum sharing as SUs access is split in time or frequency for vertical spectrum sharing and equally for horizontal spectrum sharing. Thus permitting the fair coexistence of heterogeneous networks in DSA systems.

A system was developed to learn to identify PU signal patterns in channels using supervised learning, deciphering the availability of PU channels for SUs' opportunistic use [71]. Their designed system deployed a decision tree algorithm to learn the database's SAS incumbent occupancy; it accurately predicted spectral availability. Predicted available channels were communicated to SUs, who automatically adjusted their physical layer (channel and power) to coexist with PUs safely. Similarly, a central kernel-based non-linear regression model, trained from simulated statistical characteristics of PUs in varied scenarios, learned to predict interference levels experienced by PUs in [119]. They Protected PUs with and without the use of a central database system.

3.3.2 SUs Interference Detection and Coordination

A list colouring approach was adopted for fair assignment of channels to SUs, using heuristic search and node grading for greedy assignment [120, 121]. Their algorithm improved network throughput when spectrum underlay/channel reuse was adopted. This minimized SU's contention window [121] when compared with a single-channel assignment. In demonstrating the practical implementation of SU-to-SU coexistence in [122], interference was mitigated at the edge of a femto cell's horizontal network using a fractional frequency reuse (FFR) method. Lee et al. proved that it's possible to use an algorithmic process to create fair spectral reuse among SUs with similar priority in Femtocell networks.

A database channel detection system used gaming theory's Nash equilibrium formulated solution for a decentralized channel assignment while minimizing interference among APs [123, 124]. A Data Analytics-based Spectrum Allocation (ADASA) algorithm adapted spectrum allocation to network environmental status in heterogeneous wireless networks. An optimal solution to the game theory problem is solved using a heuristic algorithm [125]. PAL users achieved optimal spectrum usage when on-demand spectrum access and blocking probability model was adopted in [126]. An interweave-based shared use strategy model (ISSU) was developed for the safe coexistence of MNOs sharing 28GHz (mmWave) resources. It achieved a 150% spectral efficiency of opportunistic use of p-MNO's spectrum when MNOs took advantage of other absent MNO's fixed allocated channels [127].

Among unequal priority users (vertical access users), a channel allocation mathematical algorithm based on the CBRS rules on spectrum allocation was built for optimal PAL and GAA resource allocation [128]. This was further explored in [129], where a geometrical approach was used to compute the optimal distribution of transmitter power limits of GAAs for their safe coexistence with PAL users.

Similarly, a safe node-channel-pair conflict graph approach was adopted in assigning varying available resources among PAL and GAA users at 3.5GHz [130]. Ying et al. designed a local search-based polynomial time algorithm that guaranteed optimal solutions for real-life WiFi datasets. This resulted in a 10.2% increase in the number of nodes. As such, it handled more demand and minimized interference than random selection. A joint two-staged spectrum and power allocation framework was designed to solve opportunistic negotiation of additional spectrum based on exclusive user schedules, maximized cell capacity, and minimized inter-cell interference [131].

These works allowed for the reuse of spectrum among homogeneous and heterogeneous networks with different reference parameters investigated. They, therefore, required extra PAL protection and limited the level of spectral underlay opportunity among GAA users. These optimization and non-learning methods were applied to vertical and horizontal access SUs operating at higher bands, as opposed to what was considered in this thesis.

A Fair Algorithm for Coexistence decision making in TVWS (FACT), modeled as an energy minimization problem with a Boltzmann machine, arrived at a Pareto optimal solution. Their central management system enabled the fair coexistence of dissimilar TVWS networks and outperformed existing 802.19 approaches in fairness and percentage of nodes served [35]. They, however, focused on spectrum sharing alone and considered scenarios where the number of available channels exceeded requesting SUs.

3.3.3 Hybrid Coordination

A coordinated dynamic spectrum-sharing framework was designed for 5G cellular networks (CBRS), allowing for the time-sharing of spectrum rather than CBRS spectrum split. Thus, to maximize the temporary unused spectrum by a base station (BS), the proposed system required the BSs to be synchronized. A timed distribution and central coordination of BSs was explored. A distributed coordinated spectrum-sharing framework was formulated to reduce access delays and permit flexible spectrum uti-

Figure 3.4: Network optimization diagram using centralized ML algorithms.

lization [132]. Thus, increasing the overall throughput, latency, and congestion when compared with existing frequency-splitting CBRS systems and WiFi-distributed systems.

3.4 Reinforcement Learning Central Coexistence Management

Resource allocation in shared spectrum systems can be coordinated distributively, centrally, autonomously, or in a hybrid format, as detailed in [64]. Centrally located RL agent coordinates other devices, as illustrated in Fig. 3.4. Central coordination includes geolocation database coordination, SAS coordination, and Master device-to-slave coordination.

The objective of all resource coordination was to optimize resources to all nodes in a network. This task had high computational costs and increased latency. Irrespective of the coordination structure, optimization methods such as game theory, stochastic approaches, graph theory, genetics, and swarm intelligence have achieved optimal resource distribution among a few SUs.

However, large networks generate more information, over which the multiple constrained resource allocation optimization problem must be solved. Therefore, the choice of method, location of the deciding entity, and size of the information pool dictate the coordination structure and influence the solution's overall performance and feasibility.

The size of the information pool influences the fundamental parameters used in formulating a DSA problem. The location of the deciding entity eliminates certain assumptions, such as subchannels. It can sometimes dictate the information pool size and determine deployment feasibility. This, therefore, means that the parameters and tools used in framing and solving a distributed resource assigning problem differ from what can be used in a central resource assignment problem.

An investigation into the coordination structure adopted in arriving at optimal resource sharing highlights the gap in the literature on addressing DSA industry needs.

3.4.1 Horizontal Access Coordination for Resource Assurance

Horizontal access coordination manages coexistence among equal-priority SUs. Nie et al. examined the application of Q-learning in sharing spectrum resources when a 49-celled mobile network system varied certain conditions (traffic distributions, time-varying traffic patterns, and channel failures). Their algorithm's ability to vary assignment as available resources changed over time was compared with a fixed allocation of resources and a popular dynamic assignment strategy, 'MaxAvail.' The Q-learning algorithm did better than the Fixed Channel Assignment (FCA) and at par with the 'maxavail', with less computational complexity than the latter [133]. No reuse of spectrum was explored in their approach.

A deep Reinforcement Learning algorithm, consisting of Q-learning and Graph Convolution Network (GCN), was used to explore channel allocation in WLAN networks (homogeneous networks). The GCN extracted the network scenario information, and a deep RL algorithm was trained to allocate channels to access points. Their selective buffering was used to avoid overfitting, and their design successfully allocated multiple APs to a few channels [134]. Their methodology differed from this thesis.

Joint power and channel Reinforcement Learning (JPCRL) algorithm assignment in a dense WLAN for improved throughput was explored in [135]. The channel and power parameters were sourced from actual measurement, and an optimal resource allocation strategy that maximized long-term system benefits was calculated. The proposed JPCRL algorithm significantly improved by reducing the WLAN network's overall interference and throughput, through offline training of a Q-learning policy. These works investigated homogeneous WLAN networks with a predefined operating frequency, while this thesis is on heterogeneous networks with dynamic channel status.

Spectrum sharing algorithm was developed for resource sharing in a dynamic IoT network. The network had unique sensors with unequal resource needs. They considered the unique demands of each sensor, the message, priority access, and periodic packet load. Their homogeneous UEs were categorized into two types based on the saturation of their packet buffers. Their base station's sub-channel allocation assumed that there were sufficient resources for sensors' varied packet sizes. Thus, it did not require the reuse channels, as is done in this thesis. However, it provided evidence that an RL sub-channel allocation achieved good network performance despite its ample action space and information pool [136].

3.4.2 Power Coordination for Interference and Energy Control

A novel centralized deep reinforcement learning (DRL) based downlink power allocation scheme for a multi-cell system was proposed to maximize the total network throughput in [137]. They propose a centralized deep reinforcement learning power optimization scheme for a network with multiple cells to optimize the overall network throughput. They achieve an optimal power allocation that outperforms fixed maximum power allocation, random power allocation, and Weighted Minimum Mean Squared Error (WMMSE) schemes in varied network sizes and hyper-parameters. In their work, only power was optimized to maximize throughput. However, this thesis improves signal-to-noise plus interference (SINR) through both power and spectrum optimization.

A central RL algorithm controlled unmanned aerial vehicles (UAV) that harvested available terrestrial spectrum in exchange for sensing [138]. The central coordinating entity used RL to schedule different tasks, such as sensing or relaying sensed data to PUs and SUs. The central control determined the actions of each UAV in terms of positioning and tasks to be performed to achieve maximum network utility. The multi-agent problem's environment modeled UAVs positioned on a grid (states), and actions were taken on them to either change positions or retain positions and perform two different tasks. Although the deciding entity with the RL algorithm was a central coordinating UAV entity, its actions, problem formulation, and objectives differed from this thesis.

3.4.3 Cell/Link Selection for Spectrum Assurance and Handover

In coordinating the choice of link, modulation, and coding schemes in a cellular heterogeneous network, a Context-Aware Radio rEsource Management scheme (CAREM) was developed in [55]. It was aimed at improving the network's latency and reliability. A similar work by [139] built RL algorithms in UEs that improved their QoE as they learned to select affiliate cells in cellular networks. Their deep learning algorithm's automated, self-learned system created an adaptable coordination of mobile user equipment in optimal cell selections.

Their UEs with RL formulated CAREM algorithms and routers and used global information, such as interference with other UEs, to decide on wireless links. They learned to choose appropriate modulation and coding schemes and cells to meet the network's Key Performance Indices (low latency, high reliability, large-scale connectivity, and data rates). These UEs were the deciding agents and used the central learning agent's access to global information for their cell/modulation selections. The software-defined radio simulation of their two devices' networks differed from this work, which focuses on the network layer of resource management operation. Their agent operated on UEs, improving UE's data rates and latency; this work operated on a spectrum manager (database), so UE parameters were unavailable. They modeled a single UE, while multiple UEs and access points are considered in this work.

Managing cognitive radios with multiple input multiple outputs (MIMO) supports more users and improves spectrum utilization; Shi et al., [109, 140] evaluated the BS (agent) to SUs selection. The BS selects SUs by observing the received signal strength at each SU based on a single MIMO base station. They also managed the coexistence of PUs and SUs and ensured a maximum number of SUs were supported using their proposed solution. They focused on the network's ability to meet a predefined rate

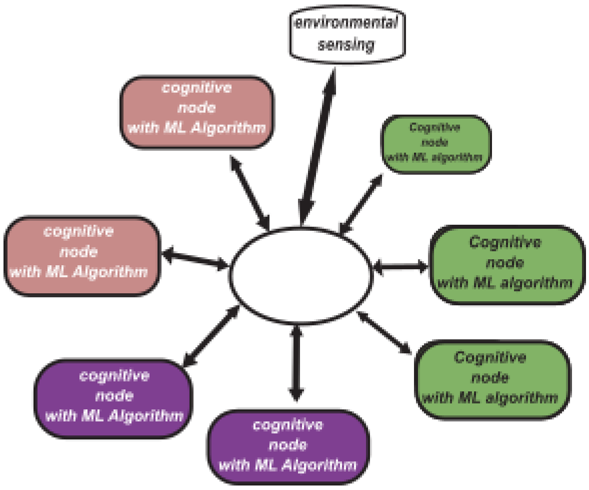


Figure 3.5: Network optimization diagram using decentralized ML algorithms.

with a specific number of SUs amid PU-to-SU coexistence. This was achieved with the least amount of information. A different problem of SU-to-SU safe coexistence is investigated in this thesis as such parameters used for optimization by the RL agents were different.

Central coordination has been explored in UAV, cellular, WLAN, and shared spectrum networks, as these usually have a central access point within their architecture. However, distributed coexistence management approaches have been explored in other types of networks.

3.5 RL Decentralized and Autonomous Coexistence Management

Decentralized or distributed coexistence management occurs when the coordinated devices contain the decision makers, illustrated in figure 3.5. There have been various ways resource distribution by SU nodes was formulated to achieve optimal performance.

Their objectives are categorized based on their goals, which include unequal priority (Vertical) and equal priority (horizontal) coordination, power control, and cell/protocol selection.

3.5.1 Vertical and Horizontal Contention Prevention using MAC Protocols

A unique autonomous secondary user search for available spectrum was proposed in [141]. Their proposed synchronous cognitive MAC protocol allowed the independent search for spectral space by SUs amid contention from other PUs and SUs. This was achieved without communication between the entities (autonomous management). Thus, they achieve an opportunistic spectrum use by controlling the spectrum use at the MAC layer while gathering information from sensors at the physical layer and traffic statistics at the application layer (which contained past decisions and observations).

A collision avoidance RL algorithm-based protocol was proposed in [142] for SUs to learn their spectrum sensing policy. Thus, they learned to minimize collision with other SUs and PUs while maximizing spectrum usage. Their proposed algorithm improved the structure of listen-before-talk, making the SU's RL agent observe its collision and false alarm probability.- Deep Q-learning and double Deep Q-learning Network (D-DQN) algorithms have been explored in detecting the type of nodes (SUs or PUs) occupying a channel in [143]. They correctly identified the type of a fixed node as a dynamic (hopping) or greedy node. They address the DSA problem of detecting the presence of other SU and PUs in a channel. They also develop a DQN and double DQN to implement optimal channel access by learning the PU's behavioral pattern without prior network knowledge.

A tabular Q-learning algorithm was built to enable SUs to choose operating channels and transmitter power, preventing them from interfering with PUs and SUs [144]. Their designed spectrum media access for PUs' and SUs' users depended on sensed available channels, with the PUs having a changing presence in the network. The users had the RL agents that learned to receive rewards for good opportunistic use of available channels. As such, this approach led to many collisions during the learning phase, before the algorithm learned correct decisions, and was formulated as a listen-before-talk MAC protocol. The LBT protocol was modified in [57] to suit a CBRS system and improve its reuse of two channels. They created an SU's RL agent that learned to vary its carrier sensing energy detection threshold (EDT). The EDT identified the presence of PUs while the agent maximized its user-perceived throughput. The SU was able to vary its EDT to suit unique PU detection challenges in a small test environment.

A decentralized channel distribution to different SUs was explored as a local altruistic and local congestion game to achieve global optimization with the least local information. Collecting the payoffs of neighboring SUs and minimizing their interfering neighbors in both games, respectively, it optimally distributed the limited number of channels to SUs [145]. Extending this, SUs were assumed to have synchronized access to the channel and learned PU's available channel pattern using collision detection and media access/carrier sensitive protocol in [146]. A learned policy influenced SUs opportunistic use of channels without prior information on future PUs and SUs behaviour.

The mean opinion score (MOS) of a 5G DSA measured the Quality of Experience (QoE) of SUs from network users. This was used to train an RL algorithm to prevent PU interference in a video and data transmission network. New SUs' RL agents learned network traffic patterns from other SU's RL policies [73]. Adopting the MOS in evaluating the performance of a fault tuning and power control Q-learning algorithm, a power control Q-learning algorithm outperformed fixed power control in [49]. Their algorithm outperformed industry standards' performance in optimized Voice over LTE (VoLTE) and its power assignment to SUs' base stations.

These works improved MAC protocol coordination through improved spectrum detection and sensing, which is not the objective of this thesis.

3.5.2 Channel and MAC Protocol selections

A distributed deep reinforcement learning algorithm was adopted in [46] to improve requesting SUs' selection of appropriate MAC protocol (TDMA, q-ALOHA, Fixed window ALOHA, DRL agent, exponential backoff ALOHA) for enhanced data throughput efficiency. Their DRL algorithm achieved faster convergence speed in arriving at higher data throughput as it could dynamically select channel, power, and appropriate MAC protocol to offload SUs data to the network compared to other MAC protocols.

An autonomous Deep Reinforcement learning algorithm with an LSTM Recursive Neural Network as the Q-value approximator for dynamic spectrum access was proposed in [147]. They attempt to solve the ever-growing state space and partial observable space of DSA systems without coordination or communication. Their DRL algorithm was framed as a multichannel random-access game of multiple users selecting limited channels. Their approach outperformed other Nash equivalent solutions and slotted Aloha protocol in various users' fair selection of channels.

These works improved MAC protocol coordination, which is different from the objective of this thesis.

3.5.3 Cell/Link, Modulation Selection or User Access and Resource Allocation (UARA)

An RL fast algorithm learned to select a modulation scheme with specific data rate and power levels to maximize each SUs' throughput in [148]. They formulated a problem for a rapidly changing mm-wave channel to enable fast resource sharing and proved that its logarithmic convergence time exceeded other algorithms. Their formulation was void of propagation models and could be deployed in mmwave channels. A fixed number of actions (modulation types and power levels) was assumed to aid scalability. In this thesis, however, the focus is on terrain-dependent lower bands that need propagation models. Also, a nonstatic action size was necessary for its problem formulation.

A Duelling Double Deep Q-Network (D3QN) was proposed to improve user access and resource allocation (UARA) coordination in downlink HetNets of Cellular networks [47]. UEs were D3QN agents who learned to select the correct base stations to operate in, such that the highest number of UEs had the best SINR experience. The UEs learned to schedule themselves to different base stations (heterogeneous networks), such as pico, femto, and macro cells, and maintain an above-threshold SINR at each UE. A high computation time was experienced for many UEs, as their problem formulation of the RL states was dependent on the number of UEs. This work was extended in [139], as they employed Deep Q-networks for improved QoE of mobile UEs. Although the parameters used were similar to this thesis, the objectives differed. They aimed to maximize the number of UEs in a cell, while this thesis focuses on optimizing the number of nodes/cells by utilizing limited spectral resources.

3.5.4 Spectrum Re-Use.

A Q-learning schedule algorithm for matching calls to dynamic channels of a cell did better in preventing interference among cells than fixed spectrum/channel assignment [133]. Similarly, a generative network powered deep distributed Q-Network (DDQN) learned to assign frequency at different time slots to maximize the network's utility [149]. Mobile sharing of resources was achieved in [150] where a cognitive radio learned from channel status, quality, traffic, quality of service, and priority status of SUs to decide when to occupy a channel. It learned to hand off mobile cognitive radios from one channel to another. The trained transfer actor-critic learning algorithm was transferred to new SUs and performed better than a temporary difference (TD) q-learning algorithm [150].

In [133], interference detection was based on distance, while call traffic was assumed to be poison-distributed. The cell and cell's available channels defined its state and established better spectrum reuse in cellular systems than fixed assignment. Their state space structure consisted of actions and states (cells and available channels), which differed from this thesis. Also, only spectrum reuse was considered, as opposed to spectrum reuse and power optimization, which were addressed in this work.

3.5.5 Power Control for Spectral Assurance and Re-use

A Deep Q-Network RL algorithm was developed to train SUs to learn to transmit at a safe transmission power from a fixed set of power limits while sharing spectral space with PUs and SUs. A Zigbee communication channel between sensed PU signals around SUs provided the necessary feedback on channel occupancy. SUs were trained to avoid occupied channels using the DQN RL algorithm while adjusting its power levels to ensure they coexisted with PUs [151]. They controlled only the power resources of SUs and depended on an external communication link between PUs and SUs. This may not be practical in some network types.

A Q-learning algorithm in each eNodeB (LTE) and WiFi access point learned to correctly select a channel in a shared spectrum network without prior knowledge. Each SU had an agent that observed a channel's idle state, successful transmission, collision, and contention and chose to occupy the channel. This was rewarded with the network's cumulative throughput. An optimal policy was achieved using an ϵ-greedy policy that balanced exploration and exploitation [25].

Inter-cell interference mitigation in [152] was achieved by each cell using the DQN policy to control its transmission power based on partial channel state information from other transmitters. Their algorithm was robust to wireless network changes and independent of the network size but depended on information (channel gain, interference plus noise power, received power) exchange between transmitters. Thus, it is suitable for networks with inter-cell communication mechanisms.

PU to SU interference is prevented in a Wireless Regional Area Network (WRAN) in [144, 153, 154], as each SU's RL agent was trained with sensed interference levels, to select appropriate transmission power [153]. This was done with the knowledge of measured interference and partially observed Markov decision problem (belief function on interference levels replaced actual measured interference levels). A transferable Q-learning and deep Q-learning policy was used to manage a single resource in [154] among PUs and SUs, replacing the database management system. They also assumed a homogeneous network scenario, which differed from the thesis's context. A power control deep Q-learning network (DQN) algorithm for cognitive shared use (CU) of orthogonal sub-channels was proposed in [155]. Thus ensuring that all CUs had SINRs of -0.5 to 2 in their unique coal mining environment. The DQN provided a better-distributed learning than their Q-learning algorithm.

These approaches had their agent operating at a different network level (UEs and nodes) with limited information pool as against a central entity as used in this work.

3.5.6 Joint Resource Allocation for Interference Mitigation

A decisive Q-Learning algorithm was proposed in [156] where a joint channel and power control were established in a Macro and femtocell network configuration. Each cell learned to choose a channel and transmit power based on other cells' trained policies. The formulation outperformed other users' independent Q-learning algorithm's optimal cell capacity and quality of service. Their state formulation comprised some global information, such as interference experienced by femtocells and the number of interfering macro and femtocells. They, therefore, assumed a form of communication between policy and information among cells. The joint resource and power assignment are the same as this work. However, they do not focus on reusing spectrum (spectral overlay and underlay) by cells. Thus, their problem formulation and network architecture differ from this thesis. Three deep reinforcement learning algorithms were proposed for sub-channel assignment and power allocation. Their joint optimization of an uplink multiuser Nonorthogonal Multiple Access (NOMA) systems [157] was different in architecture (channel scarcity and power restrictions) when compared to a DSA network.

3.5.7 Applied RL in CBRS Network

A modified Listen Before Talk scheme was proposed for a CBRS system to enhance PAL and GAA spectrum sharing in [57]. The GAA user-perceived throughput (UPT) increased as it learned to use PAL's available channels opportunistically by adapting to varied PAL's energy detection thresholds. Their Q-learning algorithm maintained good performance in hidden node scenarios, preventing interference with PAL users and efficiently utilizing the vacant PAL spectrum.

Similarly, the Licensed Assisted Access (LAA) framework for the coexistence of WiFi and LTE networks was improved despite their different MAC protocols, sensing thresholds, occupancy probabilities, and throughput in [25]. Randomly located APs and LTE (nodes) learned to select available 6 and four channels individually. Performance was evaluated based on their nodes' ability to use only idle channels and achieve successful transmission free of collision and contention [25].

These limited implementations of RL in shared spectrum networks focused on distributed access to sub-channels by APs/nodes. Previous works explored the pragmatic feasibility of improving SUs' access to sub-channels and their existing MAC protocols. This thesis, however, attempts to improve the spectrum management system in an existing DSA architecture. Thus, improving a spectrum manager's resource assignment would result in less contention management within the sub-channels, such that nodes that use or do not use the same MAC protocol can coexist.

3.6 Limitation and Further Studies

3.6.1 Limitations of RL in DSA systems.

Similar to the challenges of ML, reinforcement learning suffers some drawbacks when applied in DSA systems despite its many benefits. These include:

1. Problem Formulation: RL problems and solutions are subjective and dependent on the design problem addressed. Defining the DSA optimization problem to suit typical DSA systems is usually difficult.

2. Standard Assessment: Standardizing the performance of RL models is difficult, as each solution is tailored to the specific problem formulations. It becomes difficult to standardize or define a metric or criteria for determining a good-performing RL model.

3. Approximate Solutions: The approximate search for solutions leads to non-optimal solutions; this is like the convergence issue ascribed to ML. This means that sometimes and during RL training non optimal resource allocation would be sufficient for a DSA system.

4. RL implementation: Implementing RL algorithms in DSA systems usually requires a digital replicate of the DSA system for prior training necessary to limit approximate solutions; this DSA replicate is usually challenging to achieve.

5. Computational intensity: As with all artificial intelligence algorithms, the computation energy and time in training an RL model is usually high.

6. Regular Updates: The digital replica of the DSA system, used as an RL training environment, will need to be as dynamic as a typical DSA network. This means that changes in the DSA network have to be replicated in the RL environment to train a system that can be deployed in a real-life DSA network.

3.6.2 Further Studies.

A myriad of studies have explored automating PU-to-SU coexistence, but there are few studies on SU-to-SU coexistence management. There was also a lot of work on MAC protocols and LBT protocol modification, using RL algorithms to improve DSA performance. The adoption of RL in spectrum allocation focused on assigning abundant subchannels. There were limited studies on assignment coordination of limited resources.

Similarly, scheduling and interference monitoring were limited. Real-life studies of RL algorithms in resource management are yet to be explored. RL is also yet to be explored in maximizing the total number of deployed BS, APs, or nodes when assigning spectrum and power to nodes in a DSA system, as database automation focuses on PU-to-SU rather than SU-to-SU coordination.

A standard evaluation structure for DSA systems remains an open area for further research, as this is limited in the literature. Generally, evaluating the performance of designed coexistence models in a DSA system can be challenging as these networks vary in architecture. [158–160] designed a series of performance indexes for evaluating their dynamic spectrum access networks' models. Their proffered unique performance indices assessed their GAA-to-GAA coexistence model, framed from WInforumn's approach 1, 2, and 3 specifications. Their index showed that increased GAA users result in more significant interference, irrespective of the device configuration or location [158]. Coexistence grouping impacted interference limits experienced, which influenced bandwidth, path loss, device density, and interference trade-offs within coexistence groups [159,160].

3.7 Chapter Summary

This chapter has reviewed various approaches to spectrum management in DSA systems. A brief study of Machine Learning (ML) Algorithms and how they have been adopted into DSA systems was studied. An arm of the machine learning algorithm, reinforcement learning, was found to be predominantly useful for improving the performance of DSA systems. Despite the strides of ML in DSA systems, an overview of the potential challenges to their deployment in network management was also presented. A review of Non-learning and machine-learning approaches to checkmate DSA issues, addressed in chapter 2, were discussed.

Coexistence management issues resolved with RL algorithms are categorized based on three criteria: the location of the RL agent in a network, control elements and information pool used for decisions. These were used to classify coexistence managers as central, decentralized, or distributed and automated. More literature was on unequal priority access, PU-to-SU, than SU-to-SU (equal priority access) coexistence management. However, there have been studies on distributed coordination for both PU-to-SU and SU-to-SU. There have been limited studies on central and equal-priority coordination of limited resources in DSA systems.

Only some central RL approaches to coexistence resource management were found in typical DSA networks, and none were found in lower band coordination. However, a myriad of studies were conducted in other decentralized or distributed networks. These studies required SU MAC protocol adjustments to accommodate inter-SU communication. Therefore, this thesis proposes using an intelligent central coordination mechanism to eradicate inter-SU communication and enhance spectrum reuse in dynamic networks in Chapter 5.

Chapter 4

Design and Implementation of a Dynamic Spectrum Access system

4.1 Introduction

Databases in DSA systems are central coexistence management systems for vertical spectral access. It coordinates spectrum reuse, protecting primary or incumbent users of the spectrum. Based on the definition of DSA in Chapter 2, the database provides information on the continuously changing spectral availability (available resource prediction). The resources available are not shared using any order among competing secondary users, hence creating a high level of contention, increasing the level of unpredictability and uncertainty highlighted in Chapter 2 by industry stakeholders.

DSA systems like TVWS and CBRS use a database management system to manage resource sharing among PUs and SUs. As an early step towards demystifying the content of such databases, an end-to-end TVWS database management system has been designed with a unique design methodology. This was achieved by studying previous works of end-to-end TVWS designs in the literature, understanding methods for interference mitigation, investigating gaps, and finally, implementing a complete TVWS database.

This was applied in different locations, revealing spectrum availability in developed and developing countries. This highlighted the impact of counties' policies on such available resources. It also quantifies PU's interference protection, serving as a tool for monitoring interference in SU-SU coexistence management. This chapter provides a deeper understanding of DSA systems, shows the impact of regulatory policies on spectrum management, and identifies the gap (overhead size) in central coordination.

4.2 Database Designs and Policies

The primary role of a TVWS Database management system is to ensure an effective coexistence between SUs and PUs. The database has been designed in different studies, as aware of the PU and SU parameters. Based on this information, permitted power limits of SUs to coexist with PUs were computed using three methods discussed in section 4.3. These methods used different propagation models to calculate and design different databases.

Government policies stipulated the methodology for designing databases, power limits of SUs, and restrictions on spectrum sharing with incumbents while they are active. They also defined the propagation models to be adopted for computing estimated SU's transmit power and the protocol for database communication with nodes or devices. Several countries have their regulations on spectrum sharing, and these either promote or stifle spectral efficiency.

4.2.1 Review of Database Designs

The database management system in most reviewed works used established commercial databases or statistical assumptions to determine spectral availability. These commercial databases were utilized in Murty's evaluation of the performance of a database management system in protecting PUs. They evaluated the TV transmitters' rate of record change, database response time, and degree of PU overprotective in [33]. They reiterated the overprotective nature of PUs when distance or coverage contours were used as an interference discovery measure and suggested combining it with real-time measurement.

A comparison between the performance of a designed database and a commercial database showed that the created database was 70% in correspondence with the commercial database in [34,161]. Their designed database was based on FCC's propagation curves and the Longley Rice propagation model in estimating interference. Gurney et al. simplified database design by creating a model using propagation curves. They emphasize that databases may be the best-shared spectrum management scheme [162]. However, other researchers who believe real sensing and database predictions (a hybrid management scheme) proffer a better solution have disproved this [33, 163, 164]. These methods used distance as the interference discovery mechanism, which has been discovered to provide static protection over PUs in [33]. This thesis used the received signal strength (RSS) approach in interference discovery, which was flexible and similar to real-time sensing.

Real-time sensing at different locations was used to build a virtual TVWS database in [165]. The database statistically estimated the SU's white space device's (WSD) power, enabling safe coexistence between PUs and SUs. Sato et al. took a similar approach in creating a database using measured TV signal strength to estimate propagation loss in a wireless distribution network. Their work revealed that measured statical path-loss estimations improved the algorithm's estimated path-loss [166]. Path-loss propagation models identified the type of nodes in rural, semi-urban, and urban areas using Convolutional Neural Networks (CNN) in [167]. Kryszkiewicz identified storage and computational complexity issues with adopting Dynamic Spectrum Alliance's model when designing an accurate database in Kenya. The same model was adopted for a small-scale design in this thesis.

Similarly, a designed TVWS system compared path loss performance as the receivers' height varied, to improve PU coverage. Similarly, they studied the protection of SUs from PUs in a simulated environment to solve mathematically hidden node issues [168]. Thus, the database complemented the measured sensors' inability to discover some obstructed signals (hidden node problem), which was termed a hybrid management system. A Hybrid of database and real-time sensing was found to perform better in interference prevention than stand-alone (database or spectrum measurement) systems [164, 169–171].

Designed databases require a means to communicate safe transmission parameters to WSDs. Hwang et al developed a Protocol for communicating available channels to SUs independent of the actual communication channel in [172]. The database to master SU protocol was designed to support slave devices, while a standardized Protocol for Access to White Space (PAWS) was adopted in this thesis.

4.2.2 DSA Regulations and Use Cases

The framework for TVWS has been well established by several regulatory bodies [12–14, 26, 173, 174], with the global deployment of the technology. Spectrum has been regarded as a natural resource managed by respective governments. Respective governments exclusively license resources to service providers, referred to as a fixed assignment. A shift from fixed assignment to any other assignment depends on government regulators. Spectrum management is, therefore, dependent on government regulations, and although regulators are considering spectrum sharing to expand wireless communication services, the focus has been on protecting licensed users (PUs).

This is evident in most countries' TVWS policies' [26, 175] and CBRS documentation in the United States where priority PU's are allowed exclusive use of channels. This is necessary as the PUs remain custodians of such channels and are entitled to exclusive channels to provide a high degree of service certainty. However, technological advancement has led to other services, such as IoT services, vehicular wireless communication, drone communication, and e-health internet access, requiring temporary channels with less channel certainty. These services can be supported by a reliable shared spectrum framework, which extends the regulators' ability to cater to more services [19].

Therefore, there is a gradual shift from exclusive/fixed spectrum allocation to fixed and shared spectrum allocations in some developed countries. The technological integration of software-defined radios in new radios (NRs) supports the radical disruption of fixed spectrum allocation, thus increasing the need for a coordination strategy to regulate SUs-to-SUs coexistence, as these differ from the coexistence management of fixed-located PUs.

4.3 Database Design Methodology

Countries have adopted different methodologies in designing their database, influencing how WSD's permitted power is calculated. Luzango categorized these WSD-permitted transmitter power computing methods into three: Vectorized, Carrier to Noise plus interference and Degradation location approach [34]. These methods vary in the number of input parameters, computational complexity, and accuracy.

4.3.1 Vectorized Approach (Minimal Coupling Loss –MCL)

Vectorized Approach/MCL method is adopted by the Federal Communication Commission, USA, to estimate the coverage of every TV transmitter (digital or analog). Coverage/contour distance is computed with the least number of parameters, such as PU's transmitter power and operating frequency. This approach was used to build a database with simple computational equations and lookup tables in [74, 176]. The generated median field strength values from the lookup tables were used to compute PUs' coverage and protection distance. The FCC propagation models were used to calculate WSD transmit power so that the coverage of WSD and PU do not intersect.

It was unsafe for another SU radio to transmit on the same frequency as the PU, within the PU's coverage plus protection contour distance, as shown in figure 4.1. SUs safe transmitter power at the same frequency was computed using terrain-based propagation models in [34]. Initially, WSDs within a DTT's contour could only use adjacent channels; this was adjusted to permit co-channel use at safe power limits that maintain zero intersection of the coverage areas (spectrum overlay). This method was used extensively in the literature but not in this thesis. Fixed contour protection of PUs was considered excessive to extend unto SUs since SUs were assumed to have higher interference tolerance [33].

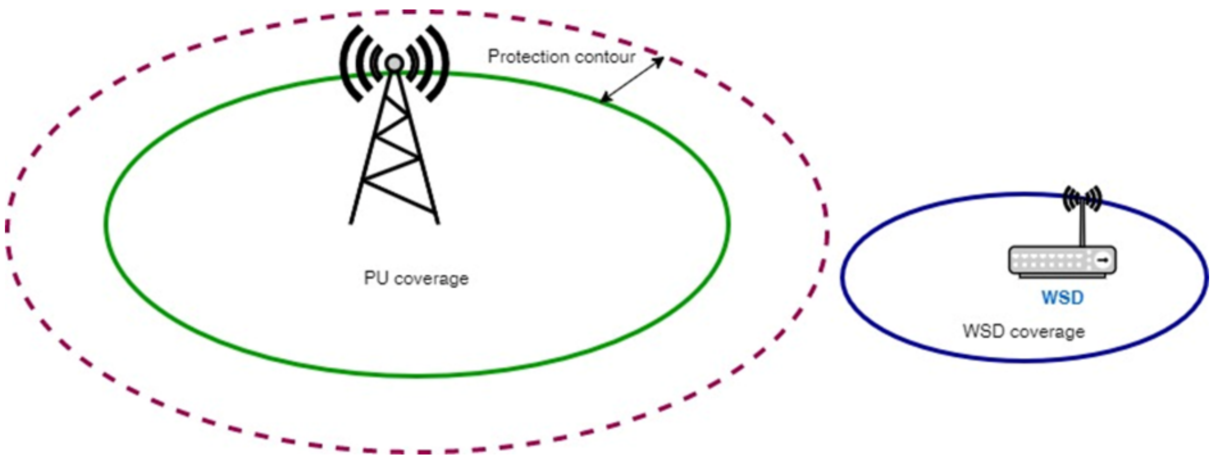


Figure 4.1: TV contour and WSD coverage

4.3.2 Carrier to Noise plus interference ratio (CNIR) threshold Approach

The CNIR approach uses a terrain-based propagation algorithm to assess the transmitted signal degradation over distance. The Received Signal Strength (RSS) at a possible TV receiver location (within a pixel) is compared with noise to generate a Carrier Noise Interference ratio (CNIR). This is compared to a CNIR threshold to assess the availability of the channel at the pixel. The RSS, Protection Ratios, and link budget are used to determine the permitted WSD power [34]. This is the method proffered by the Dynamic Spectrum Alliance model [3], deployed in the design of Kenya's TVWS database in [5] and adopted in this thesis. It requires more parameters, is more accurate than the vector approach, and allows for flexible alteration of thresholds for spectrum underlay as demonstrated in Fig. 4.2.

It, however, requires an undefined number of receivers; deciding on the number of receivers can be tricky, as too many receiver points result in more accurate WSD transmit power estimates at the cost of huge computation and data storage space [5].

4.3.3 Degradation of Location Probability Approach

Degradation in location probabilities (q%) of Digital Terrestrial Television (DTT) signals is estimated using Monte Carlo simulations. Each pixel's degradation probability

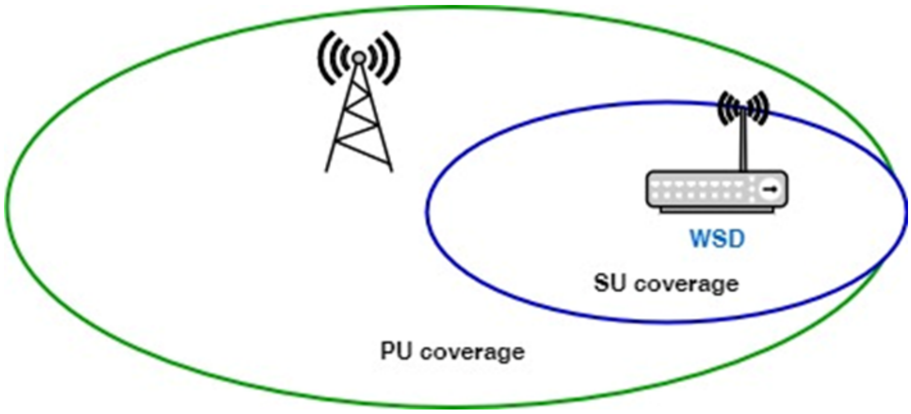


Figure 4.2: TV and SU underlay provision using CNIR approach

is measured in a zero interference mode (without a WSD), and another calculation is done in the presence of the WSD. The difference in the probability is compared to a threshold value, and a decision is taken on spectrum availability or maximum power of a WSD. Ofcom adopted this method by splitting the UK map into 100 x 100m pixels. It used Monte Carlo simulation and Digital Terrestrial Television (DTT) parameters to estimate the location probability of DTT's signals at each pixel [3, 34]. A simplified version of this used RSS's mean and standard deviation in [177]. This improved the chances of generating the fundamental RSS mean and standard deviation for locations that lack documented TV RSS statistics.

This method provided the most accurate estimation of RSS of PUs in all pixels of the country and was the most complicated [3, 34]. However, some attributes, such as using pixels in estimating coverage rather than distance, were adopted in generating the Geolocation Database (GDB) framework in this thesis.

This thesis adopts the less complex CNIR approach to estimating received signal strength and the location probability approach, which uses a precise pixel definition of coverage.

4.4 Dynamic Spectrum Access Inter-communication System

There is a need to have an established standard means of communication amongst the parts of a DSA system. Detailed information handshake protocols between a WSD and a database are provided in IETF's documentation [178].

4.4.1 Database to White Space Device Interaction

Communication between databases and WSD is necessary for the framework shown in figure 4.3. The master device sends a request to the database for access to a TV frequency for itself and any slave devices [70]. This request incorporates compulsory registration parameters required from the master WSD for documentation and accountability of the spectrum allocated. The expected standard content of the registration is summarized below [3]:

1. Manufacturer's unique alphanumeric code;
2. Manufacturer's serial number of the device;
3. Device's geographic coordinates as latitude and longitude (WSG84)
4. Device's antenna height above ground level or above mean sea level (meters, optional for personal/portable master devices);
5. Name of the individual or business that owns the device;
6. Name of a contact person responsible for the device's operation;
7. Address for the contact person;
8. An Email address of contact person;
9. A phone number of the contact person.

The above list may differ with countries' regulation [12, 26, 175, 179]. In response to a WSD request, the database sends available frequencies, permitted transmitted

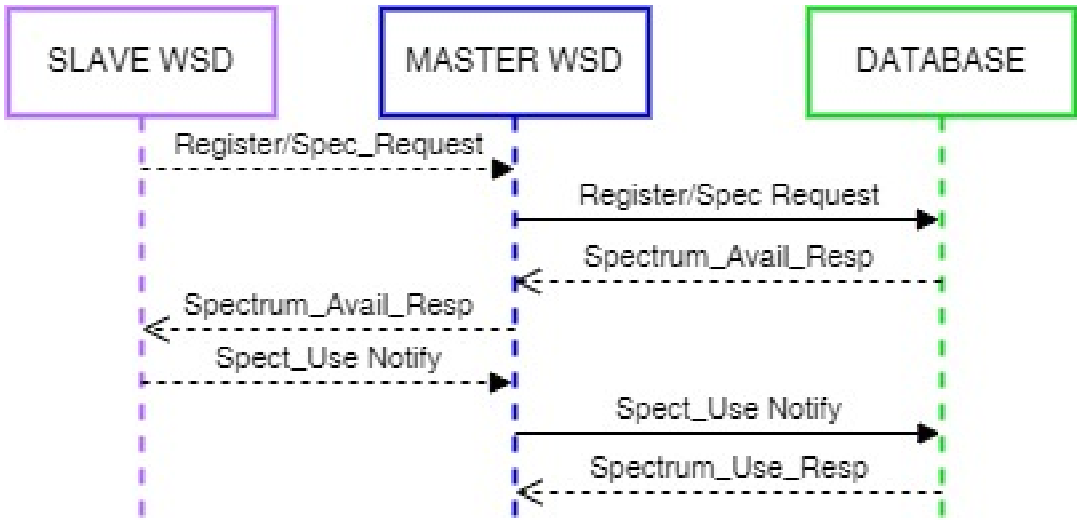


Figure 4.3: PAWS operation time sequence

power for the WSD and Time validity of parameters received. Slave WSDs send registration/requests to the Master device, which relays the information to the database. Allocation to the slave WSDs can be from the database, or the Master device can offer some of its operational parameters to the slave device. Still, it must report its actions to the database [3]. The protocol for this unique communication between a database and a WSD is the Protocol for Access to White Space Databases (PAWS).

4.4.2 IETF's Protocol for Access to White Space Databases (PAWS)

Mancuso et al. provide use cases and protocol specifications for establishing communication between WSDs and a database [77]. It was observed that strict government regulations could be incorporated into the PAW's rule set. Guidelines on the implementation of this protocol are provided in IETF's document [178]. Its time sequence of requests between a WSD and a database is shown in figure 4.3. These specifications were adopted in implementing this chapter's end-to-end DSA system.

4.5 End-to-End TVWS Design Structure

In this work, a database coexistence manager is designed to generate WSD transmitter power and available channels in a single AP location. This process was split into three stages: First, the Longley Rice propagation loss algorithm was studied and implemented in Matlab. This was used because of its terrain properties, performance compared with other path-loss models, and the DSA regulator's preference [3, 33]. Matlab's version of the Longley Rice (LR) model lacked some terrain parameters at the time of design. Hence, the LR propagation model was designed from scratch.

In the second stage, WSD transmitter power is estimated. This uses path-loss computed in the first stage, database parameters, regulations protection rules, and link budget to estimate the permitted safe power a WSD transmits. The necessary inputs or parameters from TV transmitters and WSDs are highlighted in subsection 4.5.2 and used for this design.

Finally, this information is compiled in a predefined order and saved as schemas in a MySQL database. The database is hosted on a local MySQL server and queried for spectral availability via a website or an Application Interface (API) by the WSDs. However, since spectral availability was pre-computed from the fixed location of TV transmitters, the spectral pixel map of the WSD location was relatively fixed.

Thus, changing the PU or TV transmitter location will alter the spectral pixel map and require repeating the entire design process. This becomes the state when SUs continuously change locations in a DSA system, worsening the challenge of interference monitoring in such systems.

4.5.1 Longley Rice Pathloss algorithm

Terrain-based propagation models are fundamental in designing TVWS databases because of their ultra-high frequency and signal coverage. The terrain models quantify the environment's impact on diffracting and scattering signals as they propagate in space. These models are used to implement the end-to-end design of a TVWS database.

Terrain-based propagation models are preferred at lower bands as they consider diffracted waves, which often occur at lower bands [4]. Longley Rice path loss, together with ITM's terrain-based algorithms, are useful for this purpose. However, Longley Rice was adopted in this thesis as both algorithms make use of detailed terrain parameters. The path loss models predict the degradation of PU transmitted power over a distance

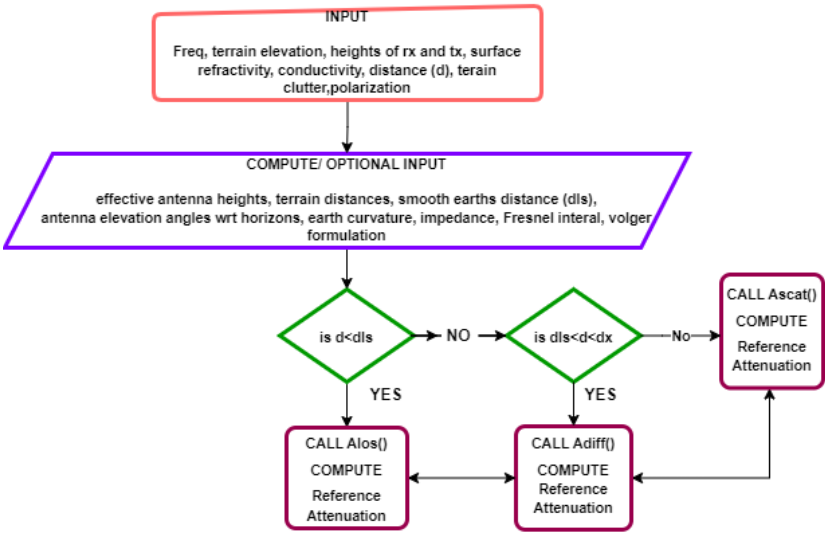


Figure 4.4: Longley Rice Main algorithm flow of calculations

Table 4.1: Input and Optional input parameters.

δ_h	h_{1g} (m)	h_{2g} (m)	N_s	f_o (MHz)	d(km)	σ	Mode (Al, Ad, As)	Pol	ϵ
90	208	1.5	370	47.7	9	0.0005	Al	v	15

from the PU transmitter. This was useful in computing the permitted power limits of WSDs reusing a PU's spectrum or adjacent spectrum. It is, therefore, extremely important in interference prediction and estimation.

Longley Rice Pathloss Algorithm is known for its complexity, and predicts signal degradation over a specific distance. Figure 4.4 provides an overview of the necessary parameters and sequence of computation in arriving at propagation loss [180]. Its input parameters include Terrain parameters: refractivity (N_s), permittivity (ϵ), terrain conductivity (σ) Light wave center frequency (f_o); TV transmitter parameters: antenna structural height (h_{1g}), and polarization (Pol); Receiver parameters: antenna height (h_{2g}) and distance (d) between transmitter and receiver, values are summarized in Table 4.1. These parameters are used to calculate other optional inputs with some preliminary equations, in equations (4.1) to (4.5) and some illustrated in Fig. 4.5. Figure 4.4 summarizes the different computational aspects of the LR propagation model, in which random siting of TV receivers is assumed.

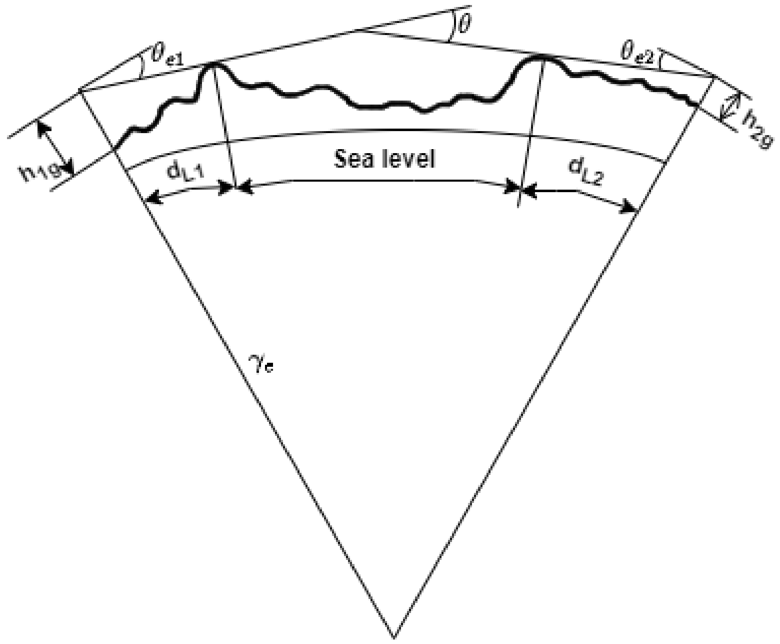


Figure 4.5: Geometry of Trans-horizon Radio Path

The appendix table C.1 details all table titles and parameter symbols' meanings.

The earth effective curvature (γ_e) is:

$$\gamma_e = \gamma_a(1 - 0.04665 \exp^{N_s/N_1}) \tag{4.1}$$

where γ_e is the earth's effective curvature, measured in units of reciprocal length

$\gamma_a = 157 * 10^{-9} \quad m^{-1}$; $N_1 = 179.3$ N-units

γ_a is the earth's curvature, defined by the terrain environment. N_s is the minimum monthly mean surface refractivity, measured in N-units. The wave number (k) is defined as:

$$k = 2\pi/\lambda = f/47.70 \tag{4.2}$$

where f is carrier/channel center frequency in MHz. The effective antenna height is:

$$h_{ej} = h_{gj} \tag{4.3}$$

if terminal j is sited randomly. Other input parameters include:

$$d_{Lsj} = \sqrt{2h_{ej}/\gamma_e} \tag{4.4}$$

$$d_{Lj} = d_{Lsj} \exp\left[-0.07\sqrt{\Delta h/max(h_{ej}, H_3)}\right] \; with \; H_3 = 5m. \tag{4.5}$$

where, k is a wave number measured in units of reciprocal length (equation (4.2). h_{ej} is effective antenna height, j is 1, 2 for transmitter or receiver, (equation (4.3) and d_{Lj} is the distance from each transmitter/receiver terminal to its corresponding radio horizon (equation (4.5). d_{Lsj} is the distance from each transmitter and receiver terminal to its corresponding smooth earth's horizon (equation (4.4) as shown in Fig. **??**.

Some optional input equations:

$$A_3 = A_{diff}(d_3) \tag{4.6}$$

$$A_{ed} = A_3 - m_d d_3. \tag{4.7}$$

where m_d is the slope of the curve of diffraction attenuation (A_{ed}) versus distance (d); were used in computing attenuation reference A_{ref}. Attenuation reference (A_{ref}) is:

$$A_{ref} = \begin{cases} max(0, A_{el} + K_1 d + K_2 \ln(d/d_{Ls})), & d \le d_{Ls}. \\ A_{ed} + m_d d, & d_{Ls} \le d \le d_x \\ A_{es} + m_s d, & d_x \le d \end{cases} \tag{4.8}$$

and propagation loss computed as:

$$\text{Propagation loss(path loss)} = 32.45 + 20\log f + 20\log d + A_{ref} \tag{4.9}$$

where f is center frequency (MHz), d is distance under review in km; these are fed into the diffraction function whose output is used by line of sight (A_{los}) or scatter A_{scat} functions.

The chosen function was dependent on the distance under investigation, as shown in Figure 4.4 and Equation (4.8). The diffraction function ($A_{diff}()$) was the central function utilized, by the line of sight function ($A_{los}()$) and scatter function ($A_{scat}()$) in equations (4.6) to (4.8). These functions are used to compute Attenuation reference (A_{ref}), which is the additional terrain-based path-loss experienced by a transmitted signal and defined in equation (4.9) [180].

The $A_{scat}()$ function in Equation (4.8) was not used as its shortest distance (d_x) was estimated at more than 200km, which exceeded the maximum distance between a protected transmitter and WSD.

Diffraction Function ($A_{diff}()$)

Optional and input parameters of the model compute attenuation distances d_3 and d_4 and these are the inputs to the function, Its output is used to calculate predicted diffracting attenuation (A_3 and A_4), estimated diffraction attenuation below free space (A_{ed}) and its slope (md) in figure 4.6. These values were components of the Attenuation reference (A_{ref}) in Equation (4.8) and used to compute (A_{los}).

Line of Sight Function ($A_{los}()$)

The flow chart for computing $A_{los}()$ function is shown in figure 4.7. It computes the A_{ref}, predicted reference attenuation with inputs A_{ed} and m_d from A_{diff} function.

Where the distance between a TV transmitter and a point receiver (d), is less than the sum of smooth earth's horizon distance (d_{Ls}) in equation 4, the reference attenuation is gotten through an $A_{los}()$ function. When this condition is not met, a diffraction function (A_{diff}) or the Scatter function (A_{scat}) is used. Parameters m_d and A_{ed} of the diffraction function are used in $A_{los}()$ function to compute A_0 and A_1 Fig. 4.7.

In the path-loss design, the transmitter polarization is observed to influence the terrain path-loss component (A_{ref}). The units in [181] adopted in this design were conflicting. As such, the modified version of the algorithm in [180] was used.

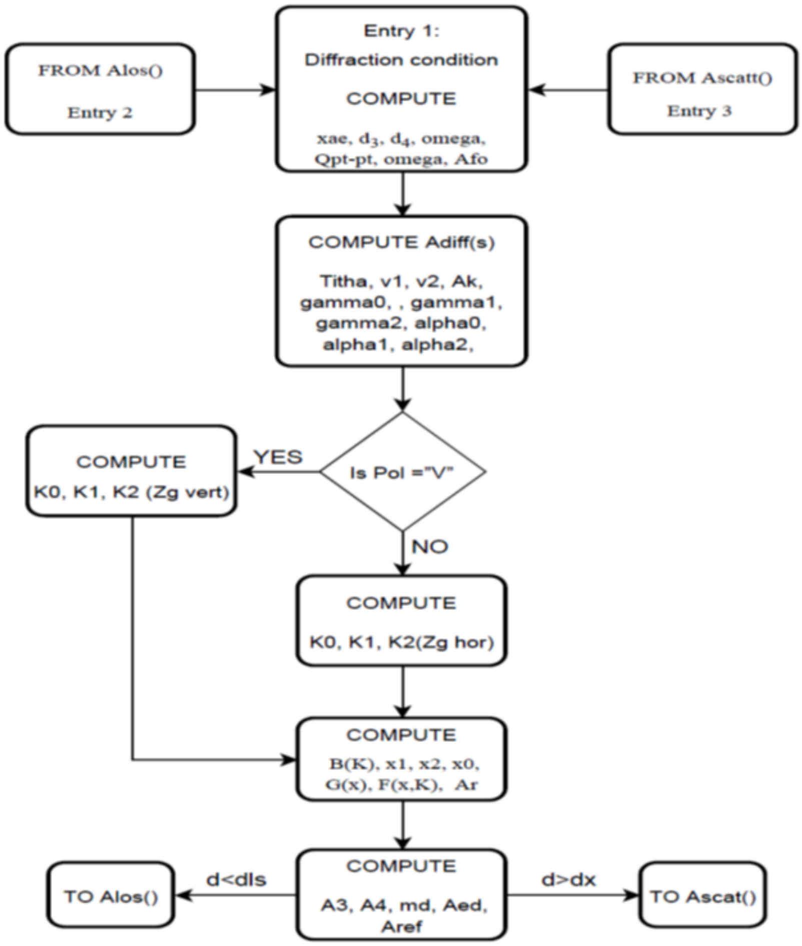


Figure 4.6: Diffraction Function.

4.5.2 Database Parameters

A summary of the inputs needed for the database computation and expected outputs are presented in section 4.6.1 and 4.6.2 respectively. Program Making and Special Events (PMSE) devices and their protection were not considered in the database design, as it was outside the scope of this work.

Database Inputs

Primary User/Protected Channel information needed by a database are:

1. Location of Transmitter

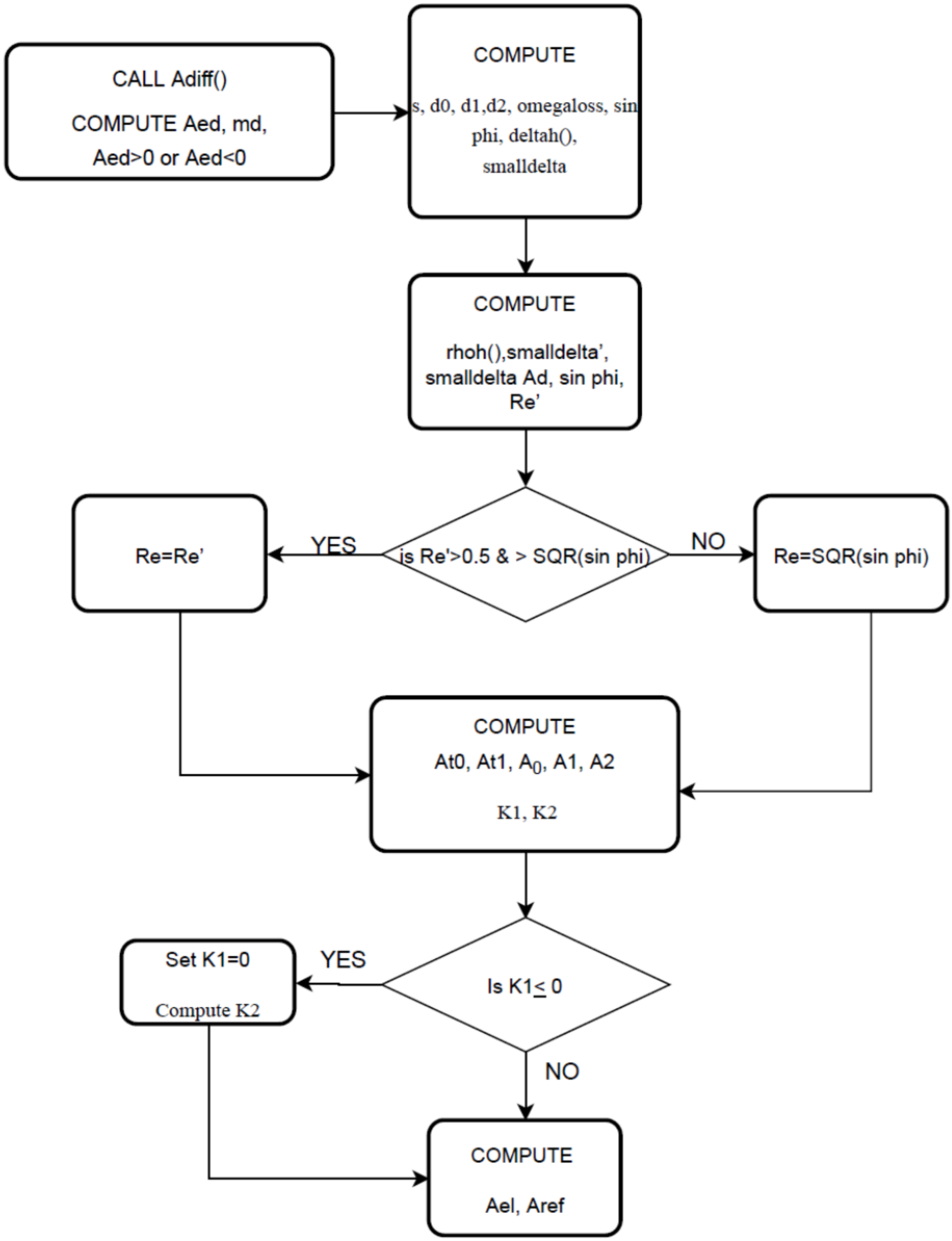


Figure 4.7: $A_{los}()$ function flow of computation

2. Transmitter Power
3. Height of transmitter (Average Ground Level (AGL))
4. The center frequency of transmission.
5. Transmitter antenna's polarization (Optional)

Inputs from the White Space Device include:

1. Location of WSD
2. Height of WSD
3. Preferred frequency (optional)

Database Output

Output for WSD:

1. Channel no.
2. Operating Frequencies
3. WSD operating frequency's maximum transmit power.
4. Check-in time with the database.

4.6 TVWS Design in Glasgow

The DSA database usually extracts PU information from a national transmitter database (DTT database as illustrated in Figure 4.8). This is represented by information from 38 television transmitters in five locations around a WSD assumed to be located in the Royal College Building, University of Strathclyde, and detailed in Appendix A. This record is kept within the designed database and used to compute permitted WSD power limits for SUs coexistence with PUs in large (country) and small geographical locations. The GDB design conformed to the capabilities listed in [182].

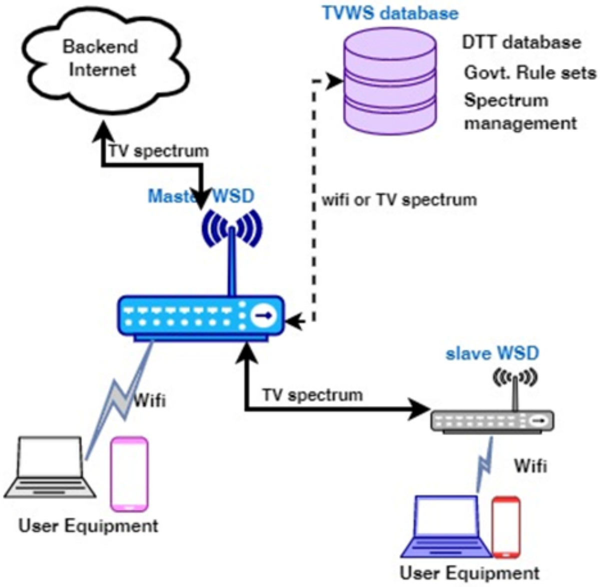


Figure 4.8: A detailed end-to-end Dynamic Spectrum Access system

The DSA database usually extracts PU information from a national transmitter database (DTT database as illustrated in Figure 4.8). This is represented by information from 38 television transmitters (detailed in Appendix A tables) in five different locations around a WSD. The WSD was assumed to be located in the Royal College Building, University of Strathclyde. This record is kept within the designed database and used to compute Permitted WSD power limits. The computed WSD power is limited to a single/small region (WSD coverage area) and can be extended to many WSDs. This was done in [5] design of Kenya's Geolocation database. The GDB design conformed to the capabilities listed in [182].

4.6.1 White Space Device (WSD) Permitted Power Estimation

The WSD was located at latitude 55.86156 and longitude -4.24614, while transmitter parameters were from five TV stations/locations. Nine randomly selected TV receiver points around the WSD that could suffer interference were selected as $(x\colon x \in X)$. The location of these points (X) and their geodesic angle ϕ (between each TV transmitter, point x, and the WSD's location) are in Table 4.2.

Table 4.2: Random locations around a White Space Device.

Lat	Long	ϕ_1 (degrees)
55.85781	-4.23895	120
55.86236	-4.2455	180
55.87328	-4.22833	120
55.86304	-4.24965	87
55.87208	-4.28369	30
55.86134	-4.25031	0
55.85141	-4.27648	40
55.85552	-4.2519	60
55.86113	-4.24419	150

The database design is in line with Dynamic Spectrum Alliance [3] computation and is implemented in two phases. First, the TV channel received signal strength, and the status of a TV channel at x locations around the WSD is determined. The second, WSD power estimate, is a reverse process. The protected TV RSS at point x is used to determine the WSD transmit power. That is, the WSD estimated power transmitted degrades to the level of the protected received signal at point x, as illustrated in Figure 4.9.

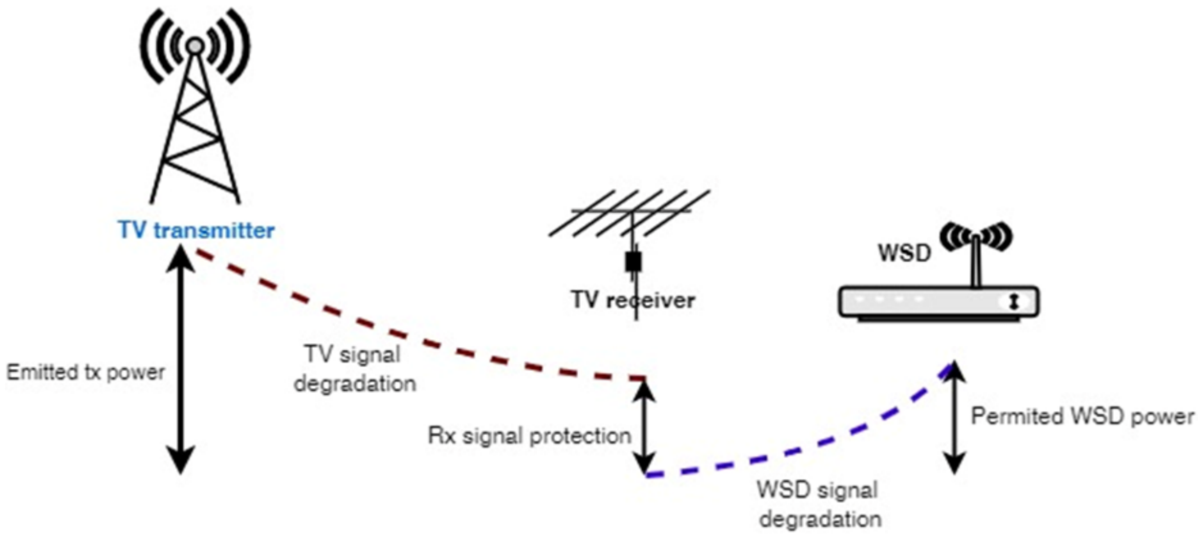


Figure 4.9: Computation of estimated WSD transmission power.

4.6.2 Received TV Signal Strength

TV signal received at each possible x location is:

$$P^i_{Rx:\,T@x} = P^i_T - L^i_{T\to x} \tag{4.10}$$

where $P^i_{Rx:\,T@x}$ is the estimated received TV signal operating at ith center frequency, at x location. P^i_T is TV transmitter power at ith center frequency and $(L^i_{T\to x})$ is its propagation loss between TV transmitter (T) and location x. The received TV signal derived from equation (4.10), uses the LR path-loss model to estimate signal degradation $(L^i_{T\to x})$. The TV receivers are assumed to have a height of 10m and their noise as:

$$P^i_{noise:\,T@X} = 10\log(10^{P_{thermal}/10} + \sum_{T',j} 10^{P^{i\leftarrow j}_{T'@X}/10}) \tag{4.11}$$

where $P^{i\leftarrow j}_{T'@X}$ is the received TV signal at x from other T' transmitters operating at the same or adjacent j channels combined with thermal noise.

The carrier signal-to-noise ratios(CNR) at each of these $'x'$ TV receiver locations are computed based on equation(4.12). The $P^i_{noise:\,T@X}$ is reduced to 105.2 dBm thermal noise over 8MHz, as TV transmitters are assumed to exist on exclusive and non-interfering channels. Each $'x'$ location's computed CNR:

$$CNR^i_{T@X} = P^i_{Rx:\,T@x} - P^i_{noise:\,T@X} - L_{Rx:\,noisefig} + G_{Rx:\,inst} - M_{Rx:\,imp} \tag{4.12}$$

where noise figure $L_{Rx:\,noisefig} =$ 7dB, installation gain of antenna $G_{Rx:\,inst} = 9.15$ dBi and implementation margin $M_{Rx:\,imp}$ = 1.5dB [3]; contributed to its occupancy status which in turn determined if the channel was occupied in that location.

A channel was considered “unoccupied” in an ’x’ location if the $CNR^i_{T@X}$ was less than 27.1, as stated in equation 4.9 in [3]. Occupied channels were protected with a fixed co-channel protection ratio of 39.5, or an adjacent channel protection ratio, equations (4.13) and (4.14). The adjacent protection ratio $r(.)$, which was a function of the received signal and the channel offset between incumbent and adjacent channels j (4.14) detailed in [3]. Locations x that had ith channel occupied were referred to as y locations, $y \in Y, and Y \subset X$. $P_{Rx:\,nuisance@y}$ is the protected received PU's signal at location y when operating at an occupied channel, in location y. The PU receiver's protection value is computed as:

$$P^{i|i}_{Rx:\,nuisance@y} = P^{i}_{Rx:\,T@y} - 39.5 \tag{4.13}$$

$$P^{j|i}_{Rx:\,nuisance@y} = P^{i}_{Rx:\,T@y} - r(P^{i}_{Rx:\,T@Y} + G_{Rx:\,inst}, \Delta f) \tag{4.14}$$

4.6.3 WSD Transmit Power Estimate

An assumed 1.5m high WSD transmitted a signal that degraded at the nine TV receiver points. This was calculated as coupling loss ($G^{i}_{WSD\to Y}$) in:

$$G^{i}_{WSD\to Y} = -L^{i}_{wsd\to y} + G_{ant@Y\to wsd}) + G_{Rx:\,inst} \tag{4.15}$$

which was a function of path-loss ($L_{wsd\to y}$) between WSD and y locations, standard antenna gain ($G_{Rx:\,inst}$) and geodesic gain receivers at y ($G_{ant@Y\to wsd}$), in equation (4.15). The geodesic angle determined the value of the geodesic gain. The consideration was on co-channel sharing. Hence, adjacent channels were ignored, $i = j$.

Estimated WSD power at each channel was the difference between the coupling loss $G^{i}_{wsd\to Y}$ and protected PU's signal $P_{Rx:\,nuisance@y}$ at each y spot, in equation (4.16). Each y-point around the WSD had a different estimated WSD power. Permitted WSD power on each channel i computed as:

$$P^{i}_{T:\,WSD|TV@Y} = P^{i}_{Rx:\,nuisance@y} - G^{i}_{WSD\to Y} \tag{4.16}$$

was the least estimated power from all y points.

4.6.4 Glasgow Database Outcome

The five PU transmitter locations (Blackhill, Darvel, Roseneath, Craigkelly, and Selkirk) had multiple TV transmitters. In each TV transmitter, the two phases were carried out, except in instances where phase one resulted in an unoccupied channel status. In such situations, the maximum permitted power of 36 dBm was allotted to the WSD.

The estimated WSD power in $'y'$ locations is computed using equations in subsection 4.6.1 for Blackhill PSB1 transmitters (*ith* channel). The received signal strength at the nine random locations, in table 4.2, around the WSD are shown in Table 4.3. In Table 4.3, the Newdis is the distance between the TV transmitter and its nine x receivers, Txptloss is $L^i_{T\to x}$, Rxpt is $P^i_{Rx:\, T@x}$ in equation (4.10). CNR is in equation (4.12), and Pnuispt is from equation (4.13). WSDdis is the distance between x receiver (y) and WSD, wsdptloss is $L^i_{wsd\to y}$, and coupleGain is $G^i_{wsd\to Y}$ in equation (4.15). The estimated WSD power (WSDPow) is described in equation (4.16).

The estimated WSD power for this channel ranged from 42.5 dBm to 5.2 dBm. However, the lowest value of 5.2 dBm was assigned as the safe WSD power in Table 4.4's 'PSB1 (BBCA)' TVtx. As expected, the gain of the receiver and transmitter antennas significantly impacted the estimated WSD power. Technically, the higher the receiver's geodesic gain, the easier it is to detect weak TV signals. A zero geodesic gain meant weak signals got extra protected, and WSD power had to be reduced to achieve this protection.

Table 4.3: Intermediate computation of WSD estimated power at nine (x) random TV receivers

Newdis	txptloss	Rxpt	CNR	Status	Pnuispt	WSDdis	wsdptloss	ϕ	Gant	coupleGain	WSDPow (dbm)
22767.1	125.2	-45.2	60.6	Occupied	-84.7	612.6	108.7	120	-16	-115.6	30.8
23171.9	125.5	-45.5	60.4	Occupied	-85.0	97.0	89.0	180	-16	-95.8	10.8
22138.4	124.9	-44.9	61.0	Occupied	-84.4	1711.8	120.0	120	-16	-126.8	42.5
23431.3	125.6	-45.6	60.2	Occupied	-85.1	273.9	100.1	87	-16	-106.9	21.8
25580.2	126.9	-46.9	59.0	Occupied	-86.4	2618.1	124.8	30	-4	-119.7	33.3
23471.9	125.7	-45.7	60.2	Occupied	-85.2	261.5	99.6	0	0	-90.4	5.2
25131.7	126.6	-46.6	59.2	Occupied	-86.1	2204.7	122.8	40	-8	-121.7	35.6
23581.3	125.7	-45.7	60.1	Occupied	-85.2	762.3	111.1	60	-16	-117.9	32.7
23090.1	125.4	-45.4	60.4	Occupied	-84.9	130.8	92.2	150	-16	-99.0	14.1

Table 4.4: Channel status in Blackhill

TVtx	Ch	$\text{Freq}_c(MHz)$	Pol	txPower (dBm)	Status	WSDPow (dBm)
'PSB1 (BBCA)'	46	674	'H'	80	"Occupied"	5.24
'PSB2 (D3+4)'	43	650	'H'	80	"Occupied"	6.63
'PSB3 (BBCB)'	40	626	'H'	80	"Occupied"	7.93
'COM4 (SDN)'	41+	634.2	'H'	80	"Occupied"	7.50
'COM5 (ArqA)'	44	658	'H'	80	"Occupied"	6.18
'COM6 (ArqB)'	47	682	'H'	80	"Occupied"	4.76
'LG'	51	714	'H'	66.99	"Occupied"	-10.29
'COM7'	55	746	'H'	76.32	"Occupied"	-3.16
'COM8'	56	754	'H'	75.93	"Occupied"	-4.12

All transmitters' channels in Blackhill are occupied in Table 4.4, and the status of all transmitters in other locations are in Table A. The power limits were generated based on assumed co-channel sharing of TV frequency. Some allocated channels were available for co-channel transmission at low estimated WSD powers (4.7 to 7.9 dBm). It was observed that although all the transmitters in location Selkirk were unoccupied (table A.5), these were already being reused in some other places.

4.6.5 Model of Designed Relational Database.

TV transmitter parameters and WSD estimated power limits in Glasgow are used to populate the MySQL database. Out of 38 channels, about ten (10) were not unique and had varied WSD power estimates. Twenty-eight unavailable unique channels had different WSD Power estimates, and 12 available channels assigned a default value of 36dBm in Table 4.5. Some estimated powers were too small for significant use, e.g., 26dBm, while others were as high as 7dBm. Channels above channel 49 were excluded from the results; they were no longer available for TV transmission in the UK, thus reducing the available channels to 4.

This table is used to create a MySQL database on a local server, which a WSD at the Royal College building queries for available WSD power and frequency. The table, therefore, informs the database's response to requesting WSDs. Channel numbers were rounded up to integers for easy manipulation in the database (which differs from the center frequency of channel 41, 634MHz).

4.7 Database construction in Owerri Nigeria

The database design process in section 4.6 was adopted with more PU receivers. The database was designed for a University in eastern Nigeria, with analog television transmitters (ATT) and Digital TV transmitters (DTT). The WSD was sited closest to the center of the Federal University of Technology Owerri, Eastern Nigeria, with latitude 523'07.0" N and longitude 659'31.8"E. A 5km x 5km square coverage around the assumed omnidirectional WSD was defined as WSD coverage for investigation. This coverage square area was then split into several pixels of 1km x 1km to make a total of 'X' number of pixels, as shown in Figure 4.10.

Figure 4.10: 100m x 100m pixels grid on the study area.

Seventeen (17) Analogue Terrestrial TV transmitters (ATT) and twenty-six (26) Digital Terrestrial TV transmitters (DTT) spanning 6 Eastern states were identified within a 200km radius of the University. Ultra High-Frequency DTT and ATT broadcast channels were extracted from the national spectrum allocation table. These channels permitted spectrum sharing in the Nigerian TVWS policy draft [175]. Twelve (12) unique ATT channels (470 to 854MHz) and 24 DTT channels (470 to 694MHz) were considered and analyzed.

TV signal degradation for 50% of the time, at 50% of the location, and 50% certainty was calculated using the designed LR path loss model between each of these TV transmitters and a TV receiver on each $'x'$ pixel ($x \in X$ pixels). The transmitter input parameters stated in section 4.6.1 for the design are provided in Appendix B.2, and the TV receiver located at each x pixel was assumed outdoor and 10m high.

The design of the Owerri Database was done after surmounting the following challenges:

1. Limited access to the necessary PUs information.
2. High computational requirement for a single WSD. As a detailed 1km x 1km mapping of the device generated over 3000 receiver points, across which received signals for all receivers had to be computed.
3. Unique spectrum terrain, as the database had to be designed to consider two types of static PUs (DTTs and ATTs), this was challenging. Hence the decision to exclude ATTs to reduce computational tasks.

4.7.1 Received TV signal strength

The transmitter and receiver parameters are used to compute path loss. The received TV signal strength at each x TV receiver terminal, for all ith TV channels, was computed with equation (4.10). Receiver Thermal noise ($P_{Th-noise}$) was computed as:

$$P_{Th-noise} = 10\log(kTB) \tag{4.17}$$

Where k was Boltzmann constant, Temperature (T) was 290K, Bandwidth B was 5MHz for ATT and 8MHz for DTT receiver [177]. The cumulative interfering noise (log addition of out-of-mask emissions and thermal noise) for every channel i was computed with Equation (4.11).

4.7.2 TV channel Availability Threshold

The received TV signal and the cumulative noise are used to determine a Carrier to Noise ratio (CNR) at the TV receiver terminals, using equation (4.12). A CNR threshold is set based on the TV signal receivers' sensitivity. In ATTs, this is 64 dBu equivalent to a CNR of 38 [183]. DTT receiver's minimum CNR default value of 19.5dBm is used in equation 4.9 in [3]. This means that DTT receivers could receive weaker DTT signals than ATT receivers.

4.7.3 WSD Transmit Power Estimate

As Nigeria completed its digital TV migration, only DTTs were used in the database design. The pixels or TV receivers that met the CNR threshold were labeled Y. The following design objective was to protect every received signal on each pixel. All the pixels had similar channel coverage because of the assumed WSD coverage area size. Each occupied channel was protected using a protection ratio derived from the WSD class' emission mask. However, a higher co-channel protection ratio of 39.9dB was used as the co-channel reuse of PU's channels was being investigated. The ratio was added to all the received signal strength to form a nuisance Power, equation (4.14). This power is the least power a TV receiver can accommodate from the WSD, as shown in figure 4.9. Computations were done in MATLAB and Python environments. Despite the drawbacks of this method highlighted in [5] on PU protection, this method provides a framework for safe co-channel sharing amongst SUs.

4.7.4 Outcome of Database Design in Nigeria

Spectrum availability and a measure of the degree to which incumbent users are protected were observed. The box plot in Figure 4.11 represents the received signal strength of channels investigated at PU receivers around the WSD. The plot reveals the dispersion of ATT received signals by all x pixels' TV receivers. The ATT receivers have about six (6) channels above the usual -100dB noise floor in Figure 4a, similar to measured results in [184]. However, most of these channels cannot be detected by conventional TV receivers, and as such, this was replaced by a threshold CNR of 38, as discussed previously.

At this threshold of 38 for ATT receivers, there were three (3) unavailable or used ATT channels, Figure 4.12. Similarly, Three out of 24 DTT local channels' received signals were above the DTT CNR threshold of 19.5 in figure 4.13, hence, the channels were declared occupied in the WSD locations. Despite the 24 DTT transmitters around the WSD location, only 3 were occupied. The transmitters' CNIR at the WSD receivers were between -22 and 18; as such, channel numbers 4 to 24 can be reused with no significant interference with DTT transmitters.

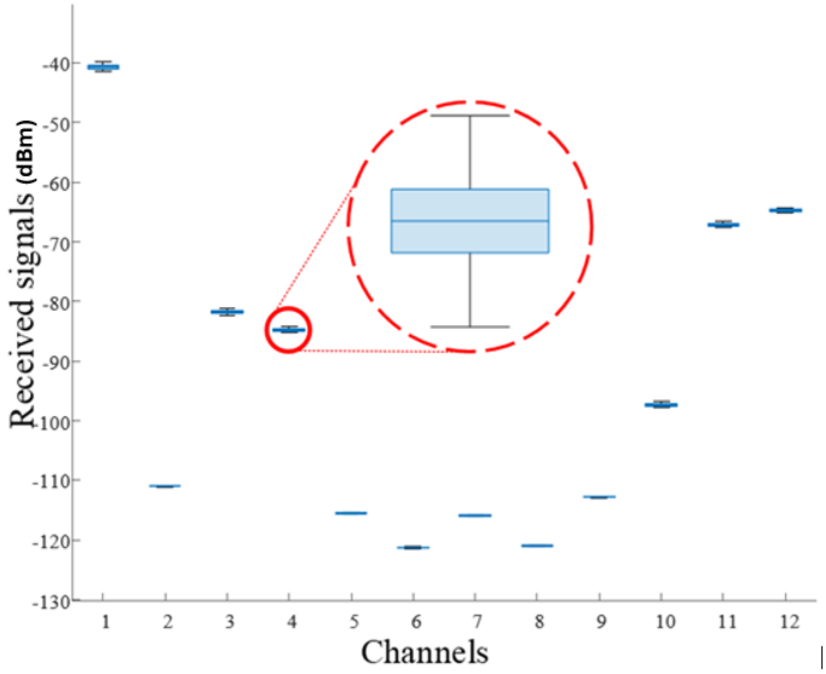


Figure 4.11: Box plot of received ATT at x-pixels.

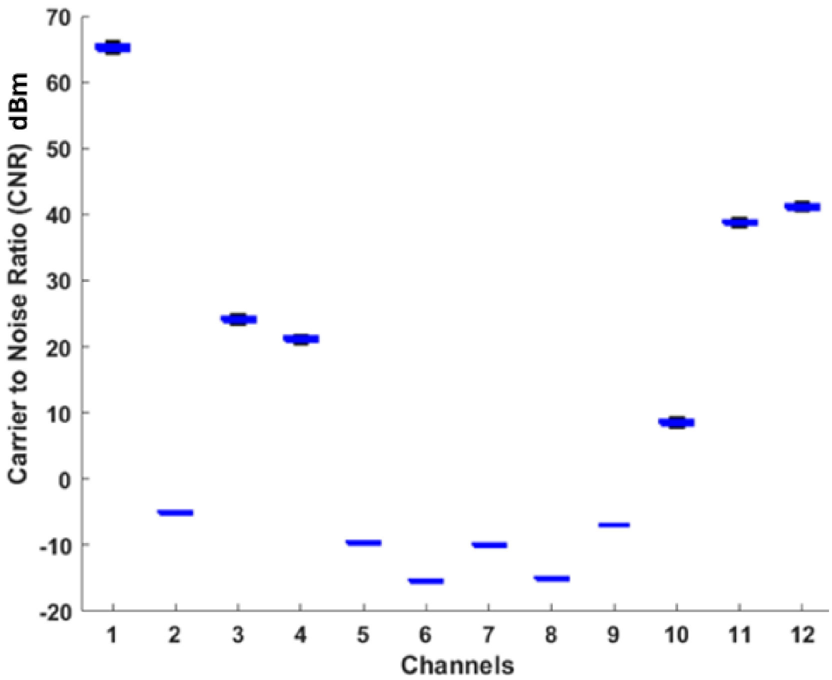


Figure 4.12: CNR distribution for ATT

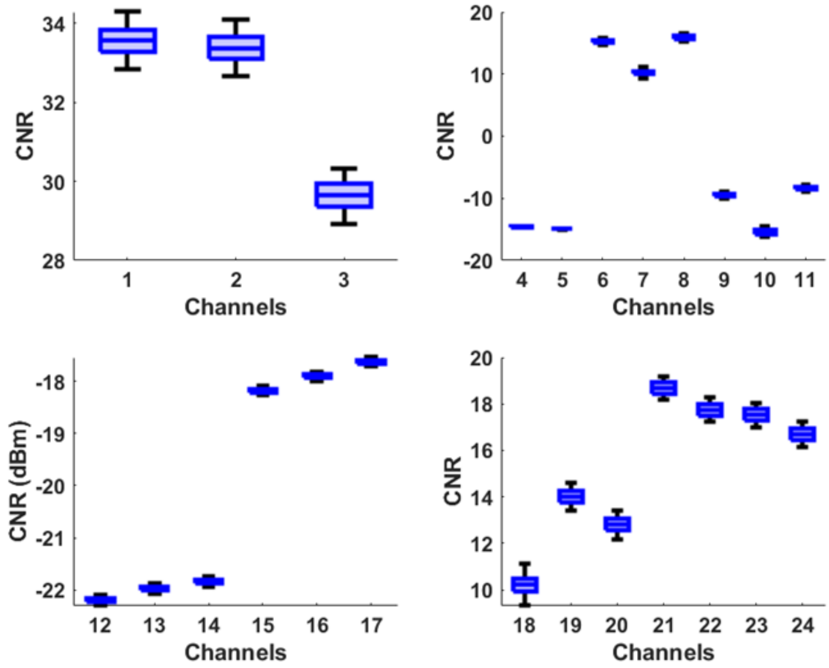


Figure 4.13: CNR distribution for DTT

In Nigeria, TVWS technology is permitted to share and coexist with PUs on twenty-nine (29) TV channels (470 to 694MHz). Although ATT ranged from 470 to 846MHz, it resulted in 48 ATT channels. Three ATT and three DTT unique channels were unavailable in the WSD coverage area, leading to a 10.3% or 3/29 channel occupancy by ATT and DTT, respectively, in Table 4.6. The TVWS policy in Nigeria provides extra protection for ATT signals by ensuring that two channels before and after a used channel are not shared. This resulted in 11 and 9 channels being unavailable for ATT and DTT channels, respectively, out of which the three unavailable channels were prohibited. This increased the percentage of occupancy of the 29 TV channels from 10.3% to 38% for ATT channels and from 10.3% to 31% for DTT channels. However, only DTT channels were used for the database design, resulting in 20 available channels for SU-to-SU sharing despite 31% of all channels being unavailable.

The effect of the protection ratio on co-channel protection (detailed in equations (4.13) and (4.14)) in all pixels within a WSD's coverage area is illustrated in Figure 4.14. It shows the permitted WSD transmit power for three DTT unavailable channels.

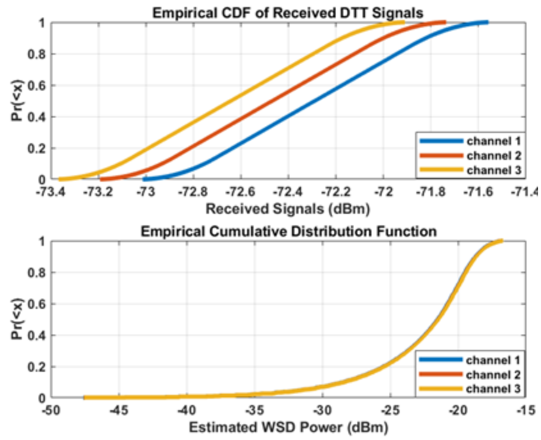


Figure 4.14: Cumulative Distribution Function of received DTT signals of channels 1 to 3 in x pixels.

Despite the weak received TV signals in channel 3, compared to channels 1 and 2, the same maximum power distribution is computed by the adopted methodology for channels 1, 2, and 3 in the figure. Thus, the permitted transmission power of the three unavailable channels was in the same range. All weak channels are, therefore, given adequate protection. This is assured as, despite the -15dBm to -47 dBm computed maximum power limits, the GDB assigns only the least power in each channel. The figure 4.15 chart represents a summary of available and unavailable channels as red bars.

4.8 Comparing GDB design and outcome in Owerri, Nigeria and Glasgow, UK.

A similar methodology in estimating WSD transmission power was used in both designs. However, more receiver points are considered (1km x 1km pixel size points around the WSD) in Nigeria as against the 9 points considered in Glasgow. Also, Nigeria had active Analogue Terrestrial TV transmitters (ATTs) and Digital Terrestrial TV transmitters (DTTs) as against only DTTs in Glasgow. In both designs, a lot of computations were required for a single WSD coexistence management.

The Glasgow database output subsection 4.6.4 outcome in table 4.5 was compared to

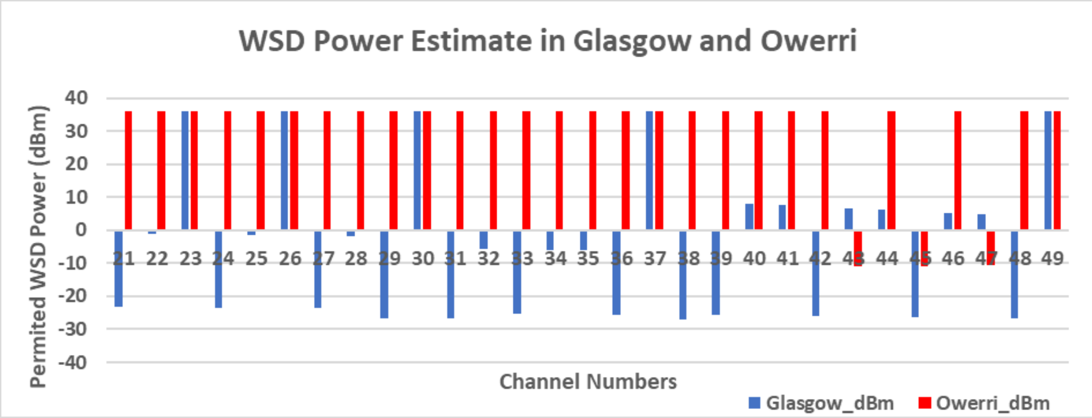


Figure 4.15: Comparing Glasgow and Owerri Available TV channels.

Owerri, Nigeria's subsection 4.7.4 outcome in figure 4.15. Since their WSDs were both in a university environment, only DTT channels were considered. There was a higher use of DTT channels (29 DTT channels occupancy in table 4.7) in Glasgow (82.8%) as compared to Owerri (10.3%), as Glasgow was a bigger urban city than Owerri. This meant that about five (5) channels were available in Glasgow (29 DTT channel occupancy in table 4.7) for shared SU coexistence as against 26 channels (89.7%) in Owerri. This was significantly reduced to 20 (69%) because of Nigeria's TVWS PU sharing policy reflected in the policy-protected (%) of table 4.7. Similarly, the UK policy prohibits co-channel coexistence with PUs, depriving six additional channels (40, 41, 43, 44, 46, and 47) in Figure 4.15 from supporting more SUs through underlay sharing.

4.9 WSD to Database Interaction

WSD needs spectrum availability information to ensure they do not interfere with PUs. Most policy documents on database spectrum management insist on regular communication between WSD and the central spectrum manager, to get updates on spectrum and power resource availability. The database also needs to be aware of any changes with respect to location and the WSD spectrum choices. It is, therefore, important to have a standard way for the database to WSD communication, hence the

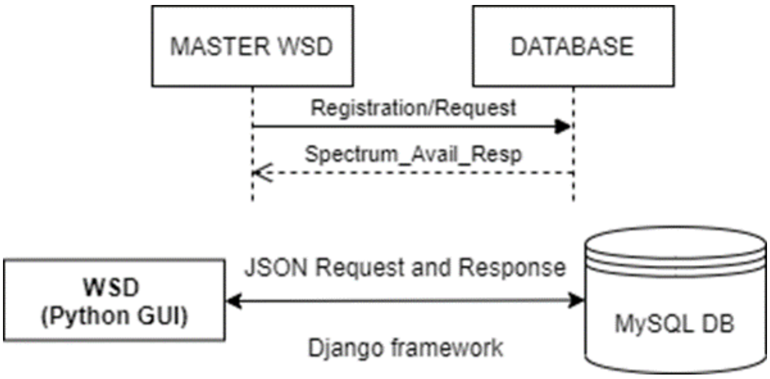


Figure 4.16: Tools and communication time between WSD to DB.

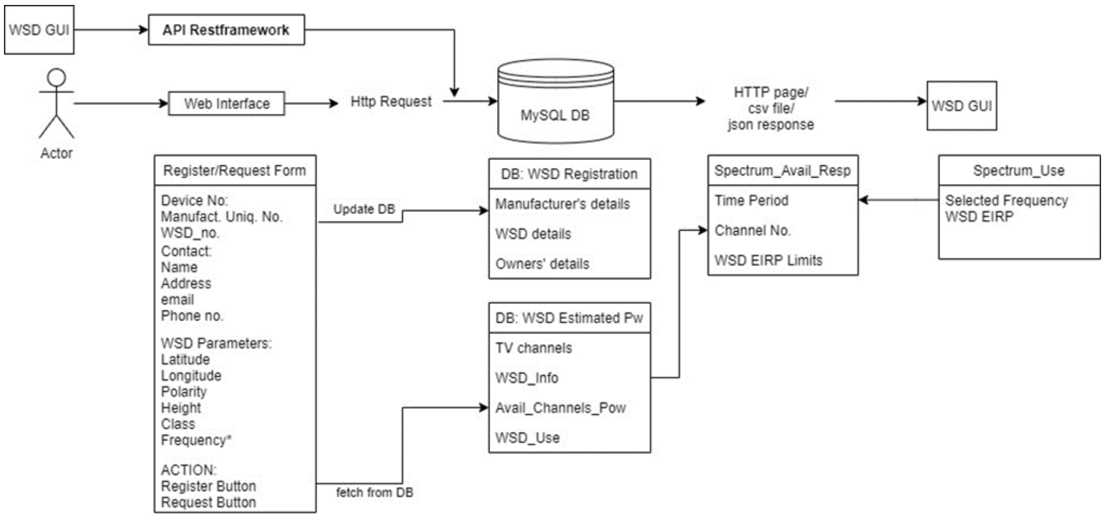


Figure 4.17: Block diagram of connections and parameters needed for WSD to DB connection.

design of Protocol for Access to White Space (PAWS).

In establishing communication between a WSD and the database, the diagram in Figure 4.3 was modified to Figure 4.16. Thus, the focus is on the master device to database/coexistence manager interactions. A virtual master device, assumed to be in the Royal College building, communicated with the MySQL local server database. The device's registration and request time were logged in the database, which responds with information on available spectral space for WSD.

4.9.1 Design Of WSD to Database Interface

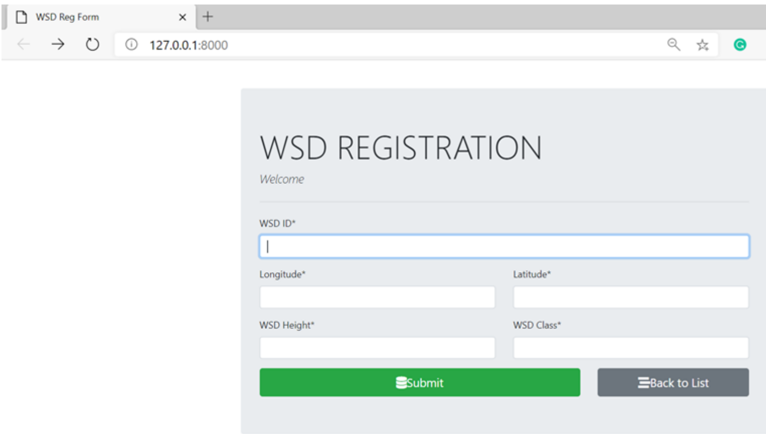
The database front end consisted of a webpage and an API designed with Django REST framework, a Python web framework for building web pages, illustrated in Figure 4.17. It is easily integrated with the MySQL database backend, providing a web page for human interaction and an API frontend for device interaction with the database. Figure 4.17 provides a detailed view of the communication and parameters needed for the interface.

The webpage was tested by manually keying in WSD registration details on the webpage, as shown in Figure 4.18a. Several queries were made to the database on the assumption that the WSD was located within at least a 100m radius around the Royal College building. These queries were recorded, retrieved in figure 4.18b, and transited to a download CSV file webpage. The CSV file contained the available TV channels and their estimated power similar to the output displayed on the webpage in figure 4.18c. In establishing communication between the WSD and the database, an API front end was initially tested through the Django frameworks API portal in Figure 4.19a and the response in figure 4.19b.

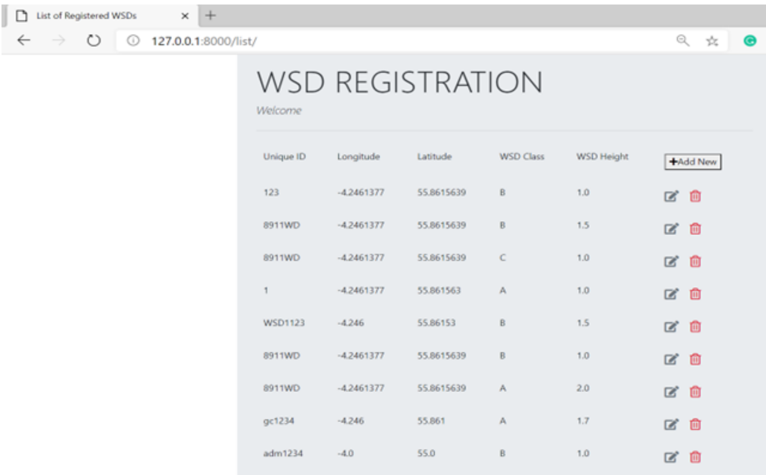
4.9.2 Standardize WSD to Database Communication using PAWS

In section 4.9.1, the communication link design was not standardized, although it achieved the device-to-database benchmark. The PAWS in [178] was implemented to standardize the communication link. The protocol stipulates the regulated terms of all communication components; these include Tables, field names, and the structure of JSON messages (shown in figure 4.21). These required several tables within the database to interact (as shown in figure 4.22) to create the necessary output structure.

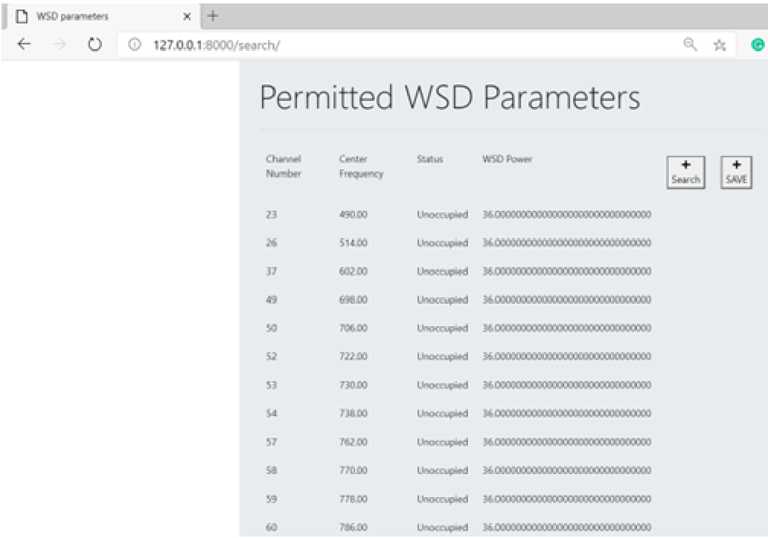
The WSD's request was stored in the database's avial_spec_req table, as shown in figure 4.22, and distributed to other tables. The Location table holds location-based parameters and WSD (fixed or mobile) information. The deviceDesc contains the device's details and the antenna properties of the WSD populate antenna table. These tables had a one-to-one relationship with the avail_spect_req table, as every entry in



(a) WSD registration webpage

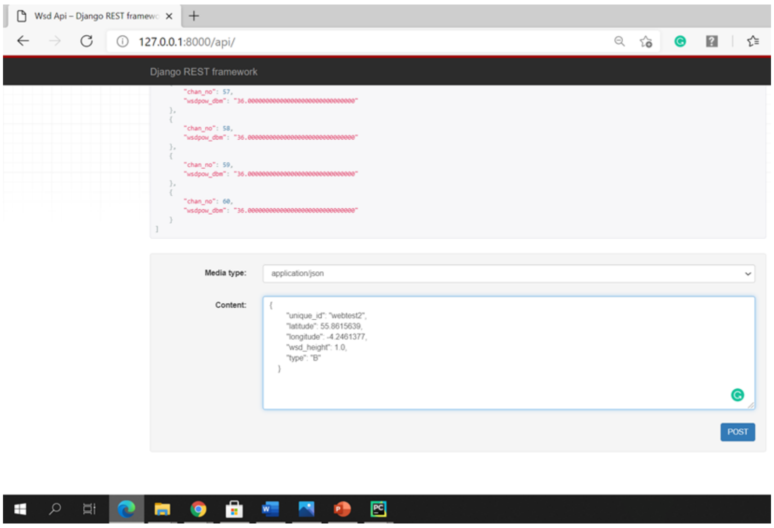


(b) WSD registration List

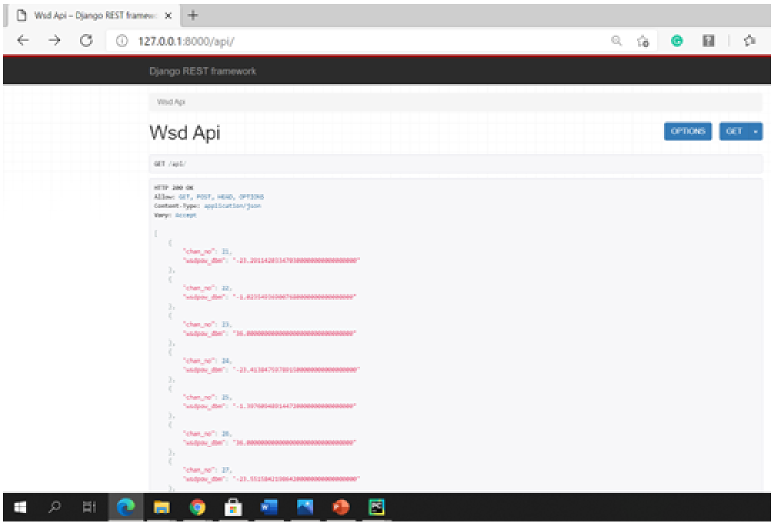


(c) DB response of spectrum and WSD permitted power limits

Figure 4.18: WSD webpage front end request and Database response

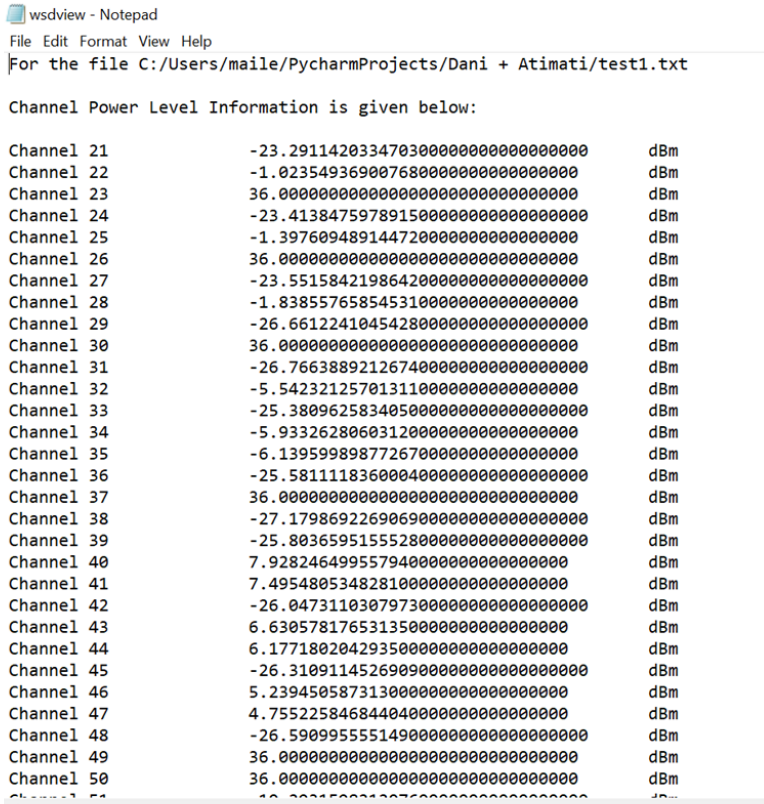


(a) API portal request



(b) Database response to API portal request

Figure 4.19: API portal posting and retrieving JSON data from the database.



```
wsdview - Notepad
File  Edit  Format  View  Help
For the file C:/Users/maile/PycharmProjects/Dani + Atimati/test1.txt

Channel Power Level Information is given below:

Channel 21            -23.291142033470300000000000000000      dBm
Channel 22            -1.023549369007680000000000000000       dBm
Channel 23            36.000000000000000000000000000000       dBm
Channel 24            -23.413847597891500000000000000000      dBm
Channel 25            -1.397609489144720000000000000000       dBm
Channel 26            36.000000000000000000000000000000       dBm
Channel 27            -23.551584219864200000000000000000      dBm
Channel 28            -1.838557658545310000000000000000       dBm
Channel 29            -26.661224104542800000000000000000      dBm
Channel 30            36.000000000000000000000000000000       dBm
Channel 31            -26.766388921267400000000000000000      dBm
Channel 32            -5.542321257013110000000000000000       dBm
Channel 33            -25.380962583405000000000000000000      dBm
Channel 34            -5.933262806031200000000000000000       dBm
Channel 35            -6.139599898772670000000000000000       dBm
Channel 36            -25.581111836000400000000000000000      dBm
Channel 37            36.000000000000000000000000000000       dBm
Channel 38            -27.179869226906900000000000000000      dBm
Channel 39            -25.803659515552800000000000000000      dBm
Channel 40            7.928246499557940000000000000000        dBm
Channel 41            7.495480534828100000000000000000        dBm
Channel 42            -26.047311030797300000000000000000      dBm
Channel 43            6.630578176531350000000000000000        dBm
Channel 44            6.177180204293500000000000000000        dBm
Channel 45            -26.310911452690900000000000000000      dBm
Channel 46            5.239450587313000000000000000000        dBm
Channel 47            4.755225846844040000000000000000        dBm
Channel 48            -26.590995551490000000000000000000      dBm
Channel 49            36.000000000000000000000000000000       dBm
Channel 50            36.000000000000000000000000000000       dBm
```

Figure 4.20: Virtual WSD's GUI output/response from GDB

the table had these details. Time stamps of requests are stored in the eventTime table.

The computed available channel and estimated WSD power in the tvchanstatust table are connected to the spectra table on a many-to-one relationship. A single spectra category of 8MHz channel size was assumed as others (like 100kHz) were not captured in UK policy. The spectra table established a many-to-many relationship with the spectrum_schedule table through an intermediary spectra_manager table.

The spectrum manager table matches each spectra table's row to a specific spectrum schedule ID. The spectrum_schedule table, therefore, contains request times and periods matched with the spectra table's link to a collection of channels and power limits. The spectrum_schedule is encapsulated in a many-to-one relationship with the spectrum_specs table, which enacts the single policy ruleset (ETSI) adopted in this work. The spectrum_specs table is embedded in the result table, extracting information from the deviceDesc table. The result table is sent to the WSD through the Avail_spect_resp

{"jsonrpc": "2.0", "params": {"antenna": {"heightUncertainty": 0, "heightType": "AGL", "height": 1}, "location": {"point": {"semiMajorAxis": 0, "semiMinorAxis": 0, "orientation": 0, "center": {"longitude": 50.3, "latitude": -4.0}}}, "deviceDesc": {"serialNumber": "test_strath_2", "etsiEnDeviceType": "A", "etsiEnTechnologyId": "Tech_001", "modelId": "virtual-001", "etsiEnDeviceEmissionsClass": 1, "rulesetIds": ["ETSI-EN-301-598-1.1.1"], "etsiEnDeviceCategory": "Master", "manufacturerId": "cwsc"}, "version": "1.0", "type": "AVAIL_SPEC_REQ"}, "method": "paws.AVAIL_SPEC_REQ", "dev_id": "strath_2"}

Figure 4.21: Structure of a typical PAWS request message sent to the database.

table to conform with the PAWS JSON structure. The avail_spect_res table was the feedback from the database on the request made in the avial_spect_req.

The designed PAWS was tested with a virtual WSD request to the database. The response from the database to the device was extracted from the device as a text file shown in Fig. 4.20. To visualize the designed database PAWs conformity, the PAWS request sent by the WSD (shown in Fig. 4.21) was replicated via a Postman app. The response structure shown in Fig. 4.23 is similar to that provided in the PAWS documentation [178]. The standard protocol in both test cases contained a complete list of available channels and the estimated transmit power limits at the WSD location.

4.10 Summary of Chapter

This chapter describes the end-to-end design and implementation of a DSA system consisting of a resource manager (a geolocation database manager) and its Device-to-database interface. It recreates a TVWS system using a unique Dynamic Spectrum Alliance methodology for the database design and adopts IETF's PAWS protocol for the interface. The methodology is implemented using a designed terrain-based Longley Rice propagation model, as TV signals travel very far and are greatly influenced by the environment. The interference discovery method was crucial in increasing sharing opportunities of the resource-managed design. The impact of the UK and Nigeria's shared spectrum policies on available resources is measured and quantified, showing the need for informed regulatory frameworks.

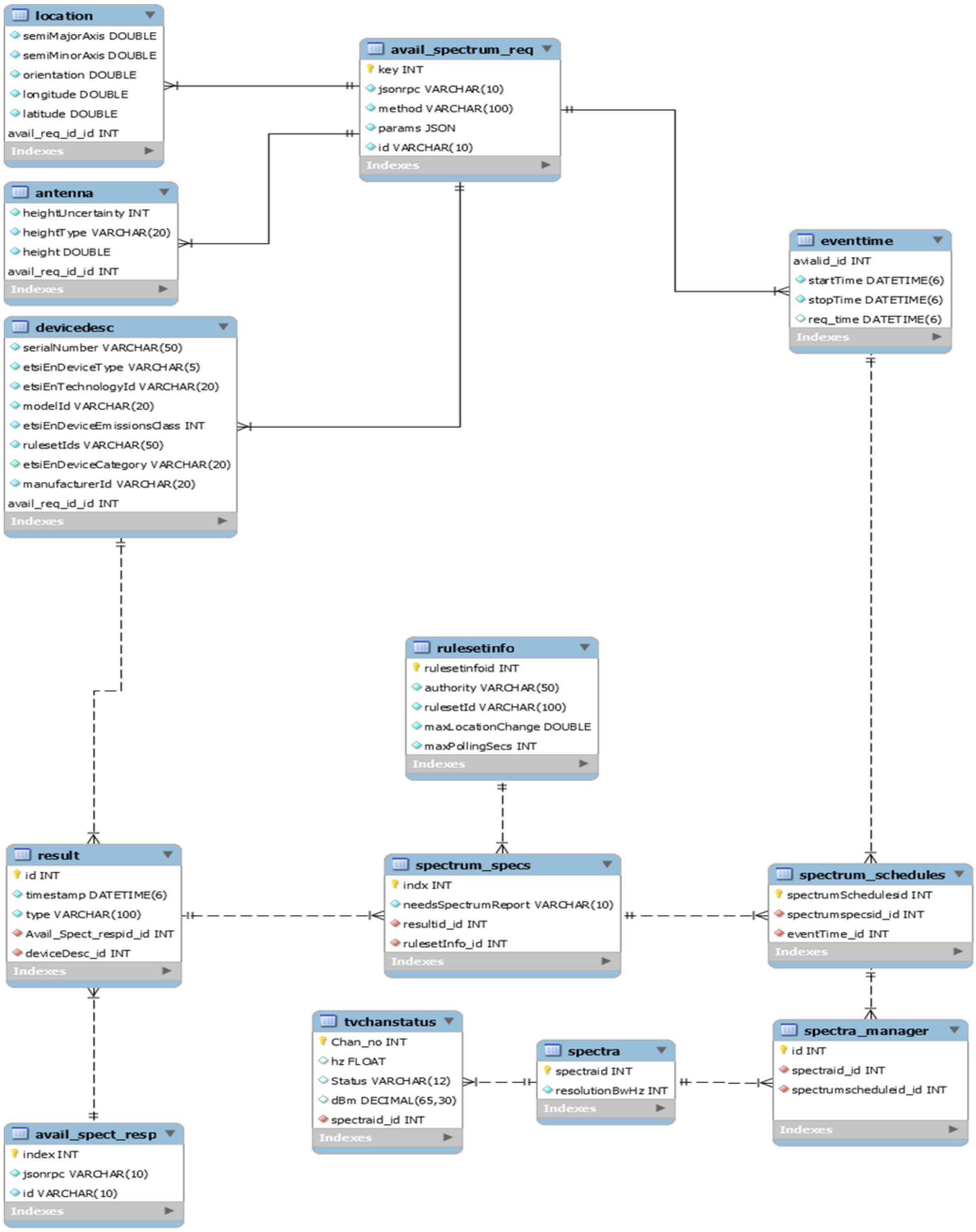


Figure 4.22: Inter-table relationship for ‘available spectrum request’

```
{
    "jsonrpc": "2.0",
    "result": {
        "type": "AVAIL_SPECTRUM_RESP",
        "timestamp": "2021-05-27T02:21:34.812318",
        "deviceDesc": {
            "serialNumber": "test_strath_2",
            "modelId": "virtual-001",
            "etsiEnDeviceEmissionsClass": 1,
            "rulesetIds": "['ETSI-EN-301-598-1.1.1']"
        },
        "spectrumSpecs": [
            {
                "rulesetInfo": {
                    "authority": "EU",
                    "rulesetid": "ETSI-EN-301-598-1.1.1"
                },
                "needsSpectrumReport": "FALSE",
                "spectrumSchedules": [
                    {
                        "eventTime": {
                            "startTime": "2021-05-27T02:21:34.780534",
                            "stopTime": "2021-05-27T02:41:34.780534"
                        },
                        "spectra": [
                            {
                                "resolutionBwHz": 8000000,
                                "profiles": [
                                    {
                                        "hz": 474200000.0,
                                        "dbm": "-23.2911420334703000000000000000"
                                    },
                                    {
                                        "hz": 481800000.0,
                                        "dbm": "-1.0235493690076800000000000000"
                                    },
                                    {
                                        "hz": 490000000.0,
                                        "dbm": "36.0000000000000000000000000000"
                                    },…
{
                                        "hz": 786000000.0,
                                        "dbm": "36.0000000000000000000000000000"
                                    }
                                ]
                            }
                        ]
                    }
                ]
            }
        ]
    },
    "id": "strath_2"
}
```


Figure 4.23: PAWS structured Output from Database to WSD.

Finally, the WSD to GDB communication interface showed a significant overhead in transmitting all available resources to a WSD in a region/location. This thesis, therefore, proposes a tailored optimal resource allocation algorithm to limit this overhead. The next chapter designs several resource allocation techniques adopted in real DSA systems, and Chapter 6 further analyses their performance.

Table 4.5: Database Table: Operating TV frequencies and estimated WSD power

$Chan_{no}$	$Freq_c$(MHz)	Status	WSDPow (dBm)
21	474.2	Occupied	-23.29114203
22	481.8	Occupied	-1.023549369
23	490	Unoccupied	36.0000000
24	498	Occupied	-23.4138476
25	506	Occupied	-1.397609489
26	514	Unoccupied	36.0000000
27	522	Occupied	-23.55158422
28	530	Occupied	-1.838557659
29	538	Occupied	-26.6612241
30	546	Unoccupied	36.0000000
31	554	Occupied	-26.76638892
32	562	Occupied	-5.542321257
33	570	Occupied	-25.38096258
34	578	Occupied	-5.933262806
35	586	Occupied	-6.139599899
36	594	Occupied	-25.58111184
37	602	Unoccupied	36.0000000
38	610.2	Occupied	-27.17986923
39	618	Occupied	-25.80365952
40	626	Occupied	7.9282465
41	634.2	Occupied	7.495480535
42	642	Occupied	-26.04731103
43	650	Occupied	6.630578177
44	658	Occupied	6.177180204
45	666	Occupied	-26.31091145
46	674	Occupied	5.239450587
47	682	Occupied	4.755225847
48	689.8	Occupied	-26.59099556
49	698	Unoccupied	36.0000000
50	706	Unoccupied	36.0000000
51	714	Occupied	-10.29315982
52	722	Unoccupied	36.0000000
53	730	Unoccupied	36.0000000
54	738	Unoccupied	36.0000000
55	746	Occupied	-12.96240719
56	754	Occupied	-12.92798199
57	762	Unoccupied	36.0000000
58	770	Unoccupied	36.0000000
59	778	Unoccupied	36.0000000
60	786	Unoccupied	36.0000000

Table 4.6: Nigeria's Channel Occupancy summary

Type	48 National TV (%)	29 National TV (%)	Policy Protected (%)	Database (%)
ATT	8.33 (4/48)	10.3 (3/29)	38	
DTT	6.25 (3/48)	10.3 (3/29)	31	31

Table 4.7: DTT channel occupancy for Glasgow UK and Owerri Nigeria

City	Relative channel occupancy (%)	29 DTT channels occupancy (%)	Policy Protected (%)	Database occupancy (%)
Glasgow	67.5 (27/40)	82.76 (24/29)	82.76	83
Owerri	6.25 (3/48)	10.3 (3/29)	31	31

Chapter 5

Resource Management Techniques for SU-to-SU coexistence

5.1 Introduction

In the previous chapter, the designed database provided WSDs with all available resources (spectrum and power) in a specific location. This chapter reviews how these resources are shared among requesting WSDs in the TVWS, CBRS, and 802.19 coexistence method's framework. These different approaches are then framed as baseline algorithms for analyzing the performance of this thesis' proposed automated approach. This chapter, therefore, designs a heterogeneous network as a test bed for comparing coexistence management algorithms (existing and new). The developed methods and algorithms are all evaluated experimentally in a simulated virtual DSA network (test bed).

These algorithms have focused on allocating spectrum only, enabling overlay spectrum sharing. An added advantage to spectrum utilization is nodes' use of different transmission powers to enable more spectrum sharing. The power allocation allows for more nodes to share while considering their ability to manage a degree of interference (underlay). Thus, a system that permits both overlay and underlay harvests the benefits of DSA systems. This can be improved with customized resource allocation to nodes, allowing spectral resources to be allocated based on real-time needs rather than fixed allocations. This prevents spectrum wastage and enables it to be used when and where needed.

5.2 Algorithm Designs

DSA coexistence management approaches are studied based on the different deployed technologies. The distributed GDB (random) and hybrid SAS approach to sharing available channels to coexistence groups are reproduced as algorithms. A pivotal aspect of centralized coexistence management frameworks is defining when interference has or may occur.

5.2.1 TVWS Random Allocation

The White Space Device (WSD), irrespective of its MAC protocol, selects a resource (channel and transmit power) from the GDB's list and informs the GDB of its choice. The reuse of channels in a typical TVWS system is left to SUs to coordinate (distributed or decentralized coordination). The database does not have a framework for the reuse of channels by SUs [12–14, 26, 174]; as such, an exclusive selection of channels on a first come, first serve basis is assumed. The IEEE 802.19 provides a modified algorithm that permits databases to influence SUs coordination and permits the reuse of assigned spectrum through its coexistence management entity in figure 2.11 [38].

The GDB, through the coexistence manager (CM), maintains the TV spectrum availability status by communicating with the GDB, CDIS, neighboring CMs, and real-time measurement from WSDs (figure 2.11). An example is the change in available channels, as each WSD exclusively or individually chooses a channel. The CM, therefore, classifies available channels as protected (occupied by PUs), operating (in use by other WSDs), coexistence (shared with other WSDs), restricted (government-limited), and unclassified. The classification of available channels assists the CM in its responsibility of central assignment of channels to WSDs [38].

In SUs distributed channel selection, SUs can use channels exclusively or share. In exclusive/individual TV channel use, as discussed in subsection 2.2.3, SUs exclusively choose channels without these channels being reused, as shown in figure 5.1. An exclusive channel assignment is usually recommended when the number of WSDs exceeds the available channels. When this is not the situation, a shared channel mode is adopted, as shown in figure 5.1. In the shared use of channels, there are no set principles on how SUs can coexist and share resources apart from avoiding interference among SUs. However, the level of interference each SU can accommodate remains unclear in the literature.

The channel assignment within TVWS networks in [38], is modified and implemented in the random assignment/allocation algorithm 1. Channels were classified as available or operating from which requesting WSDs selected their preference on a first-come, first-serve basis. The WSDs were given a random arrival time, and based on their arrival time, they continuously selected channels until all available channels were exhausted. The WSD's channel choices were reclassified as operating channels, which are reused by the remaining requesting WSDs when they share similar MAC protocols. WSDs, with uncommon MAC protocols, randomly selected spectrum from the operating channel set. The protected channel classification was excluded since resources available to SUs were void of protected channels, as shown in Table 4.5. A fundamental input to the random algorithm was the network architecture/structure on which a CM performed its random allocation task.

The random approach does not mitigate interference among SUs; it uses spectrum on a first-come, first-serve basis and continuously assigns the resource. Although the spectrum usage is documented in a central system, there is no control over the SU's choice of resources. This reflects the spontaneous access to the spectrum, which leads to a high level of contention endured by SUs when the number of nodes exceeds available resources.

The random resource assignment was independent of other WSDs' actions and unaware of resulting interference, leading to more SU conflicts and contention for resources

Algorithm 1: Random Allocation (TVWS)

```
Input: List of available channels, network structure
Output: WSD resource assignment
for All WSDs in Network do
    Create an assumed arrival time for all nodes.
    Conduct channel classification.
    if Available channel exists then
        match WSD to its selected available channel, tag channel as operating
          channel
    end
    else
        if Are there operating channels then
            WSDs select from operating channels with similar MAC protocols,
              tag as coexisting channel
        end
    end
    else
        WSD selects any operating channel
    end
    Update channel classification list.
end
```

despite the central coordination introduced. It, however, allowed the CM to reassign operating channels to multiple WSDs that coordinated this reuse with their MAC protocol. CMs also cooperated with other CMs in negotiating their operating channel reuse. Similar types of WSDs (with similar MAC protocol) make up a coexistence set, and such coexistence sets can be assigned the same channels. The latter approach was adopted in the CBRS system, in their WInnforum's CBRS approach 2 and 3 definitions of recursive channel allocation [31, 58].

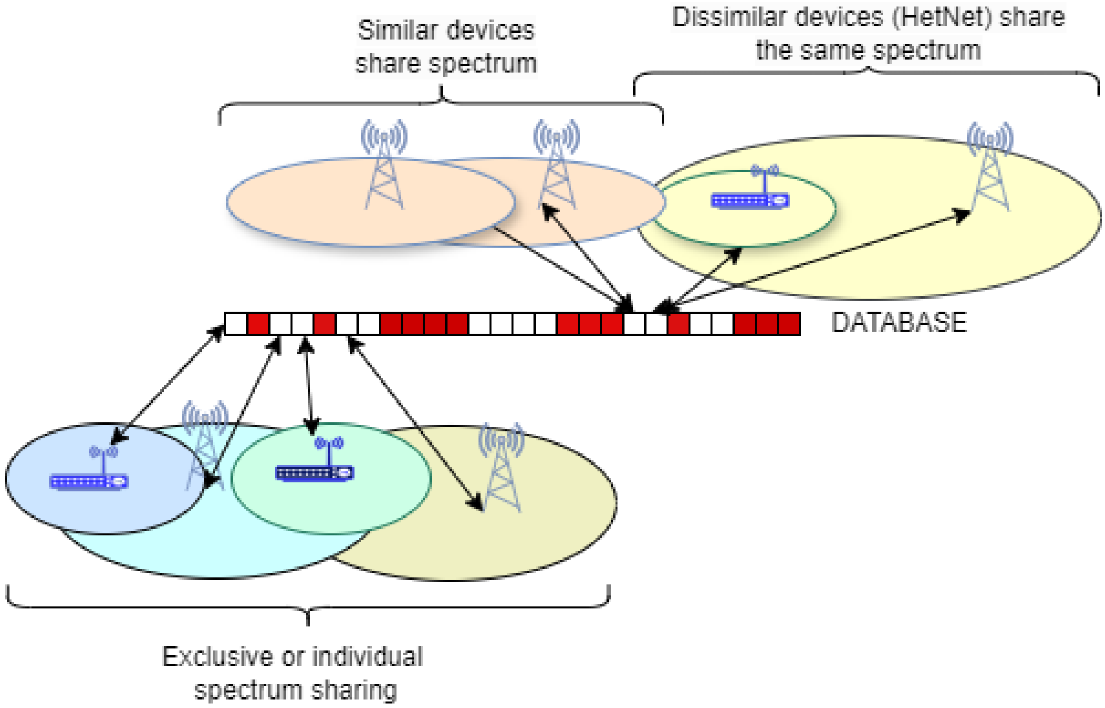


Figure 5.1: Channel Allocation Methods

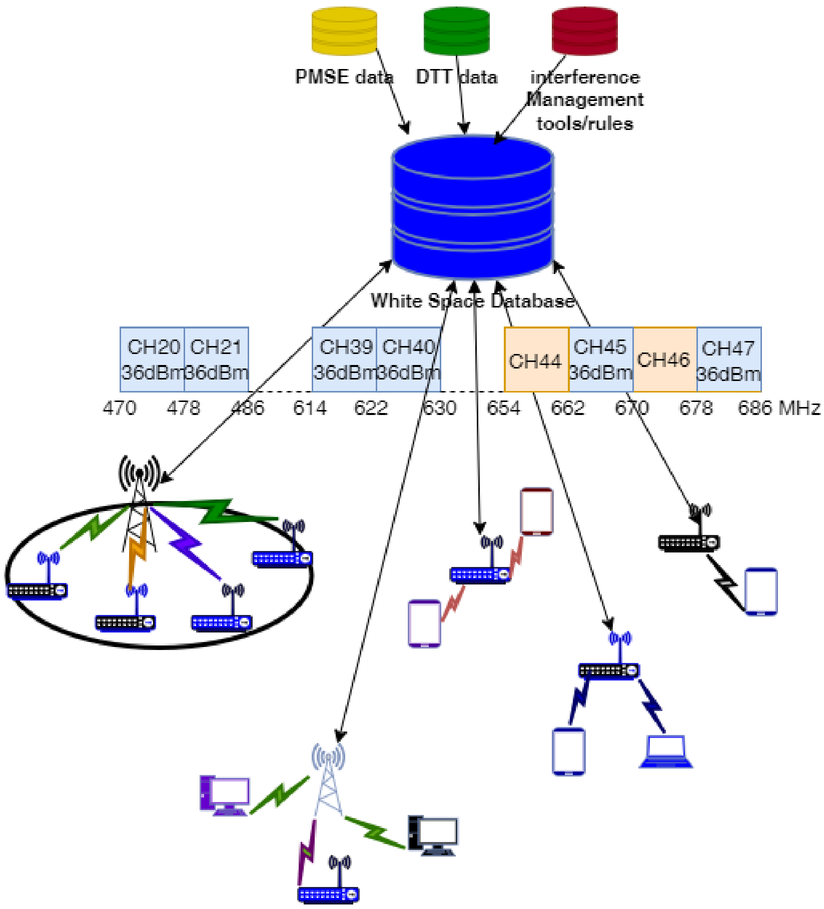


Figure 5.2: TVWS or random channel assignment

5.2.2 CBRS Recursive Allocation

In figure 5.1 [38], the shared channel mode allows for more devices and SUs to be supported by limited available resources. In CBRS, a different approach to device channel mapping is adopted. It uses coexistence groups (CxG) or coexistence sets that may be device or MNO-based. A coexistence group (CxG) was defined as one or more CBRS devices (CBSDs) capable of coordinating interference among themselves, using their interference management policy. In scenarios where SAS performs inter and intra-coordination, the interference management policy can be based on the MAC protocol adopted by CBSDs. When SAS delegates its intra-CxG coordination, the interference management policy adopted can be based on operator policies, e.g., Mobile Network

Operators (MNOs). Based on the available channels provided by the database, SAS investigates the interference between CBSDs and recommends a specific bandwidth range for CBSDs [31].

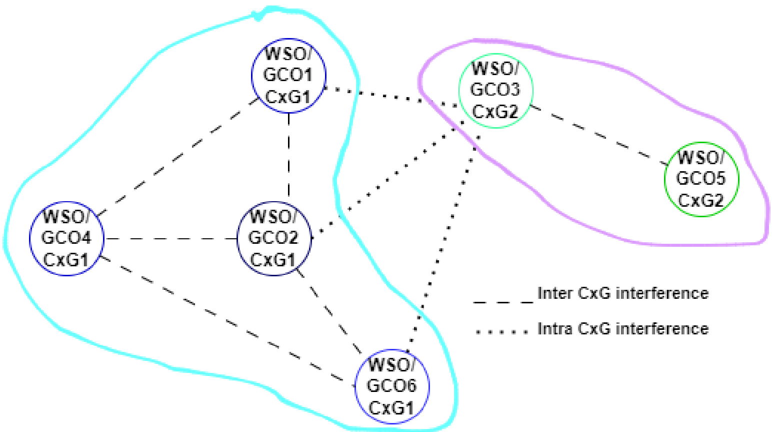
In coexistence management among GAAs [58], with equal priority users as in TVWS, the bandwidth range for each GAA is determined using a recursive cluster method. This method aims to identify the size of clusters of nodes in a connected set and the nodes that make up a connection set. A connection set is a collection of nodes with edges or interference links with nodes in other coexistence groups when transmitting at the same or adjacent channels. In interference investigation by SAS, if connection links only exist among nodes in a coexistence group (CxG_1), they are said to form a cluster size of 1. All nodes with this cluster size can share the same resource bands and internally prevent interference. When some nodes in CxG_1 connect with another CxG_2, nodes in CxG_1 and CxG_2 are said to have cluster size 2. Nodes with higher cluster sizes need to share the available resources. Generally, if there are N CxGs in a network, cluster size (k) can range from $1 \ldots N$.

Cluster spectrum is:

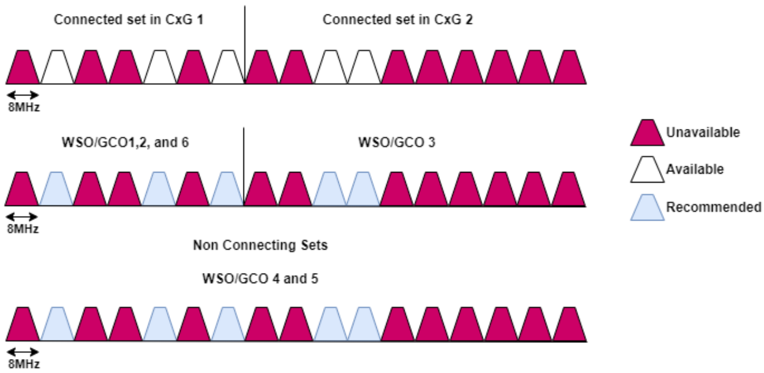
$$Spectrum = (100/k)\% \times \text{Bandwidth} \tag{5.1}$$

which is the spectrum assigned to nodes/devices that belong to specific cluster sizes as shown in Figure 5.3. However, the more coexistence groups there are, the higher the number of possible interfering groups that form the cluster size. A considerable cluster size splits the available spectrum into too small chunks that may not be useful for any coexistence group, thus limiting this approach.

In this thesis, the recursive approach was recreated to support TV bands. The spectrum bandwidth was the number of available channels, and the coexisting grouping was based on the MNOs they belonged to. Cluster groups were identified and sizes allocated, with the maximum cluster size being 2, as there were two simulated MNOs as shown in figure 5.3. A node's cluster size was established based on the number of other CxGs with which it formed an edge/interfered. Nodes not in connecting sets (single



(a) Example of Coexistence Groups with Interference Connections



(b) Example of Allocated channels for CBSDs in figure 5.3a

Figure 5.3: Recursive Allocation Method.

cluster size) but in CxGs selected any available resource. However, channel resources were split among nodes in connecting sets based on their cluster size, as shown in figure 2. Edges/Pairwise interference between CxG nodes, which determined the connection set, was established by the interference discovery algorithm in algorithm 3.

Algorithm 2: Recursive Allocation (Adopted into TVWS)

Input: List of available channels, network structure

Output: WSD resource assignment

Obtain some available channels.

Identify coexistence groups (CxG) from Network structure

Populate connection set:

for *All WSDs* **do**
    pair WSDs,
    conduct interference check using algorithm 3,
    populate connection set
end
for *WSDs* $\in$ *connection set* **do**
    if *WSD* $\in$ *connection set and* $\in$ *"n" CxGs* **then**
        WSD is tagged to have cluster size (k) = n
    end
    else
        WSD not in any cluster
    end
end

Recursively assign channels to WSDs based on tagged cluster size and equation (5.1)

5.2.3 Interference Discovery

Interference increases the noise floor of a receiver, making it hard to detect useful information from a signal with low received signal strength. Interference discovery is critical in SU-to-SU coexistence, as if multiple SU competing for spectral resources suffer a high level of interference; then no helpful information can be transmitted or received. This makes interference discovery important in the SU-to-SU coexistence.

Also, identifying available spectrum/channel is a function of the perceived presence of other nodes/SUs in that bandwidth or channel. Interference discovery, therefore, assists a spectrum manager in identifying channels and sharing these resources safely among coexisting SUs.

Interference discovery is pivotal to channel allocation and safe SU coexistence. Two methods were identified for interference discovery in [38]:

1. Algorithm based on a statistical prediction of interference.

2. Algorithm based on coverage analysis

Statistical interference prediction was adopted as it permits spectrum underlay instead of coverage analysis based on fixed signal coverage, which disallows quantifying and manipulation of interference levels. Its implementation required interference discovery between WSDs (pairwise interference), as this establishes a connection or edge between nodes (for example, nodes A and B). A pairwise interference exists when the received signal experienced by m slave devices (a B AP's receiver) from an A AP exceeds the sensitivity of m [38]. The interference level experienced by a node (AP) is statistically computed by predicting the received signal strength (RSS) around node B from node A, shown in Fig. 5.4, and defined as:

$$RSS_{B \leftarrow A} = P_{TA} + G_A + G_{Bx} - L(x) \tag{5.2}$$

where node A's transmitter power and gain are P_{TA} and G_A, node B's receiver gain is G_{Bx} and the path-loss for x distance between node B's receiver and node A is $L(x)$. The $L(x)$ was estimated with the terrain-based Longley Rice propagation model for distances greater than 1 km and with the free-space model at below 1 km.

The Interference level ($I_{level_{B \leftarrow A}}$) experienced by B from A, is the 90th percentile of A's RSS around 100 B's receivers' cumulative distribution function; as defined in equation (5.3) and (5.4) and shown in figure 5.5. In context, if the set of received signal strength at B receivers from A transmitter $rss_{B \leftarrow A} = rss_1, rss_2, \ldots, rss_{100}$. The

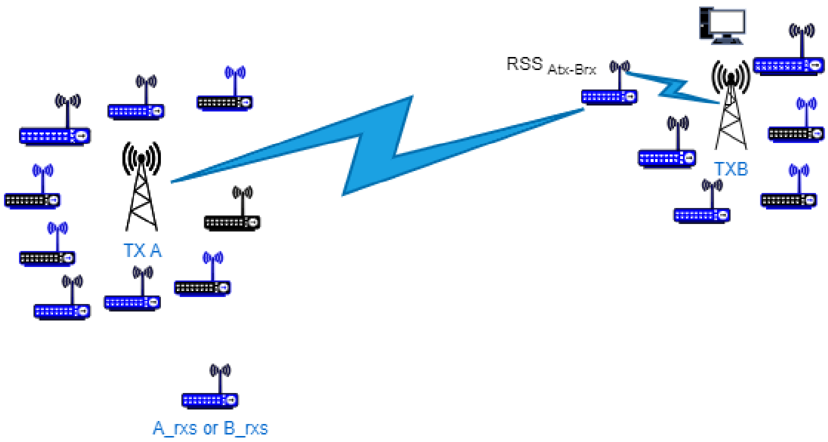


Figure 5.4: WSDs pairwise interference.

interference level from A on B receivers is:

$$I_{level_{B\leftarrow A}} = rss_{90\%} \tag{5.3}$$

defined as a the 90th percentile of $rss_{B\leftarrow A}$ cumulative distribution function (CDF) which is:

$$rss_{90\%} = min(rss) \text{ such that } F(rss_{90\%}) = P[rss \leq rss_{90\%}] \geq 90\% \tag{5.4}$$

The CDF, $F(rss)$, is the probability that a random variable rss is less than or equal to a given value $rss_{90\%}$. The $rss_{90\%}$ is the value (on the CDF $x - axis$) where the cumulative probability reaches 90%. This means that most of the rss points (x in Fig. 5.5) are less than or equal to this $rss_{90\%}$ value, (X in Fig. 5.5). The figure shows the interference level suffered by nodes A and B when they both share a blue and red channel. The interference level experienced by a node B from another node A using the same channel 2 (red) in the Fig. 5.5 is -51 dB, which is a high noise level, compared to -79 dB noise level when they share channel 1 (blue).

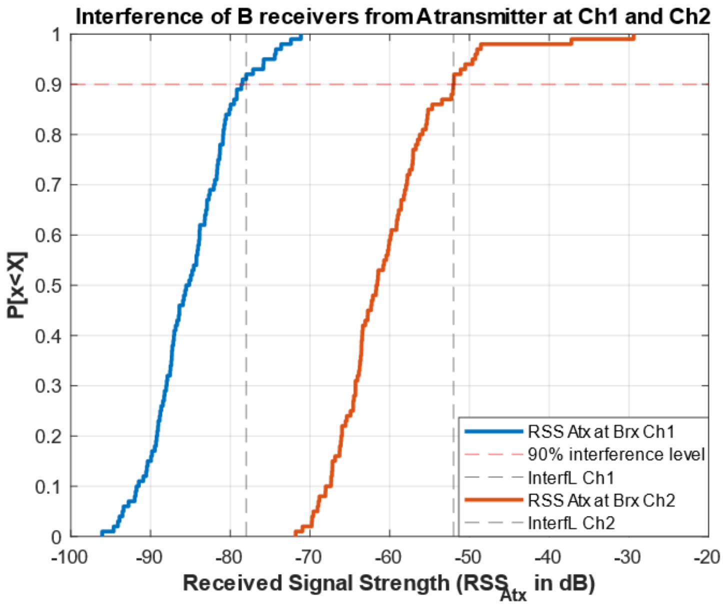


Figure 5.5: 90th percentile of RSS distribution

Algorithm 3: Interference Discovery

Input: Pair of WSDs, network parameters (WSD sensitivity), operating frequencies

Output: Individual WSD Interference Level, Interference Status of WSD pairs

Determine the location of the pair of master WSDs (WSD_A and WSD_B) from network parameters.

Identify WSD's receiver's Interference threshold (I_{th}) = I_{margin} + $sensitivity$.

Generate 100 receiver devices around each WSD.

for *each* WSD_A*'s receiver* **do**
  Compute received signal strength ($RSS_{A \leftarrow B}$) of WSD_B at WSD_A's receivers with LR propagation model in chapter 4 and equation (5.2)
end

for *each B's receiver* **do**
  Compute received signal strength ($RSS_{B \leftarrow A}$) of WSD_A at WSD_B's receivers
end

Determine WSD's Interference Level ($I_{level_{A \leftarrow B}}$) and ($I_{level_{B \leftarrow A}}$) with equation (5.3).

By plotting the cumulative distribution function of respective $RSS_{A \leftarrow B}$ and identify its 0.9 probability point on x-axis (figure 5.5

if ($I_{level_{A \leftarrow B}}$) *and* ($I_{level_{B \leftarrow A}}$) $\geq I_{th}$ **then**
  Tag WSD pair's Inteference Status (I_{Status}) = Mutual Interference
end

else
  if ($I_{level_{A \leftarrow B}}$) $\geq I_{th}$ *and* ($I_{level_{B \leftarrow A}}$) $\leq I_{th}$ **then**
    $I_{Status} = WSD_A$ Interference Victim
  end
  if ($I_{level_{A \leftarrow B}}$) $\leq I_{th}$ *and* ($I_{level_{B \leftarrow A}}$) $\geq I_{th}$ **then**
    $I_{Status} = WSD_A$ Interference Source
  end
end

else
  I_{Status} = No Interference
end

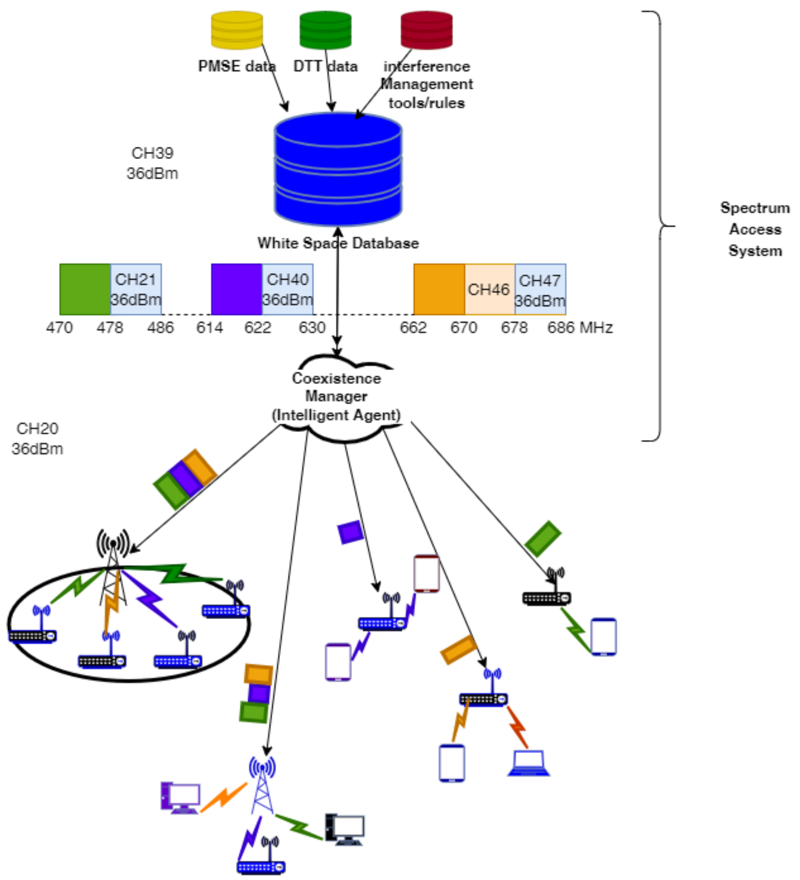


Figure 5.6: Proposed Intelligent Coexistence Manager Architecture

The previously discussed assignment, random and recursive methods, only managed the reuse of channels/spectrum among SUs, adopting an overlay methodology. It also had no control over the level of contention suffered by SUs with similar MAC protocols or within the same coexistence group. It had no optimization in its overlay sharing and did not permit any underlay sharing of resources. This thesis focused on automating the channel allocation/assignment scheme, illustrated in figure 5.1, in a network of similar and dissimilar MAC WSDs. Its central coordinating entity within the SAS or database learns to decide on optimum WSD resources (spectrum and power) as shown in figure 5.6. It learned to control the level of interference and best sharing possibilities among coexisting SUs. To achieve this, an arm of artificial intelligence, introduced in subsection 3.1.3, is adopted in solving the decision-making problem.

5.3 Central Coordination Automation

This thesis uses a virtual network environment for experimental study to evaluate the novel automated and other assignment methods. The central resource assignment problem is formulated as an optimization problem; this problem is solved with two different RL approaches, two-staged optimization(see section section 5.4) and joint optimization (section section 5.5). This provided a baseline for comparing RL algorithms and a better understanding of the effect of RL problem formulation.

5.3.1 DSA Network Design

A 10 km by 25 km study area with a heterogeneous network consisting of IEEE 802.11 Television Very High Throughput (TVHT) wireless local area network (WLAN) and IEEE 802.22 wireless regional area network (WRAN) base stations (BS) and access points (AP), described in Figure 5.2 as colored devices. Their specification is specified in table 5.1. These sent regular updates to a central coordinating system that provided them with available resources. It was assumed that the number of nodes requesting resources at any given time was always greater than the available resources. Thus, it depicts a constantly contesting environment and necessitates the scheduling of transmit power and spectrum to such requesting nodes.

The network is assumed to have continuously changing nodes in the study area. Practically, this can be pop-up networks (as base stations), WiFi router hot spots (as access points), or any master IoT node. Therefore, These dynamic nodes can appear and disappear over time and take on any location. The real-time state of the network environment is captured through nodes' requests and acknowledged information to the database/SAS; this, in turn, can inform optimal resource sharing.

In this spectrum-sharing mode and dynamic network, maximum resource sharing amid continuously changing resources and positions of heterogeneous access points is challenging. Its resource management has several constraints and a regional solution with a combinatory action space. Therefore, It is a non-deterministic polynomial-time (NP) hard complex convex optimization problem as proven in [185]. To solve

Table 5.1: DSA network

Parameter	Value
Number of APs or BSs	3 - 8
Number of UEs	100
Network Area (km^2)	10 x 25
Minimum node - UE coverage radius (km)	5
Bandwidth (MHz)	8
Maximum transmit Power (dBm)	36
Minimum transmit Power (dBm)	25
Thermal Receiver Noise (dBm)	-205
AP Sensitivity (dBm)	-65
BS Sensitivity (dBm)	-97
UE receiver sensitivity (dBm)	-65
AP height (m)	8 - 11
BS height (m)	25 - 30
UE height (m)	1.5
Pathloss Models	Longley Rice & Free Space
Total available channels	4
Channels' Centre Frequency (MHz)	490, 546, 514, 602

these NP-hard and complex optimization problems, heuristic algorithms search for optimal solutions from their regional solution. Reinforcement learning algorithms train policies that learn to conduct these searches and arrive at close to optimal solutions such that learned solutions guide future predictions of solutions. To apply a reinforcement learning algorithm to this optimization problem, the problem was formulated into a Markov Chain Problem.

5.3.2 Formulating shared spectrum automation as a Markov Decision Problem (MDP)

Decision-making processes, such as optimal WSD channel assignment/allocations, can be framed as a Markov Decision Process (MDP). An MDP usually includes sensation, action, and goals that RL algorithms can solve. Critical elements of an RL algorithm are the agent that takes action and the environment in which an action is taken; others are policy, reward, value, and model. A policy guides the actions taken by an agent at every given time step. A reward signal is fed back from the environment, assessing if the goal of a decision problem has been achieved at each time step. The agent's objective is to accumulate the maximum reward over several interactions with the environment [107].

The reward signal, therefore, influences the agent's future choices and shapes the policy's trajectory. Accumulated rewards determine a value function; it measures what states were good in the long run. The value of being in a state is the accrued future rewards by an agent for starting at that state. It measures how good it is to encounter a state over time, while rewards are immediate (every agent to environment encounter) values that the agent continuously estimates throughout its lifetime. Values are, therefore, predictive of rewards while rewards influence values [107]. The design of the reward function thus becomes critical in creating the necessary policy that solves any MDP.

5.3.3 Intelligent Central Coexistence Manager

The resource managing NP-hard problem is addressed with two-staged and joint resource allocation RL algorithms; these lie within the intelligent coexistence manager in figure 5.6. The algorithms aim to achieve optimal resource allocation while minimizing SU-to-SU interference to support future shared spectrum networks characterized by dynamic spectra bands and heterogeneous access points [25].

These algorithms use a minimum amount of information to permit the maximum number of nodes to share the spectrum while manipulating the node's power to prevent interference. The algorithms' solution must balance preventing interference through reduced transmission power and ensuring SU's APs or Base stations (nodes) have adequate user coverage.

The necessary coverage of an SU's node, its QoS, is determined by its receivers' Signal-to-Noise-plus-Interference-ratio ($sinr_{i_m}$) defined as:

$$max_P(sinr_{i_m}) \tag{5.5}$$

subject to

$$P_{min} < P < min(P_{max}, P_{db}) \tag{5.6a}$$

$$sinr_i = \{sinr_{i_1}, sinr_{i_2}, \ldots, sinr_{i_100}\} \tag{5.6b}$$

$$sinr_{i_m} = \frac{P_i H_{i,m}}{\sigma^2 + \sum_{j=1}^{N} P_j H_{j,m}} \quad i, j = 1, \ldots N; \quad i \neq j; \tag{5.6c}$$

where the i^{th} node's QoS ($sinr_i$) in equation (5.6b) is a sequence of its receivers' SINR ($sinr_{im}$) defined in 5.6c. This was maximized by increasing the SINR experienced by each node's receivers through increased node power in equation 5.6c. $H_{i,m}$ the channel characteristics, is a function of a node's antenna gain (g_i, g_m) and path loss between i and m $PL(d_{i,m})$. $PL(d_{i,m})$ is the terrain path loss and cluster loss on signal between an i^{th} node, over a long distance $d_{i,m}$ and urban m^{th} receiver. Additive White Gaussian Noise (AWGN) represents the noise power at m, (σ^2) computed with (4.17). P_i and P_j are transmitter power of nodes i and j that share a channel, and compliant with P in equation 5.6a. $H_{j,m}$ is channel characteristics between j^{th} AP/nodes and the m^{th} receiver.

Therefore, a central intelligent coexistence manager, maximizes first ($sinr_{i_m}$) experienced by i^{th} node's receivers (M) in equation (5.5), and secondly, minimizes the total pairwise interference (I_{ij}) in equations (5.7a). As these two equations have opposite impacts on $m's$ QoS, thus its solution balances interference prevention and the node's QoS.

The second optimization objective is:

$$min_I \sum_{j=1}^{N} \sum_{i=1}^{N} I_{i,j}^{k} \quad k = 1, \ldots K; \quad i \neq j \tag{5.7a}$$

subject to:

$$k_{i_{max}} = \sum_{k=1}^{K} \beta_i^k(t) = 0 \ or \ 1; \quad i = 1, \ldots N; \quad \sum_{i=1}^{N} k_{i_{max}} \to N; \tag{5.7b}$$

$$max(M_k); \quad M_k = \sum_{k=1}^{K} \sum_{i=1}^{N} \beta_i^k(t) \geq 0; \quad ; \tag{5.7c}$$

$$K < N \tag{5.7d}$$

$$\beta_i^k(t) = \begin{cases} 1, & \text{if } i^{th} \text{ node is allocated } k^{th} \text{ channel.} \\ 0, & \text{otherwise.} \end{cases} \tag{5.7e}$$

$$I_{i,j}^k = \begin{cases} 1, & \text{if } I_{level_{i \leftarrow j}} \geq sensitivity_{i_{rx}}. \\ 0, & \text{otherwise.} \end{cases} \tag{5.7f}$$

The second optimization in equation (5.7a) reduces the number of pairwise interference between nodes/access points i and j ($I_{i,j}^k$) defined in equation (5.7f). This is done while maximizing spectral reuse (M_k) in equation (5.7c) and ensuring that the maximum available channels are utilized (equation (5.7b)). $k_{i_{max}}$ and M_k are functions of β_i^k equation (5.15a). The maximum number of channels assigned to an i^{th} node/AP, ($k_{i_{max}}$) is one (equation (5.7b)), however, this channel can be shared by multiple (M_k) nodes (5.7c). Interference level threshold $I_{level_{i \leftarrow j}}$ in equation (5.7f) was derived from equation (5.3) in section interference discovery. The first and second optimizations are performed at every instance of DSA networks' (scenario) assignment.

The two methods adopted addressed the same resource management problem using different Markov decision process descriptions and constraints. This was done to study the impact of problem formulation in RL design and the efficacy of advanced RL methods in improving performance.

5.4 Two-Staged Resource Allocation

The thesis' novel intelligent coexistence manager containing an RL algorithm or agent in the database/SAS is designed. Network parameters such as the APs' ID, location, etc, and available resource information are obtained from the database to create an RL environment. Its resource management task was split into manageable spectrum assignment and power optimization problems. A model-free temporary difference RL method influenced how the policy $\pi(a|s)$ stored in a table ($Q-table$) was computed. The policy is a probability mapping of states to actions when this value is stored in a $Q-table$. A $Q-table$ is usually adopted when the state action size is relatively small. Hence, a small set of states and actions was designed in each algorithm's stage to align with the optimization objective, limiting the RL agent (external or internal) from access to restricted database/SAS information.

5.4.1 Spectrum Allocation MDP Formulation

The first phase algorithm's objective was for an agent to achieve the best channel-to-device/AP distribution to reach a resource management solution to the equation 5.7a. The Markov Decision Process for this objective was captured in the reward ascribed to an agent making independent channel/spectrum choices at each access point. A single network scenario was assumed episodic with many episodes of different starting states. In each assignment cycle/episode (epi), the agent assigned resources to devices one at a time randomly at each time step (t), that is, its starting AP and transition to unassigned APs were random. In the TSA, when all nodes were assigned the episode was terminated at time step T, which was equal to the number of nodes.

The evironment's state (s_t) in an episode was defined as the state at each time step as explained previously in subsection 3.1.3, and defined as:

$$s_t = i \in S; \quad S = \{1, ...N\}; \quad and \quad N = n\{S\} \tag{5.8}$$

It is the node's ID, since this was unique to every device. Similarly within an episode, the agent's action(a_t) in each time step is defined as:

$$a_t = a_i \in \{A\}; \quad A = \{0, k, ..., K\}; \quad K \quad channels \tag{5.9}$$

and allocates ($a_t = k$) or does not allocate ($a_t) = 0$) a specific channel (k) to devices (N) in equation (5.9). The assessment of the agent's action in optimizing equation (5.7a) is given by the environment at each time step ($t + 1$), as explained in subsection 3.1.3

as $((r_{t+1}))$ and defined as a reward function:

$$r_{t+1} = (2 + e^{-n(M_k)}) \sum_{j=1}^{M_k} \sum_{i=1}^{M_k} I^k_{i,j} \quad k = 1, \dots K; \quad i \neq j; \tag{5.10}$$

.

The reward function in equation (5.10) captures the total APs sharing a k channel, (M_k) which is a subset of all APs, $(M_k \subseteq S)$, and all interfering pair edges (i.e. when $I^k_{ij}(t)$ or $I^k_{ji}(t) = 1$). The reward's pairwise interference was computed when multiple devices shared a channel (k), when channels were not shared, a fixed reward was apportioned and when no allocation was given a zero reward was awarded.

Thus, at each time step (t) within an episode (epi), the environment starts at a random state (s_t) or device (i), on whice the agent allocates a channel a_t, causing the environment to transit to a random new state s_{t+1} rewarding r_{t+1} to the agent. This is repeated until all devices are allocated $(t = 1, 2, \dots, T)$, creating a sequence of state and action pairs: $(s_1, a_1, r_2, s_2, a_2, r_3, \dots, s_N$ that terminates at $T = N$ time steps, in an episode (epi). The agent uses the reward from each time step (t) to update its tabular Q-values.

The agent is oblivious to the environment and uses the reward/feedback from its actions on the environment to updates its tabular Q-values using temporary difference approach. Therefore as the agent tries to arrive at its optimum Q-values (Q_π) for predicting the best sequence of actions from different states $(\pi^*(s, a))$, it also optimizes the environment's reward function. As the environment's reward frames the agent's policy, as described in algorithm 4 and explained in subsection 3.1.3.

5.4.2 Power Allocation MDP Formulation

The first phase creates an optimal device-to-channel assignment with nodes operating at maximum transmission power. This is fed to this phase (shown in figure 5.7) aimed at optimizing APs/nodes' transmission power while maintaining good SINR of all nodes as formulated in equation 5.7a. A good SINR benchmark is assumed to be a node's signal-to-noise ratio (snr) when it does not share resources. The second phase arrives

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Algorithm 4: Spectrum Allocation

Input: Initialize $Q(s, a)$ values, learning rate (α), discount factor (γ) and ϵ-greedy. Initialize RL environment initial state (s_t) from equation 5.8
Output: $\pi^*(s, a) = Q^*(s, a)$
for *epi = 1 to #episodes* **do**
  for t *= 1 to #terminal time step* **do**
    from the current state $s(t)$;
    An ϵ-greedy rule:;
    if *a random number* $>$ *ϵ-greedy* **then**
      an action (a_t)= $argmax_A(Q(s, a))$ from algorithm's $Q - table$ is taken
    end
    else
      A random action (a_t) from equation 5.9
    end
    Obtain a reward $r_{(t+1)}$ equation 5.10 and a random next state ($s_{(t+1)}$) equation 5.8 from RL environment;
    To minimize number of edges in equation (5.7a) $r_{t+1} = -r_{t+1}$;
    From the Q-tables, obtain all possible next state actions' value ($Q(s', a')$;
    Update the Q-values in Q-table using equation (5.14)
  end
end

---

at this good SINR benchmark by minimizing the difference between a node's $sinr$ when sharing its resources and snr in equation (5.13).

The objective function is achieved by the second phase agent in algorithm 5 by observing the environment's state in an episode (epi), at each time step (t) as an AP's id, and its previous transmission power defined in:

$$s_t = \{i, P_i(t-1)\} \;\; P_i(t-1) \in P_i, \; in \; equation \; (5.6a) \tag{5.11}$$

. Similar to the first stage, the time step terminates (T) when all the channel matched devices have been assigned new power limits. The agent takes actions (equation (5.12)):

$$a_t = \{0, 1, 2\} \tag{5.12}$$

of a single-digit increase, decrease, or no action (when $a_t = 2$ or 1 or 0 respectively) on the observed power and is rewarded based on the reward function:

$$r_{t+1} = \|snr(t) – sinr(t)\| \tag{5.13}$$

.

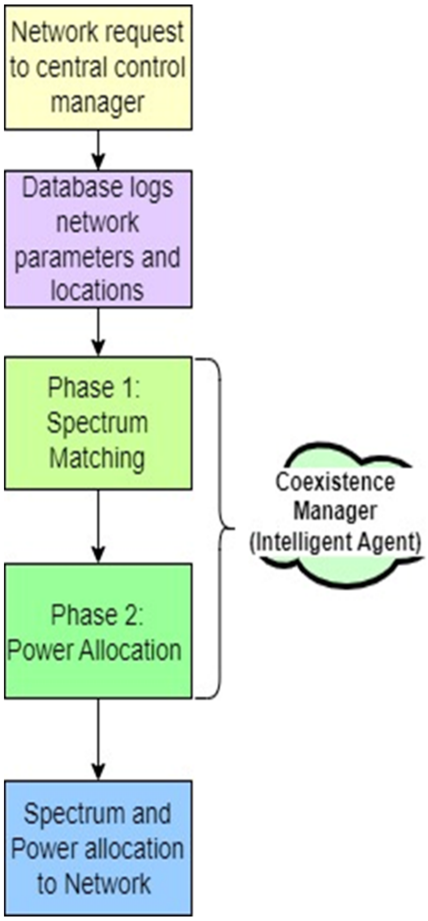


Figure 5.7: Two-Staged Apporach

5.4.3 Policy search

The algorithms (first and second) search through $2^{a(t)}$ policies while taking actions from different starting states to determine the sequence of actions that assures it of the best reward [107]. The algorithms greedily searched through these options in each time step (t) and updated a current Q-table's $Q(s, a)$ values with the equation:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[R(s, a) + \gamma \arg max_a Q(s', a) - Q(s, a)] \tag{5.14}$$

where $Q(s, a)$ is the current Q-value for the state action pair (s_t, a_t) on the Q-table and $Q(s', a) =$ are Q-values from all possible action at the next state $s_{(t+1)}$. $R(s, a)$ is

---

Algorithm 5: Power Allocation Q-Learning

Input: Initialize $Q(s, a)$ values, learning rate (α), discount factor (γ),ϵ-greedy, and RL environment initial state ($s(t)$) from equation 5.11
Output: $\pi^*(s, a) = Q^*(s, a)$
for *epi = 1 to #episodes* **do**
  for *t = 1 to T (Terminal time step)* **do**
    from the current state s_t;
    Follow an ϵ-greedy rule to generate an action: (a_t) same as algorithm 4;
    Obtain a reward r_{t+1} from equation 5.13 and a random next state (s_{t+1}) equation 5.11 from RL environment;
    Minimize change in $sinr$ in equation by $r_{t+1} = -r_{t+1}$;
    Obtain maximum of all next state actions' Q-values from Q-table $max_a(Q(s', a)$;
    Update the Q-table using equation (5.14)
  end
end

---

the reward r_{t+1} for the agent's action a_t, on the environment at (s_t, a_t) and transiting to (s_{t+1}, a_{t+1}). Learning rate α and discount factor γ are training hyper-parameters. An ϵ greedy policy that shuffles between a selection of best policy (exploitation) and a thorough search (exploration) was done in each time step to prevent the algorithms from being stuck at the local minimum.

5.5 Joint Power and Spectrum Optimization MDP

Unlike in the two-staged algorithm (TSA), where only one parameter (power or spectrum) was optimized individually, in joint optimization, both power and spectrum (resources) are assigned simultaneously. The joint algorithm learns to maximize its spectrum and power assignment while maintaining good QoS and minimizing interference. A model-free temporary difference method is used to compute the $Q - values$ that make up the policy as discussed in subsection 3.1.3.

However, deep reinforcement learning (DRL) is used to find a solution to this joint optimization task. This means that, as against a Q-table in the TSA, the policy is saved in a Deep Neural Network (DNN). The DNN serves as an approximator and, as such, uses approximate Q-values from the DNN, rather than the actual values used in TSA's from its Q-table. However, it can store larger Q-tables, thus supporting large state-action sizes. This becomes important as the number of actions (spectrum and power) are more significant in this method, increasing the action space while a small state space is retained. Thus, limited database information is utilized for its optimization task.

5.5.1 Joint Optimization Problem Modification

A Deep Reinforcement Learning (DRL) algorithm is designed to solve the dual optimization tasks defined in equations 5.5 and 5.7a. The RL algorithm learns to allocate optimal resources to nodes while maintaining good QoS. It learns to minimize inter-node interference as nodes continuously change positions. Resources assigned were labeled as numbers, thus catering to their changes, and approximation of nodes' location to the nearest km minimized the state-action space, limiting the search space as nodes increased.

In this approach, resource management is redefined to achieve the first objective of the node's SINR maximization defined in equation 5.5. It describes a good SINR as when 75% of a node's receivers have an SINR greater than two, as defined in equation 5.15d. It solves the SINR maximization problem by maximizing the number of nodes with good SINR experiences (α) in equation 5.15a, as defined in:

$$max \sum_{i=1}^{N} |\alpha_i| \tag{5.15a}$$

subject to equation 5.6a

where

$$\alpha_i = \begin{cases} 0, & \text{if } sinr_{i_{th}} \geq 2. \\ 1, & \text{otherwise.} \end{cases} \tag{5.15b}$$

$$I^k_{permit} = \begin{cases} 0, & \text{if number of AP} \leq 3. \\ 1, & \text{otherwise.} \end{cases} \tag{5.15c}$$

$$SINR_{i_{th}} = sinr_{25\%} = sinr_{max} \text{ subject to:} P[sinr < sinr_{max}] \geq 25\% \tag{5.15d}$$

$$sinr \in [SINR_{i_m}], \quad m = 1 \ldots 100 \tag{5.15e}$$

The second resource management task in equation 5.7a is made a constraint to the good node maximization in equation 5.15b and (5.15c). The algorithm minimizes the interference level by ensuring that there is no interference permitted ($I^k_{permit} = 0$) when the number of nodes in the network is few (equation (5.15c)). However, for a large network, interference between nodes is permitted ($I^k_{permit} = 1$) to accommodate more nodes with good SINR experience. This was done to accommodate a level of interference between SUs in situations where this was possible. The interference allowance permitted among SUs is not clearly defined in the literature. The multilayered interference permits proposed constraints and quickened convergence in large networks.

5.5.2 Joint Optimization Algorithm (JOA) RL Environment

The different formulation of the JOA was necessary for the non terminal time step approach adopted to solve the changing network scenarios MDP. The JOA learned to know the best sequence of action (policy) in each new network scenario within an episode. An episode like in TSA was split into a lot of time step (t), but the terminal time step (T) was not defined. The JOA had to learn in each network scenario (episode) while taking time steps (t) to realize the objective of minimizing interference and maximizing the number of good nodes.

The RL environment's state (s_t) is defined as:

$$s_t = \{x_i, y_i, I_i\} \tag{5.16}$$

where (x_i, y_i) are the coordinates of the node (i) and I_i is defined as $I^k_{i,j}$ in equation (5.5) as the paired interference between node i and any other node sharing an allocated channel k with it, at a time step (t). The interference status of a node can be either a 1 when it is a cause or victim of interference or zero otherwise. The coordinates capture the continuous changing locations of the nodes. On time step (t), the agent on a state takes an action of allocating a channel and power defined as:

$$a_t = \{a_1, a_2\} \tag{5.17}$$

where $a_1 \in 1, ...K$, of K available channels and $a_2 \in 0, P_{min}, ...P_{max}$. When the power is zero, the node is not assigned. An action is taken based on an $\epsilon - policy$ where the agent either selects a random action (exploration) or takes an action based on its π-policy/$Q_\pi(s, a)$ (exploitation), balancing exploration with exploitation.

The agent's reward $r(t + 1)$ from the environment:

$$r_{(t+1)} = \begin{cases} 0, & \text{if } \sum \alpha_i = 0. \\ \sum \alpha_i / N, & \text{otherwise.} \end{cases} \tag{5.18}$$

where N is the number of AP/nodes, α_i in equation Fig. 5.18 is the SINR experienced by the first quartile of an i^{th} node's 100 receivers; solves the resource management problem formulated in equation (5.15) by ensuring that all nodes experience good QoS ($r_{(t+1)} = 0$in equation (5.18)). When this is not the case, the instantaneous reward is normalized to limit the explosion of the reward value, which impedes the convergence of deep neural networks.

The states of the environment transition from one node to another randomly with no set probability (off policy) while ensuring that all nodes are assigned resources before starting another round of reassignment. This was to ensure that all nodes are given an assignment. In each episode (network scenario) the state action pairs: $x_1, y_1, I_1, a_1, r_2, x_3, y_3, I_3, a_2, r_3, x_2, y_2, I_2, a_3, r_4, \ldots, x_i, y_i, I_i, a_t, r_{t+1}, \ldots$ with $i \in 1 \ldots N$ and as such, the transition increases with the number of nodes. The episode terminates as soon as the JOA's objective is achieved, and the time step rewards help the initial random Q-values to gradually arrive at an optimal $Q^*(s, a)$ policy that guides the agent in making the right decisions. As the Q-values converge at this optimal policy the en-

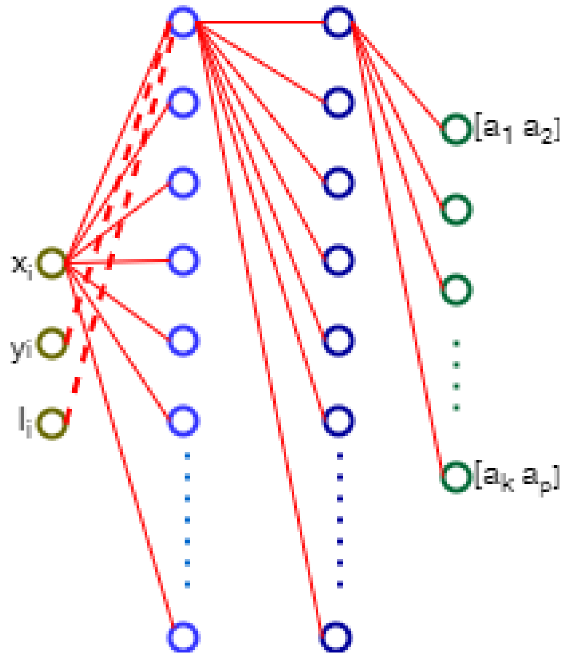


Figure 5.8: Deep Neural Network Q-value (DQN)

vironment's optimization problem is solved as this guides the update in the temporary different approach.

5.5.3 Joint Optimization Algorithm's Policy Design

The Joint Optimization Algorithm's policy as an Artificial Neural Network (ANN) is adopted as a nonlinear function that approximates the content of a typical Q-table.

Deep Neural Networks are ANNs with more hidden layers, the structure consists of input (x_i, y_i, I_i), two hidden layers, and output layers as shown in figure 5.8. Therefore, they have more neurons with weights to represent better the input features' contribution to the neural network's predictions [107]. This has the drawback of having too many weights that cause over-fitting of the dataset or limit the backpropagation of NN's error when it has too many layers. As such, the JOA had two hidden layers with 24 neurons each, thus limiting the number of weights and dept of the DNN.

The DNN approximates the policy (π), which guides the algorithm on the suitable action based on an input state. Therefore, the DNN input layer is the states' features in equation (5.16), and its output layer produces a probability of predicted actions in equation (5.17). Initially, since the weights of the DNN are random, like in the truth table, these output probabilities represent the initialized Q-values for each state-action pair. This probability, $q(x_s, a; \theta)$, becomes correct (i.e., optimal policy is reached) when it predicts the correct state-to-action decision most times [107,110]. The optimal policy's hypothetical good $Q^*(s, a)$ (an approximate of $Q^*(s, a)$))is therefore assumed to be the DNN ground truth which it strives to arrive at.

The ground truth is a future Q-value estimated in temporary difference as an accumulated future reward. This is a function of the difference between the present and next states' Q_{value} in equation (5.14) [107]. The DNN weights are, therefore, fine-tuned to the calculated Q-value from equation (5.14). The updated weights minimize the loss between the next and present state q_{values}, ($q(x_{s'}, a')$, and $q(x_s, a)$), to arrive at a stable $Q(s, a)$.

The convergence of the Q-values estimated by the DNN indicates this stability and represents the successful minimization of the DNN's objective loss function. Also, arriving at this convergence or good Q-values with the optimal policy Q^*_π, means that the agent has learned the right sequence of actions that makes it get the best rewards from the environment. This means that the environment's decision optimization problem has been solved such that its rewards to the agent are similar over continued time steps.

TheJOA's DNN was trained by 30 different networks (a new network in each episode) generating specific state-action policy $\pi_{x,a}$ that correctly predicts the spectrum and power of a new DSA network with similar x, a size. To prevent over-fitting, arrive at convergence, and capture the agent's decisions, the DNN's policy is trained in batches from a pool of the agent's decisions stored in its replay memory (D) in algorithm 6.

5.6 Chapter Summary

In this chapter, available channels/spectra achieved from Chapter Four were managed among secondary users (SUs) using TVWS random and CBRS' recursive strategies.

Algorithm 6: Deep Q-Learning Algorithm

Input: Initialize replay memory D, Initialize Q-network's random weights $(q(s, a; \theta))$, learning rate for DNN, Initialize target Q-network $(q^{'}(s, a; \theta^{'}))$. Initialize RL environment initial state $(s(t))$ from equation 5.16

Output: $\pi^{'}(s, a)$ = approximate $Q^{*}(s, a) = Q^{'}(s, a)$

for *epi = 1 to #episodes* **do**
    for *t = 1 to #steps* **do**
        from the current state $s(t)$;
        An ϵ-greedy rule:;
        if *a random number* $>$ *ϵ-greedy* **then**
            an action $(a(t))$= $argmax_A(Q(s, a))$ from algorithm's DNN
        end
        else
            A random action (a(t)) from equation 5.17
        end
        Obtain a reward $r(t+1)$ and a random next state $s(t+1)$ equations 5.18, 5.16 from RL environment;
        Store experience (s(t),a(t),r(t+1),s(t+1)) in replay memory (D)
        Randomly select samples from D ($\mathrm{s}_d(t)$, $a_d(t)$,$r_d(t+1)$, $s_d(t+1)$)
        θ is updated based on the Loss = $[r_d(t+1) + \gamma \max_{a_{d+1}} q^{'}(s_{d+1}, a_{d+1}; \theta^{'}) - q(s_d, a_d; \theta)]^2$
        Predict possible next state actions' value $(q(s(t+1), a(t+1); \theta)$
        Update $q^{'}(\theta^{'})$ from $q(\theta)$
    end
end

These non-interference-aware and interference-aware algorithms were designed to operate on a TVWS network to serve as a baseline for assignment performance evaluations. A framework for interference awareness was developed based on a unique IEEE 802.19 interference discovery methodology, which quantified the nodes' interference levels.

A novel two-staged Q-learning reinforcement learning algorithm's reward function was designed to solve a central resource coordinating problem discussed in chapter 2 and 3. The algorithm minimized interference among sharing SU and maximized the number of sharers. To address the same problem, a novel joint optimization deep Q-learning algorithm's reward function was developed. These algorithms addressed the resource assignment to randomly located nodes in a study area using different Markov Decision Processes. A detailed review of the performance of these different resource management and allocation techniques is evaluated in the next chapter.

Chapter 6

Intelligent Resource Management Performance

Intelligent resource management enables the dynamic allocation of spectrum and transmit power to dynamically located access points/base stations/nodes. The designed resource allocation algorithms discussed in the previous chapter were evaluated based on convergence, quality of service (QoS), repeatability, and scalability. Their performances were compared with existing random and recursive assignment techniques to establish their impact on spectral efficiency, SU's maximization, and satisfaction. Unlike prescriptive optimization algorithms (non -RL algorithms) discussed in chapter 3, learned algorithms generate predictive responses/allocations to dynamic network demands. This makes them responsive to future spontaneous shared spectrum networks.

To measure this, the SUs interference tolerance as suggested in [19] is defined as the level of interference permissible is not defined in any literature. This thesis therefore assumed that a permissible disturbance from another transmitter is permitted to the degree to which only the first quantile of a node's receivers are disrupted. Hence an SUs satisfaction or Quality of Service was defined as good when most of the SU's receivers (75%) had SINR greater than a $0dBm$ threshold.

Four measuring indices, Requests Assigned, Assignment Performance, Request Performance, and Probability of Total failure, were defined and used to assess resource management algorithms' assignment performance. The intelligent algorithms, therefore, learned to optimize spectrum and power (resources) assignment to nodes/APs, coexisting at the same space and time.

6.1 Algorithms Input Parameters

The designed RL algorithm's states (WSD's IDs and locations) were instantaneous and changed over time, and the actions assigned spectrum and power (resources). In the two algorithms created, the available channels were the same, while the power levels and hyperparameters differed to accommodate each algorithm's unique property.

6.1.1 Spectrum Resources.

The Resources in this study are based on the outcome of available channels on the TV band in Glasgow, UK. The available digital TV bands computed in table 4.5 were channels 23, 26, 30, and 36, as bands above channel 48 have been reassigned to other services. The available channels vary from 2 to 4 to create a manageable parameter size for detailed experimentation and observation of all algorithms.y

6.1.2 Power Resources.

A fixed maximum power of 36 dBm was used for the non-optimization algorithms, as stated in Ofcom's documentation [186]. In the two-phase algorithm, a WSD's transmission power was between a minimum of 30 dBm and 36 dBm, with a 1 dB increment, to form a set of power limits {30 dBm, 31 dBm, 32 dBm,..., 36 dBm}. This was done to limit the state space being examined. Similarly, in the Joint optimization algorithm, a minimum of 25dBm was assumed with a 2 dB increment, $P =$ {25 dBm, 27 dBm, ..., 35 dBm} for the same reason.

6.1.3 Algorithm learning parameters.

The machine learning algorithms require different learning parameters called hyper-parameters. A summary of the two-staged algorithm (TSA) hyper-parameters is pro-

Table 6.1: Training Parameters for Two-Staged Q-learning Algorithms

Parameter	Value	
	First Stage	Second Stage
Learning Rate (α)	0.1	0.1
discount factor (γ)	0.95	0.95
training episodes	5000	3000
starting ϵ	0.9	0.9
ϵ decay	0.998	0.9998

Table 6.2: Training Parameters for Joint Resource Deep Q-Learning Algorithm

Parameter	Value
Learning Rate (α)	0.2
Discount Factor (γ)	0.98
Training Episodes	30
Steps	500
Exploration Rate (start) (ϵ)	1
Exploration Decay	0.99
Batch Size	32
Replay Memory Size (D)	2000
Optimizer	Adam Mean Square Error
activation function	ReLu
NN structure	3,24,24,2

vided in table 6.1. A slow learning rate, high ϵ, and discount factor created a slow learning algorithm that explored the state space extensively with greater emphasis on immediate rewards. Similarly, the training parameters for the two-layered Deep Neural Network (DNN) in the Joint Optimization Algorithm (JOA) are summarized in table 6.2. JOA's training episodes used in this method were less, as each episode represented a new DSA network scenario on which the JOA had to achieve optimal resource assignment.

6.1.4 Intelligent Algorithms Training and Testing

Two different training approaches were adopted in the two designed intelligent algorithms (TSA and JOA). In TSA, each network scenario was trained with multiple episodes of different sequences of decisions on resource allocation in the first stage and power allocation in the second stage. The TSA, therefore, learned how to make the right spectrum and power assignment for each network scenario irrespective of its starting node. The TSA algorithm is trained and tested in each network scenario to make a sequence of spectrum and power allocation decisions.

In the JOA, a single algorithm's policy, defined by a specific number of radios and available resources, was trained with 30 dynamic and unique scenarios. The number of scenarios was determined based on the size of the study area $2500km^2$, and with each Wireless Regional Area Network (WRAN) covering about a $100km^2$, an average of 25 random locations of this node type was sufficient to capture varied possibilities within the study area without repetition. Thus, each test scenario was unique for a constrained experimental environment size, number of nodes, and node/radio types. The JOA learned to allocate spectrum and power simultaneously in each episode and the network scenario changed at each new episode. The JOA learned to assign resources irrespective of the start node and the location of the devices.

Similarly, it was assumed that 10 test scenarios were sufficient to measure the performance of all allocation algorithms. This was considered statistically sufficient to compare all allocation algorithms' ability to allocate resources in the same unique scenario, ascertaining their consistency in decision-making. The JOA was then tested together with the TSA in ten unique scenarios in section section 6.4 and with other allocation algorithms in another ten unique scenarios in section subsection 6.5.2.

6.2 Convergence

The Reinforcement Learning algorithms designed to solve the optimization problem combined trial and error search for possible solutions (exploration) and maximizing the found solutions (exploitation) to arrive at a solution. As with most optimization problems, the solutions converge when changes in the observation time lead to no significant change in the learning algorithm's decision/reward. The convergence, therefore, means that there is a possible solution to the two optimization equations formulated in equations (5.5) and (5.7a). However, the solution may be a local solution or a global solution, as observed in the performance of the two algorithms.

6.2.1 Convergence of Two-Staged Algorithm (TSA)

The convergence of the Two-Staged Algorithm (TSA) when assigning two channels to 3 and 4 nodes in network scenarios (ql_{32}, ql_{42}) is shown in the left of Fig. 6.1. It shows an upward convergence as first phase's maximization of its reward moving average (equation 5.10). Similarly the second phase of transmit power assignment to already assigned 2 channels to 3, 4, 5, and 6 nodes $(qlp_{32}, qlp_{42}, ..., qlp_{62})$ is shown the right of Fig. 6.1. the second phase's minimization of QoS difference and as such descended to a converged optimal Q-value at varied convergence speeds, as shown in the right plot of figure 6.1.

Training time for the two stages differed; convergence in the first stage was achieved after 5000 episodes and 3000 episodes in the second. The first stage took about 2 to 8 hours for different network sizes, while the second took an average of 1 to 3 hours; these ran on a cloud-based platform (Google Colab) with 12.7GB RAM. There was a continued decrease in convergence moving average value as the number of nodes sharing the two channels increased. This results from the reward function indirectly dependent on the number of sharers. Thus, the reward decreased as the number of requesting nodes increased. Convergence in the second phase was fastest when TSA shared two channels among three nodes, taking longer as the number of requesting nodes increased.

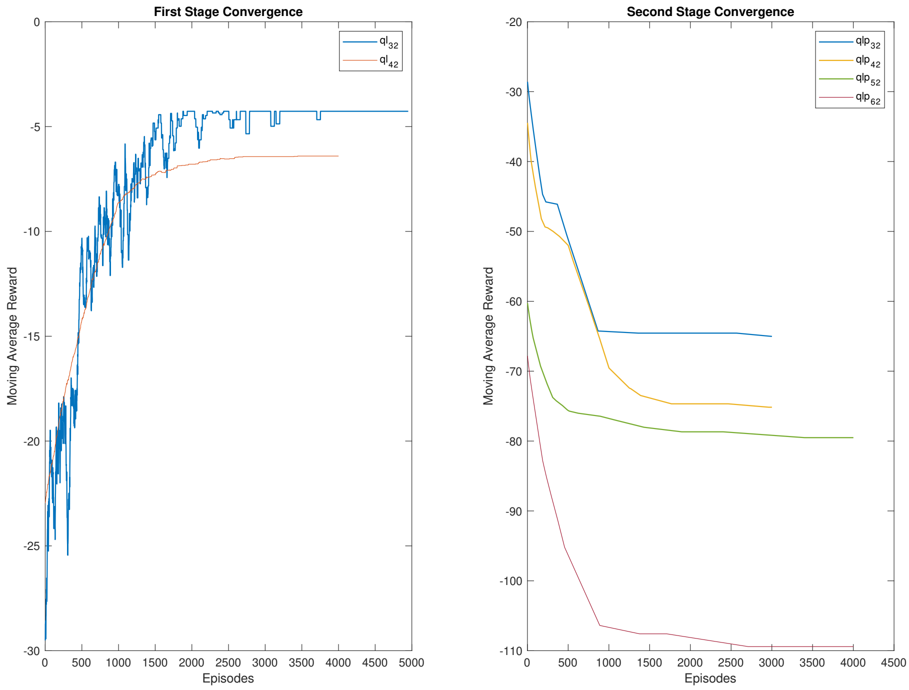


Figure 6.1: Convergence of TSA's when assigning two channels to various numbers of nodes

6.2.2 Convergence of Joint Optimization Algorithm

The Joint Optimization Algorithm (JOA) minimized the Q-value approximator's loss function explained in subsection 5.5.3. JOA assignment of 2 channels to network scenarios containing three to six nodes is represented in Fig 6.2 as a Q-value convergence plot for the networks $(q_{32}, q_{42}, ..., q_{62})$. This showed that the Q-value converged upward to an ideal Q_π policy, as it maximized the reward function in equation (5.15a) progressively in the right plot of Fig. 6.2. The right plot, therefore, shows how the RL agent arrives at the solution to the environment's MDP while the left plot shows how the agent arrives at its optimum policy Q^*_π.

Also, the loss experienced by the Deep Neural Network (DNN), for each network scenario, with a unique number of nodes, $loss_3, loss_4, ..., loss_6$, are illustrated in Fig. 6.2 The loss function shows how the weights in the DNN are being trained to achieve the optimal target DNN that achieves the correct Q*values approximates or predictions. A loss plot shows the step-wise training of the DNN weights to minimize the loss function in algorithm 6, to achieve the optimal policy Q^*_π, hence the decreasing plot to convergence.

The Fig. 6.2 convergence plot differs in steadiness from that achieved in Fig. 6.1. This is because the training episodes were framed differently. In each episode in Fig. 6.1, the TSA algorithm learned a single network scenario; as such, the nodes were static all through the training, and as such, a smooth convergence was achieved despite the fact that their reward functions were not static. In the JOA, each episode had a new network scenario, and as such, the Q-values struggle to arrive at the Q*value target for each new network scenario in Fig. 6.2.

JOA's Q-value approximation for three nodes arrived at convergence quickest after about 15 episodes, while others arrived after 25 to 28 episodes. It struggled to arrive at convergence when requesting nodes were greater than double the number of channels, as optimal solution searches were audacious as the DSA network size increased.

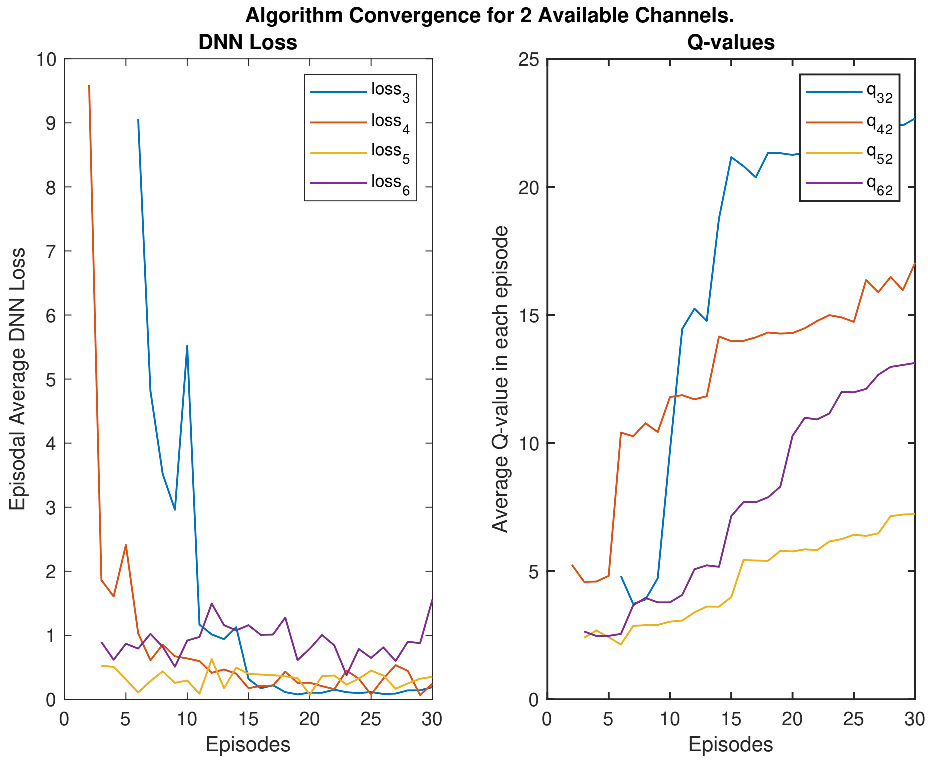


Figure 6.2: Convergence of JOA training to assign two available channels to several nodes

6.3 Quality of Service

Each network scenario studied had randomly located APs/nodes of different device types. Diamond-shaped Wireless Regional Area Networks (WRAN) base stations or APs had equal priority with circular Wireless Local Area Network (WLAN) access points or nodes. The two intelligently trained models predicted resource (spectrum indicated with different colors) assignment in each network scenario, as illustrated in the scattered plots (Fig. 6.3) in this section and section 6.4. This showcases the novel model's resource assignment to nodes changing location in different network scenarios.

Similarly, the quality of service experienced by each node in each of the network scenarios was assessed based on the signal-to-noise plus interference ratio (SINR/SNIR) experienced by its 100 receivers as stated in equation 5.6c. This is represented as a box plot to capture the device/node's first quantile SINR when assigned a specific channel (color) in Fig. 6.4. Each model's assignment in a scatter plot DSA network scenario is complemented with a performance box plot (Fig. 6.3 and Fig. 6.4). These describe TSA and JOA's model's assignment and node performance.

The threshold for good quality of service was defined as when the node/AP's set of receivers' sinr's first quantile is greater than or equal to zero. That is, when only 25% of a node's receivers experience SINRs below zero, the node is termed to have a 'good QoS.'

6.3.1 Two-Staged Resource Management QoS

The TSA trained its two-staged model for each network scenario considered. It successfully assigns resources (2 channels at different Power levels) to four nodes in figure 6.3. Despite the similar distribution of WRAN and LAN nodes in all network scenarios, only scenario 1 had all nodes with good QoS Fig. 6.4 .

The first stage's assignment of channels showed the red channel was assigned to nodes that were well apart in scenarios 1 and 2. However, the reverse was done in scenarios 3 and 4, causing the nodes to perform poorly in figure 6.4. A similar experience is observed with the blue channel (shared among dissimilar nodes) in scenario 2, resulting in node 4's poor performance. The channel assignment's inconsistency was attributed to the single state of the first stage, which was to be corrected by the second stage, appropriate power management. However, the second stage is limited by its 30 dBm minimum power constraint.

The objective of the central coordination was to limit the occurrence of these poor SINR performances as these affect the level of contention managed by MAC protocols or other intelligent distributed coordination systems. TSA showed a limited ability to achieve this, which is further quantified in section 6.4.

6.3.2 Joint Resource Management QoS

The Joint Optimization Algorithm (JOA) assigned resources (red and blue channels) to a similar DSA network with four nodes in figure 6.5a. However, the yellow-colored nodes were not assigned because of the possibility of their assignment leading to poor

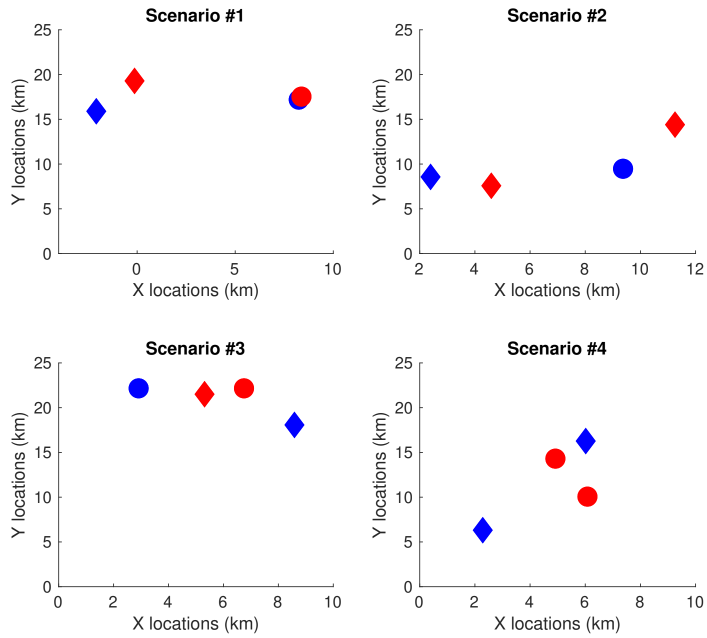


Figure 6.3: Two-Stage Algorithm's (TSA) allocation of 2 channels (colours) to 4 APs network scenario

performance. Proximity nodes had a higher risk of interference. When it assigned all available resources to WRAN in scenarios 1 and 4, all other nodes were excluded due to the node's broad coverage, arguably impeding resource sharing with other nodes. Thus, JOA prioritizes QoS experience over several shared devices, as observed in its problem formulation (equation 5.15).

Thus, in all scenarios, JOA enabled all nodes to have good QoS in figure 6.5b but limited the maximum number of sharing nodes to three in scenarios 2 and 3, figure 6.5a. This was in line with the thesis object of providing a maximum number of nodes with good QoS while managing a level of interference. A similar performance was observed when the number of channels was increased to 3 and shared among five nodes in figure 6.6a. Scenario 2 had all its nodes assigned with good QoS in figure 6.6b. However, this was rarely the case in other scenarios with proximity nodes. An elastic JOA model learned to assign five nodes, four nodes, and three nodes in different DSA network scenarios, such that nodes experience optimal QoS.

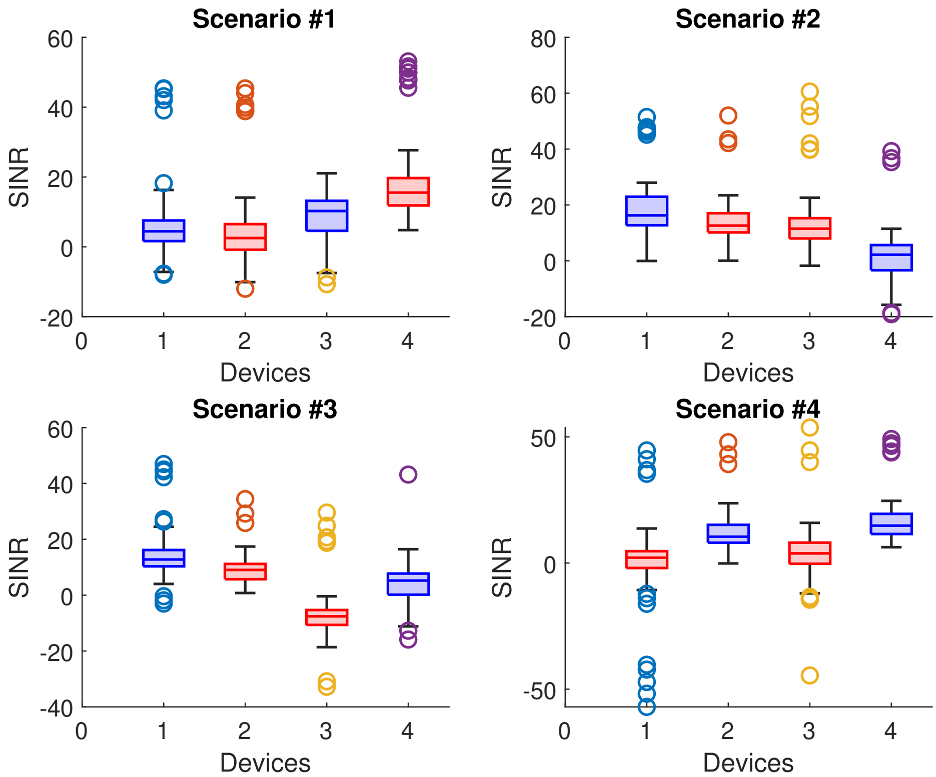
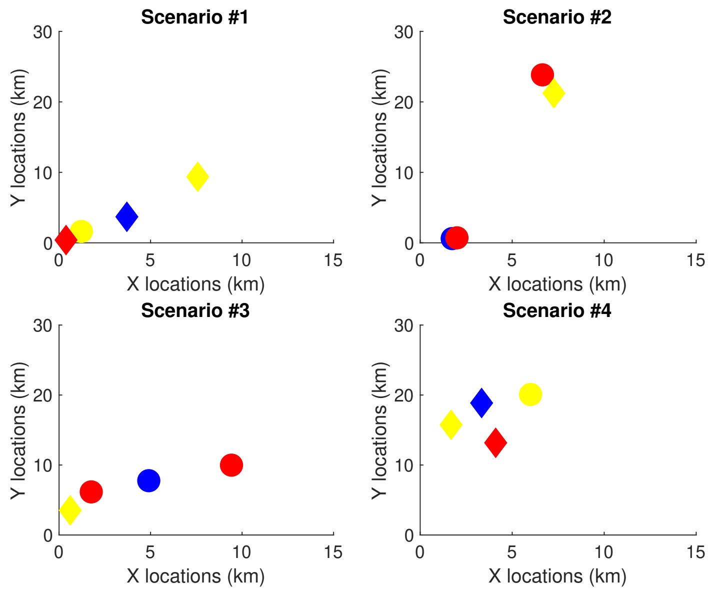


Figure 6.4: The SINR performance of TSA assignment in Fig. 6.3



(a) Joint Algorithm's allocation of 2 channels (colours) to 4 APs in diverse network scenarios

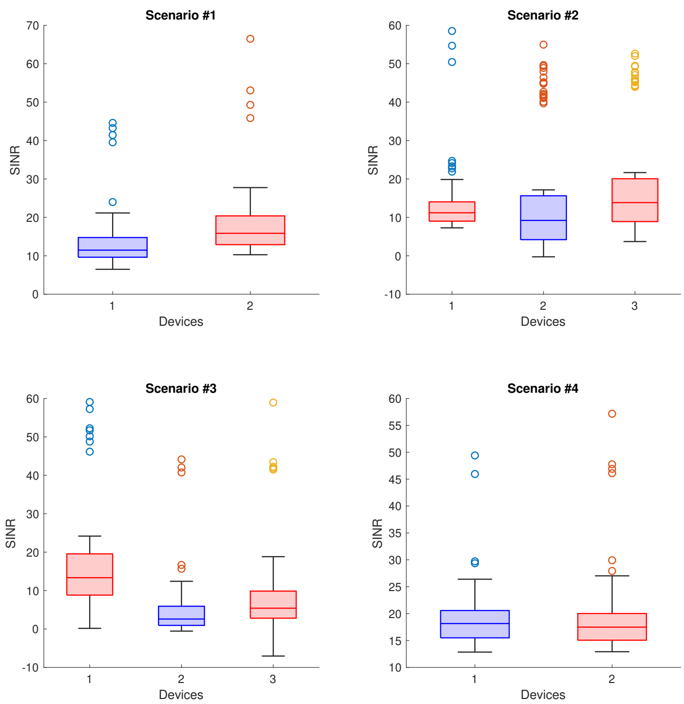
6.4 Repeatability

The two intelligent algorithms use four defined criteria to assess the frequency of good resource assignment. This is to ascertain the degree to which each algorithm could continuously maintain its good performance and the effect of this on other nodes. As discussed in subsection 3.6.2, these indices extend previous works, providing a general index to measure the performance of multiple DSA algorithms.

These four metrics provide a uniform measure of the performance of all allocation techniques compared. They assessed the technique's ability to achieve the overall thesis objective to:

1. maximize the number of nodes sharing spectrum and
2. minimize the interference between spectrum-sharing nodes.

These matrices measured satisfied request nodes (requests assigned), assessing how many requesting nodes were granted access by reusing resources. Good allocation was based on the quality of service enjoyed by a node's receivers (assignment performance). In addition, to assess the repeatability and consistency of the algorithms across differ-



(b) SNIR performance of nodes in figure 6.5a scenarios

Figure 6.5: Joint Resource Management Algorithms of 2 channels (colours) assignment to 4 APs.

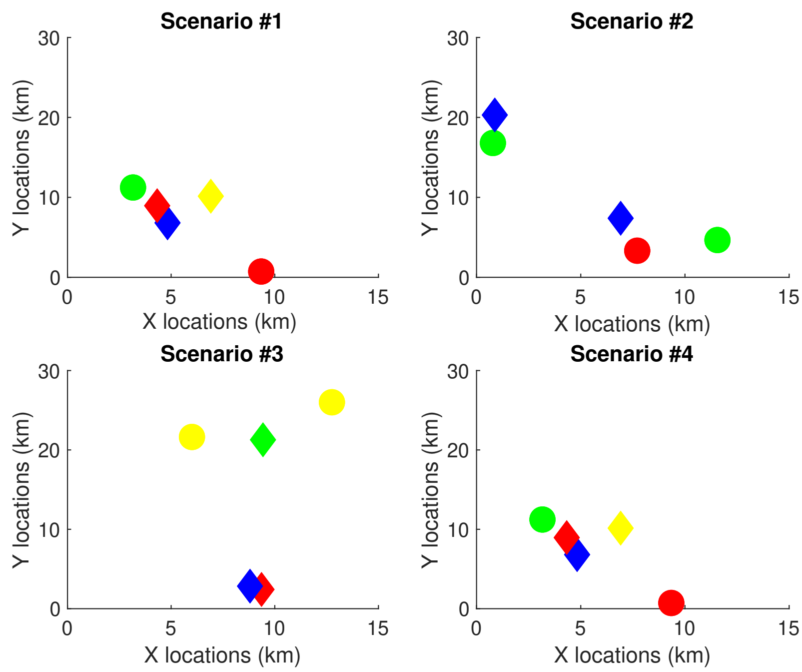
ent network scenarios, the assigned requests and the probability of total failure were introduced.

1. Requests Assigned (%): This is defined as:

$$\text{Requests Assigned} = \frac{\text{Assigned Nodes}}{\text{Requesting Nodes}} \tag{6.1}$$

in equation (6.1) as the percentage of all requesting nodes assigned channels in a DSA network scenario. It is a measure of the maximum number of nodes that an algorithm successfully assigns resources.

2. Assignment Performance (%): This was defined as:



(a) Joint Algorithms Assignment of 3 channels (colours) to 5 SU's APs in different network scenarios

$$\text{Assignment Performance (\%)} = \frac{\text{Good Nodes}}{\text{Assigned Nodes}} \tag{6.2}$$

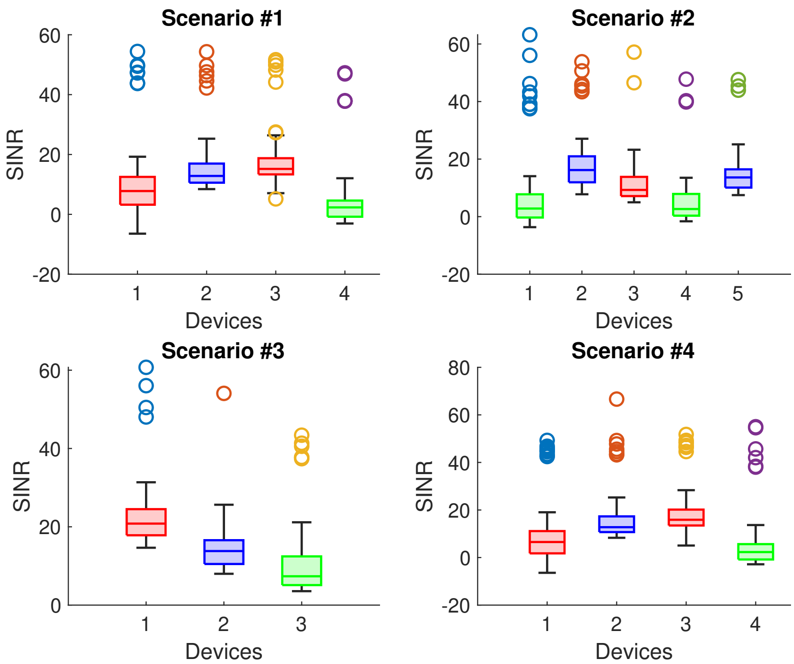
which is the percentage of all assigned nodes with good QoS in a network scenario in equation (6.2)). It measures the impact of the assignment on nodes' QoS.

3. Request Performance (%): this is defined as:

$$\text{Request Performance (\%)} = \frac{\text{Good Nodes}}{\text{Requesting Nodes}} \tag{6.3}$$

which is the ratio of assigned good QoS nodes to the total number of requesting nodes in percentage. This is the product of Assignment Performance and Requests Assigned or as stated in equation (6.3).

4. Probability of Total failure: this was the probability of all assigned nodes suffering poor QoS performance.



(b) SNIR performance of JOA assignment to nodes in figure 6.6a scenarios

Figure 6.6: Joint Resource Management Algorithms Convergence for several available channels and access points.

To further assess all algorithm's solutions to these problems, the two metrics, assignment performance and request performance, balance the trade-off between the two objectives. This is because increasing the number of nodes sharing a resource increases interference, which reduces the QoS experienced by nodes. The assignment performance and request performance together quantify an assignment/allocation algorithm's performance in balancing these two tasks.

These performance indices are used to assess each algorithm's performance in ten unique DSA network scenarios. The algorithms allocated colored available channels to WRAN (diamond-shaped) nodes and WLAN (circular-shaped) nodes.

6.4.1 Consistency of Two-Staged Algorithms

The TSA consistency in predicting the assignment of two channels (colours) to four nodes is investigated. TSA models are trained for each of the ten unique networks and assign resources to each network as shown in figure 6.7. All four nodes were assigned in all the scenarios, irrespective of the positions of WRAN and LAN nodes, thus achieving a 100% requests assigned performance.

However, the performance of these assignments could have been better (50 to 100% nodes experiencing poor QoS) in scenarios 1, 4, 7, and 10, as shown in figure 6.10. The TSA algorithm assigned resources in very challenging networks, such as scenarios 8 and 9, but failed to achieve such good performance in scenario 10. Scenario 10, a total assignment failure was experienced, as all assigned nodes experienced poor QoS. This algorithm, therefore, had a 1% probability of total failure and an unstable performance.

A summary of its performance in each of the network scenarios is provided in table 6.3. On average, the TSA algorithm was seen to have a 68% assignment performance in table 6.4 and was tagged as unstable. The limited state information (node id) of the algorithm's first stage and the limited power range constraint of the second phase may have contributed to its instability and poor performance. Thus, although TSA learned to assign spectrum when it started at different nodes, it quickly learned to assign correctly or poorly, making it unstable.

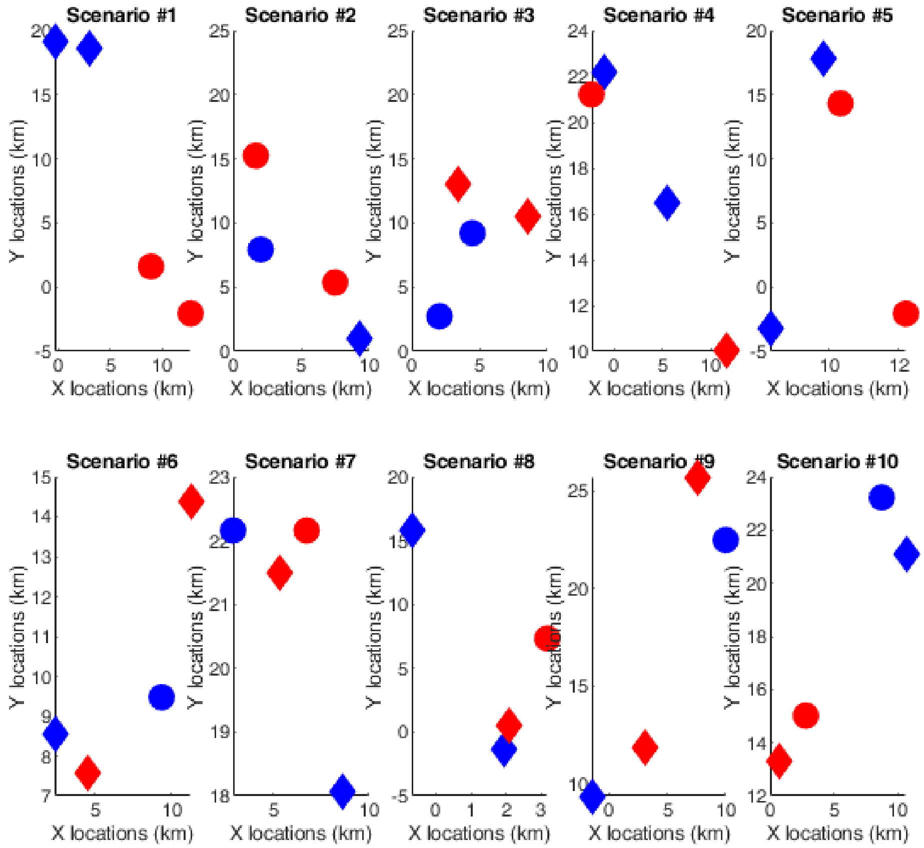


Figure 6.7: 10 Scenarios of Two-Staged algorithm's assignment of 2 channels (colors) to 4 nodes

6.4.2 Consistency of Joint Optimization Alogirthm

JOA's consistency was studied in the same ten networks as the previous section, shown in figure 6.9. The layout shows that some nodes were not assigned (colored yellow), as JOA prioritized nodes' good QoS against assigning all nodes.

A JOA is trained to provide a single model that successfully predicts assignments for 75% of its requesting nodes in 8 scenarios and 50% in 2 scenarios. This meant that the algorithm denied 25% to 50% of requesting nodes access to channels, resulting in an average of 69% requests assigned in table 6.4. This was attributed to the limited power constraint and the number of episodes used to train the algorithm, limiting the

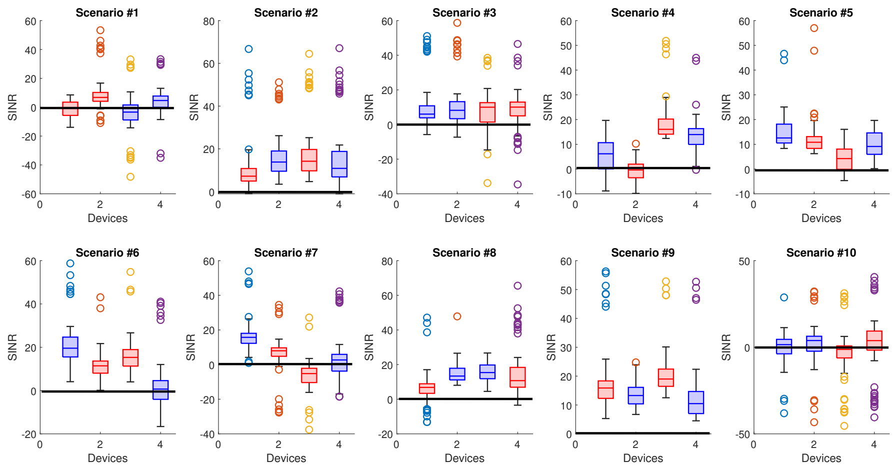


Figure 6.8: The SINR performance of Two-Staged Algorithms assignment of nodes in Fig. 6.7

models' exposure to more complex node distribution.

JOA's assignment performance was 100% in 9 out of 10 scenarios and 67% in scenario 3, as shown in figure 6.10. The average assignment performance for all scenarios was 96% (table 6.3), revealing that the algorithm's assignment consistently resulted in good QoS nodes. The JOA's consistent assignment performance achieves the thesis objective and a reasonably fair performance against TSA in table 6.3 and 6.4.

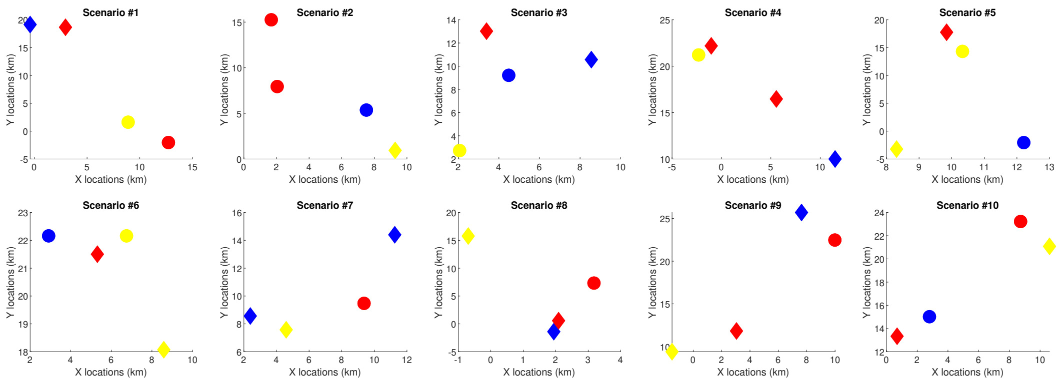


Figure 6.9: 10 Scenarios of JOA assignment of 2 channels (colors) to 4 nodes

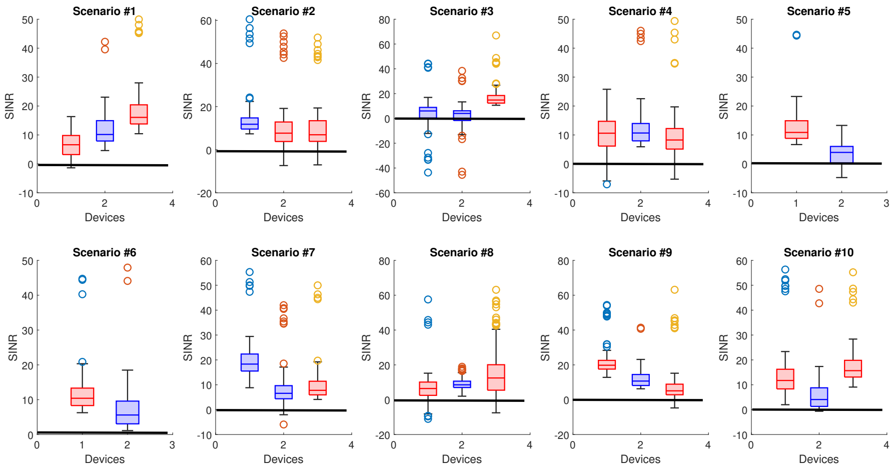


Figure 6.10: The SINR performance of Joint Optimization Algorithms' assignment of nodes in Fig. 6.9

6.5 Comparing Resource Assignment Algorithms

The comparative performance of random, recursive, TSA, and JOA resource management strategies in assigning different numbers of channels to nodes is evaluated. The methods' unique assignment performance is analyzed using bar, scatter, and box plots. The bar chart shows the number of channels each algorithm shares to devices. The scatter plots show the TSA assignment of channels (colors) to devices in their space location. The TSA, random, and recursive assignment performance is shown in the box plot in figure 6.11. The JOA assigns resources to a similar DSA network in figure 6.12, thus comparing and analyzing all algorithms' assignments.

The methods' request and assignment performance were evaluated for ten unique networks. Their average performance in these scenarios in assigning different numbers of channels to various numbers of devices is presented in figures 6.24, 6.25 and 6.26, discussed further in this section. An additional channel usage index is defined as the ratio of the number of channels assigned to the total number of available channels.

Table 6.3: Repeatability Performance of TSA and JOA in resource assignment of 2 channels to 4 nodes

Scenarios #	TSA Assignment Performance (%)	JOA Assignment Performance (%)
1	25	100
2	100	100
3	100	67
4	50	100
5	75	100
6	75	100
7	50	100
8	100	100
9	100	100
10	0	100

Table 6.4: Algorithms Average Repeated Assignment of 2 channels to 4 nodes

Algorithm	Assignment Performance (%)	Requests Assigned (%)	Request Performance (%)
TSA	68	100	68
JOA	96	69	67

6.5.1 Resource Assignment Comparison of Joint, Two-Staged, Random and Recursive methods

Allocation techniques, random (rand) and recursive(recur), were compared with the TSA (QSecd), and it behaved like other algorithms in the Figure 6.11 bar chart. On the same network, JOA performed better by assigning two nodes and ensuring they all had good QoS, as shown in figure 6.12. As earlier explained, it resulted in low request assigned performance. In contrast, the high requests assigned performance of random, recursive, and TSA methods were consistent, as the number of devices increased in figures 6.13, 6.14 but resulted in a decrease in assignment performance.

However, in assigning two channels, TSA learned to stop assigning resources to nodes when there was an increased level of contention that resulted in poor QoS in nodes, as shown in figures 6.14 and 6.16. Thus, TSA assignment resulted in 3 out of its 4 APs enjoying good QoS, in the figure's box plot, like JOA, in figures 6.15 and 6.17. In these instances, other methods reallocated these channels, resulting in poor QoS, as

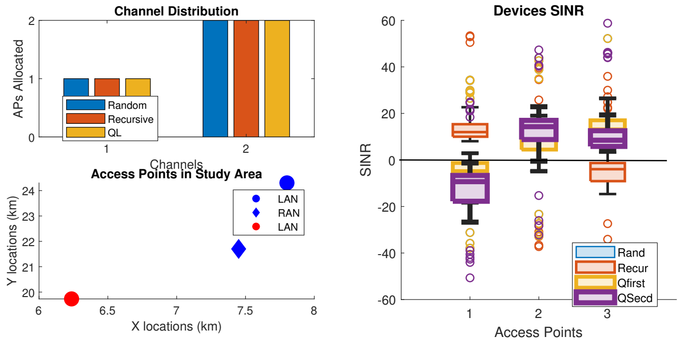


Figure 6.11: SNIR of our previous Q-learning algorithm when compared with other techniques

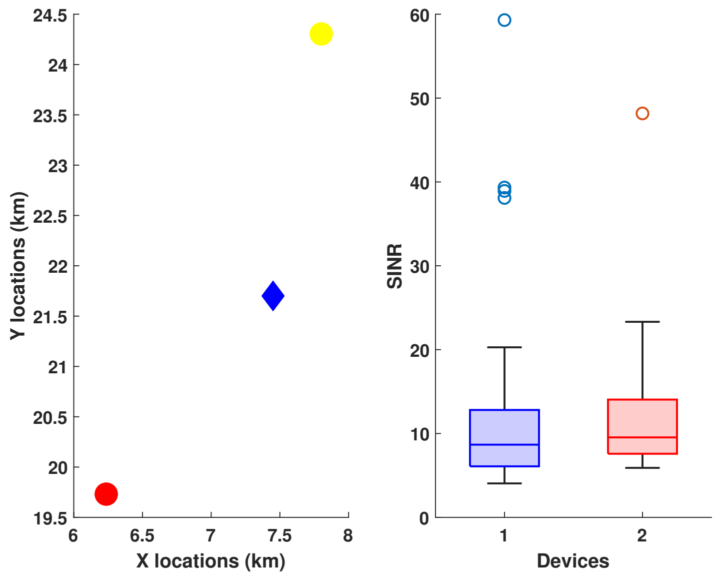


Figure 6.12: Comparing DQN with other networks.

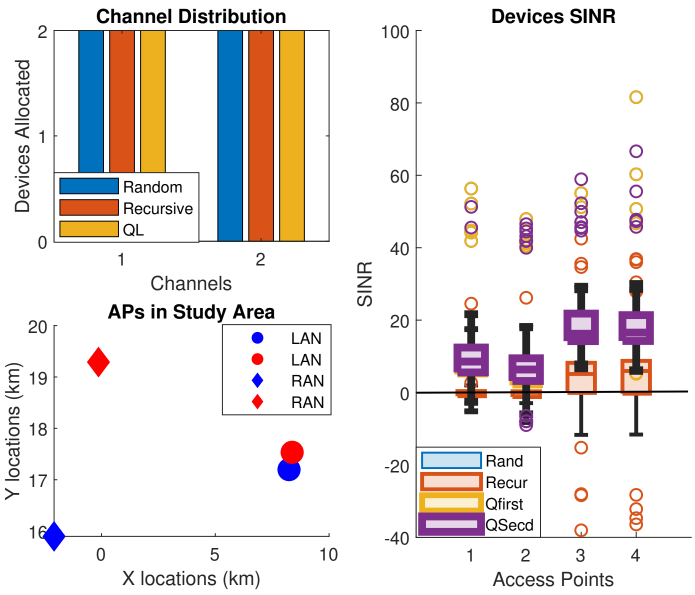


Figure 6.13: Comparing allocation techniques $N = 4$ and $K = 2$

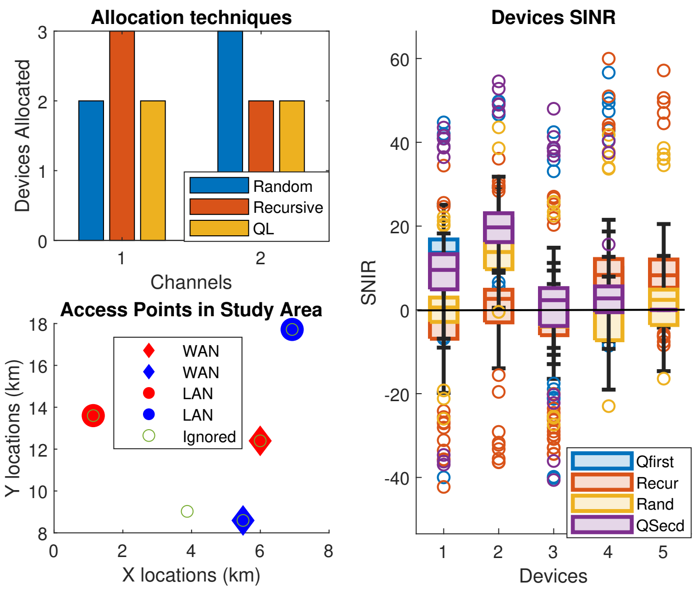


Figure 6.14: Comparing allocation techniques $N = 5$ and $K = 2$

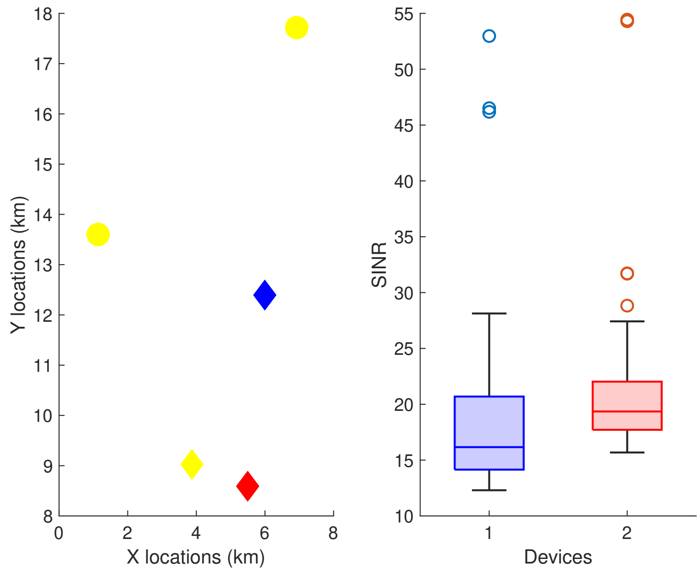


Figure 6.15: JOA assignement N = 5 and K = 2

shown in figure 6.16. Thus, TSA and JOA, in their assignment, learned to regulate their requests performance to increase their good performance.

Similarly, when the number of channels was increased to 3, and APs were few (4), TSA learned to optimize channels. It reused channels by using only two channels instead of 3 available channels, as shown in the bar chart of Figure 6.18 while ensuring good quality of service for all or most APs. Its channel usage was at 67% as against 100% for other methods. This was repeated in Figure 6.20, where it optimally matched three (3) channels to five (5) APs, maintaining a 75% channel usage, as against others' 100%. Its channel reuse slightly altered its assignment performance, which was at par with random and better than recursive assignment methods. JOA lacked adaptable channel usage, as it was designed to prioritize assignment performance over spectral reuse, as shown in its assignment of 3 and 4 channels in figures 6.19 and 6.21.

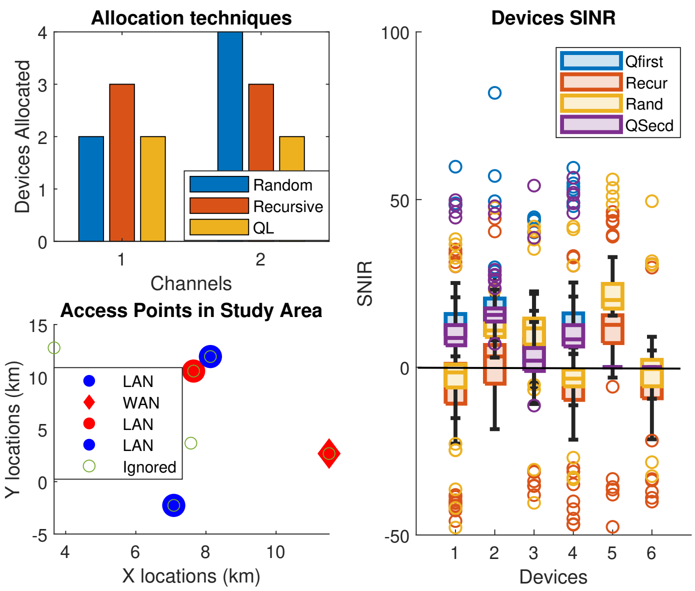


Figure 6.16: Two-Stage Algorithm Assignment and other techniques $N = 6$ and $K = 2$

6.5.2 Scalability of the Two Optimization algorithms compared with other methods

A summary of the scalability of all the methods' assignment and request performance was evaluated over increased resources in figures 6.24, 6.25, and 6.26. In figure 6.24, all algorithms assigned two channels to 3, 4, 5, and 6 nodes. Each assignment case (e.g., two channels assigned to 4 nodes) was repeated, resulting in ten unique network scenarios as shown in Fig. 6.7—these scenarios' average assignment and request performance, ascertained performance consistency with changing heterogeneous network composition. The assignment performance, therefore, quantifies the maximization of SINR performance while the requests assigned quantified the reuse of channel and number of satisfied requesting nodes/SUs.

In analyzing the figures 6.24, 6.25, and 6.26, JOA had the best assignment performance in all resources, as it had the closest assignment performance to an exclusive assignment. The exclusive assignment, described in subsection 5.2.1, assigns an available resource to a node without resource reuse. The recursive method in all the figures was least close to the exclusive assignment as they depended on the MAC or MNOs'

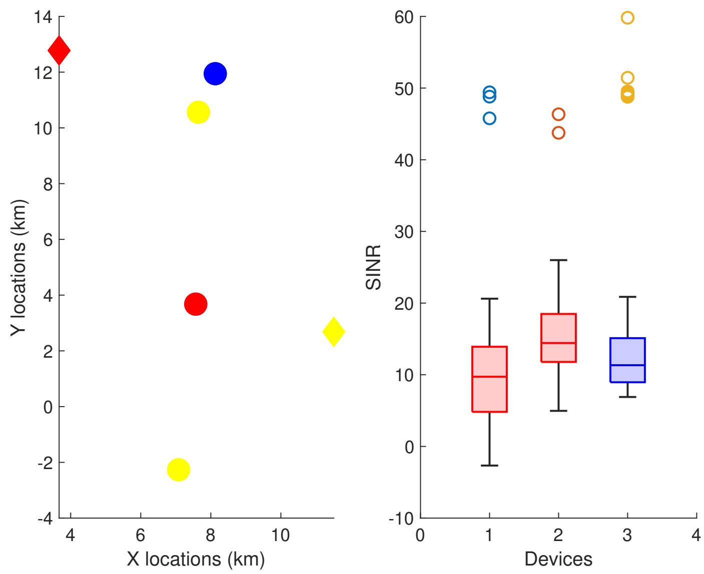


Figure 6.17: JOA assignment for N = 6 and K = 2

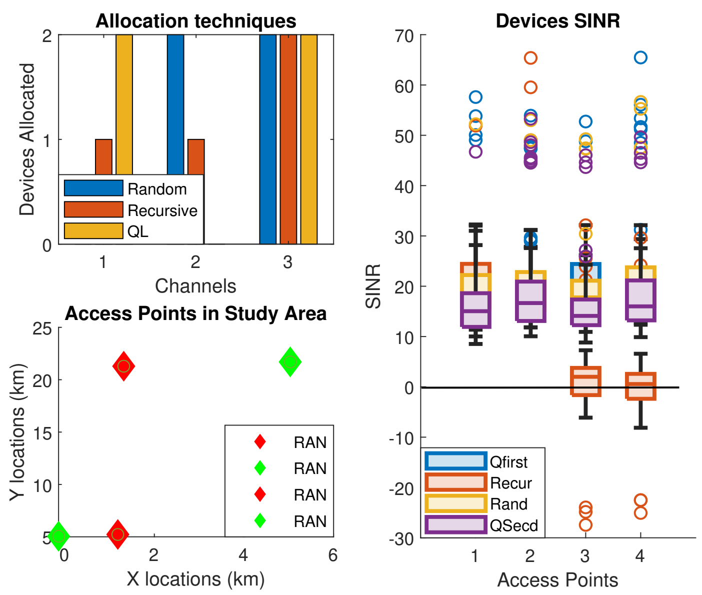


Figure 6.18: Two-Stage Algorithm Assignment and other techniques $N = 4$ and $K = 3$

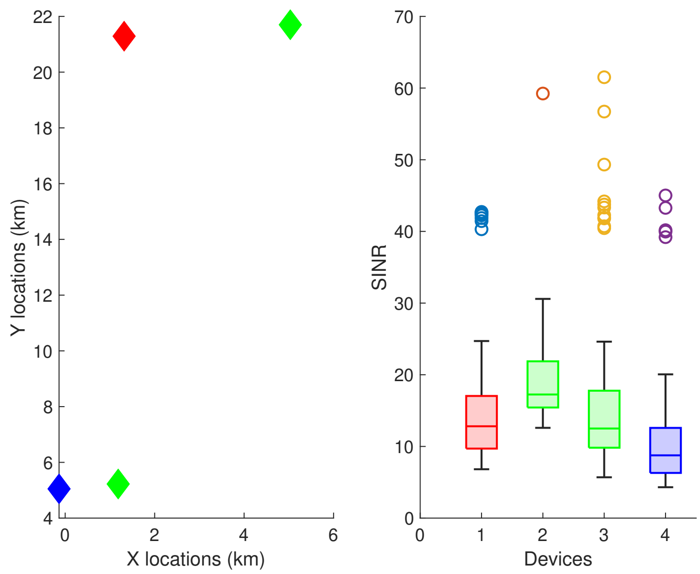


Figure 6.19: JOA assignment N = 4 and K = 3

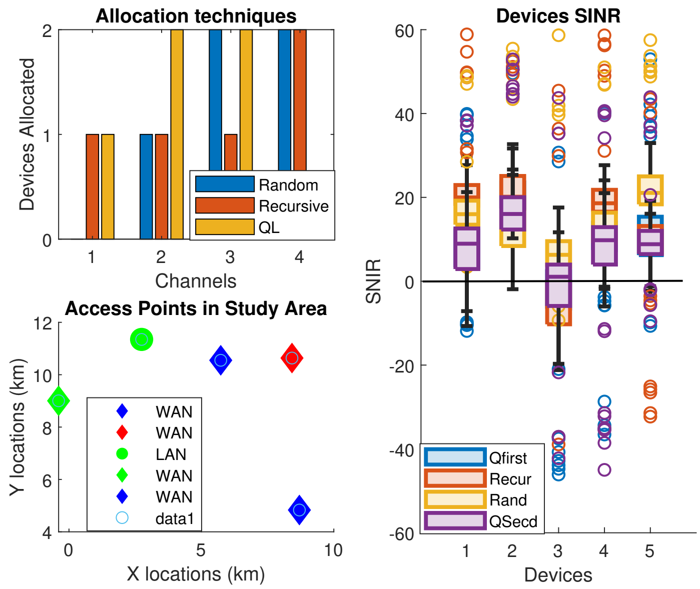


Figure 6.20: Two-Stage Algorithm Assignment and other techniques $N = 5$ and $K = 4$

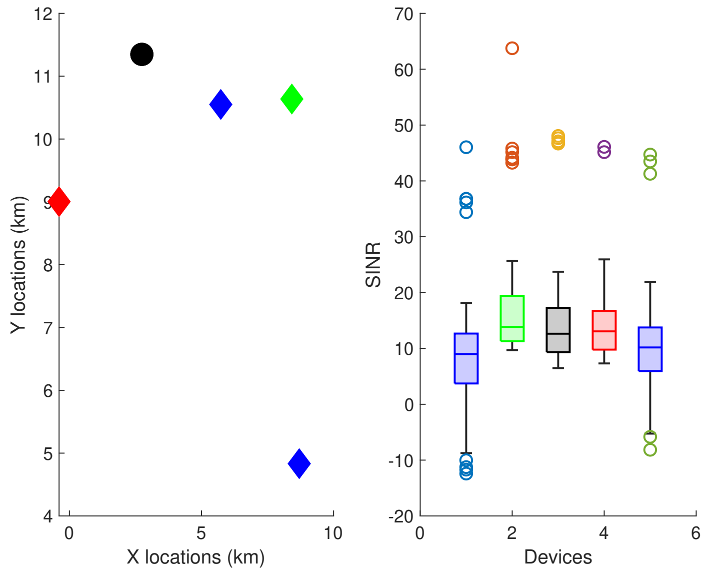


Figure 6.21: JOA assignment N = 5 and K = 4

coexistence group's coordination scheme [187], which was a scheme outside this thesis' scope. It also had no power optimization to improve the QoS experience. However, random and TSA performed at par, assigning 2 to 4 channels. Despite the absence of interference knowledge, the random assignment's first-come first-serve approach made its coordination inconsistent like TSA.

The request performance of JOA and TSA in figures 6.24, 6.25, and 6.26 showed that TSA was best in satisfying nodes' requests when 2 and 4 channels were available. TSA, therefore, performed best in request performance, and the recursive method was worst. Their overall request performance was poor despite the good request assigned performance of the random and recursive methods, as mentioned earlier. This was because they relied extensively on internal MAC protocol coordination, which managed high resource-to-device contention. However, adopting an intelligent resource manager before random and recursive assignments could harness the strengths of both intelligent and existing internal/MAC coordination schemes.

The best-performing method was based on the thesis objective of optimizing spectrum and power allocation to nodes. TSA was at par with JOA in request performance as its high requests assignment augmented its poor assignment. However, its unpredictable performance and poor assignment performance made JOA the best-performing algorithm.

To quantify the impact of the best allocation method on spectrum reuse, the JOA and the exclusive assignment are compared in allocating two channels to different numbers of requesting nodes in Fig. 6.24. The JOA provided nodes with as good a QoS as the exclusive in its assignment performance. However, the number of requesting nodes satisfied (requesting performance) increased significantly in the JOA compared to the exclusive assignment. In each quantity of devices (3, 4, 5, and 6 devices), there is an almost 20% increase in the number of satisfied nodes by JOA as against exclusive algorithms assignment of 2 channels. This means that when, for example, there are 4 requesting nodes and only two available resources, JOA reuses these 2 resources such that all nodes achieve good QoS as against what exclusive assignment permits of only two satisfied nodes.

However, as the number of nodes and available resources increased (increased search space for the JOA), the algorithm's performance dropped. In Fig. 6.26, when 4 available channels are being shared by five, six, seven, and eight nodes, the average request performance improvement of JOA, compared with exclusive, drops to 10% as against 20% when 2 channels were assigned. This becomes a major drawback of JOA, as there is a combinatorial increase in the search space as the number of available channels increases.

In summary, the Two-Staged algorithm had unique flexibility in resource assignment, as it unassigned resources and minimized spectrum usage while achieving reasonable assignment performance. Training a model for each network scenario enabled it to repeat this attribute at certain times. However, due to its limited state space, TSA's assignment predictions were inconsistent.

Similar to TSA, the Joint Optimization Algorithm was capable of not assigning resources to achieve excellent assignment performance. It was consistent in its performance and rarely suffered inferior performances. A single trained model predicted the assignment of resources for different network scenarios, making it robust. However, unlike TSA, it was not designed to be flexible in minimizing spectrum usage when resources were in excess. Therefore, JOA significantly reduced contention compared to its counterparts at the expense of satisfying all requesting APs.

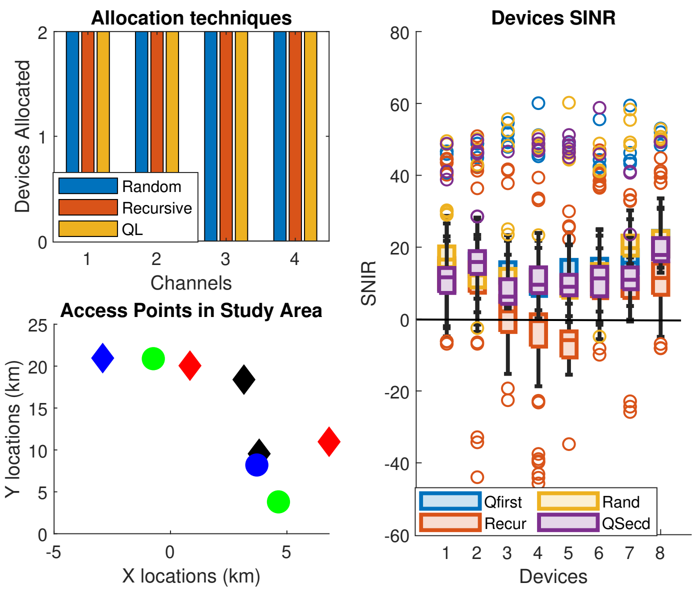


Figure 6.22: Comparing allocation techniques $n = 8$ and $k = 4$

6.6 Chapter Summary

This chapter has analyzed the performance of a novel Two-staged Q-learning reinforcement learning Algorithm (TSA). TSA learned to optimally predict the assignment of scarce spectral resources to diverse located and types of nodes in a DSA network. The low computational intense algorithm's performance was at par with existing shared spectrum techniques, like random, interference-unaware resource assignment of TVWS and recursive interference-aware resource assignment of CBRS systems. These provided a high level of resource assignment, as most requesting SUs were assigned resources, although they suffered a high degree of harmful interference (poor QoS). The TSA learned to maximize spectral reuse and stop assignment when necessary. However, it suffered a high level of inconsistency in its predictions because of the algorithm's design, despite its convergence.

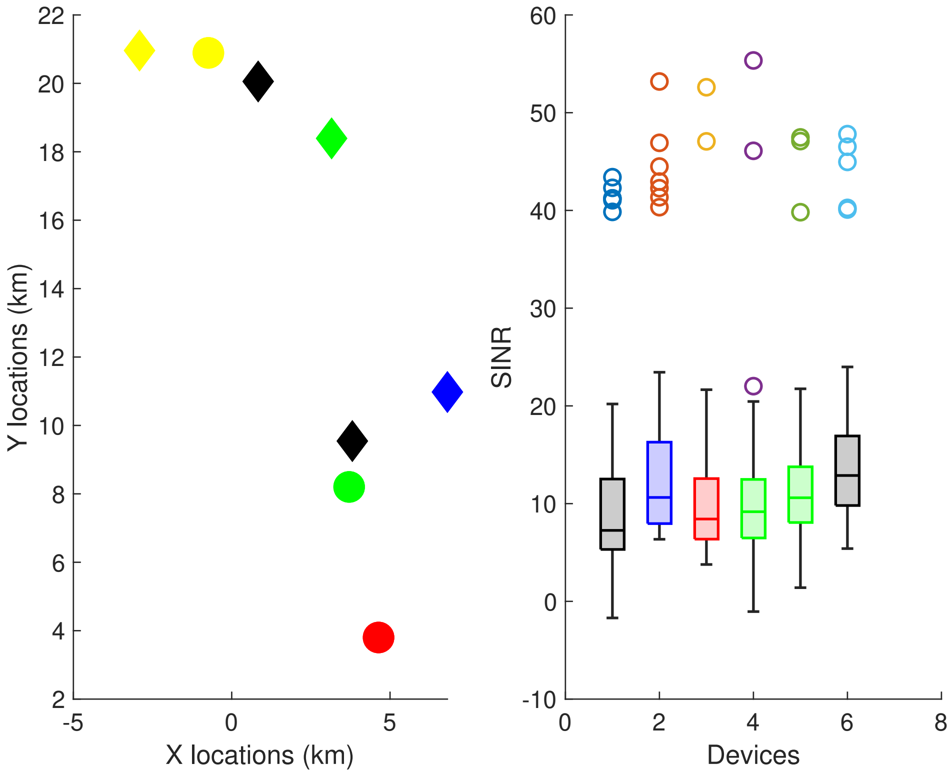


Figure 6.23: JOA assignment for N = 8 and K = 4

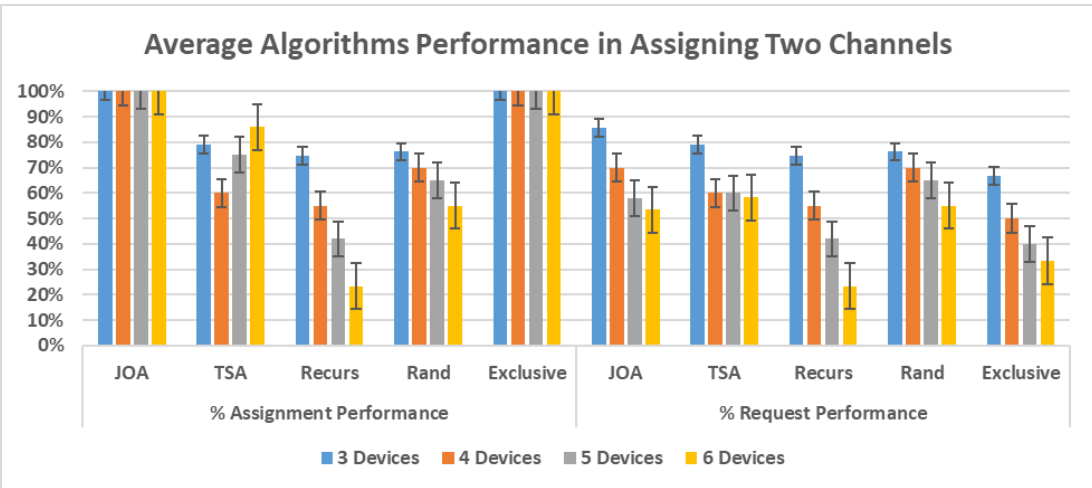


Figure 6.24: Average Assignment and Request performance of Methods in assigning two channels.

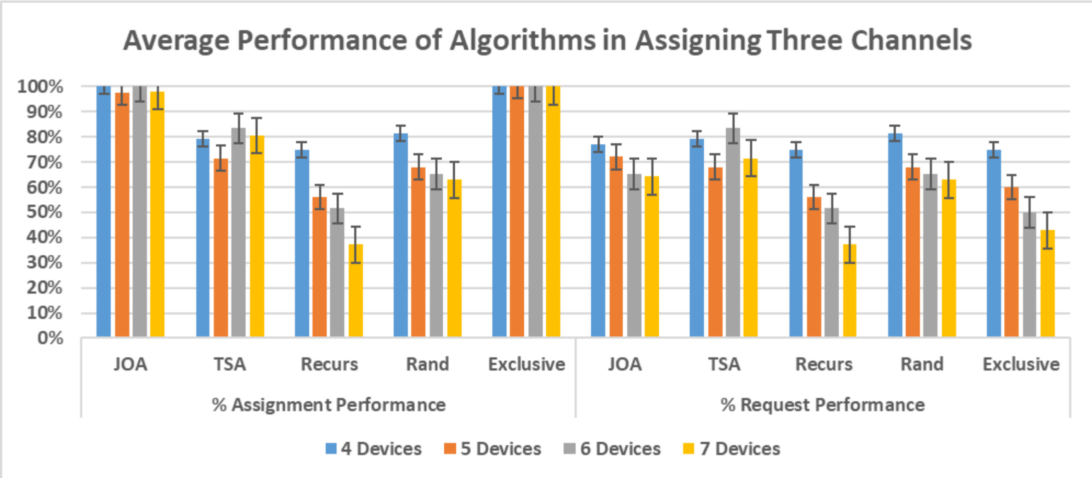


Figure 6.25: Average Assignment and Request performance of Methods in assigning three channels.

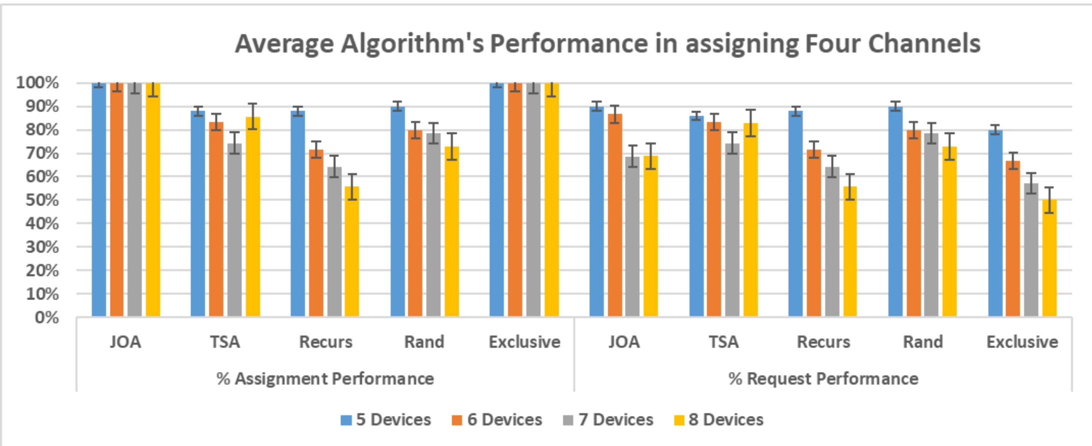


Figure 6.26: Average Assignment and Request performance of Methods in assigning four channels.

It also evaluates the novel Joint Optimization Deep Q-Learning Algorithm, which learned to assign scarce resources to dynamically located heterogeneous nodes. Its assignment performance was very high, as nodes were exclusively assigned available channels (overlay sharing) or shared resources with other nodes (underlay) while limiting interference. It learned to optimize and re-assign resources within the study area, irrespective of the nodes' location. It was consistent in its prediction and improved the QoS of SUs, increased the number of nodes, and limited SUs' resource contention. However, as the number of available channels and requesting devices increased, its reuse of resources in its assignment to many requesting nodes (spectrum reuse) dropped.

Chapter 7

Conclusion

7.1 Summary

Flexible coexistence management of future heterogeneous networks will require intelligent and dynamic resource-sharing techniques. DSA structures use databases to manage the coexistence of PUs and SUs, leaving SUs to self-manage their coexistence, thereby increasing contention among SUs. These contentions were controlled by SUs' device-specific Media Access Control (MAC) protocols. SUs with varied standards in a heterogeneous network struggle to manage this resource contention. The MAC protocols achieved distributed reuse of channels, but this needed to be improved in optimization, thus propelling the need for practical real-time coexistence management among SUs.

Intelligent use of real-time network data can be instrumental in managing resource contention. Advancements in artificial intelligence (AI) models can use this data for informed prediction and contention prevention. General challenges of adopting AI in DSA include acquiring/storing training data, long training times, and the risk of algorithms becoming obsolete (training update schedules). Despite these challenges, AI can influence the achievement of automated resource sharing in DSA systems. Reinforcement Learning is an AI algorithm used extensively in decentralized/distributed resource coordination to maximize throughput, user selection, and spectral efficiency. Limited studies have explored RL in the central coordination of resource assignment in DSA heterogeneous networks and none at lower bands. Exploring improved coordination at lower frequencies creates a smarter DSA system that leverages existing DSA database knowledge for better resource coordination among SUs.

SU-to-SU coordination in the reviewed DSA systems adopted a flexible distributed/ decentralized and central coexistence management structure that performed better in homogeneous networks and supported mainly overlay spectrum sharing. Future heterogeneous DSA networks are predicted to consist of several unique base stations and access points in need of scarce shared resources; a form of coordination to maximize limited resources becomes imminent. Improving the CBRS' overlay shared spectrum recursive approach; the proposed intelligent central resource assignment scheme enables both overlay and underlay resource sharing among SUs. It increases the number of supported SUs and reduces SUs' contention while maintaining their quality of service.

Increasing the capacity of used channels requires harvesting the maximum available channels. A design of an end-to-end DSA system provided the available spectrum in two locations and revealed the protection levels of the incumbent/PUs. A comparison of the two countries' policies in the design of DSA databases revealed that their policies impacted the quantity of available spectral resources. The central database provided guaranteed spectral access to PUs and protection from interference. This level of exclusive use of spectral was considered unnecessary for SUs, who use spectrum sporadically, with a tolerable interference threshold.

To address the unique SU-to-SU coexistence coordination, a novel two-staged intelligent Q-learning algorithm and a novel Joint optimization deep Q-learning algorithm were designed to assign resources to SUs optimally. The RL agent was assumed to be a central coordinating entity within the database/spectrum access system of the DSA architecture that used consistently updated database information for its training. The trained RL models were compared with the designed TVWS first-come first-serve resource assignment scheme (random assignment algorithm) and the CBRS recursive algorithm. These were evaluated in a designed heterogeneous network operating at lower bands with the total number of requesting base stations and access points perpetually greater than available channels.

These novel algorithms arrived at convergence for different resource-sharing scenarios examined. The deep Q-learning Joint Optimization algorithm performed best in consistently maintaining good QoS to its assigned nodes but poorly accommodating many SU requests. The two-staged Q-learning algorithm moderately assigns resources repeatedly and assigned most SU requests; it was, however, inconsistent. The poor requests performance of the DQN was attributed to the limited training dataset and its quick convergence, and the Q-learning algorithm's poor assignment performance was attributed to its limited observation space. The two designed algorithms' assignment and request performance were better than the existing random and recursive approaches examined. Therefore, infusing these novel intelligent central coordination into the designed DSA networks improves resource coordination and SU's quality of service and supports more SUs, as it allows both overlay and underlay spectrum sharing.

A fundamental benefit of resource management is the maximization or reuse of available channels by multiple service providers, increasing the capacity of networks. TVWS provides affordable connectivity to hard-to-reach regions, and CBRS's pop-up private networks (5G cellular networks) provide secure internet connectivity. Improving these systems' SU coordination can significantly increase their capacity to support more networks at high and low bands. Also, the JOA's interference management automation allows real-time interference monitoring and resource reassignment, which is useful to wireless communication network operators when deploying DSA systems such as private 5G networks (Pop-up networks).

Also, It provides regulators with a tool for maximally allocating resources to all and more services requesting licensed spectrum and promots efficient spectrum sharing, trading and spectral top-up opportunities. They can give more licensees based on special separation and transmit power limits to permit more nodes' coexistence and resource sharing. The spectrum allocation table in [65] spectrum allocation already consists of several services sharing scarce spectral resources above the 1GHz band. An intelligent spectrum manager can provide added value in sharing these bands and power limits with service providers based on their real-time demands and locations. Allowing more licenses to be issued simultaneously to several service providers. This will improve the prospect of global internet connectivity when adopted by many countries.

7.2 Key Results

The design of an end-to-end DSA network provided a detailed insight into interference discovery techniques and the gap between database information on available resources and their utilization. TVWS and CBRS systems' architecture transfer the resource management and scheduling role to equal priority SUs. This increases the level of contention among heterogeneous nodes, especially when the number of nodes is more than the number of available resources. The study also revealed that countries' regulations negatively impacted the quantity of available resources. Although there were regulations that permit the reuse of PU's spectrum by SUs (overlay spectrum sharing), there are no guidelines on interference level limits to promote underlay sharing among SUs.

Addressing the technical challenge of resource management of scarce resources, a heterogeneous DSA network (test bed) was designed. The simulation test bed's nodes' type, location, and available resources were dynamic. It was a neutral environment in which to evaluate the performance of the designed TVWS and CBRS resource assignment schemes. To solve the same resource assignment formulated problem, the design of two intelligent coordinating schemes demonstrates the impact of design formulations on algorithms' performance and creates an alternative solution.

The intelligent resource management algorithms leveraged the existing DSA architecture to provide an improved resource-sharing model for central coexistence management. A centrally coordinating deep Q-learning algorithm trained with different network scenarios learned to assign limited resources (spectrum and power) to request SUs. Its resource assignment maximized resource reuse, resulting in SUs coexisting at minimal interference, irrespective of their location within the study area. This reduced the level of contention while maintaining a reasonable interference level among SUs, improving the number of sharing SUs' and their overall QoS. The two designed learned resource management algorithms enabled more SUs to have good QoS than existing conventional non-optimizing algorithms. However, one of the algorithms was inconsistent in its performance, and the other's spectrum reuse performance depreciated as the number of available channels increased.

7.3 Further Work

Future DSA networks will comprise base stations, access points, and user equipment with different standards to make up heterogeneous networks. Therefore, the novel intelligent resource strategies must be improved to accommodate resource management across other bands. Deep Q-learning network algorithms have been framed to play multiple games; extending this to coexistence management, DQN algorithms can be built to assign resources at any band (Low and higher bands) and in any unique DSA network scenario. Thus, a single model is provided that is deployed in a DSA network to improve spectral utilization.

The measurable impact of increasing the state space of a DQN algorithm and its training episodes can be investigated. Using a few observed states and training episodes in this thesis' the DQN algorithm resulted in relatively good coordination in small-sized networks. An investigation into the level of improvement possible by increasing the number of observed states and training episodes in such small networks can be explored to inform future model designs.

The Deep Q-learning algorithm (JOA) provided a consistent assignment policy compared to the Q-learning algorithm (TSA). These DQL networks can be improved by exploring better state approximation techniques that enable convergence in large state space. This may improve the scalability of RL resource coordination in DSA networks, as large networks with large state space can achieve optimal resource assignment.

Similarly, the Q-learning algorithm's (TSA) consistency performance can be improved by evaluating other methods of Q-value computation, problem formulation, and state approximation. This may also significantly enhance its optimization performance, training time, and convergence of Q-learning algorithms. A better-performing q-learning algorithm with less computational intensity influences its adoption in DSA networks. Therefore, this low-cost algorithm can prove AI's impact on spectrum utilization by quantifying the increased number of served SUs in a DSA network.

Furthermore, evaluating the performance of intelligent coexistence management in a deployed network will prove the efficacy of embedding intelligence into coexistence management. This thesis showed an intelligent underlay and overlay use of shared spectrum that increased the total number of SUs supported in a TVWS network. More work needs to be done on deploying centrally intelligent learned algorithms and models. Implementing intelligent central coordination of resources will move the AI impact on improved spectrum utilization from theory to practice. Influencing how policymakers regulate spectrum licensing for wireless communication.

Improving spectral utilization through shared access has been extended to various bands by regulators. The UK and the USA take the lead on spectrum-sharing policies; there is a massive need to consider this in other countries. The result in Chapter Four highlights the high level of spectral availability at lower bands. Investigating the level of availability in different bands over wider regions in developing countries can inform and influence spectrum-sharing policies. Policies that forestall safe resource sharing across a wide range of bands and support more wireless services that bridge the digital divide and enhance quality of life.

7.4 Final Remark

Global connectivity is essential for countries to achieve economic, health, social, industrial, and educational benefits from digitization. With the increased demand for 5G private networks and the future trend for private 6G networks, DSA wireless networks provide affordable connectivity in hard-to-reach locations. The existing DSA framework's resource assignment strategy needs to improve network capacity in dynamic heterogeneous networks with a high level of contention.

The shared spectrum paradigm adopted in DSA networks assists regulators' shared spectrum licensing strategy, supporting them to accommodate a wide range of service providers and use cases. The increased Internet demand and use of IoT devices propels the need to increase the capacity of DSA networks and support homogeneous and heterogeneous networks. Dynamic heterogeneous networks have unique nodes in diverse locations and resources that change over time. The existing exclusive resource assignment and MAC-dependent resource coordination strategy do not optimize the spectrum, resulting in delayed spectrum access and high contention.

In this thesis, a novel central Reinforcement learning approach to optimize resources in dynamic networks is designed, implemented, and tested. The AI algorithm successfully assigned resources to a heterogeneous DSA network, enhancing the network's total capacity while maintaining nodes' good quality of service. This proves the impact of AI coordination in improving the resource management of heterogeneous DSA networks. Therefore, as the demand for wireless communication continues to grow, AI will undoubtedly play an essential role in optimal, efficient, and effective radio frequency usage in DSA networks.

Appendix A

Glasgow Digital Terrestrial TV Transmitter parameters

The tables in this appendix present five Digital TV stations around central Glasgow as of June 2021. These served as the Primary Users in the Glasgow database design in section section 4.6.

Table A.1: BlackHill Transmitters located at 55.86111 -3.87417 channel status.

Mux	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari- zation	Status	WSD Power (dBm)
PSB1(BBCA)	46	674	576	100	H	"Occupied"	5.24
PSB2 (D3+4)	43	650	576	100	H	"Occupied"	6.63
PSB3 (BBCB)	40	626	576	100	H	"Occupied"	7.93
COM4 (SDN)	41+	634.2	576	100	H	"Occupied"	7.50
COM5(ArqA)	44	658	576	100	H	"Occupied"	6.18
COM6 (ArqB)	47	682	576	100	H	"Occupied"	4.76
LG	51	714	576	5	H	"Occupied"	-10.29
COM7	55	746	576	42.9	H	"Occupied"	-3.16
COM8	56	754	576	39.2	H	"Occupied"	-4.12

Table A.2: Darvel Transmitters located at 55.57917 -4.29056 channel status.

Mux	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Status	WSD Power (dBm)
PSB1 (BBCA)	22	481.8	446	20	H	"Occupied"	-1.02
PSB2 (D3+4)	25	506	446	20	H	"Occupied"	-1.40
PSB3 (BBCB)	28	530	446	20	H	"Occupied"	-1.84
COM4 (SDN)	32	562	446	10	H	"Occupied"	-5.54
COM5 (ArqA)	34	578	446	10	H	"Occupied"	-5.93
COM6 (ArqB)	35	586	446	10	H	"Occupied"	-6.14
COM7	55	746	446	7.5	H	"Occupied"	-13.0
COM8	56	754	446	8.19	H	"Occupied"	-12.9

Table A.3: Roseneath Transmitters located at 55.99111 -4.79444 channel status.

Mux	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Status	WSD Power (dBm)
PSB1 (BBCA)	39	618	216	2	V	"Occupied"	-25.80
PSB2 (D3+4)	42	642	216	2	V	"Occupied"	-26.05
PSB3 (BBCB)	45	666	216	2	V	"Occupied"	-26.31
COM4 (SDN)	33	570	216	2	V	"Occupied"	-25.38
COM5 (ArqA)	36	594	216	2	V	"Occupied"	-25.58
COM6 (ArqB)	48	689.8	216	2	V	"Occupied"	-26.59

Table A.4: Craigkelly Transmitters located at 56.07139 -3.23361 channel status.

Mux	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Status	WSD Power (dBm)
PSB1 (BBCA)	27	522	311	20	H	"Occupied"	-23.55
PSB2 (D3+4)	24	498	311	20	H	"Occupied"	-23.41
PSB3 (BBCB)	21+	474.2	311	20	H	"Occupied"	-23.29
COM4 (SDN)	29	538	311	10	H	"Occupied"	-26.66
COM5 (ArqA)	31	554	311	10	H	"Occupied"	-26.77
COM6 (ArqB)	38+	610.2	311	10	H	"Occupied"	-27.18
LEH	30	546	311	5	H	"Unoccupied"	36.00
COM7	55	746	311	10.8	H	"Unoccupied"	36.00
COM8	56	754	311	10.8	H	"Unoccupied"	36.00

Table A.5: Selkirk Transmitters located at 55.55583 -2.79417 channel status.

Mux	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Status	WSD Power (dBm)
PSB1 (BBCA)	32	562	522	10	H	"Unoccupied"	36.00
PSB2 (D3+4)	34-	577.8	522	10	H	"Unoccupied"	36.00
PSB3 (BBCB)	35	586	522	10	H	"Unoccupied"	36.00
COM4 (SDN)	33	570	522	5	H	"Unoccupied"	36.00
COM5 (ArqA)	36	594	522	5	H	"Unoccupied"	36.00
COM6 (ArqB)	48-	689.8	522	5	H	"Unoccupied"	36.00

Appendix B

Nigeria (Owerri) Analogue and Digital Terrestrial TV transmitter Parameters.

The Analogue and Digital Terrestrial TV stations within a 200km radius of central Federal University of Technology Owerri, Imo State, Nigeria, as at June, 2022. These transmitters were located across 8 states in the eastern and southern part of Nigeria and the Analogue Terrestrial TV (ATT) transmitters were mainly owned by the Federal and state governments while DTT transmitters were dominantly owned by a private broadcasting house (Startimes).

These transmitter parameters were used in the design of a local database in section section 4.7 of this thesis, to highlight the impact of the Nigerian policy on spectrum availability.

Appendix B. Nigeria (Owerri) Analogue and Digital Terrestrial TV transmitter Parameters.

Table B.1: Analogue Terrestrial TV (ATT) Transmitter Parameters

State/Name	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Lat.	Long.
Imo/IBC	59	775.25	150	10	v	5.476	7.023
Imo/NTA Owerri		227	30	3.5	v	5.477	7.021
Enugu/ETV	50	703.25	90	20	v	6.430	7.526
Enugu/NTA Enugu		195.25	150	10	v	6.434	7.516
Anambra/NTA onitsha	5	175.25	30	3	v	6.173	6.809
Anambra/ABS	27	519.25	300	20	v	6.156	6.793
Anambra/ABS	24	495.25	300	20	v	6.231	7.080
Delta/DBS	31	551.25	85	5	v	5.543	5.728
Ebonyi/NTA Abakaliki	43	647.25	30	3.5	v	6.322	8.088
Ebonyi/EBBS	24	495.25	85	5	v	6.296	8.090
Cross River/CRBC	27	519.25	30	2	v	4.965	8.329
Cross River/CRBC Odukpani	27	519.25	300	8	v	4.965	8.329
Cross River/NTA Calabar		203	85	5	v	4.955	8.387
Abia/NTA Aba		185.6	150	10	v	5.114	7.391
Abia/BCA	47	679.45	30	2	v	5.523	7.503
River/AIT	29	535.2	300	10	v	4.870	6.948
River/RSTV	22	479.25	300	30	v	4.830	7.074

Table B.2: Digital Terrestrial TV (DTT) Transmitter Parameters

State/Name	Ch	Centre Freq (MHz)	Antenn Height (m)	Tx Power (kW)	Polari-zation	Lat.	Long.
Imo/Startimes	43	642	100	2	v	5.300	7.300
Imo/Startimes	45	658	100	2	v	5.300	7.300
Imo/Startimes	47	674	100	2	v	5.300	7.300
Enugu/Startimes	34	570	110	1.3	v	6.4362	7.5155
Anambra/startimes	33	562	90	1.3	v	5.523	7.504
Anambra	46	666	90	1.3	v	5.523	7.504
Anambra	27	518	90	1.3	v	5.523	7.504
Anambra	73	882	90	1.3	v	5.523	7.504
Delta/startimes	33	562	80	1.3	v	6.219	6.682
Delta	46	666	80	1.3	v	6.219	6.682
Delta	27	518	80	1.3	v	6.219	6.682
Delta	73	882	80	1.3	v	6.219	6.682
Ebonyi/startimes	59	770	80	1.3	v	6.216	8.331
Ebonyi	57	754	80	1.3	v	6.216	8.331
Ebonyi	56	746	80	1.3	v	6.216	8.331
Cross River/startimes	43	642	90	1.3	v	5.035	8.339
Cross River	41	626	90	1.3	v	5.035	8.339
Cross River	39	610	90	1.3	v	5.035	8.339
Abia/startimes	46	666	90	1.3	v	5.523	7.505
Abia	44	650	90	1.3	v	5.523	7.505
Abia	56	746	90	1.3	v	5.523	7.505
River/startimes	28	522	100	2	v	4.863	6.961
River	36	586	100	2	v	4.863	6.961
River	38	602	100	2	v	4.863	6.961
River	46	666	100	2	v	4.863	6.961

Appendix C

Propagation Model

The Longley Rice pathloss models predicts median transmission loss in irregular terrain. It uses established propagation theory in arriving at its equations. Equation adopted in this thesis subsection 4.5.1, were used to determine the signal degradation. These equations parameters and symbols are explained in the table C.1, and a more detailed list can be found in the annex 3 of [180].

Pathloss was used extensively through out this thesis, for database design and for the prediction of SINR of transmitter receivers in subsection 5.2.3. These were useful in establishing chapter fours conclusion and fundamental to interference discovery between nodes. It was particularly used for generating training data for the reinforcement learning algorithms, as it was used for estimating received signal strength.

Table C.1: Longley Rice Parameters

Parameter symbol	Meaning
A_1, A_2	attenuation below free space computed at the distances d1 and d2 respectively
A_3, A_4	predicted diffraction attenuation computed at distances d3 and d4 respectively
A_d	extended diffraction attenuation
$A_{diff}(di) = Ai$	diffraction function
A_{ed}	estimated diffraction attenuation below free space in dB extrapolated to zero distance
A_{el}	attenuation be low free space in dB
A_{fo}	an estimate of attenuation due to surface clutter
A_k	double knife-edge attenuation
alpha(0,1,2)	the first component of the ' "three radii" method applied to Volger's formulation'
A_r	rounded earth attenuation
A_{ref}	Predicted reference attenuation below free space.
A_t	two-ray attenuation
B(K)	Parameters used to compute modified distance x0,1,2
d	Distance between the two terminals
d_1, d_2	one of a series of equal distances at which terrain heights h. are read.
d_3, d_4	distances at which diffraction attenuation is calculated
$\delta_h(s)$	Terrain irregularity parameter
δ_h	interdecile range of terrain elevations
$d_L(km)$	The sum of $d_{L1} and d_{L2}$
$d_{L1} or d_{L2}$	Distances from each transmitter/receiver terminal to its corresponding radio horizon.
$d_{Ls}(km)$	the sum of a smooth earth's horizon distance.

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