

# ENERGY EFFICIENT RESOURCE ALLOCATION IN RIS AIDED 6G NETWORKS



By

Asma Abid

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

August 2022

## **THESIS ACCEPTANCE CERTIFICATE**

---

Certified that final copy of MS Thesis written by Asma Abid Registration No. 00000318280, 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 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 brain storming 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 their contributions as members of my committee.

My appreciation extends to my friends Ferryal Khan, Zainab Bukhari 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, encouraged me to explore new directions in life. And finally, my deepest gratitude goes to my siblings for their support and patience during study.

# Abstract

Reconfigurable Intelligent Surfaces (RISs) are emerging as a potential solution for Terahertz communication. Which pave the way to envision high energy efficiency and capacity targets beyond 5G (B5G)/6G generation. Energy-efficient resource allocation in RIS-based B5G/6G wireless network is examined in this thesis. The goal is to reduce energy consumption while maintaining the quality of service (QoS) of the network. In the last decade of wireless communication, energy efficiency (EE) has emerged as a significant performance evaluation metric of the network. This thesis presents a novel mathematical framework to maximize the EE of a RIS-based multiuser network, which is a fractional programming problem (FP). We have proposed, Charnes–Cooper transformation (CCT) to transform this fractional programming problem into a concave program. The newly formulated EE maximization problem is subjected to power, QoS, phase shift, and amplitude constraints. Then an outer approximation algorithm (OAA) is proposed for this type of concave problem, which has not been investigated yet in the literature. Proposed algorithm is assessed in terms of convergence and complexity analysis. Results achieved from the simulation testify that the impact of incorporating RIS in the system increases throughput and EE both; increasing the number of RIS elements increases the throughput and EE; on increasing the required data rate both throughput and EE decrease; and when the power is reduced, throughput decreases while EE increases. Finally, the comparison analysis suggests our proposed algorithm outperforms the mesh adaptive direct search algorithm (MADS).

# Contents

<b>1</b>	<b>Introduction</b>	<b>2</b>
1.1	Evolution of Communication Networks . . . . .	2
1.2	Motivation . . . . .	4
1.3	Reconfigurable Intelligent Surfaces . . . . .	5
1.4	Contributions . . . . .	8
1.5	Thesis Outline . . . . .	9
<b>2</b>	<b>Literature Review</b>	<b>10</b>
2.1	Background . . . . .	10
2.2	Capacity Maximization . . . . .	12
2.3	Transmit Power Minimization . . . . .	14
2.4	Energy Efficiency Maximization . . . . .	15
2.5	Common Objectives Functions and Constraints . . . . .	17
2.6	Shortcomings of Existing Literature . . . . .	18
2.7	Novelty of This Work . . . . .	18

<b>3</b>	<b>System Model and Proposed Techniques</b>	<b>20</b>
3.1	System Model . . . . .	20
3.1.1	Resource Allocation Model . . . . .	21
3.1.2	Power Model . . . . .	23
3.2	Problem Formulation . . . . .	24
3.2.1	Transformation of Fractional Problem . . . . .	25
3.3	Proposed Technique . . . . .	27
3.3.1	Primal Problem . . . . .	27
3.3.2	Master Problem . . . . .	28
3.4	Convergence Analysis . . . . .	30
3.5	Complexity of Algorithm . . . . .	31
<b>4</b>	<b>Numerical Simulations and Discussion</b>	<b>34</b>
4.1	Simulation Setup . . . . .	34
4.2	Results and Discussion . . . . .	35
<b>5</b>	<b>Conclusion</b>	<b>41</b>
5.1	Future Work . . . . .	42
	<b>References</b>	<b>42</b>



# List of Figures

1.1	Evolution of communication networks . . . . .	3
1.2	Global Mobile Data Traffic Forecast . . . . .	4
2.1	Cost Benefit Analysis . . . . .	11
3.1	System Model Illustration . . . . .	21
3.3	Computational Complexity of ESA, MADS and OAA . . . . .	32
3.2	Flow Chart of the proposed algorithm . . . . .	33
4.1	Throughput vs the different number of users . . . . .	36
4.2	EE vs the different number of users . . . . .	36
4.3	Throughput vs the different number of users for N=4, 20, 100 and 500 . . . . .	37
4.4	EE vs the different number of users for N=4,20,100 and 500 . . . . .	37
4.5	Throughput vs the number of users, for different required data rates . . . . .	38
4.6	EE vs number of UEs, for different required data rates . . . . .	38
4.7	Decrease in throughput when power is reduced to half . . . . .	39
4.8	Increase in EE when power is reduced to half . . . . .	39

4.9	Throughput-MADS versus OAA algorithm . . . . .	40
4.10	EE-MADS versus OAA algorithm . . . . .	40

# List of Tables

2.1	Study Table	19
4.1	System Parameters	35

# Notations

$[C]^T$	Transpose of matrix C
$M$	No of Antennas
$K$	No of Users
$N$	No of Reflecting Elements
$\phi$	Phase Shift of RIS
$l_n$	Reflecting Amplitude of $n^{th}$ RIS unit
$\theta_n$	Angle of $n^{th}$ RIS unit
$h_{d,k}$	Channel between the BS and $k^{th}$ user
$h_{r,k}$	Channel between RIS and $k^{th}$ user
$G$	Channel between RIS and the BS
$t_x$	Transmitted Signal from BS
$s_k$	Transmit data symbol of user k
$h_k(\phi)$	Rayleigh random channel
$h_k$	Effective Channel of the $k^{th}$ user
$r_x$	Received Signal at BS
$N_o$	Additive White Gaussian Noise (AWGN)
$\gamma_k$	Signal-to-Interference-plus-noise (SINR)
$r_k$	Information rate of the $k^{th}$ user

$R_k$	Total Data Rate of the system
$d$	BS and users distance
$d_o$	Reference distance of far-field antenna
$\alpha$	Path loss exponent
$\xi$	Gaussian random variable
$\sigma$	Standard deviation
$P_t$	Transmit Power
$\zeta$	Efficiency of transmit power
$p_k$	Power received by $k^{th}$ user from BS
$P_{BS}$	BS hardware static power
$P_{RIS}$	RIS hardware static power of
$P_n$	Power of each RIS phase shifter
$P_{Total}$	Total power of the system
$a_k$	Binary indicator
$U$	Utility function
C1–C9	Constraint 1 to Constraint 9

# Acronyms

<b>1G:</b>	First Generation
<b>2G:</b>	Second Generation
<b>3G:</b>	Third Generation
<b>4G:</b>	Forth Generation
<b>5G:</b>	Fifth Generation
<b>B5G:</b>	Beyond Fifth Generation
<b>6G:</b>	Sixth Generation
<b>CDMA:</b>	Code Division Multiple Access
<b>EE:</b>	Energy Efficiency
<b>ESA:</b>	Exhaustive Search Algorithm
<b>IoT:</b>	Internet of Things
<b>KPI:</b>	Key Performance Indicator
<b>LTE:</b>	Long Term Evolution
<b>MADS:</b>	Mesh Adaptive Direct Search
<b>BS:</b>	Base Station
<b>MIMO:</b>	Multiple Input Multiple Output
<b>MINLP:</b>	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

**RIS:** Reconfigurable Intelligent Surface

**ML:** Machine Learning

# Introduction

This chapter presents a brief introduction to the work accomplished in this thesis. The section 1.1 gives a brief overview of the communication networks in the past, present, and future. The history of the communication network is explained in. Section 1.2 explains the basic motivation of this thesis. The overview of RIS is presented in section 1.3. The primary contribution of this thesis is detailed in section 1.4. Finally, section 1.5 discusses the organization of the thesis.

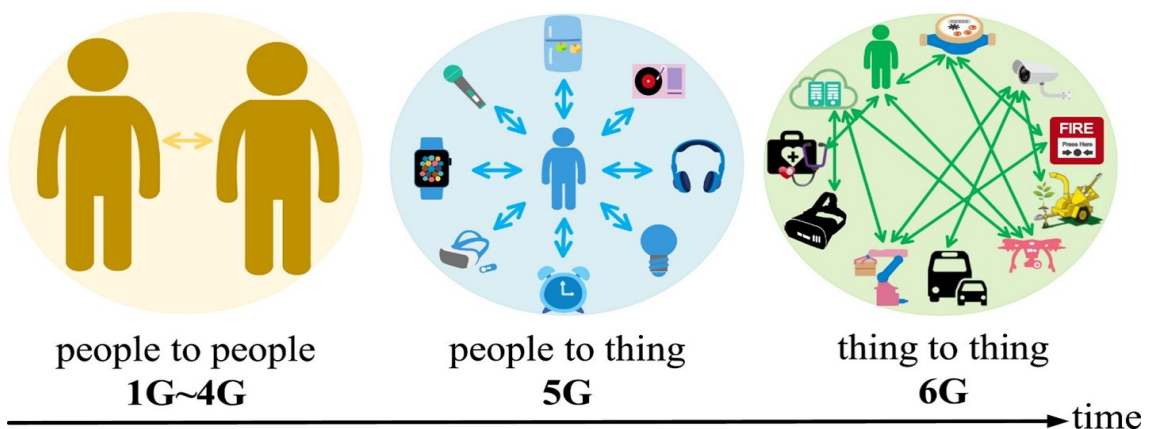
## 1.1 Evolution of Communication Networks

In wireless communication, the demand for faster data rates is on the rise. This necessitates the development of novel and economically feasible communication technologies capable of meeting the growing network capacity demand. Despite years of development, the number of cellular devices continues to rise [1].

We can observe that the service capability of mobile communication networks has improved steadily from 1G to 5G. With analogue communication technologies, 1G could only give voice services; however 2G could provide not only voice but also short text message



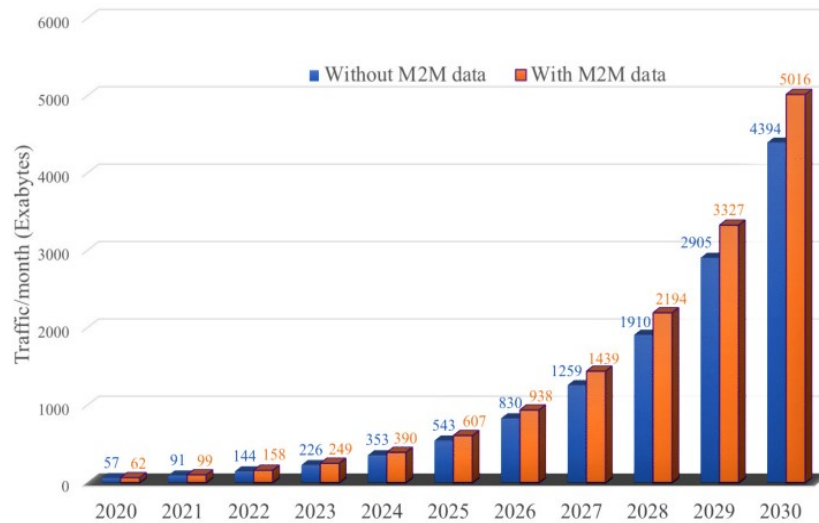
services. With the rise of the Internet, 3G was a platform for wireless multimedia services. 3G offered increased data speeds, system capacity, and bandwidth based on Code Division Multiplexing (CDMA) technology. The services were more data-driven and could provide a consistent user experience. With a 5 MHz bandwidth and modern communication methods including strong turbo codes, it could transmit data at up to 2 Mbps. The data rate supplied by 3G was, however, still restricted. With a 100 MHz bandwidth and an Orthogonal Frequency Division Multiplexing (OFDM) based technology, 4G increased wireless data transfer potential to 1 Gbps. Wireless internet became a reality thanks to 4G. 1G–4G focused on delivering services to just "people,". 5G’s potential to deliver communication services to both people and objects has been increased. 5G has a potential of a peak data throughput of 10 Gbps and performs well in eMBB situations with a bandwidth of 400 MHz and more sophisticated technologies like Low-Density Parity Coding (LDPC) and high-order modulation like 256QAM. In 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 to enable local processing with minimal latency [2]. Figure 1.1 depicts the evolution of cellular communication technologies.



**Figure 1.1:** Evolution of communication networks

## 1.2 Motivation

Wireless data rates double every eighteen months keeping in mind the statistics from the last 30 years. According to the estimate, there will be 13.1 billion connected devices in 2023. The development of the Internet of Everything (IoE) imposes increased data traffic. The global mobile traffic is likely to boost up by 5016 Exabyte/month by 2030. Figure 1.2 shows Global mobile data traffic forecast by ITU.



**Figure 1.2:** Global Mobile Data Traffic Forecast

The 5G era comprising mainly of millimeter wave (mm Wave) and massive multiple input multiple output(M-MIMO) technologies were able to pull of the peak data rate of 20 Gb/s and a bandwidth of 1GHz. These technologies face certain limitations and would not have the capacity to handle such cases. MMIMO supports large beamforming gains but it employs a lot of active components, so it deals with increased interference and signal processing complexity as the number of antennas drastically increases at the base station. The mm Wave, a higher frequency band is a substitute for massive IoT at the cost of power. It employs hybrid or digital beamforming, radio frequency (RF) chains, and antenna arrays making transceivers more complex to overcome propagation loss [3].Even 5G, however,

cannot ensure that it will fulfil all the needs of new applications in the future. With the rise of the Internet of Things, there is a need for communications between "things". 5G is being deployed in many countries of the world, researchers are now heading toward beyond 5G (B5G) or 6G era. The technologies to be used for this goal, the challenges in its implementation, and many more aspects are under study. 6G aims at scoring Tera bit/s, global coverage, low latency, energy efficiency, connectivity, and reliability. B5G/6G targets at providing enhanced hot-spot, extreme capacity x haul, remote area connectivity, mobility, automation, and robotics [4].

### **1.3 Reconfigurable Intelligent Surfaces**

Many technologies have been examined and investigated for the future of wireless communication. Some of them are Reconfigurable Intelligent Surface (RIS), Ultra-massive MIMO, Visible Light communication (VLC), Cell-Free networks, Integrated Access and Backhaul, Integrated Space and Terrestrial Networks, and Integrated Broadcast and Multicast Networks [4].

RIS is one of the key enabler technology for Terabit/s goal. It can pave the way to envision high data and capacity targets for the next generation. In literature, RIS is cited with different names which include large intelligent surfaces (LIS), software-defined surfaces, intelligent reflecting surfaces (IRS), and passive intelligent mirrors [5]. RIS is a low cost, favorable solutions to enhance network coverage, improved transmission rate, and reduced energy consumption. It can improve both spectral and energy efficiency [6]. RIS is a large array with massive number of elements. The electrical size of a single element is between  $\lambda/4$  to  $\lambda/8$ , where  $\lambda$  symbolizes radio frequency (RF) wavelength. Elements adjust the phase and amplitude of the incoming signal hence called reconfigurable. RIS

supports a reconfigurable and smart wireless environment by enhancing the signal strength and reflecting it to the desired receiver [7].

RIS creates a line of sight (LOS) link by smart reflection to overcome obstacles, which solves the “dead zone” problem in mmWave indoor coverage. There is a notable difference between typical amplify-and-forward (AF) relays and RISs. AF relays have active components-energy consuming like amplifiers, converters, filters, and mixers. While RISs have low energy consumption as it reflects the signals passively. Massive MIMO employs many antennas to obtain large beamforming gain. Hence it involves high signal processing complexity. RIS and massive MIMO renders similar SNR gains when operating conditions are the same. RIS supports high energy efficiency as it generates beamforming gains passively, consuming low power. RIS has gained a lot of recognition due to its potential in the future wireless network. It can rectify the wireless propagation environment in a configurable way. Mostly in wireless networks RIS is employed either as an RF chain free transmitter or a passive performer. Some of the advantages of employing RIS are given below

1. Installation:RIS being a passive device is simple to install. RIS can be used in a variety of structures. Unlike classic BSs, which are limited to certain sites and high-rise buildings, RISs may be placed on buildings, towers, aerial, and vehicles due to their inexpensive cost.
2. Improved spectral efficiency: Because RISs can smartly configure wireless propagation environment, which can reduce power loss over long distances. Passive beamforming may be accomplished with RISs. Passive beamforming, as contrast to active beamforming at the BS, simply means adjusting the RIS phases without actively powering the RIS antenna components to boost the received power while decreasing interference for undesired users, hence increasing the network’s total throughput.

RISs are especially beneficial in situations when the BS and mobile users' Line of Sight (LOS) links are impeded by impediments like as buildings or internal walls. RIS allows BSs and mobile users to create virtual LOS connections.

3. Environmental friendliness: RIS transmission does not require a power amplifier, making it an energy-efficient technique. RIS implementation, in practice, necessitates many low-cost phase shifters.
4. Compatibility with current networks: The RISs provide full duplex transmission because they only reflect radio frequency (RF) signals. Furthermore, RISs may be simply incorporated into existing wireless networks using industry-standard hardware. RIS-assisted communication has sparked significant study interest in the wireless networks for the reasons stated above [8].

Some of the potential applications of RIS are:

1. B5G/6G cellular networks with RIS assistance: RIS-aided cellular networks, in which it can enhance several KPIs of a network, such as spectrum efficiency, quality of service (QoS) limitations, and physical layer security. It can also be used to improve device-to-device (D2D) networks for the huge association. RISs can also be used to gather enough energy to maintain themselves in since they can be created with many antenna components
2. RIS-aided indoor communications: RISs reduces RF power losses caused by the poor propagation characteristics of mmWaves. Other indoor applications include upgraded RIS-assisted wireless fidelity (WiFi) and light fidelity (LiFi) networks, which provide greater coverage and data speeds.
3. Unmanned systems: unmanned aerial vehicle (UAV), UAV-connected cellular networks, autonsimultaneous wireless power and information transmission (SWIPT)

networks omous vehicular and robotic networks may all benefit from the RIS. The phase shifts of an RIS deployed on a UAV can be updated on a regular basis to provide a portable virtual LOS connection between two points.

4. RIS can also be used in conjunction with new technologies of communication like in MEC. The systems capability increases by incorporating RIS with MEC systems. The RIS is able to increase the devices' off-loading success rate, hence increasing the MEC systems' capability. It can also complement existing technologies like OFDM, NOMA, MMIMO, mmWave etc.,
5. RIS-enhanced Internet of Things (IoT) networks: The RIS's benefits may be extended to IoT networks to increase the utility of current networks employing IoT [8].

## 1.4 Contributions

The main contributions of this work are highlighted below

- A novel mathematical framework for EE maximization of RIS-based B5G/6G networks is proposed subjected to power, rate, QoS, amplitude, and phase shift constraints.
- The formulated problem is a concave fractional programming (FP) so CCT is applied to transform it into a concave EE optimization problem. OAA is proposed for this newly formulated problem which has not been investigated yet, as it yields a suboptimal solution within the finite number of steps and is convergent. OAA depicts low complexity when compared with the conventional approach.

- The performance of the proposed algorithm for a given model is analyzed using extensive simulations and it converges fast. The proposed algorithm effectively maximizes EE, which aids efficient resource allocation to the users.
- The performance of the proposed algorithm is benchmarked against the existing algorithm e.g., MADS.

## **1.5 Thesis Outline**

The layout of 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 EE optimization for RIS aided networks are thoroughly discussed and its existing literature's shortcomings and existing literature's problems.
- Chapter 3 presents 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.

# Literature Review

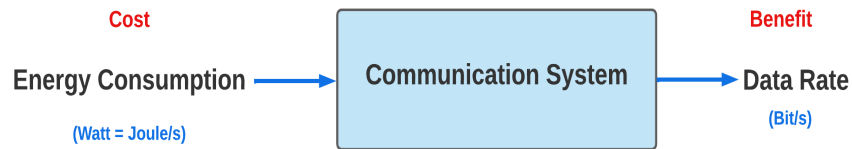
This chapter illustrates the essential background information on which the presented work is formed: in particular, sections 2.1 recalls the needs of the KPI to be optimized in this thesis. Section 2.2 discusses the literature related to capacity maximization and section 2.3 recalls the literature related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

## 2.1 Background

B5G/6G era will deal with massive amounts of data traffic with highly dense network topologies, as outlined in the preceding chapter. As a result of processing such large amounts of data and maintaining the architecture, energy consumption will drastically increase. In the last decade, EE has emerged as a significant metric for wireless network. The



aim of EE optimization is to save bandwidth and reduce power consumption. As shown in Figure 2.1 A few articles have surfaced in the literature based on RIS-aided networks



**Figure 2.1:** Cost Benefit Analysis

that maximizes throughput, energy efficiency and minimizes transmit power of the network. Different metrics have emerged to judge wireless network performance like latency, throughput, reliability, spectral efficiency, etc. In the last decade, energy efficiency (EE) has emerged as a significant metric for wireless network. By assigning the precise amount of resources to the users admitted to the network, following the data rate and channel requirements. The aim is to save bandwidth and reduce power consumption.

The following are the two primary challenges in RIS-aided networks:

- **Acquiring CSI:** Knowledge of CSI is very important in MIMO-RIS and MISO RIS wireless networks. In the earlier works, perfect CSI is believed to be accessible at the BS, RIS, and the users.
- **Phase shift Optimization:** To achieve a specific aim, each application of RIS-enhanced wireless networks necessitates the optimization of RIS phase shifts. The objective is to efficiently optimise RIS phase-shifts while simultaneously taking hardware discrepancies into account [9].

A RIS-assisted cellular wireless network is focused in this thesis, and we provide an efficient approach to improve the throughput and EE of multi-user cellular wireless systems

## 2.2 Capacity Maximization

In [10], non-orthogonal multiple access (NOMA) based downlink RIS assisted network was examined. The objective of achieving maximum throughput using a novel algorithm was proposed for a joint optimization problem involving channel, decoding, power, and reflection coefficients, which is an NP-hard type problem. Numerical results exhibit the improved performance of RIS-NOMA as compared to conventional NOMA systems. RIS-NOMA yields better throughput when compared to RIS-OMA. Careful selection of RIS location enhances a given system's performance. It lags discussion on convergence and complexity analysis of the algorithm.

In [11], RIS-based orthogonal frequency division multiplexing (OFDM) systems are presented based on the concept of adjustable delay. The goal of maximum rate was achieved using a joint optimization of reflection coefficients and power for this kind of non-convex problem. Results depict improvement in the OFDM system with RIS adaptability. The proposed algorithm shows 70 % improvement in terms of rate for the ideal case and case of practical scenarios 40 % effectiveness and had an advantage over the traditional one. It lags discussion on convergence and complexity analysis of the algorithm.

In [12], a downlink system is presented intending to optimize the rate for RIS-based systems for a practical case. A modulation scheme was incorporated to achieve a higher rate in downlink systems. An algorithm for resource allocation optimizes the rate of the system considered. Results show the convergence of the algorithm, and it can manage the tradeoff between system performance and fairness of individual performance. The algorithm con-

verges when the number of RIS elements reaches practically impossible infinity. Moreover, the complexity analysis of the algorithm is not discussed.

In [13], a downlink system of mmWave NOMA aided by RIS is examined for sum-rate maximization. This nonconvex problem was solved via alternating optimization, which improves the performance. The problem was divided into three sub-problems concerning power, phase shifts, and beamforming. Results convince that RIS-based mmWave NOMA outperforms the conventional one. The fixed experimental setup makes it less useful for the practical cases as an algorithm's complexity analysis is not discussed.

In [14], multiple device-to-device (D2D) associations in uplink cellular network aided by RIS is investigated. It helps in eliminating interference. The goal was to optimize the rate of the system using a joint optimization of power, and phase shifts. This type of MINLP problem was decomposed into two sub-problems. One was solved via gradient descent and the other via a local search algorithm. Results emphasize the impact of RIS on eliminating interference. A fixed experimental setup makes it less useful for practical cases.

In [15], a cognitive radio RIS-based multiuser network is considered. RIS aids in removing interference. Beamforming and phase shift joint optimization at the BS and RIS respectively to achieve sum-rate maximization. This kind of non-convex problem was investigated keeping in view the maximum interference. Results prove the effectiveness of employing RIS in cognitive radio networks and great improvements in the rate of the system using the suggested algorithm. It lacks discussion on convergence and complexity analysis of the algorithm used.

[16] presents a comparative study between relays and RIS. The transmit beamforming and reflecting coefficient at the RIS are tuned together to maximize throughput. The alternating weighted MMSE method is used for the MIMO setup having multiple antennas at the receiver as well as the destination. Results justify the comparative study declaring relays to

be more complex and RIS to be passive or semi-passive devices. This work lags discussion on complexity and convergence analysis of the algorithms used.

[17] presents a downlink RIS-based network having single antenna BS and multiple users. Throughput maximization of the network is achieved via constraint and block coordinate ascent and some relaxations. Results show the effectiveness of the algorithm used for the only users that are gathered in the clusters.

In [18], a RIS aided SIMO is presented with a novel transmission protocol. The objective of throughput maximization was achieved via the semidefinite relaxation method (SDR) and strongest tap maximization STM method. The results show the significant improvement achieved via protocol as compared to the existing one. STM method provides better low complexity compared to SDR, but the main drawback is that it experiences a small loss in terms of performance of the system. This work also lags discussion on complexity and convergence analysis.

## **2.3 Transmit Power Minimization**

In [19], a RIS aided multiuser and multi-antenna communication was considered. The objective was to minimize transmit power which belongs to MINLP solved via joint phase and amplitude optimization. Both single and multiuser cases were considered for optimal and suboptimal solutions. Results show significant power saving. A rigid experimental setup makes it less useful for practical cases. Moreover, it lags discussion on complexity and convergence analysis of the algorithms used.

In [20], a system employing multi-antenna access point (AP) and multi-user communication was studied that was aided by RIS to minimize power at AP i.e., transmit power, by thoughtfully adjusting signal reflection. A joint optimization technique was used to achieve

this objective. The performance of RIS's beamforming was compared with the traditional beamforming. Simulation results suggested an improved performance for the given system. SDR converges slowly. Moreover, this work lags in complexity and convergence analysis.

## 2.4 Energy Efficiency Maximization

In [21], an energy-efficient model was considered for transmitting power and phase shift of RIS elements. RIS aids the multiuser communication from the multi-antenna base station. Gradient descent and fractional programming are used for this type of non-convex optimization problem. This work discussed resource allocation in radio/cellular communications for the first time. Unfeasible scenarios were also encountered during the simulation and a very fixed experimental setup was considered.

In [22], the uplink multiuser MIMO communication was studied. Which considered the consequential tradeoff between EE and spectral efficiency (SE). RIS aided the communication by assuming partial channel state information (CSI) setup among RIS, users, and base stations. This type of trade-off study was framed using alternating optimization (AO) optimization. Optimization problems involving bicriterion scenarios lead to increased complexity and simulation time.

In [23], a RIS cell-free network is studied to improve SE keeping power minimum. This work also investigated the fairness of EE in the network, which is a precoding problem solved using an iterative approach for the worst user case in wideband using FP and Lagrangian transform. Results support the idea of an increase in EE of cell-free RIS-aided networks. A fixed experimental setup makes it less useful for practical cases. Also, it lags complexity and convergence analysis of the algorithm used.

In [24], a multi-input-single-output (MISO) system was investigated to optimize the EE of

a downlink communication, given the CSI between users and RIS is known. This type of non-convex problem was decomposed into two subproblems. Both subproblems are then solved via successive convex approximations based iterative algorithm. Results insist on the effectiveness of the algorithm to achieve suboptimal results. This thesis also investigates the impact of the number of elements on EE. It lags discussion on convergence and complexity analysis of the algorithm.

In [25], EE maximization was studied. Joint modeling of transmitted beamforming and reflecting coefficients at AP and RIS respectively was done keeping the consideration of limited constraints of backhaul. An alternating descent algorithm was proposed for this non-convex problem. Multi RIS network is considered for the first time in literature. A more complicated environment was created due to multiple reflected links via multiple RISs in the network. The iterative algorithm needs frequent updates and takes a long time to converge.

In [26], considers a MIMO-based cell-free system aided by multiple RISs. RIS was set up near BS for providing complementary conditions for propagation. As the reflection is reconfigurable so it is a low-cost setup for enhancing cell-free communications. EE maximization is achieved by hybrid beamforming- digital and analog beamforming at BS and RIS respectively. An iterative algorithm was used for this type of optimization problem. The multi-RIS-based network presented considers perfectly known CSI which is not a practical approach when the real-time environment is considered. A more complicated environment was created due to multiple reflected links via multiple RISs in the network.

In [27], a D2D communication network aided by RIS to maximize EE was studied. Passive beamforming and power control of RIS and users have been jointly considered. This forms a non-convex optimization problem solved via FP and Dinkelbach method. RIS-aided D2D communications were considered for the very first time. The SDR yields high complex-

ity and hence it is not favorable in practical scenarios. An incomplete power model was considered with a very fixed simulation setup for the fixed location of RIS.

In [28], wireless powered communication networks (WPCNs) incorporating RIS were studied. Which assists power stations that are having multiple antennas to transfer energy to users. Users communicate with the receiver using OFDM mode. EE maximization is achieved by joint optimization of active and passive beamforming of user and RIS respectively, transmit power, energy harvesting time, and subcarrier allocation keeping energy harvesting and throughput constraint in view. It lags discussion on convergence and complexity analysis of the algorithm. A fixed experimental setup makes it less useful for practical cases.

## 2.5 Common Objectives Functions and Constraints

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

- RIS Phase shift and amplitude: To fully utilize the ability of RIS to intelligently configure the wireless environment, we consider that the reflecting amplitude can take values between  $\{0, 1\}$  and the reflecting angle can take values between  $\{0, 2\pi\}$ .
- QoS constraint: It guarantees that the data rate assigned to the user is greater than or equal to the operator's minimal threshold. The user will not be able to connect to the specified BS if the channel circumstances do not allow for a data rate greater than or equal to the threshold.
- 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.

## **2.6 Shortcomings of Existing Literature**

After carefully examining the literature review, it is concluded that all the existing techniques could not either completely cater to convergence analysis, complexity analysis, lagged effective power models or the time of execution was long. This work addresses all these gaps. Moreover, most of the models considered in the literature have considered fixed locations of distributed RIS, whereas proposed experimental setup, considers the random distribution of RIS and BS, which adds to the flexibility of the model and is a more practical approach.

## **2.7 Novelty of This Work**

After carefully examining the literature review and table 2.1 it is observed that the previous work mostly lacks energy- efficient joint resource and power allocation in RIS-based network which is the key reason of 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 power 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 fixed locations of distributed RIS, whereas our proposed experimental setup, considers the random distribution of RIS and BS, which adds to the flexibility of the model and is a more practical approach.

Summary of the literature review is given in table 2.1 below:



**Table 2.1: Study Table**

LITERATURE REVIEW: **P.A**-POWER ALLOCATION, **R.A**-RESOURCE ALLOCATION, **BS**-BASE STATION, **NW**-NETWORK, **EE**-ENERGY EFFICIENCY, **DE**-DETERMINISTIC EQUIVALENT, **MINLP**—MIXED INTEGER NON-LINEAR PROGRAMMING, **SDR**-SEMI-DEFINITE RELAXATION, **SCA**-SUCCESSIVE CONVEX APPROXIMATION, **AO**-ALTERNATING OPTIMIZATION, **GEMM**-GRADIENT EXTRAPOLATED MAXIMIZATION MINIMIZATION, **BCA**-BLOCK COORDINATE ASCENT, **MMSE**-MINIMUM MEAN SQUARE ERROR

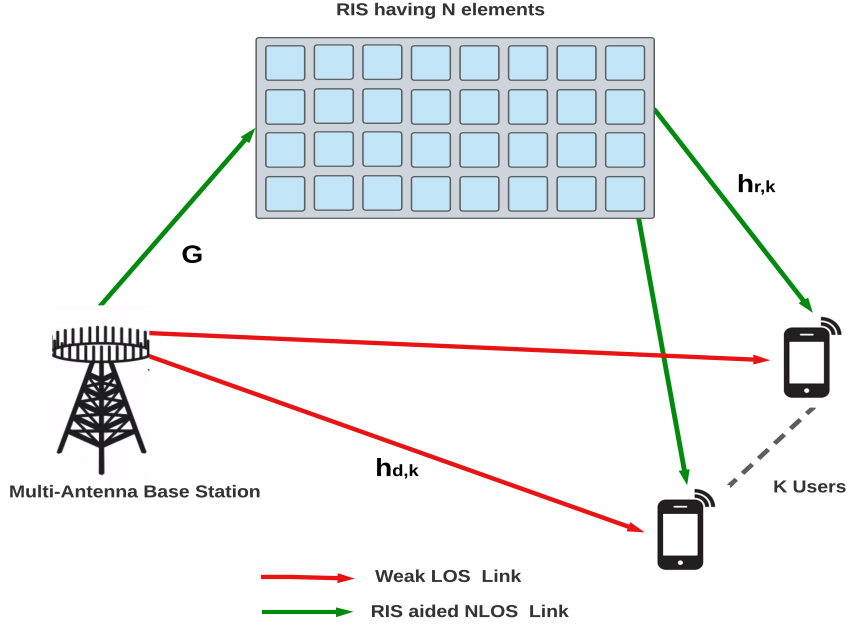
Ref	Objective	Constraints	Optimization type	P.A	R.A	Downlink	Multi-Antenna BS	RIS aided NW	Solution/Algorithm
[10]	Maximize system throughput	Transmission power, reflection coefficient	MINLP	✓	✓	✓	✓	✓	Novel resource allocation algorithm
[11]	Maximize average rate	unit-modulus reflection	Non-Convex	✓		✓		✓	AO, Strongest Tap Alignment method
[12]	Maximize sum rate	Reflection coefficient, Transmit power, Capacity	Non-Convex		✓	✓	✓	✓	Reflection Phase Selection Algorithm, Resource allocation algorithm
[13]	Maximize sum-rate	rate,transmit power	Non-Convex	✓		✓	✓	✓	Alternating Manifold Optimization, SCA, AO
[14]	Maximize rate	power constraint, discrete phase shift	MINLP	✓				✓	DC programming, local search algorithm
[15]	Maximize sum rate	Phase shift, Unit modulus, Power	Non-Convex		✓	✓	✓	✓	AO, SCA
[16]	Maximize throughput	Unit modulus, Power	Non-Convex			✓	✓	✓	Alternating weighted MMSE
[17]	Maximize throughput	semidefinite relaxation, and sequential rank-one relaxation	Non-Convex			✓		✓	BCA, SDR, sequential rank-one constraint relaxation
[18]	Maximize throughput	unit-modulus reflection	Non-Convex				✓	✓	SDR, Strongest Tap Maximization
[19]	Minimize transmit power	SINR, discrete phase shift, Zero forcing	MINLP	✓		✓	✓	✓	Zero forcing and MMSE precoder based algorithm
[20]	Minimize transmit power	Phase shift, unit-modulus, rank one, SINR	Non-convex	✓		✓	✓	✓	AO, SDR
[21]	Maximize EE and SE	QoS, unit modulus, transmission power	Non-convex	✓	✓	✓	✓	✓	Gradient descent, Sequential fractional programming
[22]	EE-SE tradeoff	power constraint, discrete phase shift	Non-convex	✓	✓		✓	✓	DE, Quadratic Transformation, iterative Weighted MMSE, GEMM based algorithm, AO based Resource efficiency
[23]	EE fairness	Rate, Phase shift, transmit power	Non-Convex	✓	✓		✓	✓	Lagrangian transform and fractional programming
[24]	Maximize EE	Outage probability, power constraint, QoS	Non-convex	✓		✓		✓	SCA
[25]	Maximize EE	Backhaul capacity constraints, rate, power	Non-convex	✓	✓	✓	✓	✓	Alternating Descent-based Iterative Algorithm
[26]	Maximize EE	power, phase shift	Non-convex	✓		✓	✓	✓	Analog and digital beamforming algorithms
[27]	Maximize EE	phase-shift, power, transmission rate	Non-Convex	✓			✓	✓	fractional programming, SDR, Dinkelbach method
[28]	Maximize EE	power, phase shift	Non-convex		✓	✓	✓	✓	Dinkelbach's method, matching theory, and AO
This Work	Maximize EE	Rate, Phase shift, power, QoS	MINLP	✓	✓	✓	✓	✓	Outer approximation algorithm

# 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. Proposed technique for the optimization problem along with the convergence and complexity analysis of the algorithm is given in section 3.3

## 3.1 System Model

Following a model used in [29] with possible refinements, a RIS-based multiuser communication system is studied in this thesis. A wireless network consisting of multiple BS with  $M$  antennas and  $K$  users. This is a RIS-based communication, consisting of a large number of passive reflecting elements, that could reconfigure the phase and amplitude of the incoming signal. The wireless channel between the BS and users can be LOS or non-line-of-sight (NLOS). Assuming the direct link is weak between BS and users so that the effectiveness of RIS can be observed. Figure 3.1 illustrates the system model used.



**Figure 3.1:** System Model Illustration

### 3.1.1 Resource Allocation Model

Consider the RIS with  $N$  RIS elements, the phase shift matrix  $\phi$ , with  $n$ th element having  $l_n$  amplitude and  $\theta_n$  phase, where  $\mathcal{N} = \{1, 2, 3, \dots, N\}$  is given as [30]

$$\Phi = \text{diag}(\phi), \text{ for } \phi = [l_1 e^{j\theta_1}, \dots, l_N e^{j\theta_N}]^T \quad (3.1.1)$$

Furthermore, we assume the network undergoes quasi-static flat fading channels. So, the BS can access channel state information (CSI). Let  $K$  be the set of users in the network i.e  $\mathcal{K} = \{1, 2, 3, \dots, K\}$ , then the channel between BS and  $k^{\text{th}}$  user is given by  $h_{d,k}$ , a channel between RIS and  $k^{\text{th}}$  user is given by  $h_{r,k}$ , the channel between BS and RIS is given by  $G$ . Amplitude and phase of the RIS elements are smartly configured to generate a controllable wireless channel. Here  $t_x$ ,  $h_k(\phi)$ ,  $r_x$  and  $P_t$  represents transmitted signal, effective channel,

received signal, and transmit power respectively, where  $h_k(\phi)$ . Mathematically given as:

$$t_x = \sum_{k \in \mathcal{K}} P_t s_k \quad (3.1.2)$$

$$h_k(\phi) = G\Phi h_{r,k} + h_{d,k} \quad (3.1.3)$$

$$r_x = \sum_{k \in \mathcal{K}} h_k(\phi) t_x + N_o \quad (3.1.4)$$

$N_o \in \mathbb{C}^{M \times 1}$  represents additive white Gaussian noise (AWGN),  $N_o \sim CN(0, \sigma_0^2)$ . Antenna gain is represented by  $G_o$  and  $\xi 10^{\xi/2}$  represents log-normal shadowing,  $\xi$  denotes a gaussian random variable having zero mean with  $\sigma$  standard deviation. The gain of channel  $h_k$  is formulated as  $h_k = h_k(\phi) \xi G_o (\frac{d_o}{d})^\alpha$ , where  $d$  denotes the distance between BS and users,  $d_o$  is the reference distance of an antenna in the far-field,  $\alpha$  is a path loss exponent,  $h_k(\phi)$  is a rayleigh random variable [31]. The SINR of the  $k^{th}$  user is given as

$$\gamma_k = \frac{p_k h_k}{N_o} \quad (3.1.5)$$

The allowed data rate of the  $k^{th}$  user  $r_k$  is modeled using Shannon's formula [32]

$$r_k = \log_2(1 + \gamma_k) \quad (3.1.6)$$

$$r_k = \log_2\left(1 + \frac{p_k h_k}{N_o}\right) \quad (3.1.7)$$

The system's total data rate  $R_k$  is given as

$$R_k = \sum_{k \in \mathcal{K}} a_k r_k \quad (3.1.8)$$

Let  $a_k$  be the binary indicator that shows the user  $k$  is connected or not to the RIS. Mathematically given as

$$a_k \in \{0, 1\}, \forall k \in \mathcal{K} \quad (3.1.9)$$

### 3.1.2 Power Model

We use the power model considered in [33]. The total power consumed to employ RIS in the network includes  $P_C = \zeta^{-1}P_t$ , where  $\zeta$  is transmit power amplifier's efficiency along with the static hardware power used by BS, users, and RIS. As RIS comprises passive elements it does not consume transmit power. RIS aids in reconfiguring the phase shifts of the incoming signal that helps in producing amplification gains.  $p_k$ , is the power received by  $k^{th}$  user from BS, while  $P_{BS}$  and  $P_{RIS}$  denote the total static hardware power consumption at BS and RIS respectively. Putting all the above together, the total power  $P_{Total}$  can be expressed as

$$P_{Total} = P_C + P_{RIS} + P_{BS} + \sum_{k \in \mathcal{K}} p_k \quad (3.1.10)$$

The power consumed by RIS having  $N$  similar elements, is given as

$$P_{RIS} = NP_n(b), \forall n \in \mathcal{N} \quad (3.1.11)$$

where  $P_n$  denotes the power consumption and  $b$  denotes bit resolution of each phase shifter. The power consumption of RIS depends on the resolution and type of its individual element [9].

$$P_{Total} = \zeta^{-1}P_t + NP_n(b) + P_{BS} + \sum_{k \in \mathcal{K}} p_k \quad (3.1.12)$$

## 3.2 Problem Formulation

If the data rate of the system is measured in bit/s and power consumed in joule/sec or watts, then EE is given in bit/joule or bit/sec/watt.

$$EE[\text{bit/Joule}] = \frac{\text{TotalDataRate}[\text{bit/s}]}{\text{TotalPower}[\text{Joule/s}]} \quad (3.2.1)$$

This thesis discusses problem of EE maximization, mathematically formulated with an objective function  $U$ , mathematically state

$$\max_{a,p,\theta,\phi} U(a,p) = \frac{\sum_{k \in \mathcal{K}} a_k r_k}{P_C + P_{RIS} + P_{BS} + \sum_{k \in \mathcal{K}} p_k} \quad (3.2.2)$$

subject to following constraints:

$$C1 : \sum_{k \in \mathcal{K}} a_k \leq 1 \quad (3.2.3)$$

$$C2 : p_k \geq 0, \forall k \in \mathcal{K} \quad (3.2.4)$$

$$C3 : \sum_{k \in \mathcal{K}} p_k \leq P_{BS} \quad (3.2.5)$$

$$C4 : p_k \leq a_k P_{BS}, \forall k \in \mathcal{K} \quad (3.2.6)$$

$$C5 : \sum_{k \in \mathcal{K}} a_k r_k \geq a_k R_k \quad (3.2.7)$$

$$C6 : |\phi_n| \leq 1, \forall n \in \mathcal{N} \quad (3.2.8)$$

$$C7 : l_n \in \{0, 1\}, \forall n \in \mathcal{N} \quad (3.2.9)$$

$$C8 : \theta_n \in \{0, 2\pi\}, \forall n \in \mathcal{N} \quad (3.2.10)$$

The objective function in Eq. (14) is energy efficiency maximization subjected to con-

straints C1 to C8. C1 is an indicator constraint that shows whether the  $k^{th}$  user is connected or not to the RIS [34]. C2 ensures the minimum power of each user i.e., the power of  $k^{th}$  user must be greater than zero to ensure communication. C3 indicates that the maximum power assigned to base station  $P_{BS}$  must be greater than the power received by the user  $k$ , from BS  $p_k$ . C4 certifies that when the user is not connected to BS and RIS, it will experience zero power. C5 ensures the required rate must be less than the minimum rate of the users to ensure QoS of the network. The above constraint C6 holds since  $\phi_n = l_n e^{j\theta_n}$  from eq (3.1.1). In C7 and C8 the  $l_n$  and  $\theta_n$  represent the reflecting amplitude and phase of the  $n^{th}$  RIS element respectively. To fully utilize the ability of RIS to intelligently configure the wireless environment, we consider that the reflecting amplitude can take values between  $\{0, 1\}$  and the reflecting angle can take values between  $\{0, 2\pi\}$ .

### 3.2.1 Transformation of Fractional Problem

The utility function is a fractional programming problem i.e., a ratio of two nonlinear functions [35]. We have applied Charnes-Cooper transformation (CCT) to convert the FP of equation into a concave fractional program (CFP), where  $p = \frac{y}{t}$ . CFP is a problem having non-negative and concave numerator while the denominator is positive and convex [36]. The equivalent concave optimization problem is given as follows:

$$\max_{y, t, \theta, \phi} U(y, t) = t \sum_{k \in \mathcal{K}} a_k \log_2 \left( 1 + \frac{y_k h_k}{t N_o} \right) \quad (3.2.11)$$

subject to:

$$C1 : \sum_{k \in \mathcal{K}} a_k \leq 1 \quad (3.2.12)$$

$$C2 : y_k \geq 0, \forall k \in \mathcal{K} \quad (3.2.13)$$

$$C3 : \sum_{k \in \mathcal{K}} y_k - P_{BS}t \leq 0 \quad (3.2.14)$$

$$C4 : y_k - a_k P_{BS}t \leq 0, \forall k \in \mathcal{K} \quad (3.2.15)$$

$$C5 : \sum_{k \in \mathcal{K}} a_k \log_2 \left( 1 + \frac{y_k h_k}{t N_o} \right) \geq a_k R_k \quad (3.2.16)$$

$$C6 : |\phi_n| \leq 1, \forall n \in \mathcal{N} \quad (3.2.17)$$

$$C7 : l_n \in \{0, 1\}, \forall n \in \mathcal{N} \quad (3.2.18)$$

$$C8 : \theta_n \in \{0, 2\pi\}, \forall n \in \mathcal{N} \quad (3.2.19)$$

$$C9 : t(P_C + P_{RIS} + P_{BS}) + \sum_{k \in \mathcal{K}} y_k = 1, \forall n \in \mathcal{N} \quad (3.2.20)$$

This EE maximization-based problem is MINLP, such problems are NP-hard in nature. Such problems involve both continuous  $y$  and discrete variable  $a$ . On increasing the number of users, the search space increases exponentially. An exhaustive search algorithm (ESA) ensures near to an optimal solution for binary variables with known values which is a convex optimization. In the case of ESA, the search space is  $2^{|\mathcal{K}|}$  for a binary variable which means we need to analyze  $2^{|\mathcal{K}|}$  optimizations problems. Considering the increased complexity of ESA, we propose a relatively low complexity algorithm - OAA which ensures value near to an optimal solution and guarantees convergence. The next section provides a detailed overview of the proposed algorithm for EE maximization.



### 3.3 Proposed Technique

This article discusses a novel mathematical framework for EE optimization, which is a non-linear fractional programming (FP) problem. We have proposed, Charnes–Cooper transformation (CCT) to convert this type of problem into a concave optimization problem. Then outer approximation algorithm (OAA) is applied to achieve the sub-optimal solution [35].

Let us represent an objective function with  $U$  and  $\Phi_{C1-C8}$  denote constraints from C1 to C8.  $Y = \{y_k\}$  and  $A = a \cup Y$ . We can prove that eq above satisfies the following assumptions:

1.  $Y$  is convex, non-empty, and compact. The objective function  $U$  and constraints  $\Phi_{C1-C8}$  both are convex in  $Y$ .
2. Fixing the value of  $Y$ ,  $U$  and  $\Phi_{C1-C8}$  are once differentiable.
3. The NLP problem is obtained by fixing  $A$  can be exactly solved.

OAA converges within finite number of iterations [37].

#### 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 problem 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

$$\min_Y -U(A_k, Y) \quad (3.3.1)$$

subject to:

$$\Phi_{C1-C8}(A_k, Y) \leq 0 \quad (3.3.2)$$

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  $\Phi_{C1-C8}$  linear and apply OAA. Solution of master problems yields  $A_{k+1}$ , which is used in the next iterations. The algorithm is executed iteratively, the difference between upper and lower bounds keeps on reducing until it terminates when the gap between two bounds is less than  $\epsilon$  [35]. Mathematically problem given in eq (3.3.1) is given by

$$\min_A \min_Y -U(A_k, Y) \quad (3.3.3)$$

subject to:

$$\Phi_{C1-C8}(A_k, Y) \leq 0 \quad (3.3.4)$$

The above eq (35) is rewritten as:

$$\min_A -\vartheta(A) \quad (3.3.5)$$

such that:

$$\vartheta(A) = \min_Y -U(A_k, Y) \quad (3.3.6)$$

subject to:

$$\Phi_{C1-C8}(A_k, Y) \leq 0 \quad (3.3.7)$$

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

$$\min_A \min_Y -U(A_k, Y_k) - \nabla U(A_k, Y_k) \begin{pmatrix} Y - Y_k \\ A - A_k \end{pmatrix} \quad (3.3.8)$$

subject to:

$$\Phi_{C1-C8}(A_k, Y_k) - \nabla \Phi_{C1-C8}(A_k, Y_k) \begin{pmatrix} Y - Y_k \\ A - A_k \end{pmatrix} \leq 0 \quad (3.3.9)$$

The equivalent minimization problem is stated by introducing a new variable  $\eta$  given as

$$\min_{A, Y, \eta} \eta \quad (3.3.10)$$

subject to:

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

$$\Phi_{C1-C8}(A_k, Y_k) - \nabla \Phi_{C1-C8}(A_k, Y_k) \begin{pmatrix} Y - Y_k \\ A - A_k \end{pmatrix} \leq 0 \quad (3.3.12)$$

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

### 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  $\eta$  is greater than  $U(A_k, Y_k)$ , this ensures the optimality of  $Y$ . For the case when  $\eta$  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 [30].

### 3.5 Complexity of Algorithm

The complexity of our algorithm and its comparison with ESA and 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  $p \times q$  with  $q \times s$  results in  $2pqs$  flops [38]. In the case of proposed algorithm, one flop is consumed for the first five steps of the algorithm. Step six, involving a while loop, consumes  $2KM$ , steps seven, and eight consumes  $4KM\beta$  each. Step nine consumes  $2KM\beta$ , step ten consumes two flops, step eleven consumes two, and step thirteen again consumes one flop. The total count of the flops  $F_{OAA}$  is given as

$$F_{OAA} = 5 + 2KM + 4MZ\beta + 4KM\beta + 2KM\beta + 1 + 2 + 1 \quad (3.5.1)$$

$$F_{OAA} \approx 2KM + 10KM\beta \quad (3.5.2)$$

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

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

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  $\mathcal{C}_{ESA}$  for ESA where  $K$  represents the number of users.

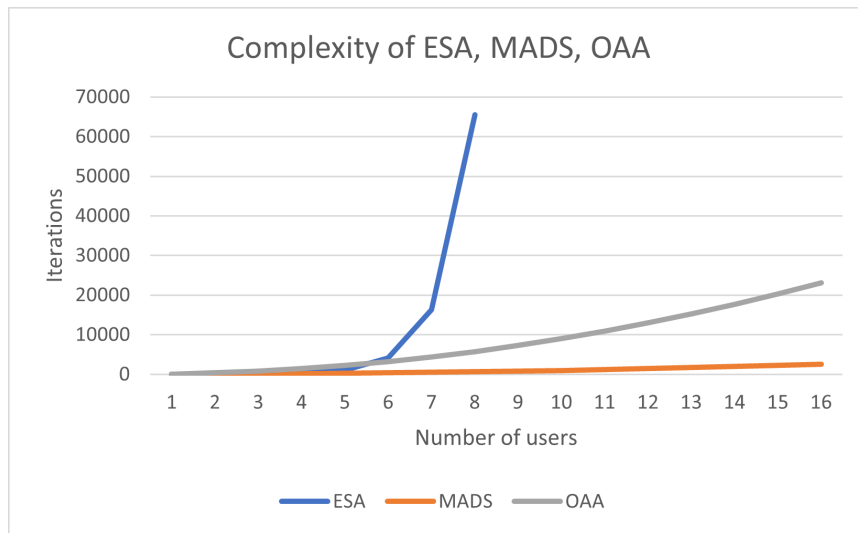
$$\mathcal{C}_{ESA} = 2^{2K}$$

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  $\mathcal{C}_{MADS}$  of MADS [34]. Mathematically:

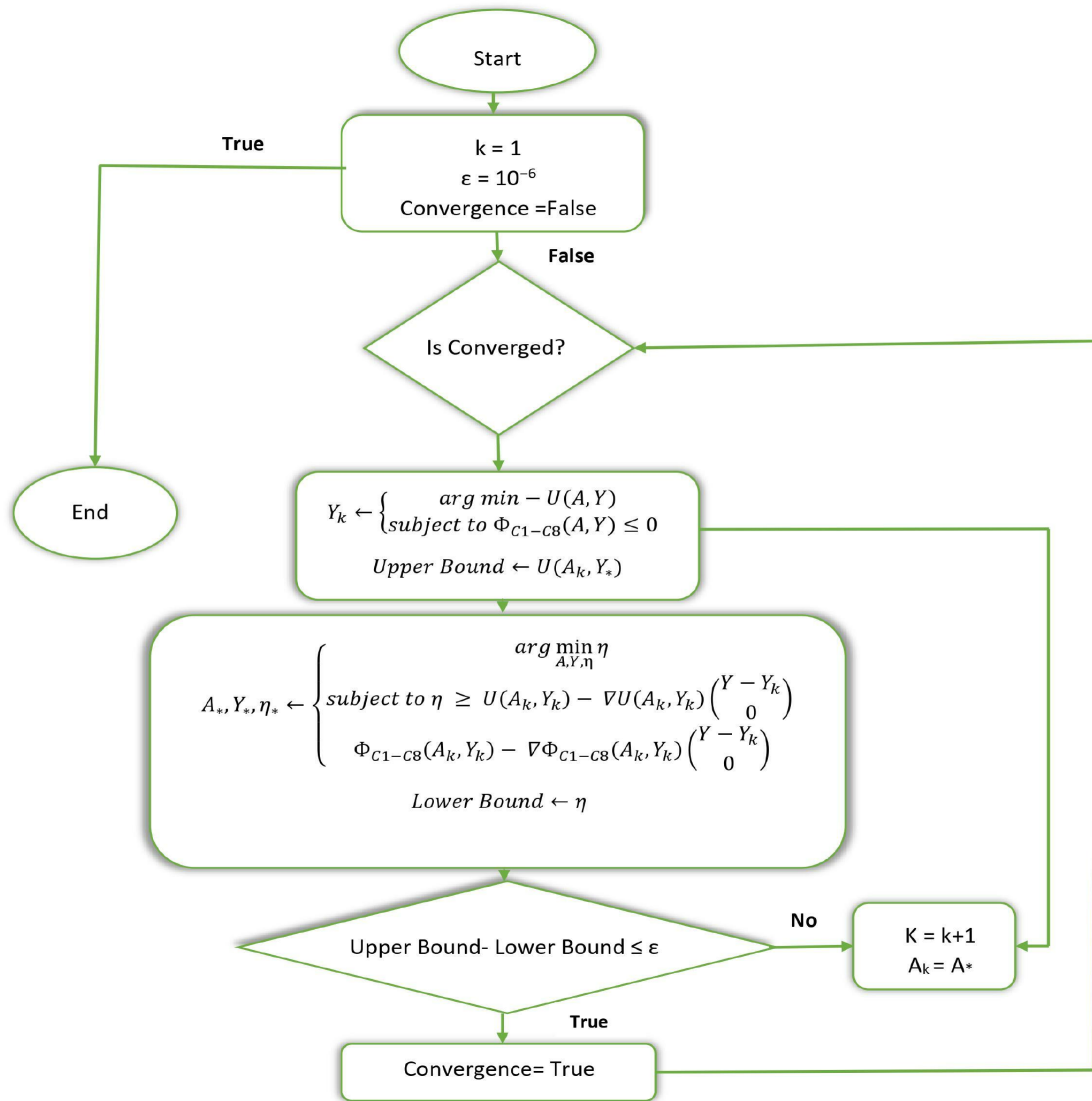
$$\mathcal{C}_{MADS} = \frac{K^2}{\varepsilon}$$

There exists a trade-off between the 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.

The Figure 3.3 shows the complexity analysis of all three algorithms.



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



**Figure 3.2:** Flow Chart of the proposed algorithm

## Numerical Simulations and Discussion

Experimental results obtained by the simulation setup, depict the performance of our proposed approach to solve a FP problem of EE and throughput of the network. The MINLP optimization problem is solved using the BONMIN solver [39].

### 4.1 Simulation Setup

Table 4.1 contains system parameters. A wireless network consisting of multiple BS with 4 antennas and 450 users with the increment of 50 users. Minimum 2 users are allowed and distributed uniformly throughout the network. BS sends the signal to RIS, having identical reflecting elements, and then to the users. As we have assumed that the direct link is weak. The maximum power assigned to  $P_c$ ,  $P_{BS}$ , and  $P_{RIS}$  is  $10^{-6}$ , 10, and 10 watts respectively. The minimum required data rates are  $\{100, 500, 1000\}$  Kbps. Set the close-in reference distance  $d_o$  according to antenna far-field to 10m, acknowledging that  $d$  must be greater than  $d_o$ . The path-loss exponent  $\alpha$  is set to 2 and the gaussian random variable having zero mean for shadowing  $\xi$  is assigned 10 dB.



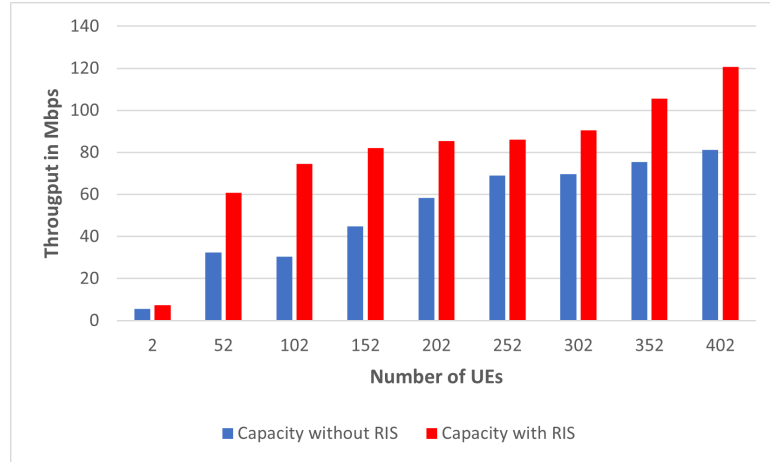
**Table 4.1:** System Parameters

Parameter	Value
M	4
N	4, 20, 100, 500
Min users	2
Max users	450
User increment	50
$P_c$	$10^{-6}$
$P_{BS}$	10W, 5W
$P_{RIS}$	10W, 5W
$r_{min}$	{100, 500, 1000} Kbps
$G_o$	50
$d_o$	10m
$\alpha$	2
$\xi$	10dB

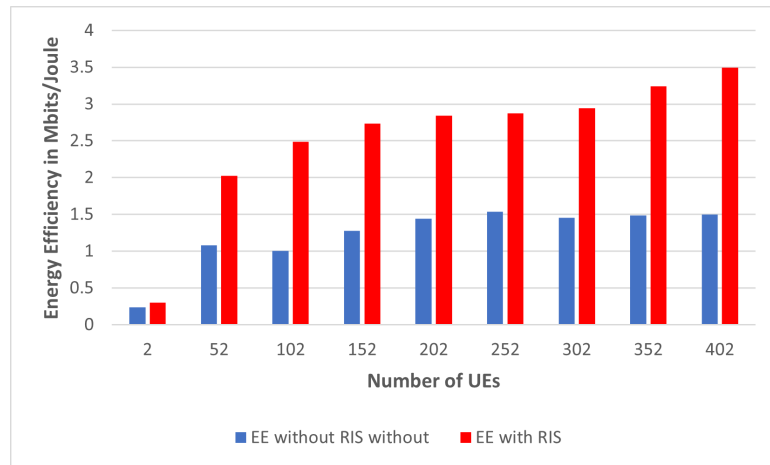
## 4.2 Results and Discussion

We examine the effect of different parameters on system performance specially two KPIs i.e., throughput and EE. Figure 4.1 shows the comparison of the system throughput in the presence of a RIS and without it. After observing the results we conclude that system throughput increases significantly in the presence of RIS when compared to conventional systems.

Figure 4.2 shows the comparison of the EE in the presence of a RIS and without it. After observing the results, we conclude the same result as that for system throughput, EE increases significantly in the presence of RIS when compared to conventional systems.



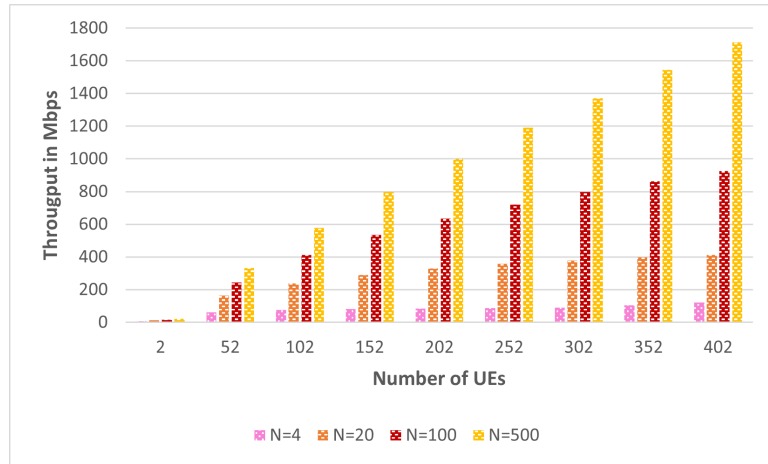
**Figure 4.1:** Throughput vs the different number of users



**Figure 4.2:** EE vs the different number of users

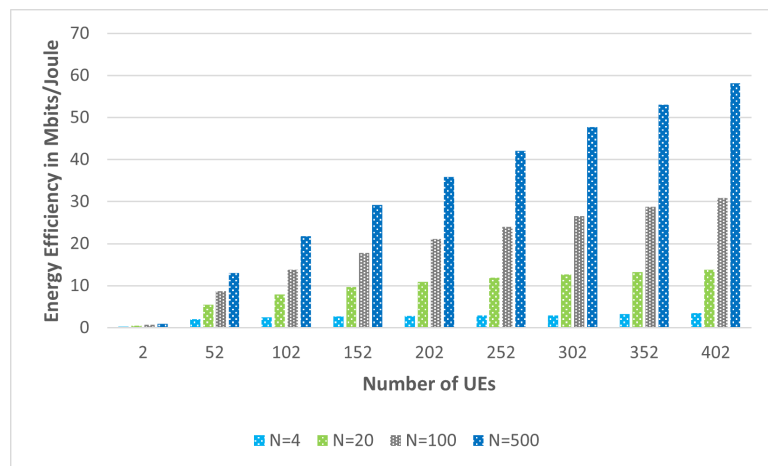
Both throughput and EE increase with the increase in the number of users. On increasing the number of users beyond a certain limit in a wireless environment, without RIS, EE slightly decreases. RIS aids in enhancing the both the KPIs of the network. We conclude from the simulation results that as the RIS is integrated into the network, throughput and EE surpasses the conventional system, under the minimum rate constraint to ensure QoS of the system. Figure 4.3 demonstrate the impact of increasing the number of RIS elements by 5x on throughput. As the number of RIS elements increases from 4 to 500 throughput

increases significantly.



**Figure 4.3:** Throughput vs the different number of users for N=4, 20, 100 and 500

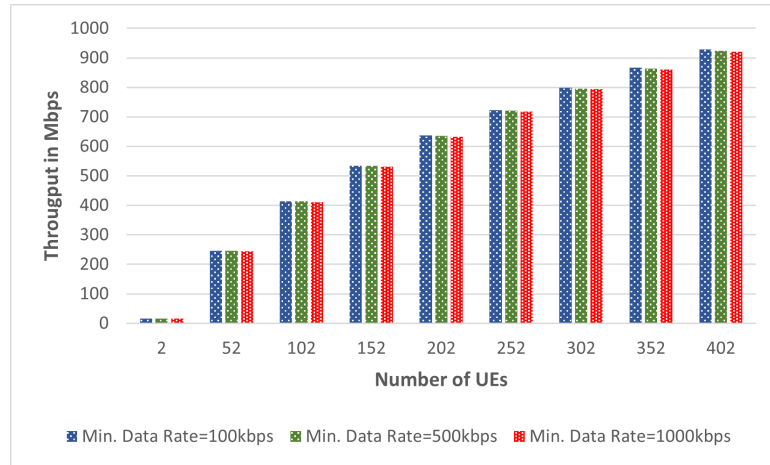
Figure 4.4 demonstrate the effect of increasing the number of RIS elements by 5x from 4 to 500 on the EE. As the number of RIS elements increases, EE also increases. Less bandwidth consumption is linked with the increase of RIS elements which increases both KPIs. Note that the increase in the number of RIS elements would result in ultimately increasing the hardware cost as well as the power consumption [32].



**Figure 4.4:** EE vs the different number of users for N=4,20,100 and 500

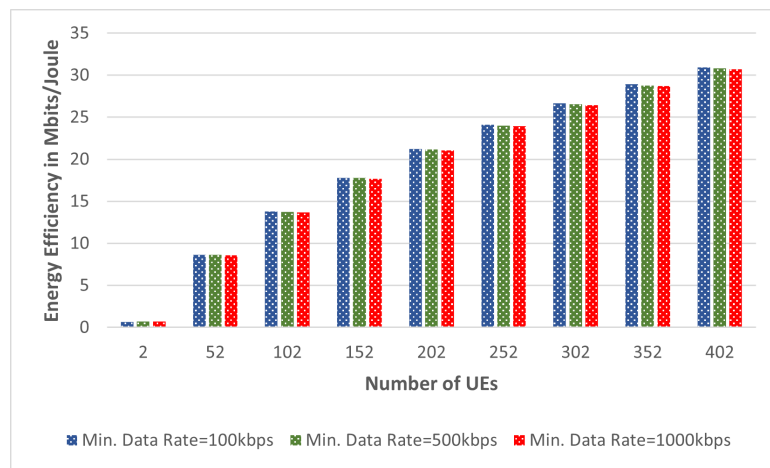
Increasing the required rate decreases the throughput. Figure 4.5 depicts throughput con-

cerning the required data rate. Throughput appears to decrease slightly as the data rate demand increases. This happens when users do not match the QoS constraints, the system rejects them. Throughput can only transfer as much data as the bandwidth allows.



**Figure 4.5:** Throughput vs the number of users, for different required data rates

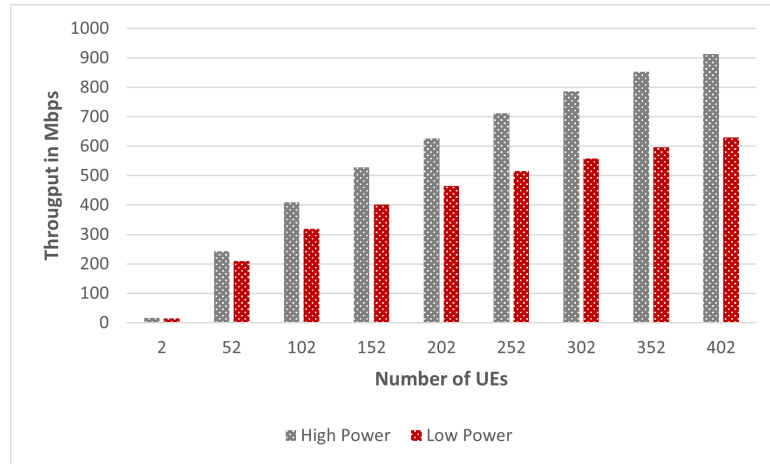
The trend suggests that EE must decrease as the data rate required increases. This is due to the reason that network denies service to the users not satisfying QoS constraints. Figure 4.6 depicts, that EE decreases as we increase the required data rate.



**Figure 4.6:** EE vs number of UEs, for different required data rates

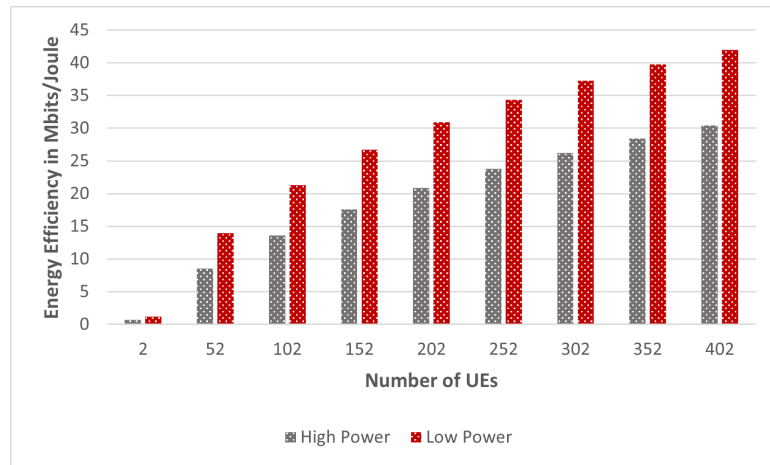
Figure 4.7 depict the impact of low power on the throughput of the system. The trend

suggests that as the power is reduced, throughput decreases.



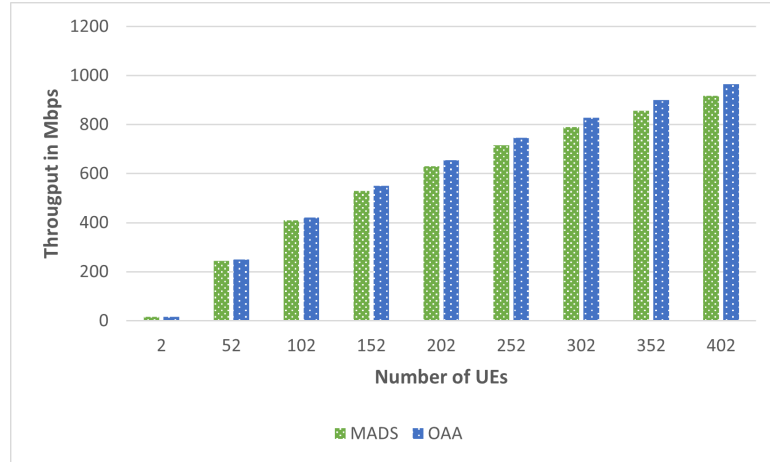
**Figure 4.7:** Decrease in throughput when power is reduced to half

Figure 4.8 shows the impact of low power on the EE of the system. The EE increases as the power is reduced to half. However, to satisfy strict QoS constraints the power must be greater than the power required to operate the network.



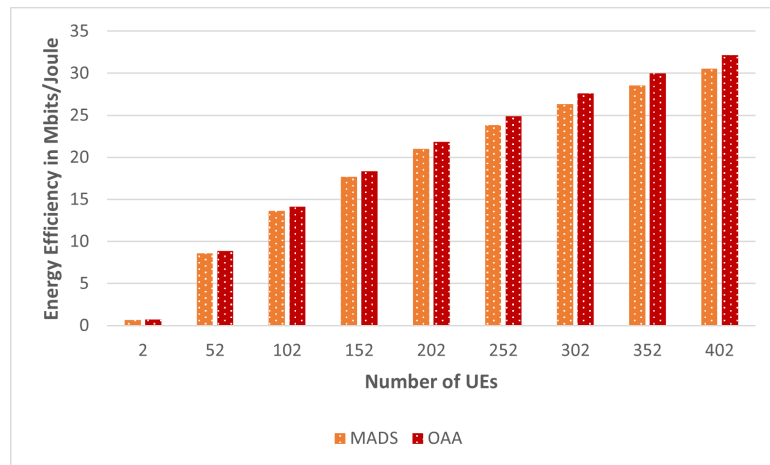
**Figure 4.8:** Increase in EE when power is reduced to half

Figure 4.9 shows the comparisons of two algorithms ( MADS and OAA ) in terms of throughput. Both the algorithms depict a similar trend but OAA shows slightly higher values of throughput than MADS algorithm.



**Figure 4.9:** Throughput-MADS versus OAA algorithm

Figure 4.10 shows two algorithms ( MADS and OAA ) are compared in terms of EE. OAA shows slightly higher values in case of EE also than MADS algorithm. This can be justified by the complexity analysis discussion in chapter 3. The improved values of the desired KPIs show the effectiveness of our algorithm.



**Figure 4.10:** EE-MADS versus OAA algorithm

# Conclusion

In this thesis, EE maximization in the RIS-aided B5G/6G network is discussed. The problem of EE maximization is concave fractional programming. We applied CCT transform to convert it into a concave programming problem. We propose OAA to solve this type of problem, which possesses lower complexity as compared to the typical approach, hence converging fast and providing an optimal solution. Simulation results suggest throughput and EE increase on increasing the number of users. For the network employing RIS, further improves throughput and EE as compared to the network without it. Increasing the number of RIS elements further improves throughput and EE. As the number of elements increases the simulation time and complexity of the problem increase. The impact of increasing the required data rate decreases both the throughput and EE. The trend suggests that low power decreases throughput but increases EE. Finally, the comparison between MADS and OAA suggests that our algorithm outperforms MADS in performance and gives better values for throughput and EE.

## 5.1 Future Work

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

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

Moreover, up-link communication scenario can be studied for the same system. System employing multiple RISs can be studied. Different algorithms can be studied for the different scenarios. Future directions for this study can also include different nature of system model incorporating different technologies like mm Wave, OFDM, SWIPT, MMIMO, and MEC etc., AI and ML approaches can also be integrated for RIS based networks.



# Bibliography

- [1] F. Rinaldi, H.-L. Maattanen, J. Torsner, S. Pizzi, S. Andreev, A. Iera, Y. Koucheryavy, and G. Araniti, “Non-terrestrial networks in 5g & beyond: A survey,” *IEEE Access*, vol. 8, pp. 165 178–165 200, 2020.
- [2] Y. Zhou, L. Liu, L. Wang, N. Hui, X. Cui, J. Wu, Y. Peng, Y. Qi, and C. Xing, “Service-aware 6g: An intelligent and open network based on the convergence of communication, computing and caching,” *Digital Communications and Networks*, vol. 6, no. 3, pp. 253–260, 2020.
- [3] Y. Liu, J. Zhao, Z. Xiong, D. Niyato, C. Yuen, C. Pan, and B. Huang, “Intelligent reflecting surface meets mobile edge computing: Enhancing wireless communications for computation offloading,” *arXiv preprint arXiv:2001.07449*, 2020.
- [4] N. Rajatheva, I. Atzeni, S. Bicaïs, E. Bjornson, A. Bourdoux, S. Buzzi, C. D’Andrea, J.-B. Dore, S. Erkucuk, M. Fuentes *et al.*, “Scoring the terabit/s goal: Broadband connectivity in 6g,” *arXiv preprint arXiv:2008.07220*, 2020.
- [5] E. Björnson, Ö. Özdogan, and E. G. Larsson, “Reconfigurable intelligent surfaces: Three myths and two critical questions,” *IEEE Communications Magazine*, vol. 58, no. 12, pp. 90–96, 2020.

- [6] X. Wei, D. Shen, and L. Dai, “Channel estimation for ris assisted wireless communications—part i: Fundamentals, solutions, and future opportunities,” *IEEE Communications Letters*, vol. 25, no. 5, pp. 1398–1402, 2021.
- [7] M. Jung, W. Saad, M. Debbah, and C. S. Hong, “On the optimality of reconfigurable intelligent surfaces (riss): Passive beamforming, modulation, and resource allocation,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 7, pp. 4347–4363, 2021.
- [8] S. Basharat, M. Khan, M. Iqbal, U. Hashmi, S. A. R. Zaidi, and I. Robertson, “Exploring reconfigurable intelligent surfaces for 6g: State-of-the-art and the road ahead,” 2022.
- [9] H. Ur Rehman, “Reconfigurable intelligent surface-assisted multi-user wireless communications systems,” Master’s thesis, 2021.
- [10] J. Zuo, Y. Liu, Z. Qin, and N. Al-Dhahir, “Resource allocation in intelligent reflecting surface assisted noma systems,” *IEEE Transactions on Communications*, vol. 68, no. 11, pp. 7170–7183, 2020.
- [11] J. An, C. Xu, D. W. K. Ng, C. Yuen, L. Gan, and L. Hanzo, “Reconfigurable intelligent surface-enhanced ofdm communications via delay adjustable metasurface,” *arXiv preprint arXiv:2110.09291*, 2021.
- [12] M. Jung, W. Saad, M. Debbah, and C. S. Hong, “On the optimality of reconfigurable intelligent surfaces (riss): Passive beamforming, modulation, and resource allocation,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 7, pp. 4347–4363, 2021.
- [13] Y. Xiu, J. Zhao, W. Sun, M. Di Renzo, G. Gui, Z. Zhang, and N. Wei, “Reconfigurable intelligent surfaces aided mmwave noma: Joint power allocation, phase shifts, and

- hybrid beamforming optimization,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 12, pp. 8393–8409, 2021.
- [14] Y. Chen, B. Ai, H. Zhang, Y. Niu, L. Song, Z. Han, and H. V. Poor, “Reconfigurable intelligent surface assisted device-to-device communications,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 5, pp. 2792–2804, 2020.
- [15] D. Xu, X. Yu, and R. Schober, “Resource allocation for intelligent reflecting surface-assisted cognitive radio networks,” in *2020 IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*. IEEE, 2020, pp. 1–5.
- [16] Q. Gu, D. Wu, X. Su, J. Jin, Y. Yuan, and J. Wang, “Performance comparison between reconfigurable intelligent surface and relays: Theoretical methods and a perspective from operator,” *arXiv preprint arXiv:2101.12091*, 2021.
- [17] D. Zhang, Q. Wu, M. Cui, G. Zhang, and D. Niyato, “Throughput maximization for irs-assisted wireless powered hybrid noma and tdma,” *IEEE Wireless Communications Letters*, vol. 10, no. 9, pp. 1944–1948, 2021.
- [18] S. Lin, B. Zheng, G. C. Alexandropoulos, M. Wen, F. Chen *et al.*, “Adaptive transmission for reconfigurable intelligent surface-assisted ofdm wireless communications,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 11, pp. 2653–2665, 2020.
- [19] Q. Wu and R. Zhang, “Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts,” *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1838–1851, 2019.

- [20] ———, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 11, pp. 5394–5409, 2019.
- [21] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 8, pp. 4157–4170, 2019.
- [22] L. You, J. Xiong, D. W. K. Ng, C. Yuen, W. Wang, and X. Gao, “Energy efficiency and spectral efficiency tradeoff in ris-aided multiuser mimo uplink transmission,” *IEEE Transactions on Signal Processing*, vol. 69, pp. 1407–1421, 2020.
- [23] K. Liu and Z. Zhang, “On the energy-efficiency fairness of reconfigurable intelligent surface-aided cell-free network,” in *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*. IEEE, 2021, pp. 1–6.
- [24] K. Wang, Z. Xiong, Z. Hu, X. Chen, and L. Chen, “Joint beamforming and phase-shifting optimization in miso with ris-assisted communication,” in *2020 IEEE/CIC International Conference on Communications in China (ICCC)*. IEEE, 2020, pp. 348–353.
- [25] Q. N. Le, V.-D. Nguyen, O. A. Dobre, and R. Zhao, “Energy efficiency maximization in ris-aided cell-free network with limited backhaul,” *IEEE Communications Letters*, vol. 25, no. 6, pp. 1974–1978, 2021.
- [26] Y. Zhang, B. Di, H. Zhang, J. Lin, C. Xu, D. Zhang, Y. Li, and L. Song, “Beyond cell-free mimo: Energy efficient reconfigurable intelligent surface aided cell-free mimo communications,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 2, pp. 412–426, 2021.

- [27] S. Jia, X. Yuan, and Y.-C. Liang, "Reconfigurable intelligent surfaces for energy efficiency in d2d communication network," *IEEE Wireless Communications Letters*, vol. 10, no. 3, pp. 683–687, 2020.
- [28] Z. Gao, Y. Xu, Q. Wang, Q. Wu, and D. Li, "Outage-constrained energy efficiency maximization for ris-assisted wpns," *IEEE Communications Letters*, vol. 25, no. 10, pp. 3370–3374, 2021.
- [29] N. A. Chughtai, M. Ali, S. Qaisar, M. Imran, M. Naeem, and F. Qamar, "Energy efficient resource allocation for energy harvesting aided h-cran," *IEEE Access*, vol. 6, pp. 43 990–44 001, 2018.
- [30] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Transactions on Wireless Communications*, vol. 18, no. 11, pp. 5394–5409, 2019.
- [31] Y. Zhang, B. Di, H. Zhang, J. Lin, C. Xu, D. Zhang, Y. Li, and L. Song, "Beyond cell-free mimo: Energy efficient reconfigurable intelligent surface aided cell-free mimo communications," *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 2, pp. 412–426, 2021.
- [32] M. Ali, S. Qaisar, M. Naeem, S. Mumtaz, and J. J. Rodrigues, "Combinatorial resource allocation in d2d assisted heterogeneous relay networks," *Future Generation Computer Systems*, vol. 107, pp. 956–964, 2020.
- [33] Y. Xiu, J. Zhao, W. Sun, M. Di Renzo, G. Gui, Z. Zhang, and N. Wei, "Reconfigurable intelligent surfaces aided mmwave noma: Joint power allocation, phase shifts, and hybrid beamforming optimization," *IEEE Transactions on Wireless Communications*, vol. 20, no. 12, pp. 8393–8409, 2021.

- [34] P. Mursia, V. Sciancalepore, A. Garcia-Saavedra, L. Cottatellucci, X. C. Pérez, and D. Gesbert, “Risma: Reconfigurable intelligent surfaces enabling beamforming for iot massive access,” *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1072–1085, 2020.
- [35] M. Ali, S. Qaisar, M. Naeem, and S. Mumtaz, “Energy efficient resource allocation in d2d-assisted heterogeneous networks with relays,” *IEEE Access*, vol. 4, pp. 4902–4911, 2016.
- [36] A. Charnes and W. W. Cooper, “Programming with linear fractional functionals,” *Naval Research logistics quarterly*, vol. 9, no. 3-4, pp. 181–186, 1962.
- [37] A. Y. Awan, M. Ali, M. Naeem, F. Qamar, and M. N. Sial, “Joint network admission control, mode assignment, and power allocation in energy harvesting aided d2d communication,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 3, pp. 1914–1923, 2019.
- [38] K. Liu and Z. Zhang, “On the energy-efficiency fairness of reconfigurable intelligent surface-aided cell-free network,” in *2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring)*. IEEE, 2021, pp. 1–6.
- [39] P. Bonami, P. Belotti, J. Forrest, L. Ladanyi, and C. Laird, “Basic open-source non-linear mixed integer programming,” *accessed on Aug*, vol. 1, 2019.