Efficient Resource Allocation in Cognitive Radio Network

By

NS Osama Zaheer

(Registration No: 00000359451)

Supervisor

Assoc Prof Muhammad Imran, PhD

A thesis submitted to the faculty of Electrical Engineering Department, Military College of Signals, National University of Sciences and Technology, Islamabad, Pakistan, in partial fulfillment of the requirements for the degree of MS in Electrical (Telecommunication) Engineering

May 2023

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS Thesis written by **NS Osama Zaheer** Registration No. **00000359451**, of **Military College of Signals** has been vetted by undersigned, found complete in all respect as per NUST Statutes/Regulations, is free of plagiarism, errors and mistakes and is accepted as partial, fulfillment for award of MS degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have been also incorporated in the said thesis.

Signature: ____________________________

Name of Supervisor: Assoc. Prof Muhammad Imran, PhD

Date: ________________________________

Signature (HOD):______________________

Date: _____________________________

Signature (Dean/Principal):_______________

Date: _____________________________

Declaration

I hereby declare that work carried out in this thesis has not been submitted in support of any degree or professional qualification either at this institution or elsewhere.

Dedication

I dedicate my work to my parents, siblings and teachers for their guidance and endless support.

Acknowledgement

All praises and glory to Allah Almighty for blessing me with the motivation to execute this work.

My sincerely thankful to my supervisor Dr. Muhammad Imran for his constant encouragement and dedicated guidance, which enabled me to undertake this research. This dissertation would not have been possible without his continuous support, patience, and insightful analysis. I could not imagine having an enlightened mentor for my MS thesis. Besides my advisor, I also acknowledge my Co-Supervisor Dr. Mudassar Ali whose contributions are really significant. I am grateful for his constant guidance and suggestions throughout the thesis writing process, his guidance and brainstorming motivation remained with me like a beacon.

Special thanks to Dr. Humayun, and Dr. Safia Akram. I am thankful for their encouragement, insightful comments, hard questions, and contributions as members of my committee.

My appreciation extends to my seniors Asma Abid and Alishba Azam whose interest and encouragement enabled me to accomplish this herculean task.

Above ground, I am indebted to my family. Through the many years, my parents have always supported me and encouraged me to explore new directions in life. And finally, my deepest gratitude goes to my siblings for their support and patience during my study.

Abstract

Cognitive radio network based on Device to Device and the heterogeneous network has attracted wide attention as they can resolve spectrum shortage problems and efficiently utilizes spectrum resources. However, resource allocation considering stochastic behavior has not been considered in any work. In this thesis, the proposed work aimed for maximizing the throughput of the overall network considering multiple users under the umbrella of the Cognitive radio network assisted by amplify and forward relay. The constraints are treated as chance constraints with a probability of satisfaction in them, which leads to a nonconvex Mixed integer nonlinear problem which is an NP-Hard problem. To solve this problem an exhaustive search solution for optimal results is required. However, the computational burden always increases with the user equipment. Therefore, to obtain an optimal solution with having low computational burden, Outer Approximation Algorithm is utilized in this research. To evaluate the desired results, extensive simulations have been carried out. The effectiveness of the proposed algorithm is verified by results in terms of throughput maximization under the impact of chance constraint formulation in the cognitive radio networks.

Contents

List of Figures

List of Tables

Notations

M	No of Primary Users
K	No of Secondary Users
L	No of Relays
U	Users Equipment's
r_k^{su}	Capacity for SUs
$r_{m,k}$	Capacity for both SUs and PUs
ρ_m^{pu}	Received Power for PUs
ρ_k^{su}	Received Power for SUs
Z_l	Noise in Channel
p_r^{max}	Maximum Relay Transmitted Power
h_l^{pu}	Channel gains from relay to PUs
h_l^{su}	Channel gains from relay to SUs
$\Gamma_{k,l}^{su}$	SINR of K SUs
I_{max}^{pu}	Maximum PUs interference
I_{max}^{l}	Maximum Relay interference
$L_{k,l}$	Distance between SBS and Relay

$g_{k,l}$	Gain between l and SUs
P^s_{max}	Maximum source power both PBS and SBS
x^k_l	For relay assignment
$g^l_{m,k}$	Channel gain between PUs and SUs
α	Threshold level for satisfaction
ξ	Perturbation factor
Φ^{-1}	Represents CDF distribution
σ	Variance factor
$h(x)$	Probabilistic form
$g(x)$	Deterministic form
C	Constraints

Acronyms

1G: First Generation

2G: Second Generation

3G: Third Generation

4G: Forth Generation

5G: Fifth Generation

B5G: Beyond Fifth Generation

6G: Sixth Generation

CDMA: Code Division Multiple Access

EE: Energy Efficiency

ESA: Exhaustive Search Algorithm

IoT: Internet of Things

KPI: Key Performance Indicator

LTE: Long Term Evolution

MADS: Mesh Adaptive Direct Search

BS: Base Station

MIMO: Multiple Input Multiple Output

MINLP: Mixed Integer Non Linear Programming

NOMADS: Nonlinear Optimization using Mesh Adaptive Direct Search

OAA: Outer Approximation Algorithm

OFDMA: Orthogonal Frequency Domain Multiple Access

QoS: Quality of Service

RF: Radio Frequency

SE: Spectral Efficiency

SWIPT: Simultaneous Wireless Information and Power Transfer

SINR: Signal to interference plus noise ratio

CRN: Cognitive Radio Network

ML: Machine Learning

Chapter 1

Introduction

This chapter presents a brief introduction to the work accomplished in this thesis. The section 1.1 gives a brief overview of the evolution of communication networks in the past, present, and future. Section 1.2 explains the basic motivation of this thesis. The overview of CRN is presented in section 1.3. The research gaps that lag in previous work are represented in section 1.4. The primary contribution of this thesis is detailed in section 1.5. Finally, section 1.6 discusses the organization of the thesis.

1.1 Evolution of Communication Networks

Over the last few decades, wireless communication has experienced tremendous innovation due to rapid growth in mobile devices, and multimedia applications (MMS) [1]. This becomes a cause of establishing the latest technologies to overcome such demand and provide a reliable and convenient way of communication [2, 3, 4, 5, 6].

Technology has gone through a major change in terms of "Generation", simply evolving from 1G to 5G [7, 8, 9]. That rapid development directly links to the consumption of existing radio resources and increasing data-hungry applications [10, 11, 12]. The first generation (1G) was an analog form of communication that works fine in its era and provides voice service [13]. The second generation (2G) was a digital form and promised to provide further capabilities as compared to previous analog communication. Such as voice and sms. Due to the rapid involvement of multimedia applications in our lives third generation (3G), a next step towards wireless technology was introduced to provide high speed, high capacity, and bandwidth with the latest Code Division Multiplexing technology (CDMA). The fourth generation (4G) can handle speeds up to 100 Mbps through Orthogonal Frequency Division Multiplexing (OFDM) which provides each user with an orthogonal link together to provide efficient allocation of bandwidth and a high data rate [14]. Thus, MMS and entertainment applications can easily be served by this technique [15]. It has coupled existing and latest technology together in order to provide roaming service for customers so that they can easily switch from existing to new technology without interruption. 4G cannot handle such stringent latency and reliability requirements that are expected to increase among different applications such as healthcare, security, logistics, automotive industry. To support network flexibility and reliability, fifth generation (5G) is a promising technology that has arrived which not only solves the current increasing data rate requirement but can handle up to 50 billion devices in near future [16] [17]. Wireless communication from 1G to 4G can provide service to only "people". 5G technology handles communication between "people and things". As a result, the communication between people and objects gradually increased when such a system is implemented. 5G system is based on Non-orthogonal multiple access (NOMA) which multiplex data both on time and frequency which provide an edge on spectrum allocation. It will drive the overall demand of high traffic for data-hungry applications such as augmented reality and virtual reality. It will increase the data rate about 1000 times to fulfill the current demand up to (10 Gbps peak data rates) [18]. It is based on Low-Density Parity Coding (LDPC) and a higher modulation scheme of 256 QAM to full fill stringent latency, and reliability requirements that have been raised at this current time. In ultra-reliable low latency communication (uRLLC) applications, however, latency becomes a significant performance criterion that is impossible to achieve with traditional communication protocols. As a result, 5G combines computing capacity at cell edges, i.e., Mobile Edge Computing (MEC), to avoid cloud computing and enable local processing with minimal latency. Even 5G, however, cannot ensure that it will fulfill all the needs of new applications in the future. With the rise of the Internet of Things, there is a need for communication between "things”. Fig. 1.1 depicts the evolution of cellular communication technologies.

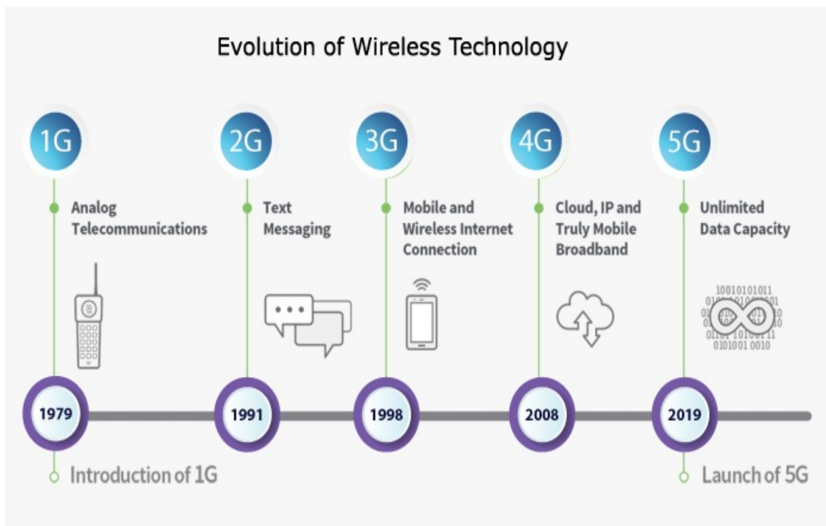

Figure 1.1: Technology Evolution from 1G to 5G

1.2 Motivation

The demand for wireless devices increases rapidly as compared to the last decade. Mobile traffic has experienced 70 percent growth since 2014 [19]. According to the latest survey, there are about 13.4 billion devices that are connected in 2023 [20]. Emerging technology gadgets such as the Internet of Things (IoT) and small handheld devices have increased the data rate up to 5016 Exabytes/month by 2040 [21]. 4G cannot handle such stringent latency and reliability requirements that are expected to increase among different applications such as healthcare, security, logistics, automotive industry.

To support network flexibility and reliability, 5G is a promising technology that has arrived. 5G magnifies the system bandwidth, and data rate, reduces round-trip latency, and shows massive connectivity for wireless devices. The 5G era has introduced HetNet, where various small devices of different network types combine and access technology. Various femto base stations cover multiple small base stations (BS). 5G also comprises millimeter wave (mm-Wave) and massive multiple input and multiple outputs (M-MIMO) technologies that increased data rate up to 20Gb/s of 1Ghz bandwidth. Such a system can reduce interference by using beam-forming techniques and provide low latency. But it cannot handle the large capacity requirement of the network. Massive MIMO is employed with advanced antenna arrays whose width and tilt can be controlled vertically and horizontally [22]. It employs a lot of active components that increase interference and complexity. So, researchers are now moving forward to bring new advancements in 5G technology bringing it up to beyond 5G with increased throughput capabilities. Spectrum sharing is the major issue that is faced during the evolution of wireless technologies. Spectrum sharing means efficiently utilizing the existing system so that any user can easily get accommodated in existing bandwidth. Cognitive radio network (CRN) for 5G is a promising technique to efficiently utilize the availability of spectrum and underline radio resources [23].

The sixth generation (6G) is the expansion of the existing 5G technology, the main aim of this generation is to enhance the existing 5G infrastructure to raise throughput, spectrum efficiency, low latency in the network, and wider coverage [24]. Intelligent network devices such as IoT, and small sensor-based devices are in demand for today's communication and need extremely fast computation and low latency requirements so these things can be achieved by 6G easily. An endogenous security arrangement or a coordinated practical security configuration will be utilized in the 6G organization. Fig. 1.2 depicts the overall data rate and device handling capability of different generations.

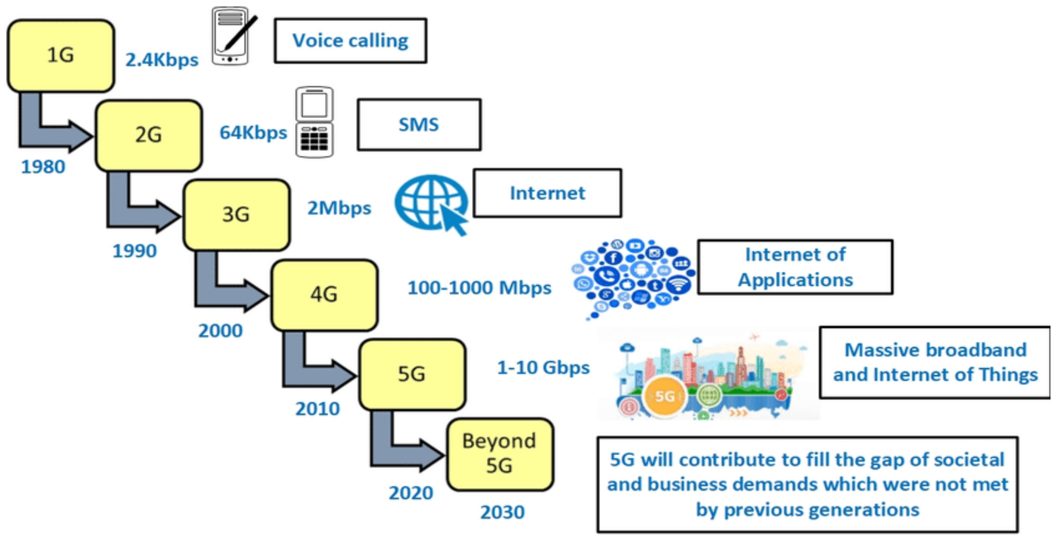

Figure 1.2: Data Rate Representations for Different Generations

6G can operate at a high frequency such as a millimeter wave, or tetra hertz. It promised flexible and reliable communication to achieve an approximate data rate of Tb/s as compared to 5G. It is now adopted to have in building artificial algorithm implementation to modify the existing classical networks to data-centric [25]. 6G has self-discernment capacities, constant powerful investigation abilities, risk transformation abilities, and certainty evaluation abilities. It will assist this with accomplishing internet security by presenting trust and security systems. 6G includes computing, detection, navigation, and radar detection algorithm in wireless networks [26]. 6G technology is integrated with cloud computing, artificial intelligence, and blockchain capabilities [27]. Implementing a Cognitive network scenario with 5G/6G is another approach toward generating a spectral efficient network model which not only deals with bandwidth utilization problems but also counters the interference that occurs due to an increasing no of users. The cognitive scenario always considers in the latest technological model because in the telecommunication spectrum utilization is the primary goal of any operator because its revenue depends on its utilization. Any telecommunication industry tries its best to adopt efficient ways that utilize existing spectrum availability to accommodate multiple users. Fig. 1.3 depicts the evolution of communication towards 6G.

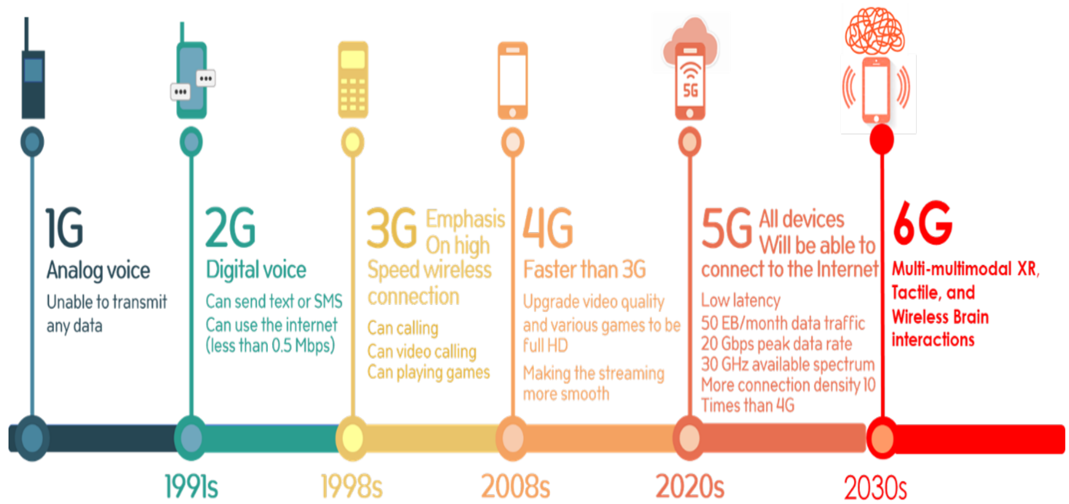

Figure 1.3: Communication Evolving Towards 6G

1.3 Cognitive Radio Network

The rapid development in the field of wireless networks causes a burden on allocating radio resources in an efficient manner. Fixed spectrum assignment strategy causes bottlenecks for efficient utilization of spectrum. The efficient usage of the spectrum has diverted the attention of service providers to reduce such bottlenecks in order to reduce revenue losses. The concept of Cognitive radio network (CRN) has received great attention in recent years to address spectrum scarcity issues for wireless networks. [28].

A CRN is a promising technology that enables users to efficiently utilize the underline spectrum, known as dynamic spectrum access (DSA) [29]. A cognitive network has the ability to sense the environment and gathers information such as power, frequency, and interference level. With this sensing ability, secondary users (SU) can identify the vacant spectrum and utilize it. With this ability, SUs can adjust their operational parameters according to sensed information to establish the quality of service (QoS). Primary users (PU) have a priority to carry on their transmission and co-exist with SUs. When PUs are in the transmission phase then desired parameters such as interference temperature, and QoS needs to be undermined by SUs [30]. SU needs to detect the presence of PU first and then start its transmission in accordance with it.

The following approaches are used to differentiate the working model of CRN. In the underlay and overlay model, transmission between PU and SU continues until performance degradation does not occur between them. The underlay model consists of some predefined noise threshold that always tunes its parameter to restrict SU transmission flow so that no interference can occur between them. Interweave is based on an opportunistic spectrum sensing mechanism to dynamically utilized spectrum in absence of PU transmission. This method continuously observes spectrum occupancy and allows SU transmission [31].

Underutilized frequencies are the target for cognitive network scenarios, where frequencies from that pool are used to satisfy SU. CR sense the environment for the availability of gaps in unused spectrum pool from which they can be assigned to SU. Following are the ways mentioned below to provide spectrum sensing capabilities for detecting PU in the environment

1. Cooperative spectrum sharing technique: In this method cognitive radio work together to detect PU presence. In a centralized manner, each radio gathers information regarding spectrum occupancy and shares this information with the Central controller. This controller processes the information and uses it to map the spectrum for each cognitive radio. This is helpful to mitigate multi-path fading problems and solve the issue of dreaded hidden points. These points occur when cognitive radio

has a good line of sight but fails to detect another PU. Cooperation among different radio networks can solve this problem in a good manner.

2. Matched filter detection technique: It is sometimes called coherent detection, which is a spectrum observation detection method that requires prior knowledge about PU such as its modulation type, pulse shape, and packet format. This information is correlated with the unknown PU signal since it maximizes SINR. A desired result can be achieved in less time and with low complexity.

3. Cyclostationary-based detection: In cyclostationary signals have mean or autocorrelation a periodic function over time. In the modulation phase, the signal is multiplex with the sine wave and it is repeated with a spreading sequence of codes thus such a technique renders its periodicity and any noise that might occur during environmental impact will have nonperiodic nature. This cyclostationary technique can differentiate the original signal from noise. Using the spectrum correlation method one can detect cyclostationary signals from noise easily such a method can play a vital role in detecting PU signals. It has several advantages such as it can detect noise from low-power signals with less SNR.

4. Interference-based spectrum sharing technique: In this method, the receiver actually measures the level of received signal interference strength. When an RF signal is received at the receiver end, the receiver determines whether its interference temperature is up to the prescribed level or not. If a signal interference strength is within the threshold then cognitive users can utilize sharing bands for communication.

Cooperative relay technology has emerged in recent years to modernize the existing RF network. Cooperative relay aided with the cognitive network can provide better performance gain by utilizing white space in the spectrum [32]. It generally enhanced the performance of the resource constraint network. The idea of relaying is generally attractive to provide a better quality of service. Some are decoded and forward relays that decode the respective signal and forward it to the desired destination when the source is not transmitting. If amplify and forward relay is used for the cognitive network then it simply amplifies the received signal amplitude and forwards it to the desired destination [33].

A wireless sensor node (WSN) is another promising solution that can be integrated with cognitive network scenarios to gather the existing environmental data and transmit it to a base station or transmitter which can easily understand the current situation through these data and model its parameter to achieve efficient reliable communication. CR-WSN accompanies CR network infrastructural which are battery powered but utilizes the available spectrum [34].

Some of the potential applications for cognitive radio networks:

1. CR can be employed in any WSN which covers the area for facility management, surveillance management, preventive maintenance, roadside security, and monitoring of the indoor and outdoor environments.

2. CR scenario can be implemented in a military perspective such as a battlefield scenario where communication between troops within the required bandwidth is our main objective. Some military require maximum bandwidth, channel access, and delay requirement so CR-WSN can be used.

3. Wearable body sensors are widely used in healthcare systems like telemedicine. On patients, several wireless sensor nodes are positioned to collect crucial data for remote monitoring by healthcare professionals. By reducing these issues with bandwidth, jamming, and worldwide operability, "CR wearable body wireless sensors" can increase reliability.

4. CR can be joined with a Mobile edge computing (MEC) platform to successfully offload the resources to nearby systems in order to provide efficiency in the overall network. Device-to-device (D2D) networks can be used in conjunction with CR. As multiple devices can communicate with the help of nearby devices Cognitive scenarios can provide spectrum efficiency and interference efficient network.

5. Due to their hefty bandwidth demands, multimedia applications including on-demand or live video streaming, audio, and still images over resource-constrained WSNs are incredibly difficult. Some WSN applications, including those used in hospitals, vehicles, tracking, surveillance, etc., have significant temporal and spatial fluctuations in the data density, which are connected with node density. These applications are bursty, bandwidth-hungry, and have unbearable delays. CR-WSN is ideally suited for these kinds of bandwidth-hungry applications because SUs can access multiple channels whenever accessible and required.

1.4 Research Gaps

Following are the main open areas that previous work didn't mention such as chance constraint-based formulation.

- Usually few works undertake this aspect but skip to consider uncertainty or some sort of perturbation factor present in constraint which always vary its optimal solution from the desired point.

- Power sources are considered in previous work but how to control its parameter to reduce the amount of interference among cognitive users is not discussed more in previous work.

- Relay-assisted network interference is not discussed more in previous work. As this parameter is important because it causes interference in the network when relay power is increased to a high level.
- The traditional wireless network utilizes a single channel for transmission, this cause burden on existing infrastructure and loss of packet during transmission. CR network utilizes multiple channels to transmit the data in order to avoid a collision.
- During a natural disaster the existing wireless network get damaged by earthquake, tsunami, and storms so the CR network can utilize its spectrum to provide access to voice and another mode of communication.
- As in the CR scenario, the PU can benefit from SU when SU demands its utilization from the PU band PU can adjust some agreements for leasing its resource to SU to enhance its revenue. In this way, the PU can benefit from such a scheme.

1.5 Contributions

Based on the summary of the literature review and a close look at Table 2.1 it is evident that a huge work has been done in the field of RA considering HetNet, D2D, V2X, or Cognitive scenarios. But there is no proper work being done on Chance constraint formulation based upon stochastic behavior assisted by any networks". The main contribution of the proposed work is summarized as follows:

- A mathematical formulation is proposed for efficient resource allocation (RA) assisted by the cognitive network under probabilistic interference models subject to power, amplify, and forward relay (AF) interference, and combined source interference constraint. The uncertain parameter is generalized with known distribution which caused perturbation under constraint transformation.

- It is shown that the proposed intractable problem involves probabilistic constraint and MINLP. This probabilistic constraint is converted into a deterministic one by employing an outer approximation algorithm (OAA), which has not been investigated by any previous work, OAA is used to produce an optimal solution with less complexity and a fast convergence rate for the proposed MINLP.
- Performance of proposed work is analyzed by extensive simulations. The proposed solution for the chance constraint works efficiently to maximize the throughput of CRN assisted by relay.
- Proposed solution can be considered as a benchmark technique that gives maximum throughput while dealing with the cognitive scenario. Achieved results also show that the proposed solution efficiently counters the perturbation factor and satisfies the requirement of our network under desired probability level.
- Comparison of OAA results with Mesh Adaptive Direct Search (MADs) reveals that the proposed algorithm always perform better in complexity scenario.
- To the best of the author's knowledge there exists no work that caters to complexity and perturbation factor in RA. This work would cover all those existing gaps and provide an efficient way for RA to consider probabilistic constraints.

1.6 Thesis Outline

The layout of the rest of the thesis is as follows:

- Chapter 2 presents a concise background on the main subjects relevant to this work such as previous work done on Throughput maximization based on AF relay-assisted

CRN are thoroughly discussed and its existing literature's shortcomings and existing literature's problems.

- Chapter 3 presents the system model, problem formulation, and proposed algorithm along with the convergence and complexity analysis of the algorithm.

- Chapter 4 presents the numerical simulation and discussion to illustrate the applicability of the proposed solutions.

- Chapter 5 presents the conclusions and direction for future work.

Chapter 2

Literature Review

This chapter illustrates the essential background information on which the presented work is formed: in particular, sections 2.1 recalls the needs of the KPI to be optimized in this thesis. Section 2.2 discusses the literature related to capacity maximization and section 2.3 recalls the literature related to transmitting power minimization. Section 2.4 contains the literature related to EE optimization of CRN. Section 2.5 contains some of the constraints common in all the literature. The summary of the literature is concluded in table 2.1. Section 2.6 discusses a summary of problem formulation. Finally, at the end of this chapter in section 2.7, the requirement of the proposed work is justified.

2.1 Background

5G/6G era will deal with massive amounts of traffic having different network topologies as outlined in the preceding chapter. As the result, the overall demand for throughput will gradually rise with time. Throughput is a significant requirement to have a satisfactory level of communication. Throughput optimization aims to efficiently utilize the available resources to optimize overall network performance and QoS parameters. A few articles have surfaced to highlight the importance of cognitive network that considers throughput, energy efficiency (EE), and spectrum efficiency (SE) and minimizes system power to limit interference between users. RA is the main topic of the proposed research to efficiently utilizes the given resources and provide QoS network performances. Constraints that impact the proposed objective function have to deal with uncertainty and probability threshold levels to satisfy the overall optimization efficiency. The following are the main challenges

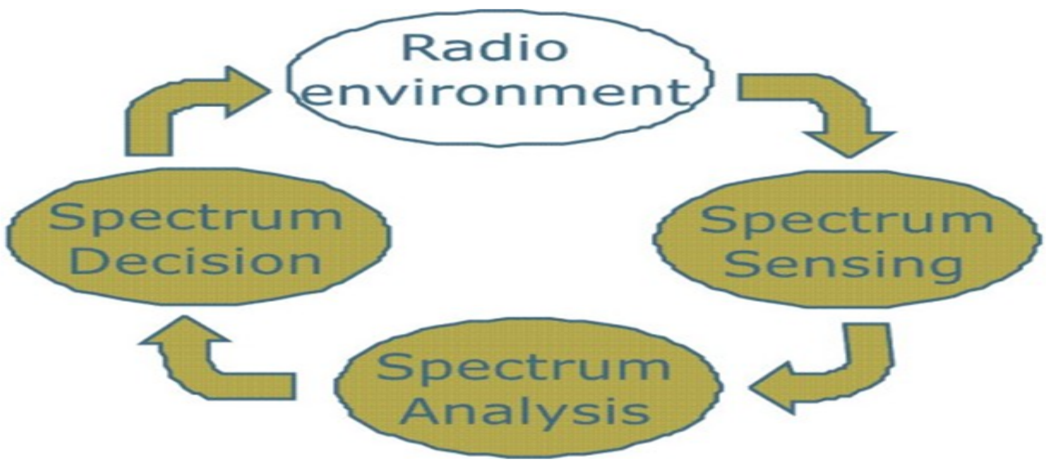

Figure 2.1: Cognitive Radio Scenario

that CRN experiences:

- Acquiring CSI: Knowledge about CSI is very much important for any communicating device. In the existing works, perfect channel conditions are assumed between transmitter and receiver which are too idealistic to have in any wireless setup. So proposed work goal is to consider such channel uncertainties present in the environment.

- Interference temperature constraint: To have QoS communication between PU and SU then there should be a threshold adjustment for interference level in a wireless network. The objective should be set to overcome total interference between communicating devices [35].

- Mobility of the CR users: Normally CR may change their location with time so it is obvious that their channel also be remain changed along with time. The main challenge that always underlies is to consider uncertain channel parameters with respect to different location points. The goal is to consider such mobility and maintained SINR within the target.

A CRN assisted by an AF relay source is considered in this thesis, and we provide a solution for the throughput maximization of cellular wireless systems.

2.2 Throughput Maximization

In [36], the Cognitive network model based on a power control mechanism was examined. The objective is to maximize network utility under the presence of probabilistic interference constraints. The channel between SU and PU was modeled by log-normal shadowing and small-scale fading, which was approximated by the Fento-Wilkinson method. Nonconvexity was treated with Kush kuhn tucker (KKT) algorithm to obtain the optimal solution. Numerical results showed that overall network utility maximized under the prescribed SINR threshold. It lags behind discussions on convergence and complexity analysis.

In [37], the Cognitive network model based on interference was examined. The objective of achieving throughput under the controlled interference level and power of the network source. This work considered channel gains of interference for SUs to be uncertain. Chance constraint-based formulation was considered, and nonconvexity was tackled by utilizing robust optimization (RO). Numerical results showed maximized throughput under the presence of a controlled interference level. This works lags in considering uncertainty in constraint formulation.

In [38], the Robust power allocation algorithms were examined in this paper. The objective was to maximize sum capacity under the presence of power and probabilistic interference considering a massive cognitive network. The given problem was solved through Newton's method of searching reasonable power levels and using the second derivative for better results. Numerical results showed capacity maximization considering uncertain PU and SU locations. This work lags in considering different channel models.

In [39], the NOMA-based multi-subcarrier and multi-relay assisted communication model was examined in this paper. An advanced multiplexing technique was used compared to OFDMA, whose objective was to maximize the sum rate in the presence of power control, and subcarrier pairing for multi NOMA network. This work used the Hungarian algorithm for efficient subcarrier pairing and successive convex optimization (SCA) for the optimal solution. This work lags in analyzing the impact of interference when massive users share the same spectrum.

In [40], the UAV-based relay-assisted model for the cognitive network is considered where UAV will assist SU in decoding and forward, assuming infinite battery power from SU for energy harvesting (EH). The objective was to maximize throughput under the presence of causality of SU energy usage, and interference temperature for relay and relay transmit power. Different hovering trajectories under a block fading environment were considered, and the problem was treated with Lagrange dual method. Simulation results showed that the proposed solution produces maximization of the data rate of the overall network along with power control. This work lags considering probabilistic satisfaction for interference constraint.

In [41], D2D network was proposed along with energy harvesting phenomena assisted with CR. The goal was to optimize the maximization of throughput by considering power allocation, user pairing, and channel assignment. D2D users harvest energy from CR users. The existing problem was nonconvex, solved by duality theory, and the Hungarian algorithm was utilized for optimal sub-carrier pairing. Numerical results showed that throughput maximizes along with increasing users and maximum tolerable outstanding against raising interference. This work lags in satisfying QoS for different applications.

In [42], Femto-based heterogeneous networks under the presence of channel uncertainties were examined. The goal was to optimize the overall sum rate while avoiding interference encounters within the macro base station and maintaining the required data rate for femto users. A Gaussian distributed model for CSI feedback was analyzed and a robust optimization problem was solved by Lagrange dual theory and subgradient algorithm. Numerical results showed that the proposed algorithm achieved desired data rate requirement. This work lags the discussion to consider the complexity factor when users increase.

In [43], Backscatter (BackComm) based on a cognitive network consisting single primary base station with a single PU, and a single SU with multiple secondary base stations were examined in this work. The goal of this work was to provide an energy harvesting mechanism to multiple secondary base stations from the primary base source. The objective was to optimize secondary transmitter throughput under the presence of energy, QoS, and transmit power constraints. The present problem was nonconvex which was treated with SCA and desired result produces maximum throughput under users, SINR, and iteration comparison. This work lags considering probabilistic satisfaction terminology in constraint.

In [44], EH based on a cognitive network consisting of multiple secondary users was examined. The goal of this work was to provide a self-sustainable approach to secondary devices, considering the Markov approach of PU activity. The objective was to maximize throughput using point-based value and heuristic point-based iteration methods. Numerical results show an efficient EH mechanism along with a throughput maximization approach. This work lags in the probabilistic approach dealing with channel uncertainties.

In [45], the NOMA-based SU assignment approach assisted by the cognitive network was examined in this work. The goal of this work was to optimize throughput under the controlled power allocation, interference, and maximum SU sub-channels. This problem was nonconvex which was solved by SCA, numerical results showed that this solution achieved maximum throughput under controlled interference temperature. But this work lags in considering complexity and chance constraint-based approach.

In [46], UAV-assisted cognitive networks were examined. UAV approach was undermined for safety and disaster scenario. The goal of this work was to consider the probabilistic LOS of UAVs and optimize throughput under co-channel interference. The proposed solution was achieved by particle swarm and numerical results showed efficient raise in throughput while considering co-channel interference in mind. This work lags in the implementation of chance constraint under interference constraint and also considers the complexity factor.

2.3 Transmit Power Minimization

In [47], Hybrid OFDM and NOMA-based cognitive networks were examined in this work. The goal of this work was to provide power minimization under the presence of rate demand, probability of success, SIC, and power control constraints. The given problem was nonconvex, and the Successive convex algorithm (SCA) technique was used to convert the nonconvexity of its nature. Numerical results showed an improved sum rate under low power. But this work lags in considering uncertainty in constraints as constraints can never remain the same under any condition.

In [48], NOMA with OFDM hybrid-based wireless network was examined. The goal of this work was to provide power minimization under the presence of capacity and positive power constraints. The given problem was nonconvex, converted into convex by the interior point method. Numerical results showed power efficiency along with optimum users. This work lags the cognitive network scenarios in its scope.

In [49], Multi-objective based cognitive networks were examined in this work. The goal of this paper was to study power management in the presence of minimum delay, intervention, and the error rate of packet transmission. This problem was solved by an evolutionary algorithm whose results showed optimal behavior of power minimization. This work lags in considering chance constraint-based formulation.

In [50], Multi-objective scenarios based on a cognitive network of IoT were examined. The goal of this work was to jointly optimize the power, delay, and rate of cognitive users. Optimization problem includes minimization of power, delay, and maximization of rate for SU under the presence of BER, interference, and channel limitations. The author has analyzed how rate, power, and delay variation in accordance with to increasing in BER and packet size. A branch and cut polyhedral algorithm was proposed whose results showed optimal power minimization and maximization rate of the CR network. This work lags in considering advanced algorithms that can cater to complexity factors when multiple variables are possessed in calculations.

In [51], the Cognitive network with NOMA technology has been examined. The author has considered wireless information and energy transfer (SWIPT) along with the design of transmitting beamformers and power splitting. The goal of this work was to optimize power efficiency in the presence of EH requirements for SUs and maximum interference constraints for the primary users' side. The given problem was solved by semi-definite and SCA. Numerical results showed that EH is achieved with low power consumption. This algorithm takes a long time to converge and increases computational complexity.

2.4 Energy Efficiency Maximization

In [52], UAV-based overlay cognitive network models were examined. The goal of using such a model was to provide UAVs with sensing transmission capabilities which are popular now's a day. CR opportunistically utilizes the underlying spectrum and UAV periodically senses the availability of spectrum and passed this information to BS. The objective was to maximize energy efficiency in the presence of sensing time and transmission power constraints. This problem was solved by using the dichotomy method, whose results show energy efficiency by restricting power. This work lags in investigating energy harvesting and flight trajectories for UAVs.

In [53], Multi-carrier decodes and forward relay-assisted cognitive networks were examined. The goal of this work was to optimize the objective function considering uncertain channel gains. The objective was to maximize EE in the presence of relay transmit power, subcarrier pairing, and minimum rate requirement constraints. The dinkelbach method was used to solve the quasi-concave problem and for optimal relay selection dual decomposition method was used. Numerical results showed an energy-efficient system with low complexity. This work lags chance constraint-based formulation and perturbation factor which can be a vital scope to undertake uncertainty inside constraint formulation.

In [54], Energy-efficient algorithms for OFDM-based femto devices were examined. The goal of this work was to study the impact of QoS on densely populated femto users. The objective was to maximize energy efficiency in the presence of minimum throughput, required tolerance, and fairness. SCA algorithm was proposed to solve the combinatorial nonconvex problems. Numerical results showed better convergence analysis for energy efficiency.

In [55], WSNs based on EH mechanisms were examined. The goal of this work was to utilize TDMA-based EH protocol where at one-time slot energy is harvested and at another time slot, energy is transmitted. The objective of this work was to maximize EE by considering time scheduling parameters and power consumption. To extend WSN life our objective was to keep energy consumption and energy harvest equal to them. The problem was solved by SCA and results showed optimal performance in energy decline as compared to another algorithm. This work lags considering complexity and convergence analysis.

In [56], EH-CRN has been examined. This work considered multiple secondary users and one primary base station. The objective was to minimize overall PBS transmitting energy provision while satisfying minimum throughput requirements. The nonconvex problem was solved by golden section search and bisection search algorithm to obtain optimal energy transfer time for PBS. The numerical results showed that this algorithm achieved energy efficiency with a minimum rate requirement. This work lags in considering complexity factors and convergence analysis.

In [57], D2D-based EH based on underlying UAV networks was examined. Usually, in ideal conditions, perfect knowledge of channel uncertainties was discussed in earlier work. However, in this work author optimizes energy efficiency along with minimum rate requirement in presence of outage constraints of flight altitude, ground terminal nodes, and minimum harvest energy constraint. This problem was transformed by a variable relaxation approach and produced valuable results in terms of energy efficiency and reduces outage probability. This work lags in analyzing complexity analysis.

In [58], the Robust energy minimization approach considering harvest while scattering for wireless enable communication was examined. Usually, the active nodes (AN) disperse energy and the passive node (PN) harvest this energy from them. PN scatter that energy for transmitting RF signal towards the receiver. The goal of this work was to consider time delay in which some PN uses the time when others are involved in transmission. The objective was to minimize energy consumption in presence of QoS constraint. A channel training approach was utilized for collecting PN activity. This problem was solved with an iterative algorithm for less complexity. Numerical results showed us the optimal response in energy minimization consumption. This work lags behind to mention of uncertainty in constraint formulations.

In [59], NOMA-based cognitive networks for energy maximization were studied. Earlier work considered perfect channel conditions which is too ideal to be considered in any case as the channel cannot remain the same. The goal of this work was to consider the EE maximization problem with maximum transmission power and interference constraints. A Gaussian error model for CSI has been used for a closed form of outage probabilities. SCA and parametric transformation convert this problem to a geometric transformation approach. Numerical results showed the effectiveness of the proposed algorithm for EE maximization and outage probability. This work lags in considering perturbation factors in constraint formulations.

In [60], the author described 5G-HCRAN which is into the system to reduce overall energy consumption. EH technique is employed to harvest energy from ambient resources such as solar and wind. A joint optimization problem consisting of user association, power control, and admission control is integrated to solve the EE problem in a grid-based system. Mesh adaptive direct search algorithm was used to solve this optimization problem. Numerical results showed optimal performance of the proposed algorithm for EE maximization with less complexity. This work lags in considering chance constraint-based formulation.

In [61], Heterogeneous wireless networks with multihomed user equipment were examined. A two-phase optimization problem consisting of the maximization of EE and maximization of data rate was considered in the presence of QoS, and power constraints. The mixed integer nonlinear problem was solved by Lagrange dual method and continuous relaxation approach. Two-phase optimization provides sub-optimal EE results with less complexity. Numerical results showed efficient energy reduction with increasing power and less complexity. However, this work lags to include a probabilistic approach to treat constraints along with another efficient algorithm for even less complexity and better convergence.

2.5 Common Objectives Functions and Constraints

After carefully analyzing the literature in the previous section, some common objectives and constraints can be extracted. A few of the common objective functions are listed below:

- Throughput Maximization: To fully utilize the ability of the wireless network, devices must operate under the maximum achievable data rate. It is considered the proposed objective function to provide reliability requirements for the proposed wireless network.

- Transmit power minimization: This limitation ensures that the overall transmit power of the BS must be less than or equal to the transmit power of all BS connections. Similarly, the user's transmit power must be lower than or equal to its total transmit power.

- Interference Minimization: This factor is very much common for any communication scenario because network reliability is directly affected by it. The user must transmit its power to some limit that does not cause interference between communicating devices.

- Relay-assisted network: Relay used to provide cooperation for achieving reliable communication within less latency.

2.6 Summary of Problem Formulation

According to the described literature, most of the existing work discussed general constraint formulation without considering the probability factor while satisfying the given constraint. Constraints can never remain the same when communication happens so there is no proper work has been done to consider the uncertainty factors which cause perturbation or any technique has not been used to deal with this uncertain behavior. However, the impact of power allocation on interference is not further provided. Thus, it is necessary to provide an efficient resource allocation model that maximizes throughput while considering chance constraint-based formulation under uncertain behavior.

2.7 Novelty of Proposed Work

After carefully examining the literature review and Table 2.1 it is observed that the existing work mostly lacks efficient resource allocation for 5G/6G CRNs using probabilistic interference models which is the key reason for motivation for the proposed work. Moreover, it is concluded that all the existing techniques could not either completely cater to convergence analysis, complexity analysis, lagged effective interference models or the time of execution was long. This thesis satisfies all these gaps. Most of the system models considered in the literature have considered deterministic constraint formulation with no probability of satisfaction. Whereas the proposed experimental setup considers the known distribution for perturbation factor along with probabilistic satisfaction of constraints which adds flexibility in getting an optimal result.

A summary of the literature review is given in Table 2.1

Table 2.1: Study Table

SCA-Successive Convex Approximation, CoMP-Coordinated Multi point, D2D-Device to Device, WET-Wireless Energy Transfer, UAV-Unmanned Aerial Vehicle, V2X-Vehicle to Everything, FBS-Femto Base Station, GP-Geometric Programming, KKT- kush kuhn tucker, SCA-Sub Carrier Allocation, LDM-Lagrange dual method, DC-Distance between two concave approximation, CC: Chance constraint

Ref	Objective	Constraints	Problem Type	Uncertainty model	Technology Application	Solution Domain	Strength	CC
[29]	Maximize EE of SU	Data rate, Interference temperature, max power, channel assignment	Non-Convex MINLP	Robust PA under Gaussian and worst error model	Cognitive network	GP Algorithm, Dual Decomposition, Lagrange and subgradient method	Less outage probability, and higher EE	✗
[30]	Maximize data rate	Interference threshold,Average SINR	Probabilistic MINLP	Robust Resource Allocation based on worst case or stochastic uncertainty	Femto networks	DC approximation,SCA	Low complexity,high data rate	✗
[11]	Minimizing total power	SINR	Non convex	Robust Network Utility maximization	Cognitive networks	Sequential GP,Fenton-Wilkinson method	Improved SINR	✗
[16]	Maximizing data rates	Interference,Minimum rate requirement	Non convex MINLP	Robust Power allocation for Hetnet	Femtocells	Convex optimization	Effectiveness in convergence performance	✗
[31]	Energy Minimization	QoS	Non Convex	Distribution ally robust energy minimization	WET model	CaVR,Iterative algorithm	Quick convergence,Minimizes energy consumption	✗
[26]	Minimizes the up link power	QoS,target data rate	Non Linear Optimization problem	Distributed and Robust Power allocation	Cooperative relay system(DF)	Semi distributed algorithm	Optimal relay selection and power allocation	✗
[21]	Maximize Total System Rate	Subcarrier matching,Power allocation,User Pairing	Non Convex MIP	Joint Resource allocation optimization	Multiple relay assisted network (NOMA)	Mixed binary integer programming,Hungarian algorithm	Improved transmission and low complexity	✗
[22]	Optimizing Throughput and QoS	SINR,minimum tolerable outage probability	Non Convex MIP	Support based distribution ally robust resource allocation	V2V	SDP,Hungarian algorithm,	Less complex and more throughput	✗
[32]	Maximizing the total IE of FU	QoS,max power,sub carrier assignment	Non Convex	Chance constraint RA for joint power allocation and sub carrier assignment	Macro Femto (OFDMA Hetnet)	Convex solution,Quadratic transformation	Superiority in terms of IE and less interference	✗
[33]	Maximizing EE	User association, power,flight altitude	Non Convex MIFP	Robust EE maximization based on coordinate uncertainty	UAV assisted D2D networks	Variable relaxation,Lagrange dual theory	Higher EE and strong robustness	✗
[34]	Maximizing EE	Transmit power,SINR,subcarrier pairing,rate	Non Convex Mixed binary integer programming	Robust Energy Maximization	DF cognitive relay network	Dual decomposition method	Low complexity	✗
[13]	Maximizing throughput capacity	Interference,Transmit power	Non Convex Non Linear program	Robust Power allocation	Cognitive	Convex theory,Interior point,Newton Method	Higher performance of SC	✗
[35]	Robust Energy maximization	Max interference threshold,transmit power,outage probability	Non Convex Non Linear program	Robust Energy maximization	Cognitive network	SCA,parameter transformation method,Lagrange theory	Protects performance of PU due to outage threshold	✗
[36]	Maximizing throughput,SE of network	QoS,max power,interference to relays	Non Convex MINLP	Robust radio resource allocation,chance constraint for robustness	D2D relay assisted network	Gradient dual decomposition,Polynomial-time distributed algorithm	Relays improves D2D network performance	✗
[37]	Maximum utility and minimum processing delays	Task offloading,server recruitment	Convex NLP	Robust Task offloading	Fog network computing system	MAB,RV-UCB	Reduce long term Task assignment delays	✗
[14]	Maximizing CR rate overall frequency bands	CR transmit power,PU interference	Convex NLP	Robust Power control	Cognitive network	Convex approximation	More data rate and less PU interference	✗
[38]	Minimizing the energy consumed, maximizing the data rate	Min energy, data rate extraction	Convex MINLP	Robust Optimization	WET network	Convex uncertainty model such as polyhedral, ellipsoidal models	Mean objective values and smaller deviation for a better wide range of problem parameters	✗
[39]	Minimum estimation error of channel	QoS parameters,Minimum SINR target	Convex Linear optimization	Robust Channel Estimation	5G network scenario	Non cooperative game to adjust filter gains in worst case scenario	Effectiveness in terms of low estimation error and high data rate	✗
[40]	Maximize the rate of data transmission	QoS,power,channel covariance	Non convex linear problem	Robust energy efficient data allocation	6G	MLE based channel estimation	Superiority in terms of high energy efficiency and throughput	✗
This Work	Maximize the throughput	Probabilistic, interference,relay	Non convex MINLP	Efficient RA in Cognitive network	5G	OAA	Optimal result under less complexity	✓

Chapter 3

System Model and Proposed Techniques

In this chapter the system model and proposed technique are discussed. Section 3.1 gives the details of the system model along with the resource allocation and power models. The problem formulation is explored in section 3.2. The proposed technique for the optimization problem is given in section 3.3. The convergence and complexity analysis of the algorithm is given in section 3.4

3.1 System Model

Following a model used in [62] with possible refinements, a cognitive network assisted by relay communication is studied in this thesis. A wireless network consisting of one Secondary base station (SBS) and one Primary base station (PBS) with their respective K secondary users (SUs) and M primary users (PUs). The cognitive network model opportunistically utilizes the availability of the existing spectrum and accommodates SU when there is a vacant spectrum hole present in the primary band. L relay assisted model inside the cognitive network to provide reliability in transferring RF signal when no source

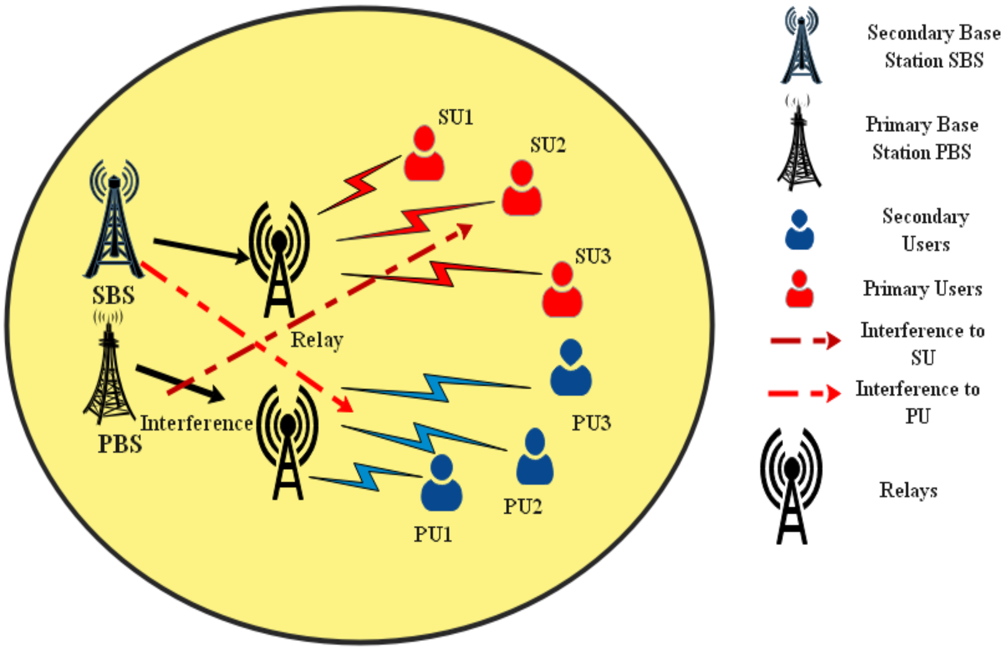

Figure 3.1: System Model Illustration

is transmitting. The wireless channel between CR users can be a line of sight (LOS) or nonline of sight (NLOS). Efficient allocation of power in the network can be the purpose of our thesis to carry out reliable communication between CR devices. Figure 3.1 illustrates the system model used.

3.1.1 Resource Allocation Model

CRN is considered with one primary base station (PBS) and one-second base station (SBS). PBS provides service to M PUs where as SBS provides service to K SUs. L is the relay that assists the communication between them as shown in fig.2. Where $m = \{1,2,3...M\}$, $k = \{1,2,3...K\}$, and $l = \{1,2,3...L\}$. The user equipment that is served by the relay is represented by U_l such that $U \subseteq \{k \cup M\}$. AF relay model is considered which transmits signals in two-time slots. In the first time slot, a signal is received from PBS by l relay is $\sqrt{\rho_m^{pu}} h_l^{pu} + Z_l$, similarly for SBS signal received would be $\sqrt{\rho_k^{su}} h_l^{su} + Z_l$. ρ_m^{pu}, ρ_k^{su}

represents the received power of PU and SU to the relay, and Z_l is the noise in the channel. The maximum power that is transmitted by the relay is p_r^{max}, and by source, power is p_{max}^s. h_l^{pu} is the channel gain from relay to PUs and h_l^{su} is the channel gain from relay to SUs. SINR of k SUs is given as

$$\Gamma_{k,l}^{su} = \frac{\rho_{k,l}^{su}|h_{k,l}|^2}{\sum_{i=k+1}^{K}\sum_{j=l+1}^{L}\rho_{i,j}^{su}|h_{k,l}|^2 + I_{max}^{pu} + I_{max}^{l} + \sigma_{\zeta}^2} \tag{3.1.1}$$

where I_{max}^{pu} is the maximum interference of PUs faced by SUs. I_{max}^{l} is the maximum relay interference. $h_{k,l} = L_{k,l}g_{k,l}$, where $L_{k,l} = \frac{1}{\sqrt{d_{k,l}}}$ is the distance between SBS and relay. $g_{k,l}$ is the channel gain between l relay to k secondary users which is model by Rayleigh fading coefficients [30]. σ_{ζ}^2 is the noise of the channel.

According to the Shannon formula, the maximum achievable data rate of SUs are

$$r_k^{su} = \sum_{i=k+1}^{K} \log_2(1 + \Gamma_{k,l}^{su}) \tag{3.1.2}$$

The overall power constraint for SUs are

$$Pr\left[\sum_{k=1}^{K}\sum_{l=1}^{L}\rho_{k,l}^{su} \le P_{max}^{s}\right] \ge \alpha_1 \tag{3.1.3}$$

PBS and SBS are actually transmitting their signal towards respective PUs and SUs. So, both transmitters must transmit power in a desirable way in order to avoid disruption in communication. SBS power should always remain less than PBS.

P_{max}^{s} represents the maximum source power of the CR system. Power for SU should remain under the total CR system power, otherwise having too much power causes interference with PU devices.

The interference power experienced by PUs from SUs should be less than the overall total

I_{max}^{pu} to have reliable SU transmission.

$$Pr\left[\sum_{k=1}^{K}\sum_{l=1}^{L}\rho_{k,l}^{su}g_{k,l}^{2}\leq I_{max}^{pu}\right]\geq\alpha_{2} \tag{3.1.4}$$

Here the relay interference is related to CR when the transmission is carried out through the relay source from SBS to SUs and PBS to PUs, it should remain under the total relay interference threshold, and $g_{m,k}^{l}$ shows the relay channel gain between PUs and SUs. Because crossing the required threshold means the system will suffer a decrease in overall throughput.

$$Pr\left[\sum_{k=1}^{K}\sum_{l=1}^{L}x_{r}^{k}p_{r}^{max}|g_{m,k}^{l}|^{2}\leq I_{max}^{l}\right]\geq\alpha_{3} \tag{3.1.5}$$

$x_{r}^{k}=\{0,1\}$ represents the relay connection towards SUs transmission. In our network case, the relay is in active mode and entertains CR users. transmission.

$$\sum_{k}x_{r}^{k}\leq 1 \tag{3.1.6}$$

Here, the presence of α_1, α_2, and α_3 means that the constraint must be satisfied under the probability threshold.

3.2 Problem Formulation

Here, the mathematical model is discussed for cognitive networks considering power, interference, and data rate in the proposed system. Abbreviations and notations that are used in the system model are listed in Table II. The aim of this paper is to maximize the throughput based on the probabilistic model of interference.

$$max_{m,k} \sum_{m=1}^{M} \sum_{k=1}^{K} r_{m,k} \tag{3.2.1}$$

subject to the following constraints:

$$C1 : Pr\left[\sum_{k=1}^{K} \sum_{l=1}^{L} \rho_{k,l}^{su} \leq P_{max}^{s} + \xi_1\right] \geq \alpha_1 \tag{3.2.2}$$

$$C2 : Pr\left[\sum_{k=1}^{K} \sum_{l=1}^{L} \rho_{k,l}^{su} g_{k,l}^{2} \leq I_{max}^{pu} + \xi_2\right] \geq \alpha_2 \tag{3.2.3}$$

$$C3 : Pr\left[\sum_{k=1}^{K} \sum_{l=1}^{L} x_r^k p_r^{max} |g_{m,k}^{l}|^2 \leq I_{max}^{l} + \xi_3\right] \geq \alpha_3 \tag{3.2.4}$$

$$C4 : \sum_{k} x_r^k \leq 1 \tag{3.2.5}$$

Eq (3.2.1) objective function achieves throughput maximization under the constraint from Eq (3.2.2) to Eq (3.2.5). Constraint (3.2.2) ensures that the power of each SUs should be under the total power of CRN, which must full fill the required probability threshold. Eq (3.2.3) represents the user's interference threshold on the probability range. Eq (3.2.4) represents the relay interference that should be below some threshold. Eq (3.2.5) represents that relay can be assigned to only one secondary user. ξ_1, ξ_2, ξ_3 represents perturbation inside constraint formulation. Normally constraint doesn't remain the same as it gets altered when under the influence of channel uncertainty. So dealing with this perturbation parameter in our formulation causes MINLP and intractability.

3.2.1 Transformation of Chance Constraint Problem

The existing constraints are considered to be Chance Constraints due to their probabilistic nature. But as the constraint couldn't be remained the same due to some perturbation factor so it is necessary to consider ξ under some known distribution. Considering some generalized equation of uncertainty parameter

$$Pr(g(x,\xi) \leq 0) \geq \alpha \tag{3.2.6}$$

$$Pr(h(x) \leq \xi) \geq \alpha \tag{3.2.7}$$

$$h(x) \leq \phi^{-1}(1-\alpha) \tag{3.2.8}$$

where ϕ^{-1} is equal to inverse CDF, any type of distribution can be considered for this unknown parameter.

$$\phi\left(\frac{z-\mu}{\sigma}\right) \tag{3.2.9}$$

$$z \geq \mu + \sigma\phi^{-}1(1-\alpha) \tag{3.2.10}$$

Based on Eq (3.2.7) to Eq (3.2.10) our constraint can be transformed from (3.2.2) to (3.2.5), with perturbation factor ξ considering CDF of known distribution.

$$max_{m,k} \sum_{m=1}^{M} \sum_{k=1}^{K} r_{m,k} \tag{3.2.11}$$

Subject to the following constraints:

$$C5 : \sum_{k=1}^{K} \sum_{l=1}^{L} \rho_{k,l}^{su} \leq P_{max}^{s} + \mu_1 + \sigma_1 \phi_1^{-1}(1-\alpha_1) \tag{3.2.12}$$

$$C6 : \sum_{k=1}^{K} \sum_{l=1}^{L} \rho_{k,l}^{su} g_{k,l}^{2} \leq I_{max}^{pu} + \mu_2 + \sigma_2 \phi_2^{-1}(1-\alpha_2) \tag{3.2.13}$$

$$C7 : \sum_{k=1}^{K} \sum_{l=1}^{L} x_r^k p_r^{max} |g_{m,k}^{l}|^2 \leq I_{max}^{l} + \mu_3 + \sigma_3 \phi_3^{-1}(1-\alpha_3) \tag{3.2.14}$$

$$C8 : \sum_{k} x_r^k \leq 1 \tag{3.2.15}$$

The problem mentioned in Eq (3.2.2) to Eq (3.2.4) is based on Chance Constraint [63] consisting of uncertain factor ξ. But after the transformation of the given optimization problem, the uncertain factor is converted into a deterministic with known distribution which turns its convexity back shown in Eq (3.2.12) to Eq. (3.2.14). But this problem is MINLP and NP-hard in nature, difficult to solve. Such problems include discrete and continuous variables. As the number of users increases, the search space also increases gradually, if there are 2^S search spaces then it means that 2^S optimization problems are required to solve. Considering the increase in complexity during several iterations, the proposed work will consider the OAA algorithm to provide optimal solutions under the required convergence.

3.3 Proposed Technique

The proposed work presents a novel mathematical framework for Throughput maximization, which is a nonlinear mixed integer programming (FP) problem. Outer approximation algorithm [63] (OAA) is applied to achieve the sub-optimal solution. Let us represent an objective function with U and Φ_{C5-C8} denote constraints from C5 to C8. $Y = \{y_k\}$ and $A = \mathsf{a} \cup Y$. We can prove that Eq (3.2.11) satisfies the following assumptions:

1. Y is convex, non-empty, and compact. The objective function U and constraints Φ_{C5-C8} both are convex in Y.
2. Fixing the value of Y, U and Φ_{C5-C8} are once differentiable.
3. The NLP problem is obtained by fixing A can be exactly solved.

OAA converges within a finite number of iterations.

3.3.1 Primal Problem

The original problem is split into two parts - nonlinear and mixed-integer. Each part of the problem is separately evaluated and the results are then combined to conclude the result. The nonlinear part of the problem is known as the primal problem. A primal problem is comprehended by solving the main problem for binary variables rendering a feasible solution. It provides an upper bound to the main problem.

3.3.2 Master Problem

The mixed-integer part is known as a master problem, both primal and master problems are derived from the main problem which is MINLP. The master problem is then formulated as MILP for binary variables to get new results. It provides a lower bound to the main problem. The iterative process then continues until the difference between the bounds is considerably small, which serves as the terminating condition for the algorithm.

Mathematically the primal problem is given by

$$\min_{Y} -U(A_k, Y) \tag{3.3.1}$$

subject to:

$$\Phi_{C5-C8}(A_k, Y) \leq 0 \tag{3.3.2}$$

Solving the problem stated above in eq (3.3.1), gives the values of Y_k that are further used by the master problem. The solution to primal problem Y_k, aids in deriving a master problem. Make U and Φ_{C5-C8} linear and apply OAA. The solution of master problems yields A_{k+1}, which is used in the next iterations. The algorithm is executed iteratively, and the difference between upper and lower bounds keeps on reducing until it terminates when the gap between two bounds is less than ε [63]. Mathematically problem given in Eq (3.3.1) is given by

$$\min_{A}\min_{Y} -U(A_k,Y) \tag{3.3.3}$$

subject to:

$$\Phi_{C5-C8}(A_k,Y) \leq 0 \tag{3.3.4}$$

The Eq (3.3.3)is rewritten as:

$$\min_{A} -\vartheta(A) \tag{3.3.5}$$

such that:

$$\vartheta(A) = \min_{Y} -U(A_k,Y) \tag{3.3.6}$$

subject to:

$$\Phi_{C5-C8}(A_k,Y) \leq 0 \tag{3.3.7}$$

This problem given is a projection of utility function on A space. For the primal problem, all the constraints hold, for all A_k, so a projection problem solution can be written as

$$\min_{A}\min_{Y} -U(A_k,Y_k) - \nabla U(A_k,Y_k)\begin{pmatrix} Y-Y_k \\ A-A_k \end{pmatrix} \tag{3.3.8}$$

subject to:

$$\Phi_{C5-C8}(A_k,Y_k) - \nabla\Phi_{C5-C8}(A_k,Y_k)\begin{pmatrix} Y-Y_k \\ A-A_k \end{pmatrix} \leq 0 \tag{3.3.9}$$

The equivalent minimization problem is stated by introducing a new variable η given as

$$\min_{A,Y,\eta} \eta \tag{3.3.10}$$

subject to:

$$\eta \geq -U(A_k,Y_k) - \nabla U(A_k,Y_k)\begin{pmatrix} Y-Y_k \\ A-A_k \end{pmatrix} \tag{3.3.11}$$

$$\Phi_{C5-C8}(A_k,Y_k) - \nabla\Phi_{C5-C8}(A_k,Y_k)\begin{pmatrix} Y-Y_k \\ A-A_k \end{pmatrix} \leq 0 \tag{3.3.12}$$

The problem stated in Eq (3.3.10) is a master problem that gives a lower bound. And is equivalent to the utility function Eq (3.2.11)if the propositions (1,2, and 3) are satisfied. Eq (3.3.10) denotes a MILP problem that can be solved via any iterative algorithm. The flow chart of our proposed algorithm is given in Fig. 3.2.

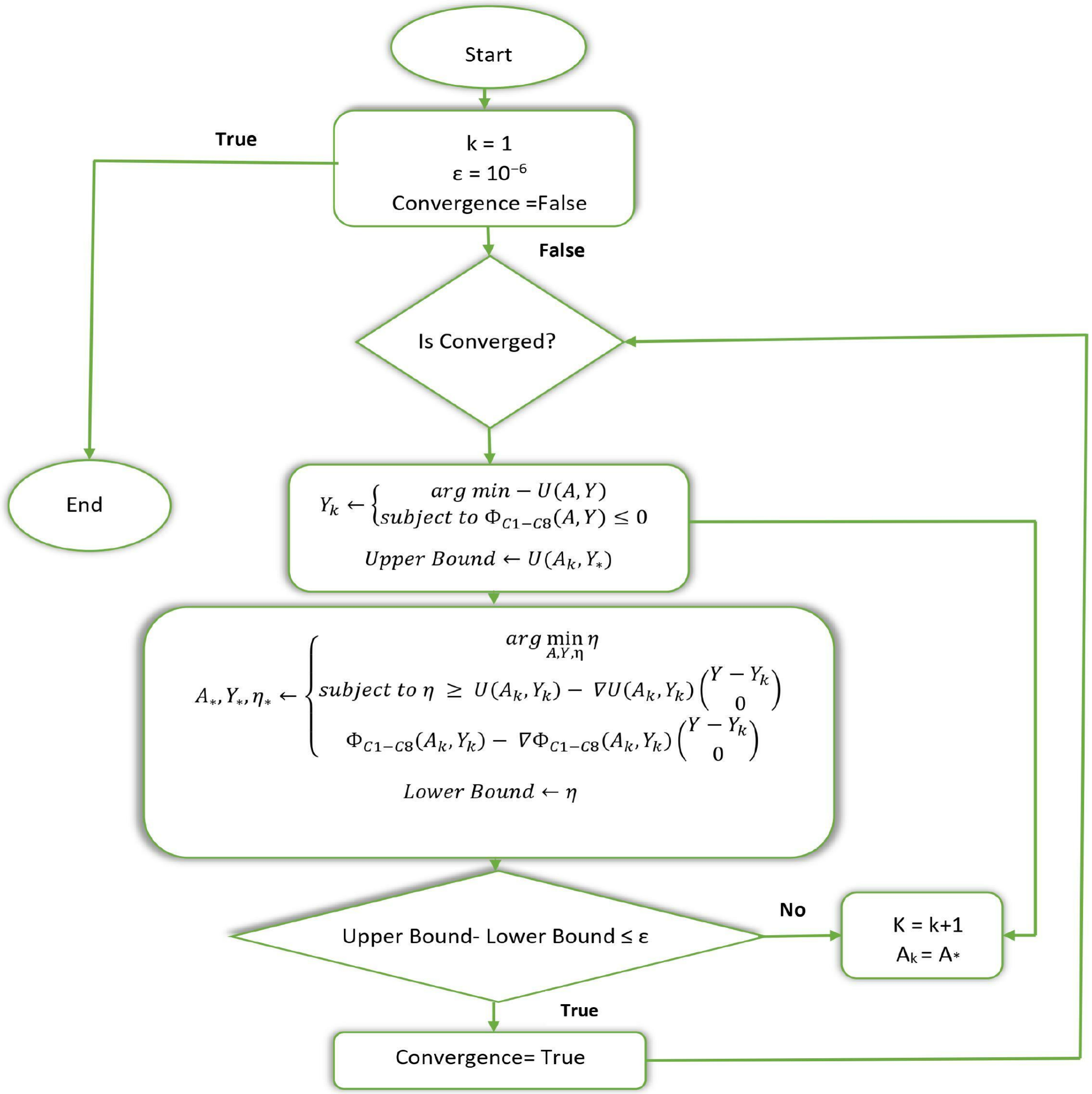

Figure 3.2: Flow Chart of The Proposed Algorithm

3.3.3 Transformation of Uncertainty

The existing constraints are considered to be Chance Constraints due to their probabilistic nature. But as the constraint couldn't be remained the same due to some perturbation factor we take ξ under some known distribution. If we have some generalized equation of uncertainty parameter

$$Pr(g(x,\xi) \leq 0) \geq \alpha \tag{3.3.13}$$

$$Pr(h(x) \leq \xi) \geq \alpha \tag{3.3.14}$$

$$h(x) \leq \phi^{-1}(1-\alpha) \tag{3.3.15}$$

where ϕ^{-1} is equal to inverse CDF, we can consider any type of distribution for this.

$$\phi\left(\frac{z-\mu}{\sigma}\right) \tag{3.3.16}$$

$$z \geq \mu + \sigma\phi^{-}1(1-\alpha) \tag{3.3.17}$$

3.4 Convergence Analysis

The OAA converges linearly. It gives near to optimal solution at $\varepsilon = 10^{-6}$. It poses branch and bound-type architecture. This proves to be an optimal algorithm when the utility function, as well as the constraints, are convex, and A has fixed values. The algorithm terminates within a finite number of steps provided all three propositions are satisfied and A is also finite. For a point to be feasible, η is greater than $U(A_k, Y_k)$, this ensures the optimality of Y. For the case when η is less than $U(A_k, Y_k)$, the solution is not feasible for the master problem. If the feasible solution does not exist for any value of A_k then it will not be considered for the successive master problem. This directs towards the convergence of the algorithm [50].

3.4.1 Complexity of Algorithm

The complexity of the proposed algorithm and its comparison with the exhaustive search algorithm (ESA) and mesh adaptive direct search (MADS) is discussed in this section. Complexity is a measure of the number of flops. Flop is a real floating-point operation. One flop is added in case of real addition, multiplication, division, or removal of elements from any set in the process of program execution. Two flops are added in case of complex addition and for complex multiplication, four flops are added. The matrix multiplication of p x q with q x s results in *2pqs* flops [51]. In the case of the proposed algorithm, one flop is consumed for the first five steps of the algorithm. Step six, involving a while loop, consumes *2KM*, and steps seven, and eight consume $4KM\beta$ each. Step nine consumes $2KM\beta$, step ten consumes two flops, step eleven consumes two, and step thirteen again consumes one flop. Fig. 3.2 shows the description of the following steps. The total count of the flops F_{OAA} is given as

$$F_{OAA} = 5 + 2KM + 4MZ\beta + 4KM\beta + 2KM\beta + 1 + 2 + 1 \quad (3.4.1)$$

$$F_{OAA} \approx 2KM + 10KM\beta \quad (3.4.2)$$

K in the above expression represents the total number of users; M shows the number of antennas employed on the BS, β represents the number of constraints for a given optimization problem, β must be between 0 and 1. ε represents the error tolerance. The gap between the sub-optimal and optimal solution is ε. The computational complexity of OAA $\mathscr{C}_{OAA}$ is given as:

$$\mathscr{C}_{OAA} = \frac{K^2\beta}{\varepsilon}$$

ESA yields a globally optimal solution but at the cost of increased complexity. On increasing the number of users, the complexity of ESA increases exponentially. Let the computational complexity be $\mathscr{C}_{ESA}$ for ESA where K represents the number of users.

$$\mathscr{C}_{ESA} = 2^{2K}$$

In the case of MADS algorithm, within a finite number of iterations, the optimal solution is achieved. MADS algorithm converges without the knowledge of the initial point and the gradient of the objective function. Let the computational complexity be $\mathscr{C}_{MADS}$ of MADS [49]. Mathematically:

$$\mathscr{C}_{MADS} = \frac{K^2}{\varepsilon}$$

There exists a trade-off between complexity and performance. OAA yields better results as compared to MADS but at the cost of complexity, OAA exhibits higher complexity than MADS by the number of constraints times.

Figure 3.3 shows the complexity analysis of all three algorithms.

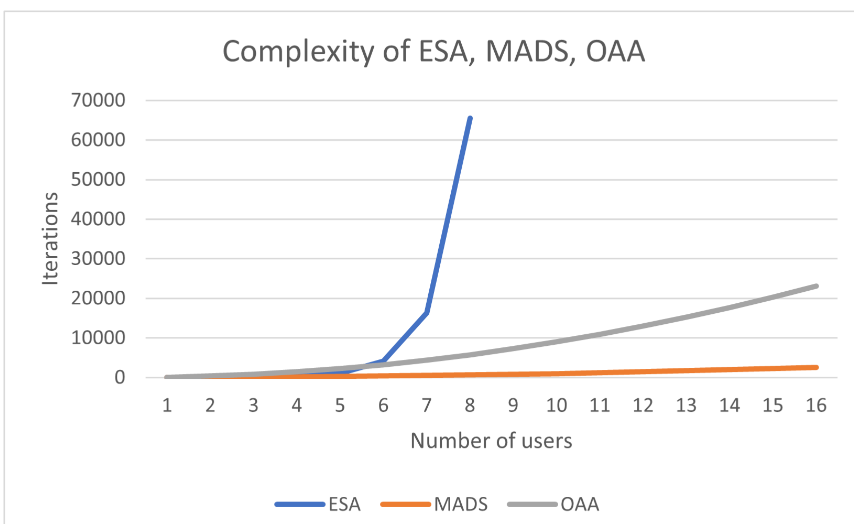

Figure 3.3: Computational Complexity of ESA, MADS, and OAA

Chapter 4

Numerical Simulations and Discussion

The MINLP in (3.2.11) is solved by using OAA and desired results are formulated using the proposed solution. The results depict efficient resource allocation to maximize throughput under stochastic constraint behavior. Basic open-source nonlinear mixed integer programming (BONMIN) software is used for OAA.

4.1 Simulation Setup

Table 4.1 shows the system parameters that are used in simulations. A wireless network considers of a Primary base station and a secondary base station with a 100m distance between them. There is a cognitive network scenario among them in order to satisfy the allocation of the available spectrum. Presently there are a total of 14 SUs present with 4 PUs which are incremented along with simulations. Total P_s is set to 10 Watts and I_{max} to 10^{-4} watts for overall wireless network.

Table 4.1: System Parameters

Parameter	Value
M	4
K	4,6,8,10,12,14
L	10
PU increment	1
SU increment	2
P_s	10 Watts
I_{max}	10^{-4}
α	0.01 to 0.09
d_{max}	100m
σ	10,20,30

4.2 Results and Discussion

The proposed work examines the effect of different parameters on system performance, especially one KPI i.e., throughput.

Fig. 4.1 depicts the plot for Iteration versus Throughput, where the total no of SU is 14 and PU is 4. Iteration is gradually increased from 12 to 25. Normal distribution for the uncertain parameter has been observed in all constraints and tightened the constraints value of alpha to 0.01. As it is observed that throughput increases with the iteration factor, comparing OAA and MADs together. Increasing iterations raises the complexity factor of the current algorithms. OAA performance in presence of complexity is very much better than MADs, as MADs results decrease with the passage of increasing iteration because in complexity its results fluctuate. As OAA performance surpasses MADs.

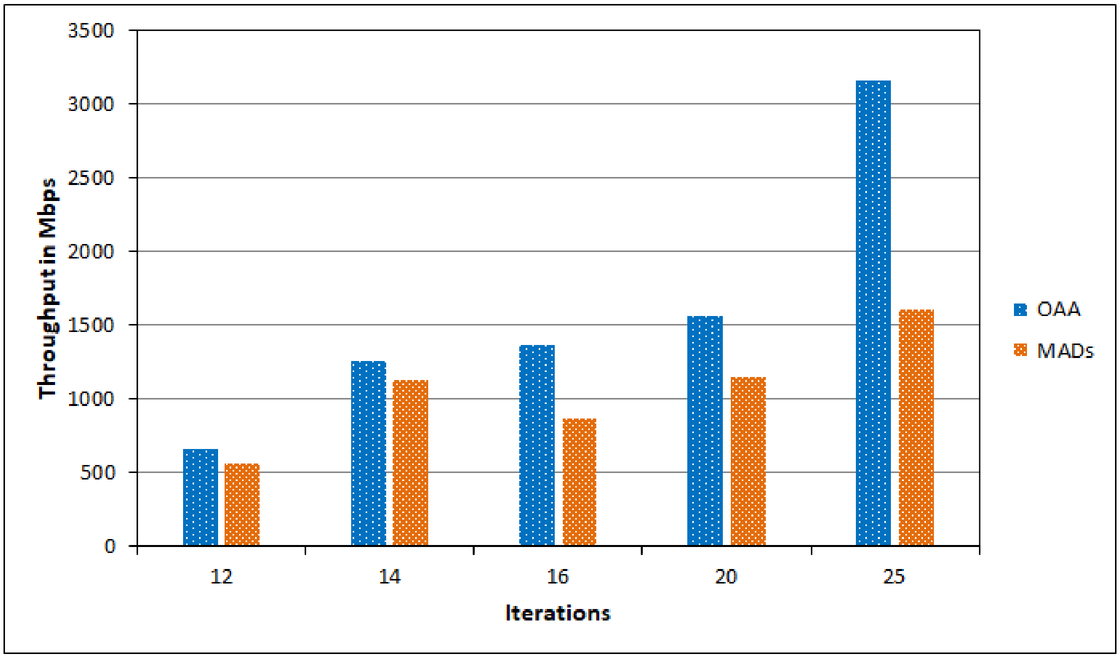

Figure 4.1: Iterations vs Throughput

Fig. 4.2 depicts the plot for Throughput versus UE, where SUs increase gradually from 4 to 12 by keeping PU to 4, to analyze the impact of throughput performance. Normal distribution for the uncertain parameter has been observed in all constraints and tightened the value of the constraint by alpha to 0.01. At user 4, there is a slight increase in throughput for the OAA case. As SU is increased to 10 and the same result has been observed where OAA performance is very much highlighted as compared to MADs. When SU reached 12 in the presence of PU which are 4, then it is observed that the presence of many users increases interference among them. As a result, the proposed throughput decreases with increasing SU, this is an obvious case in any cognitive wireless network. But it is observed that the performance of these two algorithms from the simulation point of view shows that OAA always produces a peak in throughput demand when users increase up to the limit as compared to MADs.

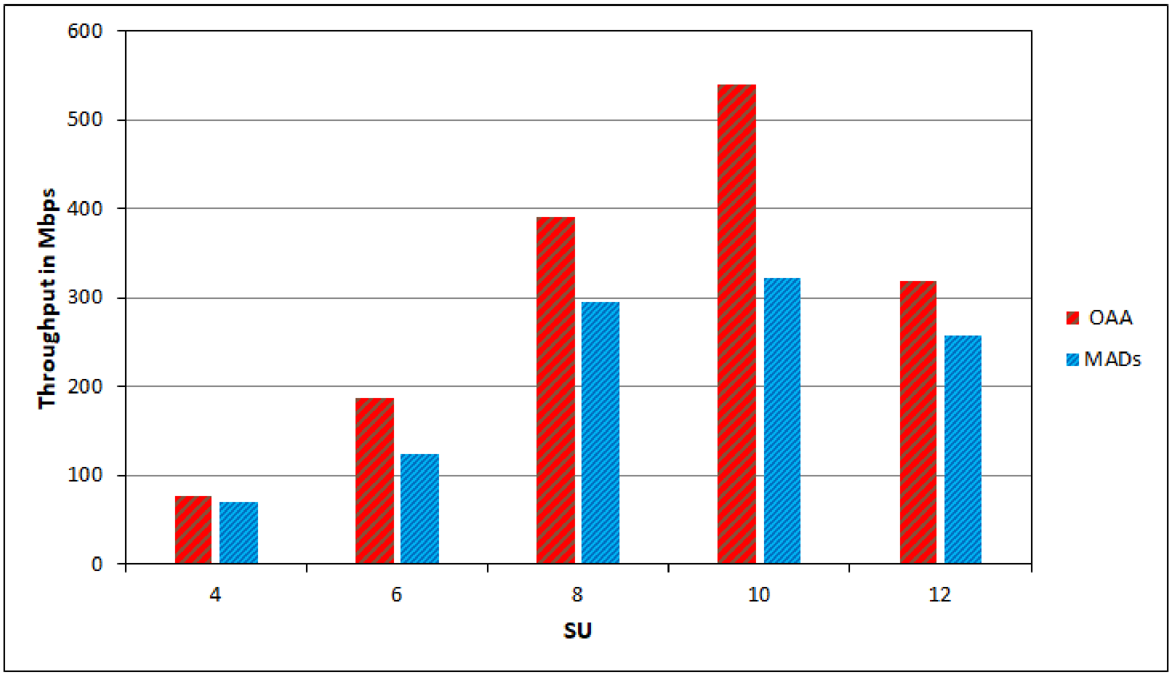

Figure 4.2: Throughput vs SU

Fig. 4.3 depicts the plot for Throughput versus Alpha, where alpha denotes the probability of satisfaction for any constraints. Normal distribution for random variables has been observed. When the constraints have tightened by setting its values from 0.01 to 0.09 and restricting its probability of violation. In the proposed result, it is analyzed that the alpha with 0.01 has higher throughput in the OAA case while moving towards 0.09 proposed throughput gradually reduces because the constraint has been relaxed towards violation. As alpha values reach 0.09, the proposed constraint violates to a greater extent so that is the reason for the reduction in overall throughput results. After tightening the constraint, the complexity factor raises and it has been observed that OAA always shows maximum throughput as compared to MADs.

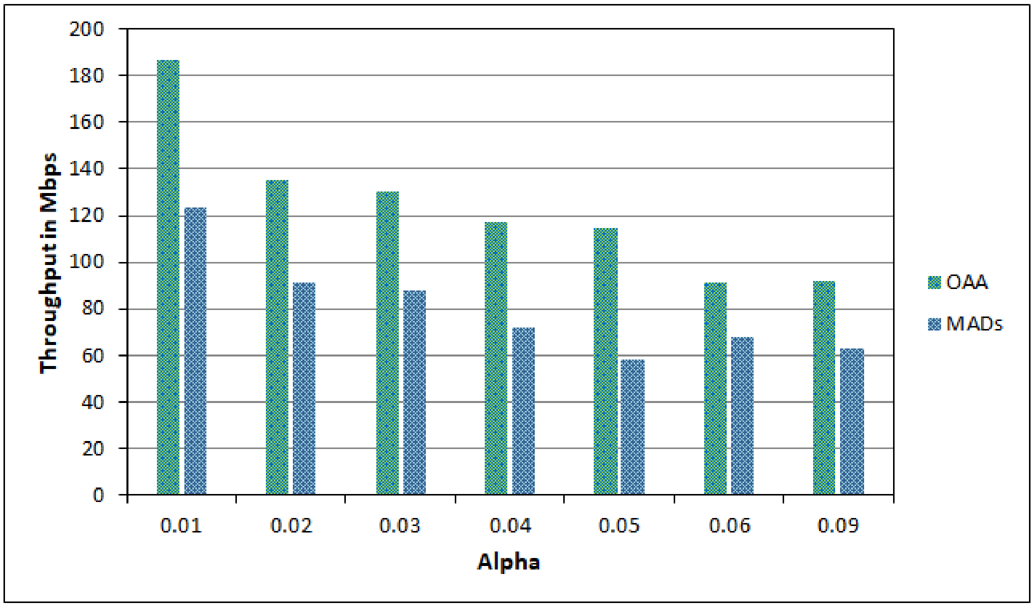

Figure 4.3: Throughput vs ALPHA

Fig. 4.4 depicts the Plot of UE versus Throughput under influence of different alpha values to tighten the constraints while increasing UE. SUs are varied from 4 to 12 while testing its throughput results on both 0.01 and 0.03 alpha values by taking a total of 2 iterations. From the simulation, it has been observed that throughput will decrease when users increase gradually because interference increases in the network. On tightening the constraints with alpha 0.01 and then increasing SU from 4 to 12, maximum throughput for the OAA case is achieved as compared to MADs. And throughput decreases further increasing users. On the same simulation process for alpha 0.03, constraints are relaxed for small violations, and the throughput increases for OAA as compared to MADs and then decreases with SU. But comparing the overall performance of both alpha 0.01 and 0.03, maximum throughput has been observed for the OAA case for alpha 0.01 as compared to alpha 0.03. Because OAA performs better than MADs when constraints are tightened rather than violating the situation.

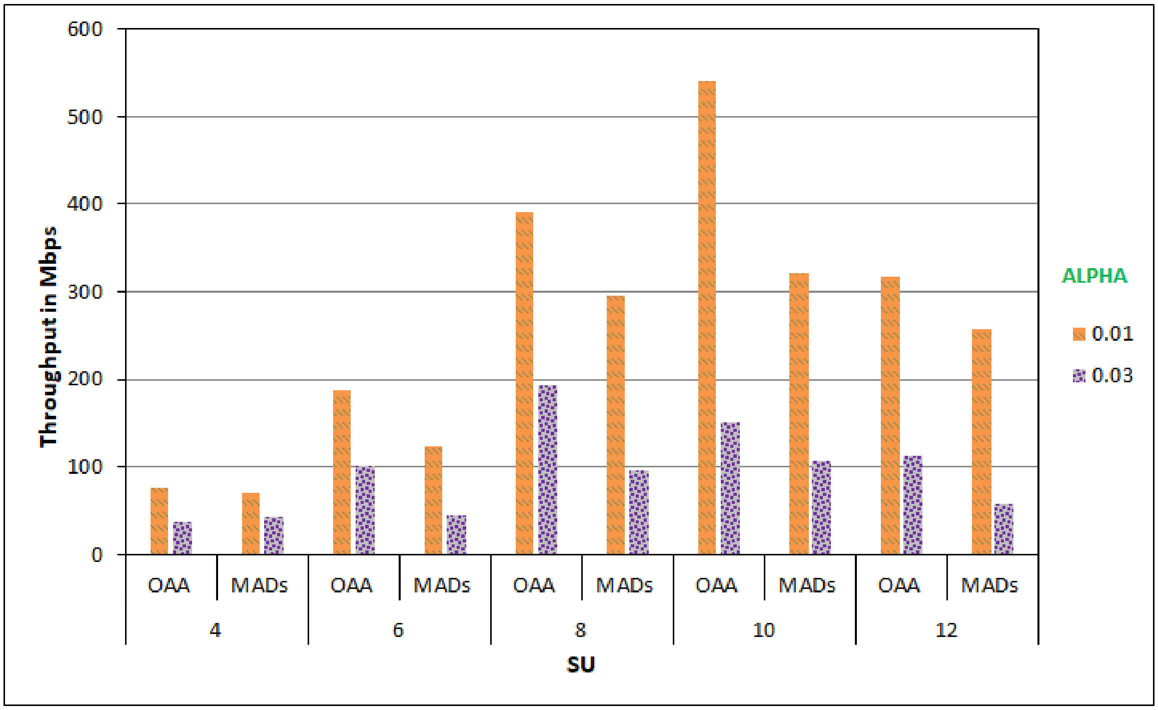

Figure 4.4: Throughput vs SU With Different Alpha Value

Fig. 4.5 depicts the plot for Interference Threshold versus Throughput, as when the interference threshold varies from $1e^{+2}$ towards $1e^{+6}$, the overall interference in the proposed network increases. So according to described theory, the proposed throughput must decrease with increasing interference value. An alpha of 0.01 is set to always tighten the constraint towards maximum satisfaction criteria. It is shown in the desired graph that throughput can reach a peak for small interference values and then gradually decreases with increasing interference level. And in this case, OAA is, as usual, outperform when compare to MADs because OAA always gives better results in cases of complexity and convergence.

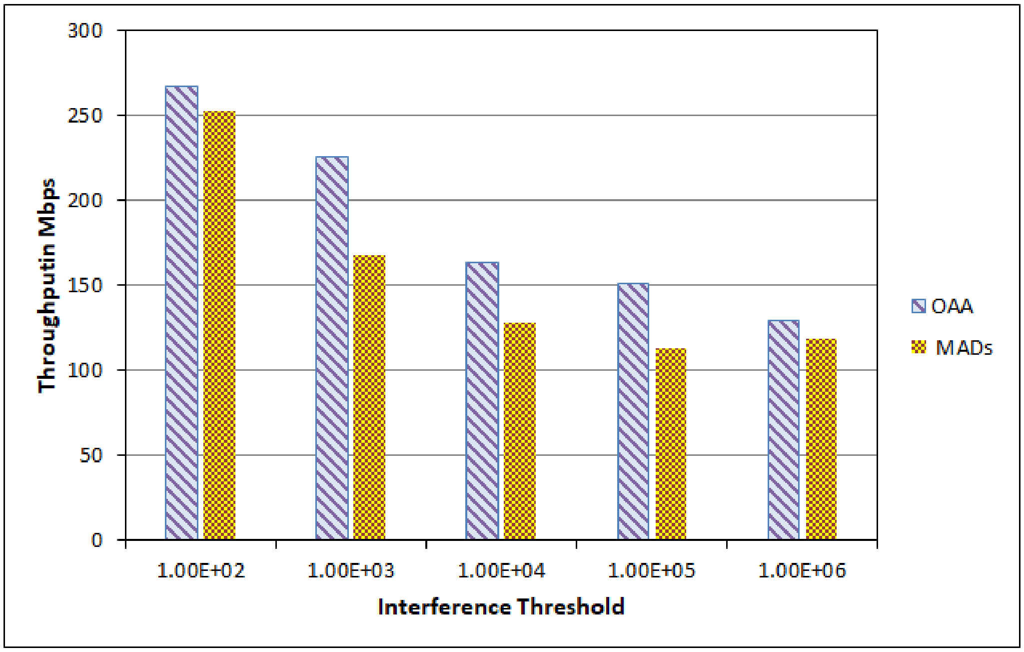

Figure 4.5: Interference Threshold vs Throughput

Fig. 4.1 to 4.5 depicts that the proposed work achieved maximum throughput under the presence of uncertain probabilistic constraints. As we have observed clearly that by tightening the constraint we restrict them to violate which optimizes our objective function and thus it maximizes throughput. By relaxing it we actually violate the constraints which in return decreases our throughput shown in the given graphs. The proposed solution works efficiently under the presence of complexity as we analyze this by varying SUs and iterations. In our network model, we generalized that system throughput decreases when interference and SUs increase beyond the limit shown in Fig. 4.2 and Fig. 4.5. OAA always performs better then MADs as shown in the given figures.

Chapter 5

Conclusion

The thesis investigates the Throughput maximization in CR considering the 5G/6G network. The problem of maximizing throughput is intractable due to chance constraints based on probabilistic nature. CDF of known distribution for uncertain parameters is considered which converts its intractability issue. The proposed formulated problem is solved by OAA which possesses less complexity and provides an optimal solution. Extensive simulations have been carried out to evaluate the proposed algorithm. Chance constraint based on the uncertain parameter is vital to be considered while achieving maximizing the throughput of overall CRN. In the proposed work, the alpha factor restricts our constraint violation in the presence of uncertain parameters which causes perturbation. Proposed simulated results show a peak in terms of throughput when SU increases in the presence of PU under tightened constraints. After analyzing the impact of increasing iteration factor proposed work proves OAA performs better in increasing complexity. While it is shown that throughput gradually decreases while increasing the probability of violation. The interference threshold is varied to analyze the impact on throughput which shows as interference increases throughput decreases. Finally, in comparison between OAA and MADs, OAA surpasses MADs in performance and gives better throughput.

5.1 Future Work

The proposed work in this thesis deals with a few issues of managing utility resources in CR-based networks. However, there are still a lot of unresolved problems. Listed below are a few research directions:

1. CRN and NOMA
2. CRN-aided mmWave communications
3. CRN-aided mobile edge computing
4. CRN-assisted SWIPT
5. UAV and CRN
6. CRN-assisted IoT networks
7. D2D Communication and CRN
8. MIMO and CRN

Moreover, the up-link communication scenario can be studied for the same system. A system employing multiple CRNs can be studied. Different algorithms can be studied for different scenarios. Future directions for this study can also include different uncertainty models incorporating different distributions and stochastic nature. Following technologies like mm-Wave, Fog Computing, SWIPT, MMIMO, and MEC, etc., AI and ML approaches can also be integrated into CR-based networks.

Bibliography

[1] C. Buratti, A. Conti, D. Dardari, and R. Verdone, "An overview on wireless sensor networks technology and evolution," *Sensors*, vol. 9, no. 9, pp. 6869–6896, 2009.

[2] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5g wireless networks: A comprehensive survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 3, pp. 1617–1655, 2016.

[3] R. Baldemair, E. Dahlman, G. Fodor, G. Mildh, S. Parkvall, Y. Selén, H. Tullberg, and K. Balachandran, "Evolving wireless communications: Addressing the challenges and expectations of the future," *IEEE Vehicular Technology Magazine*, vol. 8, no. 1, pp. 24–30, 2013.

[4] K. Zhu, D. Niyato, and P. Wang, "Network selection in heterogeneous wireless networks: Evolution with incomplete information," in *2010 IEEE Wireless communication and networking conference*. IEEE, 2010, pp. 1–6.

[5] M. M. Nasralla and M. G. Martini, "A downlink scheduling approach for balancing qos in lte wireless networks," in *2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. IEEE, 2013, pp. 1571–1575.

[6] S. Hossain, “5g wireless communication systems,” *American Journal of Engineering Research (AJER)*, vol. 2, no. 10, pp. 344–353, 2013.

[7] T. Mshvidobadze, “Evolution mobile wireless communication and lte networks,” in *2012 6th international conference on Application of information and communication technologies (AICT)*. IEEE, 2012, pp. 1–7.

[8] W. H. Chin, Z. Fan, and R. Haines, “Emerging technologies and research challenges for 5g wireless networks,” *IEEE Wireless Communications*, vol. 21, no. 2, pp. 106–112, 2014.

[9] Z. Feng, C. Qiu, Z. Feng, Z. Wei, W. Li, and P. Zhang, “An effective approach to 5g: Wireless network virtualization,” *IEEE Communications Magazine*, vol. 53, no. 12, pp. 53–59, 2015.

[10] K. Ha, P. Pillai, G. Lewis, S. Simanta, S. Clinch, N. Davies, and M. Satyanarayanan, “The impact of mobile multimedia applications on data center consolidation,” in *2013 IEEE international conference on cloud engineering (IC2E)*. IEEE, 2013, pp. 166–176.

[11] N. Zhang, N. Cheng, A. T. Gamage, K. Zhang, J. W. Mark, and X. Shen, “Cloud assisted hetnets toward 5g wireless networks,” *IEEE communications magazine*, vol. 53, no. 6, pp. 59–65, 2015.

[12] E. Halepovic, C. Williamson, and M. Ghaderi, “Wireless data traffic: a decade of change,” *IEEE network*, vol. 23, no. 2, pp. 20–26, 2009.

[13] G. P. Kaur, J. Birla, and J. Ahlawat, “Generations of wireless technology,” *International Journal of Computer Science and Management Studies*, vol. 11, no. 02, pp. 435–441, 2011.

[14] M. K. Iqbal, M. B. Iqbal, I. Rasheed, and A. Sandhu, "4g evolution and multiplexing techniques with solution to implementation challenges," in *2012 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*. IEEE, 2012, pp. 485–488.

[15] J. Liu, Y. Chen, X. Tang, and C. Yu, "Mms entertainment system based on mobile phone," in *Proceedings of the Second International Conference on Internet Multimedia Computing and Service*, 2010, pp. 193–198.

[16] Y. Xu, G. Gui, H. Gacanin, and F. Adachi, "A survey on resource allocation for 5g heterogeneous networks: Current research, future trends, and challenges," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 668–695, 2021.

[17] M. Olsson, C. Cavdar, P. Frenger, S. Tombaz, D. Sabella, and R. Jantti, "5green: Towards green 5g mobile networks," in *2013 IEEE 9th international conference on wireless and mobile computing, networking and communications (WiMob)*. IEEE, 2013, pp. 212–216.

[18] S. Manap, K. Dimyati, M. N. Hindia, M. S. A. Talip, and R. Tafazolli, "Survey of radio resource management in 5g heterogeneous networks," *IEEE Access*, vol. 8, pp. 131 202–131 223, 2020.

[19] F. Xu, Y. Li, H. Wang, P. Zhang, and D. Jin, "Understanding mobile traffic patterns of large scale cellular towers in urban environment," *IEEE/ACM transactions on networking*, vol. 25, no. 2, pp. 1147–1161, 2016.

[20] R. Wei, "Evolving mobile media: Changing technology and transforming behavior," *Mobile Media & Communication*, vol. 11, no. 1, pp. 25–29, 2023.

[21] S. Hannah, A. Deepa, V. S. Chooralil, S. BrillySangeetha, N. Yuvaraj, R. Arshath Raja, C. Suresh, R. Vignesh, K. Srihari, A. Alene *et al.*, "Blockchain-based

deep learning to process iot data acquisition in cognitive data," *BioMed Research International*, vol. 2022, 2022.

[22] W. S. H. M. W. Ahmad, N. A. M. Radzi, F. Samidi, A. Ismail, F. Abdullah, M. Z. Jamaludin, and M. Zakaria, "5g technology: Towards dynamic spectrum sharing using cognitive radio networks," *IEEE access*, vol. 8, pp. 14 460–14 488, 2020.

[23] C. X. Mavromoustakis, A. Bourdena, G. Mastorakis, E. Pallis, and G. Kormentzas, "An energy-aware scheme for efficient spectrum utilization in a 5g mobile cognitive radio network architecture," *Telecommunication Systems*, vol. 59, pp. 63–75, 2015.

[24] S. Iyer, R. J. Pandya, R. Kallimani, K. Pai, R. Khanai, D. Torse, and S. Mavinkattimath, "Survey on internet of things enabled by 6g wireless networks," *arXiv preprint arXiv:2203.08426*, 2022.

[25] G. Bindu, V. R. Kanakala, G. Niharika, B. E. Raj *et al.*, "Impact of blockchain technology in 6g network: A comprehensive survey," in *2022 International Conference on Inventive Computation Technologies (ICICT)*. IEEE, 2022, pp. 328–334.

[26] A. Shafie, N. Yang, C. Han, J. M. Jornet, M. Juntti, and T. Kurner, "Terahertz communications for 6g and beyond wireless networks: Challenges, key advancements, and opportunities," *IEEE Network*, 2022.

[27] A. A. A. Solyman and K. Yahya, "Evolution of wireless communication networks: From 1g to 6g and future perspective," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 4, p. 3943, 2022.

[28] B. Wang and K. R. Liu, "Advances in cognitive radio networks: A survey," *IEEE Journal of selected topics in signal processing*, vol. 5, no. 1, pp. 5–23, 2010.

[29] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE journal on selected areas in communications*, vol. 23, no. 2, pp. 201–220, 2005.

[30] T. C. Clancy, "Achievable capacity under the interference temperature model," in *IEEE INFOCOM 2007-26th IEEE International Conference on Computer Communications*. IEEE, 2007, pp. 794–802.

[31] R. H. Tehrani, S. Vahid, D. Triantafyllopoulou, H. Lee, and K. Moessner, "Licensed spectrum sharing schemes for mobile operators: A survey and outlook," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 4, pp. 2591–2623, 2016.

[32] A. K. Sadek, K. R. Liu, and A. Ephremides, "Cognitive multiple access via cooperation: Protocol design and performance analysis," *IEEE Transactions on Information Theory*, vol. 53, no. 10, pp. 3677–3696, 2007.

[33] E. Hossain, D. I. Kim, and V. K. Bhargava, *Cooperative cellular wireless networks*. Cambridge University Press, 2011.

[34] R. Joon and P. Tomar, "Cognitive radio wireless sensor networks: A survey," in *2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT)*. IEEE, 2022, pp. 216–222.

[35] Y. Xu, F. Shu, R. Q. Hu, and Y.-C. Liang, "Robust resource allocation in noma based cognitive radio networks," in *2019 IEEE/CIC International Conference on Communications in China (ICCC)*. IEEE, 2019, pp. 243–248.

[36] E. Dall'Anese, S.-J. Kim, G. B. Giannakis, and S. Pupolin, "Power control for cognitive radio networks under channel uncertainty," *IEEE Transactions on Wireless Communications*, vol. 10, no. 10, pp. 3541–3551, 2011.

[37] I. Kim and H.-W. Lee, “Robust power allocation in cognitive radio networks with uncertain knowledge of interference,” in *2014 IEEE International Conference on Communications (ICC)*. IEEE, 2014, pp. 1609–1613.

[38] L. Wang, G. Ren, J. Chen, G. Ding, Z. Xue, and H. Wang, “Robust power allocation for massive connections underlaying cognitive radio networks with channel uncertainty,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2016, pp. 1–11, 2016.

[39] Z. Liu, C. Liang, Y. Yuan, K. Y. Chan, and X. Guan, “Resource allocation based on user pairing and subcarrier matching for downlink non-orthogonal multiple access networks,” *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 3, pp. 679–689, 2021.

[40] H. Li and X. Zhao, “Throughput maximization with energy harvesting in uav-assisted cognitive mobile relay networks,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 1, pp. 197–209, 2020.

[41] M. Waqas, S. Aslam, Z. Ali, G. A. S. Sidhu, Q. Xin, and J. W. Jang, “Resource optimization for cognitive radio based device to device communication under an energy harvesting scenario,” *IEEE Access*, vol. 8, pp. 24 862–24 872, 2020.

[42] Y. Xu, Y. Hu, and G. Li, “Robust rate maximization for heterogeneous wireless networks under channel uncertainties,” *Sensors*, vol. 18, no. 2, p. 639, 2018.

[43] Q. Li, “Sum-throughput maximization in backscatter communication-based cognitive networks,” *Wireless Communications and Mobile Computing*, vol. 2022, 2022.

[44] A. F. Tayel, S. I. Rabia, A. H. Abd El-Malek, and A. M. Abdelrazek, “Throughput maximization of hybrid access in multi-class cognitive radio networks with energy harvesting,” *IEEE Transactions on Communications*, vol. 69, no. 5, pp. 2962–2974, 2021.

[45] L. Xu, H. Xing, Y. Deng, A. Nallanathan, and C. Zhuansun, “Fairness-aware throughput maximization for underlaying cognitive noma networks,” *IEEE Systems Journal*, vol. 15, no. 2, pp. 1881–1892, 2020.

[46] Y. Pan, X. Da, H. Hu, Y. Huang, M. Zhang, K. Cumanan, and O. A. Dobre, “Joint optimization of trajectory and resource allocation for time-constrained uav-enabled cognitive radio networks,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 5, pp. 5576–5580, 2022.

[47] H. B. Salameh, R. Tashtoush, H. Al-Obiedollah, A. Alajlouni, and Y. Jararweh, “Power allocation technique with soft performance guarantees in hybrid ofdma–noma cognitive radio systems: Modeling and simulation,” *Simulation Modelling Practice and Theory*, vol. 112, p. 102370, 2021.

[48] P. Bélis, R. Bonnefoi, H. Farès, and Y. Louët, “Optimal power and resource allocation for transmit power minimization in ofdma-based noma networks,” in *2019 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2019, pp. 1–7.

[49] W. Haoxiang *et al.*, “Multi-objective optimization algorithm for power management in cognitive radio networks,” *Journal of Ubiquitous Computing and Communication Technologies (UCCT)*, vol. 1, no. 02, pp. 97–109, 2019.

[50] B. Ssajjabbi Muwonge, T. Pei, J. Sansa Otim, and F. Mayambala, “A joint power, delay and rate optimization model for secondary users in cognitive radio sensor networks,” *Sensors*, vol. 20, no. 17, p. 4907, 2020.

[51] S. Mao, S. Leng, J. Hu, and K. Yang, “Power minimization resource allocation for underlay miso-noma swipt systems,” *IEEE Access*, vol. 7, pp. 17 247–17 255, 2019.

[52] Y. Pan, X. Da, H. Hu, Z. Zhu, R. Xu, and L. Ni, “Energy-efficiency optimization of uav-based cognitive radio system,” *IEEE Access*, vol. 7, pp. 155 381–155 391, 2019.

[53] Z. Liu, C. Liang, Y. Yuan, and X. Guan, “Energy efficient resource allocation based on relay selection and subcarrier pairing with channel uncertainty in cognitive radio network,” *Computer Networks*, vol. 161, pp. 82–92, 2019.

[54] N.-T. Le, L.-N. Tran, Q.-D. Vu, and D. Jayalath, “Energy-efficient resource allocation for ofdma heterogeneous networks,” *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7043–7057, 2019.

[55] H. Azarhava and J. M. Niya, “Energy efficient resource allocation in wireless energy harvesting sensor networks,” *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 1000–1003, 2020.

[56] K. Zheng, H. Ge, K. Chi, and X. Liu, “Energy provision minimization of energy-harvesting cognitive radio networks with minimal throughput demands,” *Computer Networks*, vol. 204, p. 108721, 2022.

[57] Y. Xu, Z. Liu, C. Huang, and C. Yuen, “Robust resource allocation algorithm for energy-harvesting-based d2d communication underlaying uav-assisted networks,” *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 17 161–17 171, 2021.

[58] Q. Yao, A. Huang, H. Shan, and T. Q. Quek, “Wet-enabled passive communication networks: Robust energy minimization with uncertain csi distribution,” *IEEE Transactions on Wireless Communications*, vol. 17, no. 1, pp. 282–295, 2017.

[59] Y. Xu, R. Q. Hu, and G. Li, “Robust energy-efficient maximization for cognitive noma networks under channel uncertainties,” *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8318–8330, 2020.

[60] N. A. Chughtai, M. Ali, S. Qaisar, M. Imran, and M. Naeem, "Energy efficiency maximization in green energy aided heterogeneous cloud radio access networks," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*. IEEE, 2020, pp. 1–6.

[61] R. Liu, M. Sheng, and W. Wu, "Energy-efficient resource allocation for heterogeneous wireless network with multi-homed user equipments," *IEEE Access*, vol. 6, pp. 14 591–14 601, 2018.

[62] A. Kaur and K. Kumar, "A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 34, no. 1, pp. 1–40, 2022.

[63] M. A. Duran and I. E. Grossmann, "An outer-approximation algorithm for a class of mixed-integer nonlinear programs," *Mathematical programming*, vol. 36, pp. 307–339, 1986.