ENERGY EFFICIENT RESOURCE ALLOCATION AND TASK OFFLOADING IN SATELLITE ASSISTED INTERNET OF THINGS NETWORKS

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THESIS ACCEPTANCE CERTIFICATE

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I, **Muhammad Abdullah** declare that this thesis titled **Energy Efficient Resource Allocation and Task Offloading in Satellite Assisted Internet of Things Networks** and the work presented in it are my own and has been generated by me as a result of my own original research.

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Muhammad Abdullah,
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DEDICATION

This thesis is dedicated to

MY ADMIRABLE PARENTS AND DEAR SISTER,

HONORABLE TEACHERS AND FRIENDS

whose unwavering affection, boundless assistance, and

unwavering motivation have been the cornerstone of my journey

ACKNOWLEDGEMENTS

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NOTATIONS

Definitions	Notations
Set of IoT devices	$\mathbf{I}$
Set of cloudlets	$\mathbf{J}$
Set of data files stored	$\mathbf{S}$
Set of data files computed	$\mathbf{C}$
Admission indicator	x_i
Association indicator	$y_{i,j}$
IoT fairness index	$\alpha_{i,j}$
Max power of IOT device	P_i
Power allocated by IoT device in the UL	$p_{i,j}$
Channel gain between IoT device and LEO-cloudlet	$h_{i,j}$
Antenna gain	G
Transmit Antenna gain of IoT device	G_i^{Tx}
Receive Antenna gain of LEO-cloudlet	G_j^{Rx}
Minimum QoS data rate	$\Psi_{i,j}$
Maximum allowed QoS latency	$D_{i,j}$
Minimum QoS UFI	Q_{UFI}
QoS rate requirement of user	Q_u
Minimum QoS RFI	Q_{RFI}
Attenuations in Channel	$\xi_{i,j}(t)$
Channel Bandwidth	$b_{i,j}(t)$
Number of Resource Block	$\gamma_{i,j}(t)$
Signal to interference and Noise Ratio	$\Phi_{i,j}(t)$
Intensity of Rain Fall	$\Re^{\mu_r}$
Total circuit power	P_c
Zero mean Gaussian random variable	ξ
Rayleigh random variable	$\bar{g}$
Gaussian white noise variance	σ^2
propagation delay	$l_{i,j,\rho}(t)$
Total RBs available	T_{RB}
ESA's computational complexity	$Ç_{ESA}$
OAA's computational complexity	$Ç_{OAA}$

ACRONYMS

Definitions	Abbreviations
Geosynchronous Earth Orbit	GEO
Earth Station	ES
Low Earth Orbit	LEO
Internet of Things	IoT
Satellite Assisted Internet of Things	S-IoT
Inter Satellite Links	ISL
3^{rd} generation	$3G$
4^{th} generation	$4G$
Long Term Evolution	LTE
5^{th} generation	$5G$
Resource Blocks	RBs
Quality of Services	QoS
Quality of Experience	QoE
Energy Efficiency	EE
Radio Access Network	RAN
Base Station	BS
User Equipment	UE
Information Communication Technology	ICT
Tracking, Telemetry, and Command	TTC
Effective Isotropic Radiated Power	$EIRP$
Mixed Integer Non-Linear programming	$MINLP$
Non-Linear Programming	NLP
Mixed Integer Linear Programming	$MILP$
Non-deterministic polynomial-time hard	$NP-Hard$
Charnes Cooper Transformation	CCT
Concave Fractional Programming	CFP
Outer Approximation Algorithm	OAA
Exhaustive Search Algorithm	ESA
Basic Open-source Nonlinear Mixed Integer Programming	$BONMIN$
Floating-point Operation	$Flop$
Cycle Per Unit	CPU
Task Nodes	TNs
Upper Bound	UB
Lower Bound	LB

ABSTRACT

Satellite-assisted IoT networks have emerged as a promising solution to provide global coverage and seamless connectivity. However, resource allocation and task offloading in such networks pose significant challenges due to the unique characteristics of satellite communication systems. The findings of this research contribute to the development of energy-efficient and reliable satellite-assisted IoT networks. The work investigates the impact of different Quality of Service (QoS) requirements on resource allocation and task offloading strategies. It explores the trade-offs between energy efficiency, network throughput, and fairness in the distribution of resources among IoT devices. The proposed techniques OAA can enable seamless connectivity and efficient utilization of resources.The problem under consideration is a concave fractional programming problem that is transformed into a concave optimization problem using the Charnes-Cooper transformation. To solve this concave optimization problem, an innovative outer approximation algorithm is employed.The performance of the epsilon-optimal solution is evaluated by executing the algorithm with different system parameters, such as the number of IoT devices, their association, fairness among devices, and resource block fairness.

Chapter 1

INTRODUCTION

These days, Internet of Things (IoT) devices are an integral part of our daily lives. The conveniences brought by the development of smart technologies and applications are increasing. More power is used by the numerous continuously running apps that are driven by communicated information than by non-intelligent devices [1]. In recent years, cloud computing has been put to use in a broad range of contexts, from cloud radio access networks (C-RANs) to heterogeneous networks (HetNets) to vehicle ad hoc networks (VANETS) to social networks.

The board aims to respond to questions about energy use and real-time communication after receiving several scientific proposals. While storing information in a centralized cloud server has numerous advantages, there are also some drawbacks to this kind of computing, managing the increased traffic, longer processing times, more energy consumption, and higher costs is becoming increasingly difficult for fifth-generation networks. Globally dispersed communication networks are a major contributor to the rapid rise in energy use. Carbon emissions from the world's telecommunications companies are estimated to be about 3 percent of the total.

Geosynchronous Earth Orbit (GEO), Medium Earth Orbit (MEO), and Low Earth Orbit (LEO) are the three main categories that may be used to categorise the present satellite based communication system. In the future, integrated satellite and terrestrial networks will rely heavily on low-earth-orbit (LEO) satellites because they have the lowest engendering delay of the three satellite framework types.Recent corporate and standardization efforts suggest that satellite communication systems will serve as a driving force behind the next generation of wireless networks, 5G, which will be able to provide ubiquitous, high-speed Internet access [2].

IoT networks in cities might use 3G, 4G, or 5G to gather data. Using LEO satellites in conjunction with global access networks enables geo-distributed Internet of Things networks. IoT gateways based on low-Earth orbit satellites have a hard time caching data [3]. Satellite base communication framework can give extraordinary adaptability as they can be conveyed without geological requirements not just in remote or normal catastrophe hit regions yet additionally in regions previously having correspondence infrastructure to decongest terrestrial wireless networks. Wireless communication networks are on the cusp of an unrest and internet of Things (IOT) method is being normalized and anticipated worldwide deployment. It is well understood that existing and future networks will soon have to deal with the incessant traffic demands of end-client devices. As a result, it's become crucial to make sure that all areas of the world have access to high-speed Internet. There have been significant advancements in terrestrial technology, but many areas, especially in provincial or other hard-to-serve locations, are still too far for the constrained earthbound backhaul network structure.

As the number of linked devices in the IoT grows by the thousands every day, optimising energy efficiency offers a viable solution for addressing the need for more effective use of all networked assets and for reducing energy consumption overall. [4]. For handling IoT applications that require low latency, green fog computing offers promising solutions. However, in order to prevent dormancy in fog computing, novel resource allocation and network modelling techniques are needed for power assignment, energy utilization, reserving, cost, delay, and other issues.

The main motivations for this effort are to increase cache availability, storage capacity on fog nodes, energy efficiency, and connect them with GEO/LEO. We will figure out a decency fairness aware planning issue to limit the most extreme undertaking execution delay among IoT devices, by means of mutually upgrading the affiliation control, transmission power and data transfer capacity distribution.

1.1 Significance Advantages of Satellite IoT

Satellites can play an important role in supporting IoT networks, especially in remote or rural areas where terrestrial networks may not be available or reliable. Satellite IoT networks can provide global coverage, which is essential for applications that need to track assets or monitor conditions in remote areas.

There are a number of reasons why satellite IoT is significant. Some of the most important reasons include:

- **Global coverage**: Satellite IoT networks can provide global coverage, which is essential for applications that need to track assets or monitor conditions in remote areas.

- **Long battery life**: Satellite IoT devices can have long battery life, which is important for applications where it is difficult or impossible to replace batteries, such as in environmental monitoring or asset tracking applications.

- **Reliable connectivity**: Satellite IoT networks can provide reliable connectivity, even in areas where terrestrial networks are unreliable or unavailable.

- **Low cost**: Satellite IoT can be a cost-effective solution for applications that require global coverage, long battery life, and reliable connectivity.

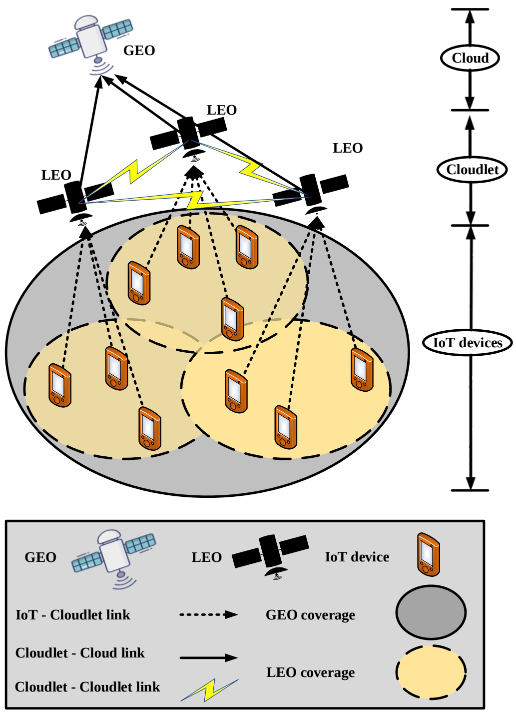

Figure 1.1: **LEO/GEO Architecture**

1.2 Applications of S-IoT

Satellite IoT can be used in a wide range of applications, including:

- **Asset tracking**: Satellite IoT can be used to track assets, such as vehicles, containers, and livestock. This can help to improve efficiency and reduce costs.

- **Environmental monitoring**: Satellite IoT can be used to monitor environmental conditions, such as air quality, water quality, and climate change. This can help to protect the environment and improve public health.

- **Security and surveillance**: Satellite IoT can be used for security and surveillance applications, such as border control, maritime surveillance, and wildlife monitoring. This can help to protect people and property.

- **Smart cities**: The utilization of Satellite IoT presents an opportunity to engender intelligent urban landscapes, colloquially referred to as ”smart cities”. These urban ecosystems harness the potential of cutting-edge technologies to augment the efficacy of various services, encompassing the domains of transportation, energy, and waste management. The integration of these innovative solutions holds the promise of ameliorating the overall quality of life for denizens, engendering a harmonious coalescence of convenience, sustainability, and holistic well-being.

1.3 Energy Consumption in Satellite IoT Networks

The energy consumption of satellite IoT networks is affected by a number of factors, including:

- **The distance between the IoT device and the satellite**: The further the distance, the more power is required to transmit data.

- **The data rate**: The higher the data rate, the more power is required to transmit data.

- **The type of modulation and coding scheme**: Different modulation and coding schemes have different energy efficiencies.

- **The efficiency of the satellite terminal**: The efficiency of the satellite terminal can vary depending on the design and manufacturing process.

1.3.1 Approaches to Reducing Energy Consumption in Satellite IoT Networks

There are a number of approaches that can be used to reduce energy consumption in satellite IoT networks. Some of the most promising approaches include:

- **Power control**: Power control is a technique that can be used to reduce the transmission power of IoT devices. This can be done by adjusting the transmission power of the IoT device based on the distance to the satellite and the required data rate.

- **Data rate adaptation**: Data rate adaptation is a technique that can be used to adjust the data rate of the IoT device based on the available bandwidth and the required data rate. This can be done by reducing the data rate of the IoT device when the available bandwidth is low.

- **Cooperative communication**: Cooperative communication is a technique that can be used to improve the energy efficiency of satellite IoT networks by allowing IoT devices to communicate with each other without going through the satellite.

- **Sleep mode**: Sleep mode is a technique that can be used to reduce the energy consumption of IoT devices by turning them off when they are not in use.

1.4 Energy Efficiency

Energy Efficiency (EE) is delineated as the quotient derived from the division of the quantum of transmitted bits emanating from a given node vs the quantum of energy expended in terms of watts over a specific temporal interval.

$$EE = \frac{R_B}{P_T} \tag{1.1}$$

Herein, the symbol R_B signifies the data rate expressed in terms of bits per second, while P_T designates the aggregate power consumption measured in watts. Ergo, the unit of Energy Efficiency (EE) manifests itself as bits per second per watt or alternatively as bits per joule.

1.5 Energy Efficient Resource Allocation in S-IoT

Energy efficient resource allocation is a critical challenge in satellite assisted IoT networks. The goal of energy efficient resource allocation is to maximize the network lifetime, which is the time until the battery of the last IoT device dies.

There are a number of factors that can affect the energy efficiency of satellite assisted IoT networks, including:

- The distance between the IoT device and the satellite
- The transmission power of the IoT device
- The bandwidth of the satellite link
- The data rate of the IoT device
- The type of modulation and coding scheme used

1.5.1 Resource Allocation Schemes

There are a number of different resource allocation schemes that can be used to improve the energy efficiency of satellite assisted IoT networks. Some of the most common resource allocation schemes include:

- **Power Control**: Power control is a technique that can be used to reduce the transmission power of IoT devices. This can be done by adjusting the transmission power of the IoT device based on the distance to the satellite and the required data rate.
- **Bandwidth allocation**: Bandwidth allocation is a technique that can be used to distribute the available bandwidth of the satellite link among the IoT devices. This can be done by assigning different amounts of bandwidth to different IoT devices based on their priority or their distance to the satellite.
- **Data rate adaptation**: Data rate adaptation is a technique that can be used to adjust the data rate of the IoT device based on the available bandwidth and the required data rate. This can be done by reducing the data rate of the IoT device when the available bandwidth is low.

1.5.2 Challenges

There are a number of challenges that need to be addressed in order to develop effective energy efficient resource allocation schemes for satellite assisted IoT networks. Some of the most important challenges include:

- **Heterogeneity**: IoT devices are heterogeneous in terms of their energy consumption, data rate requirements, and mobility. This makes it difficult to develop a single resource allocation scheme that can meet the needs of all IoT devices.

- **Limited feedback**: IoT devices often have limited feedback capabilities, which makes it difficult to accurately estimate the channel conditions and the energy consumption of the IoT devices.

- **Dynamicity**: The traffic patterns in satellite assisted IoT networks are often dynamic, which makes it difficult to develop static resource allocation schemes.

Energy-efficient resource allocation poses a formidable predicament within the realm of satellite-assisted IoT networks. Various resource allocation strategies abound, aiming to enhance the energy efficiency of said networks. Nonetheless, the development of efficient and effective resource allocation schemes in the context of satellite-assisted IoT networks demands meticulous attention to a multitude of challenges.

1.6 Related Work

Table 1.1: **Literature Review and Novelty**

System Parameters	[5] **2021**	[6] **2021**	[7] **2021**	[3] **2020**	[8] **2019**	[9] **2021**	[10] **2022**	[11] **2022**	[12] **2022**	[13] **2021**	[14] **2021**	[15] **2021**	[16] **2020**	Our Work
Transmission in UL				✓	✓					✓			✓	✓
IoT Admission														✓
IoT Association	✓		✓							✓			✓	✓
Power limit	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Geo satellite (cloud)	✓	✓	✓								✓	✓		✓
Leo satellite (cloudlet)	✓	✓	✓							✓		✓	✓	✓
Effect of Rain														✓
Movement of Satellite														✓
Processing delay				✓			✓			✓	✓	✓	✓	✓
Transmission delay			✓	✓							✓	✓	✓	✓
Propagation delay						✓							✓	✓
Queuing delay													✓	✓
Cache enabled									✓		✓	✓	✓	✓
Data computation									✓		✓	✓		✓
Data storage									✓		✓	✓	✓	✓
Fair IoT distribution														✓
Fair RBs distribution														✓
Energy efficiency	✓						✓	✓			✓	✓		✓

In Paper [5], the author examined global connectivity's difficulties and possible solutions. To achieve this objective author proposed a 5G smart connectivity platform. The platform's pervasive networking features can manage service lifespan. Because of the platform's automation, all of this is feasible at little cost. We need satellites, UAVs, and long-range, low-power IoT network technology to bring 5G cellular coverage to the sky, sea, and other unreachable locations. Reliable service requires integrating these technologies. In reference [6], In this article, the author takes a look at a satellite communication system that uses both GEO and LEO satellites. A joint beam management and power allocation (JBMPA) strategy was presented by the author to improve SINR and reduce the likelihood of outages. Allocating transmit power for active LEO satellites is a challenging problem, and this paper proposes using a deep Q-network (DQN) to help with the process. Applying the non-orthogonal multiple access (NOMA) technique to a frequency coexistence setting improves spectral efficiency. To effectively analyze system performance. A theoretical formulation of the ergodic capacity derivable in terms of Meijer-G functions was developed by the author of Reference [7], who studied the capacity performance of a two-layer GEO/LEO satellite network. Authors in [5, 6, 7] explore IOT association for GEO LEO satellite base networks. However these research articles doesn't consider any fairness in IOT distribution and delays for establishing the data access.

In paper [3], In this article, the author investigates the possibility of offloading work in hybrid GEO-LEO satellite networks through the use of cooperative user association and resource allocation. The complex problem is split into two more manageable ones: first, ensuring efficient task scheduling, and second, ensuring dynamic user association and the most efficient use of all available communication and processing resources. Then, CUARA is suggested, which makes use of DRL. The author came up with a combined optimization for power allocation and sub-band assignment to boost IoT cellular networks' throughput in Reference [8]. Two new methods for sub-band allocation and power regulation are proposed, each with a two-stage optimization process that takes into account the effect of spectral leakage. The author of reference [9] formulated the resource allocation problem for a QKD network that uses both GEO and LEO satellites as trusted repeaters to generate secret keys used in GS pair-to-pair encryption key exchanges through the BB84 protocol with decoy-state. The topic author has offered two sub-optimal strategies for achieving the goal of minimizing total energy use. One method for reducing computing time is to examine how task processing time relates to overall energy usage. Another way is to use a low-complexity heuristic resource allocation technique utilizing Hessian matrices. Author proposes relay selection and power allocation to improve energy efficiency and load balancing in RLNC D2D communications supporting HetNets in reference [11]. Because simultaneously optimising for both energy efficiency and load balancing is so challenging, the author simplified the issue into a ”pseudo-optimal” single-objective optimization. Authors in [3, 8, 9, 10, 11] investigate transmission in upper link but we are not connecting IOT and its fairness distribution via satellite Link.

In reference [12] for combination work offloading and software cache optimization author proposed an iterative technique. The author proposed a computation-based multi-tier system in which task nodes (TNs) offload their work to neighbouring massive MIMO-aided relay nodes (MRNs) with slack cache resources. Caching frequently used services again decreases the delay of task execution. A low-latency edge computing service for IoT devices provided by flying UAVs and ubiquitous cloud access is provided by satellites, as the authors in [13] evaluated. We jointly scheduled association control, computing job allocation, transmission power and bandwidth allocation, computation resource allocation for autonomous aerial vehicles (UAVs), and deployment position optimization to reduce the maximum calculation delay among IoT devices. The authors created a new alternating optimization technique that guaranteed to converge based on block coordinate descent and sequential convex approximation. In reference [14] The author has formulated a constrained optimization problem titled ”Joint Node Association and Energy Efficiency (JNAEE) maximization” specifically tailored for IoT-Fog networks. This problem takes into account optimal power allocation and node association while adhering to constraints related to latency and data rate. The author found a suboptimal solution using a simple linearization strategy based on mesh adaptive direct search (MADS). For latency minimization, in [15] authors have proposed Outer Approximation Algorithm (OAA). A mixed-integer non-linear programming kind of joint optimization problem is discussed here. Power allocation, admission control and Cloudlet selection are all taken into account simultaneously in the defined issue. In paper [16], for fog networks, made possible by the cache, the author posed the issue of combined resource and power allocation. The problem posed can be categorized as an NP-hard mixed-integer non-linear programming problem (MINLP). The suggested challenge aims to minimize end-to-end energy consumption by addressing issues including QoS constraints, cache capacity, under power, and network latency. Network KPIs including throughput, number of connected devices, and minimum requirements for data rates and latency are used to measure the success of the suggested algorithm. Consider data processing delays or use GEO LEO without fairness of distribution in [12,14,14,15,16] delays for approaching cloud and cloudlet, data computation and storage while making connection via satellite but we are not bounded by fairness of IOT distribution and this is our research gap. This is summarized in Table 1.1.

1.7 Motivation and Contributions

Looking at the summary of the past work presented in Table 1.1, we are focusing on the resource allocation and task offloading challenge where IoT devices intends to associate with LEO-cloudlets in the UL, transmit data files for storage and computation at LEO-cloudlets, to offload their of where

Given the complex nature of the challenges at hand, we put forth a novel approach aimed at enhancing processing, communication, and caching capabilities within large Multiple-Input Multiple-Output (MIMO)-enabled Mobile Cloud (MC) systems. This method is designed to effectively tackle and overcome the aforementioned obstacles. However, offloading work adds some overhead due to the interaction required between mobile devices and processing servers. Due to the adverse effects on energy usage and latency introduced by this additional communication requirement, we focus on it extensively in our research. We describe a multi-tier computation-based system that uses sizeable MIMO-aided relay nodes (MRNs) with unused caching resources to address these problems. Offloading jobs from TNs to MRNs nearby not only allows for more effective task execution but also makes use of caching frequently used services to cut down on latency. We can jointly optimize the allocation of computing resources and service caching by considering the complex interplay between task execution delay, service caching, and optimal power allocation. The resulting non-convex optimization problem makes it difficult to find a unique solution. We suggest a specialized alternating optimization method that separates the optimization of network traffic, data storage, and processing to address this difficulty. Using this method, we can address the issue of allocating MRN power in conjunction with offloading tasks and caching software packages. We have devised an iterative technique to optimize work offloading and software caching further. 1.1 outlines these original contributions and shows how they differ from the current gold standard in important ways. In sum, our research offers a novel approach to the simultaneous enhancement of computational, communicative, and caching capabilities in MC systems that use massive MIMO. The proposed techniques and algorithms pave the way for significant advancements in enhancing system performance and addressing the challenges posed by resource allocation in such complex environments.

1. Our study involves the development of multi-tier task scheduling and service caching systems, which are supported by large-scale MIMO technology. Nearby MRNs set up compute and caching nodes (CCN) to store copies of frequently used services. We develop a system for efficient task execution based on this strategy, which executes task offloading along with service caching and communication resource allocation.

2. In light of the inherent complexity arising from the NP-hard nature of the joint task scheduling and service caching optimization problem, we introduce an alternative optimization methodology. Our proposed approach aims to address the intricate challenge associated with task offloading, service caching, and power allocations. To effectively tackle the original joint optimization problem, we decompose it into three discrete subproblems: task offloading, service caching, and MRN power allocation.

3. To solve the power allocation subproblem, we transformed it into a linear optimization problem. Then, we utilized the Lagrange partial relaxation method to loosen restrictions on task offloading and caching. It led to the formulation of the dual dilemma, where we had to make choices about both simultaneously. Our research resulted in an iterative optimization method that finds the best combination of power management, task offloading, and software caching. We also provide formal evidence of the method's convergence.

4. By conducting extensive and meticulous simulations, we thoroughly evaluate the effectiveness of the proposed large-scale Multiple-Input Multiple-Output (MIMO) augmented multi-tier Multi-Carrier (MC) systems. The simulation outcomes demonstrate the substantial superiority of the suggested algorithm compared to conventional approaches across a wide range of system configurations and scenarios.

1.8 Thesis Organization

Thesis is structured into six chapters as shown in Figure 1.2. Chapter wise details are as follows:

Chapter: 2 Satellite Assisted Internet of Things (S-IoT) Network in 5G This chapter focuses on the crucial aspects of fairness in IoT device association (IoTA) and spectrum allocation for the maximization of energy efficiency (EE) in heterogeneous networks enhanced with GEO satellites. The objective is to ensure ubiquitous global access to IoT devices within the network, regardless of time and location. These challenges serve as the foundation for the proposed solutions in subsequent sections of the thesis. A comprehensive examination of joint admission control, IoTA, and power allocation is conducted to address the goal of achieving fairness in IoT device association in hybrid LEO/GEO satellite networks, as well as ensuring fairness in the allocation of spectrum resources to associated IoT devices. The ultimate aim is to maximize EE in hybrid LEO/GEO satellite networks and attain optimal solutions for enhanced performance in terms of energy efficiency.

Chapter: 3 System Model and Problem Formulation This chapter delves into the communication model specifically designed for GEO/LEO satellite networks, aiming to provide IoT devices within the network with ubiquitous global access, particularly in remote areas lacking conventional telecom infrastructure. The model encompasses various communication links, encompassing both LEO and GEO satellites. A comprehensive mathematical model is formulated to address the hybrid GEO/LEO scenario, incorporating fairness-based admission control, IoT device association (IoTA), power distribution, and the maximization of energy efficiency (EE) in the uplink (UL) transmission. The ultimate objective of the proposed optimization model is to maximize EE, ensuring optimal resource utilization and performance enhancement in the network.

Chapter: 4 Proposed Algorithm In this chapter, the ϵ-optimal algorithm is leveraged to tackle the challenges posed by fairness in IoT device association (IoTA) and spectrum allocation, with the primary goal of maximizing energy efficiency (EE) in the hybrid LEO/GEO Satellite network. The algorithm's execution showcases the attainment of ϵ-optimum solutions using the outer approximation algorithm (OAA) across various system parameters, including IoT device association (IoTA), IoT fairness (IoTF), resource block (RB) fairness, and energy efficiency (EE). Through this analysis, the effectiveness and performance of the proposed solutions are demonstrated, shedding light on the achieved levels of fairness and efficiency within the hybrid LEO/GEO Satellite network.

Chapter: 5 Simulations and Results This chapter presents the simulation results that demonstrate the benefits of the proposed algorithm, as discussed in **chapter:4**, in achieving fairness-based admission control, IoT device association (IoTA), power distribution, and maximization of energy efficiency (EE). The obtained results not only highlight the advantages of the proposed algorithm but also offer valuable insights into its convergence behavior. By analyzing these simulation results, a comprehensive understanding of the algorithm's effectiveness and performance is gained, further validating its ability to address the objectives of fairness, optimal IoT device association, efficient power distribution, and EE maximization.

Chapter: 6 Conclusion This section provides a concise summary of the contributions made in this thesis. The dissertation's structure and organization are visually presented in Figure 1.2, illustrating the logical flow of the research and the arrangement of its various components.

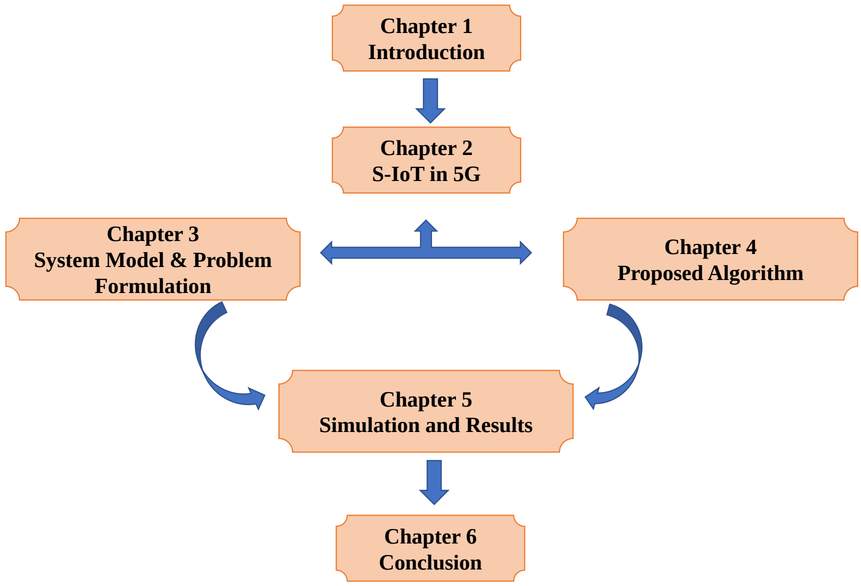

Figure 1.2: **Thesis organization**

Chapter 2

Satellite Assisted Internet of Things (S-IoT) Network in 5G

2.1 Internet of Things (IoT)

Information and data can be sent, received and shared seamlessly through Internet of Things (IoT). IoT is a connection of multiple physical devices over internet. IoT basically increases comfort, convenience and efficiency of users by automating tasks. IoT empowers physicals devices to perform task with a very negligible human effort. IoT is predominant in current and next era of communication due to its applications. Privacy, security, authentication is very vital in IoT applications because of exponentially growing cyber threats and attacks and IoT architecture also recovers some amendments to make it secure and safe for its users and maintain privacy of users. It is important to identify possible threats and designing architecture accordingly.

2.1.1 Evolution and Growth of IoT Devices

Connection of physical devices over internet around us is increasing briskly. Number of connected devices was 8.4 billion in 2020 and this number will raise to 20.4 billion in 2022 according to Gartner report [17]. Machine to machine (M2M) connections will increase from 5.6 billion to 27 billion between 2016 and 2024. Increase in these numbers is making IoT vast upcoming market important for digital economy. Revenue generated by IoT industry in 2018 was 892 billion and is expected to be 4 trillion in 2025 [18]. Smart cities, smart farming, smart retail and smart grid are few examples of machine to machine (M2M) connectivity [19]. Figure 2.1 shows evolution in architecture of IoT.

As shown in Figure 2.1 in future devices will not be only connected through internet but also able to communicate directly without any cloud or fog node. Another emerging concept is Social IoT (SIoT) through which socially networked users can share devices over internet [20].

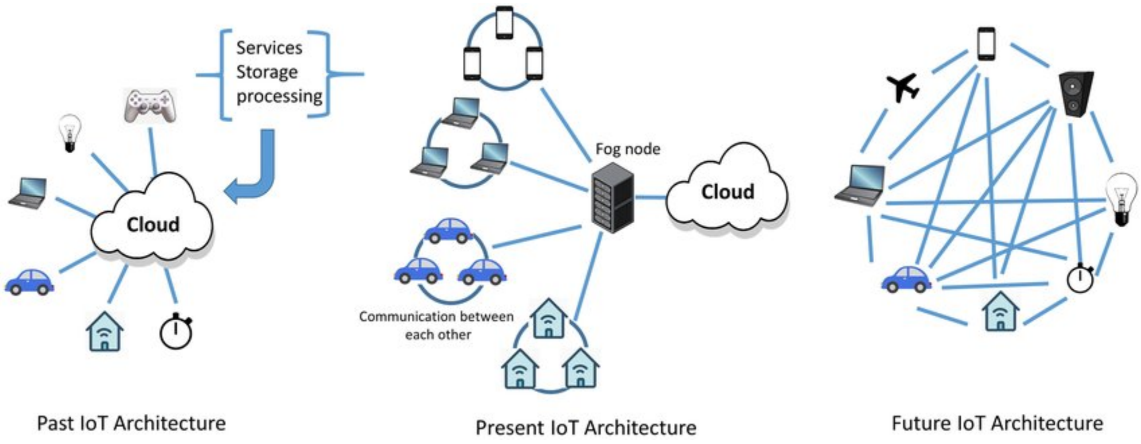

Figure 2.1: **Architecture of IoT**

With vast stretched applications, IoT also faces security and privacy issues. Without trustworthy security and operability IoT applications and ecosystem, significance of IoT will be overlooked. Devices networked in IoT are widely dependent on hardware and software and hold certain shortcomings that increases urge of careful provisioning regarding security measures. IoT may have heterogeneous technologies that makes it strenuous to secure and surges attack surface. These issues make IoT difficult to secure than securing normal Information Technology (IT). As IoT is widely dependent on internet, cellular data and WSNs their security issues will create security, privacy and authentication challenges in IoT.

IoT applications have already faced various security attacks across the globe. In Mirai attack, Distributed Denial of Service (DDoS) attack was launched on almost 2.5 million connected devices. Hajime and Reaper were almost same type of botnet attacks [21]. Due to diversity of technology used in IoT vulnerability scale has been highly increased giving more room and making it easy for attackers. IoT is now more than just connection of things or devices because implantable devices are being used to monitor organs of human body and medical information and data gathering for medical purpose this info and data can be accessed and altered by attackers and this attack could be swear. Although this type of attack in which implantable devices are compromised didn't took place yet but this threat could not be overlooked [22].

Growth of IoT highly benefitted Cyber Physical Systems (CPS) in which physical devices are monitored according to physical changes. CPS is important asset to power grids and transportation systems and vulnerabilities in theses systems can cause serious damage.

IoT ecosystem consist of four important layers. First layer includes sensors and actuators with varying functionalities for data and info perception. Second layer is communication layer for transmitting perceived data. Third layer is middleware connecting network and application layer and fourth layer consists of end-to-end applications. Each layer has its own specific security challenges apart from these challenges the gateways connecting these layers and responsible for movement of data also have their specific vulnerabilities.

2.1.2 Applications and Use Cases of IoT Devices

IoT applications are rapidly growing and becoming a vital part of modern-day technology industries. As a result, security for these applications is also paramount. While developers of these applications may provide rigid security features, this does not guarantee the security of IoT applications.

2.1.2.1 Security Critical IoT Applications

Some of the security critical IoT applications are discussed below:

Smart Cities

To improve quality of living, governments across the globe are enforcing and implementing concept of smart cities which include smart homes, smart utilities, smart traffic and disaster management. Smart cities involve vast computation and communication resources. Smart application along with improving quality and convenience of living raise some serious security threats like putting card details of users at risk, location tracking application could be lethal if hacked.

Smart Environment

IoT application such as monitoring snow level, earthquake detection, fire detection in forests, preventing land sliding and weather forecast are a part of smart environment. Security regarding smart environment is very critical because these applications are directly related to life of human beings. Any vulnerability or security can generate false positives and false negatives, and both could cause a serious damage. Precision of these applications is very crucial. Let's say if an application fails to detect earthquake it will cause loss of property and life and if it predicts earthquake falsely it will lead to monetary losses.

Smart Metering and Smart Grids

Smart metering includes applications like electric power consumption monitoring and measurement also this application has proved itself a helping hand against electricity theft. Smart metering applications are used in water level, gas level and oil level in storage tanks. Smart metering is also used in solar energy plants for monitoring and optimization.

Security and Emergencies

This IoT application is used in factories and industrial areas depending on sensitivity of products, materials and chemicals for generating alarms in dangerous situations, detection of leakage of hazardous gas or liquors and generating alarms when radiation level is high. Vulnerabilities and breach in such applications could seriously harm human life such as false radiation level alarm could lead to serious disease.

Smart Agriculture and Farming

Saving farmers from monetary losses and achieving high yield by selective irrigation in dry zone, controlling humidity and temperature levels has been possible using smart agriculture and farming application of IoT. On other hand if these applications are compromised it will affect health of animals and yield of crops and could also lead to theft.

Home Automation

Home automation application of IoT includes remotely controlling electricity appliances, intrusion detection on entrances and exits (i.e doors, windows) and monitoring energy and water consumptions to save resources. But if attacker gains access to IoT devices it will be easy to harm residents.

2.1.2.2 Security Threats in IoT Applications

IoT applications use diverse technology and as discussed earlier IoT application is divided in to four layers: sensing layer, network layer, middleware layer and application layer. Each of these layers possess certain security threats and these threats are discussed in this section

Sensing Layer

IoT application consist of sensors and actuator and these devices work at sensing layer. Sensors sense data according to their features and physical phenomenon happening and actuators performs physical actions according to that data. Various type of sensors are smoke detection sensors, humidity sensors, camera sensors and temperature sensors. The perception layer is often the most resource-constrained layer in an IoT device. This is because the sensors and other components in this layer need to be small and lightweight in order to be battery-powered. The security threats that could possibly faced at sensing layer are:

- Node Capturing
- Malicious Code Injection Attack
- False Data Injection Attack
- Side-Channel Attacks (SCA)
- Eavesdropping and Interference
- Sleep Deprivation Attacks
- Booting Attacks

Network Layer

The transmission of received data from sensing layer to computational unit is managed by network layer. It can use a variety of communication technologies, such as Wi-Fi, Bluetooth, and cellular networks. The network layer is also often the most complex layer in an IoT device. This is because it needs to be able to handle a variety of different communication technologies and to ensure that data is transferred reliably and securely. The security issues that could be encountered at this layer are:

- Phishing Site Attack
- Access Attack
- DDoS/DoS Attack
- Data Transit Attack
- Routing Attacks
- Unlawful Attacks
- Common Attacks

Middleware Layer

Powerful computing and storage capabilities in IoT applications are provided by middleware layer [23] this layer is responsible for abstraction between network layer and application layer. APIs are provided by this layer for proper functioning of application layer. Like other layers of IoT applications middleware layer also prone to security issues that are:

- Flooding Attack in Cloud
- Cloud Malware Injection
- Signature Wrapping Attack
- SQL Injection Attack
- Man-in-the-middle Attack

Gateways

Gateways are responsible for encryption, decryption and translation of protocols. Gateways connects multiple devices, things and cloud services and communicates different layers [24]. Heterogeneous property of IoT systems increase number of gateways and these gateways encounters some security challenges that are:

- Secure On-boarding
- Extra Interfaces
- End-to-end Encryption
- Firmware Updates

Application layer

The application layer is often the most user-facing layer in an IoT device. This is because it is responsible for providing the user with a way to interact with the device and to view the data that it collects. The application layer can be implemented in a variety of ways. It can be implemented on the device itself, on a server, or in the cloud. The choice of implementation depends on the specific application and the requirements of the user. This layer consists of applications like smart grids, smart cities and smart meters etc. Data breach and privacy issues are challenges that are commonly encountered in application layer.

- Data Theft Attacks
- Access Control Attacks
- Service Interruption Attacks
- Illegal Intervention Attacks
- DDoS Attacks
- Malicious Code Injection Attacks
- Sniffing Attacks
- Reprogram Attacks

2.1.3 Components of IoT devices

Sensors

Sensors are the most important components of IoT devices. They are used to measure physical quantities such as temperature, pressure, humidity, light, motion, and sound.

They convert these physical quantities into electrical signals that can be processed by the processor. The data collected by sensors is used to control devices, monitor systems, and collect data for analysis.

Actuators

Actuators are the opposite of sensors. They are used to control physical objects. They convert electrical signals from the processor into physical movements. Actuators are used in a wide variety of applications, such as controlling lights, opening and closing doors, and moving objects.

Processor

The processor is the brain of the IoT device. It is responsible for processing data from sensors, controlling actuators, and communicating with other devices. The processor is typically a small, low-power processor that is designed to operate on battery power.

Memory

The memory stores data that is being processed by the processor. It can be either volatile memory, which loses its contents when power is lost, or non-volatile memory, which retains its contents even when power is lost. Volatile memory is typically used to store data that is being processed by the processor, such as sensor data and actuator commands. Non-volatile memory is typically used to store data that needs to be retained even when power is lost, such as firmware and configuration data.

Communication interface

The communication interface is used to transmit data from the IoT device to other devices. It can use a variety of communication technologies, such as Wi-Fi, Bluetooth, and cellular networks. The choice of communication technology depends on the specific application and the environment in which the IoT device is deployed.

2.1.4 Communication Protocols for IoT Devices

Communication protocols are the rules that govern how data is exchanged between two or more devices. They define how data is formatted, how it is transmitted, and how it is received. There are a variety of communication protocols that can be used for IoT devices. The choice of protocol depends on the specific application and the environment in which the IoT device is deployed. Some of the most common communication protocols for IoT devices include:

Wi-Fi

Wi-Fi is a wireless networking technology that operates in the 2.4 GHz and 5 GHz frequency bands. It uses radio waves to transmit data between devices. Wi-Fi is a good choice for IoT devices that need to be connected to the internet and that need to be able to transmit data over long distances. However, Wi-Fi can be power-hungry, so it is not a good choice for IoT devices that need to operate on battery power.

Bluetooth

Bluetooth is a short-range wireless technology that operates in the 2.4 GHz frequency band. It uses radio waves to transmit data between devices. Bluetooth is a good choice for IoT devices that need to be connected to other devices in close proximity, such as wearable devices and home automation devices. However, Bluetooth has a shorter range than Wi-Fi, so it is not a good choice for IoT devices that need to be able to transmit data over long distances.

Zigbee

Zigbee is a low-power wireless technology that operates in the 2.4 GHz frequency band. It uses radio waves to transmit data between devices. Zigbee is a good choice for IoT devices that need to operate on battery power. Zigbee has a shorter range than Wi-Fi and Bluetooth, but it consumes less power. Zigbee is a good choice for IoT devices that need to be connected to other devices in close proximity, such as smart home devices and industrial automation devices.

Thread

Thread is a low-power wireless mesh networking technology that is designed for IoT devices. Thread operates in the 800 MHz frequency band. It uses radio waves to transmit data between devices. Thread is a good choice for IoT devices that need to be connected to other devices in a mesh network. Thread has a shorter range than Wi-Fi and Bluetooth, but it consumes less power. Thread is a good choice for IoT devices that need to be connected to other devices in close proximity, such as smart home devices and industrial automation devices.

LTE-M

LTE-M is a cellular network technology that is designed for low-power IoT devices. LTE-M operates in the 1.4 GHz and 1.9 GHz frequency bands. It uses radio waves to transmit data between devices. LTE-M is a good choice for IoT devices that need to be connected to the internet and that need to be able to transmit data over long distances. LTE-M consumes less power than traditional cellular networks, such as 4G LTE. LTE-M is a good choice for IoT devices that need to operate on battery power.

NB-IoT

NB-IoT is a cellular network technology that is designed for low-power, wide-area IoT devices. NB-IoT operates in the 900 MHz frequency band. It uses radio waves to transmit data between devices. NB-IoT is a good choice for IoT devices that need to be connected to the internet and that need to be able to transmit data over long distances. NB-IoT consumes less power than traditional cellular networks, such as 4G LTE. NB-IoT is a good choice for IoT devices that need to operate on battery power.

Factors for choosing a communication protocol

- **The range of the communication**: The range of the communication protocol determines how far apart the devices can be and still be able to communicate with each other

- **The power consumption of the communication**: The power consumption of the communication protocol determines how much power the devices will use when they are communicating with each other

- **The security of the communication**: The security of the communication protocol determines how secure the data is when it is being transmitted between the devices

- **The cost of the communication**: The cost of the communication protocol determines how much it will cost to implement the protocol

2.1.5 Challenges and Limitations of IoT Devices

Standardization

There is no single standard for IoT devices. This can make it difficult to connect and interoperate devices from different manufacturers. Some of the things you can do to address the lack of standardization include:

- Use open standards whenever possible
- Work with your devices' manufacturers to develop standards for your specific use case

Data management

The sheer volume of data generated by IoT devices can be overwhelming. It is important to have a plan for collecting, storing, and analyzing this data. Some of the things you can do to manage your IoT data include:

- Collect only the data that you need.
- Store your data in a secure location.
- Use data analytics tools to analyze your data

Heterogeneity

IoT devices are a diverse set of devices, each with its own unique capabilities and limitations. This can make it difficult to manage and maintain a large IoT network. Some of the things you can do to manage your IoT network include:

- Use a central platform to manage your devices
- Use a device management software to update and configure your devices
- Use a monitoring system to track the performance of your devices

Security and privacy

IoT devices are often connected to the internet, which makes them vulnerable to cyberattacks. Data collected by IoT devices can be used for malicious purposes, such as identity theft or fraud. It is important to take steps to secure IoT devices and protect their data. Some of the things you can do to secure your IoT devices include:

- Use strong passwords and change them regularly
- Keep your devices up to date with the latest firmware
- Use a firewall to protect your devices from unauthorized access
- Use a VPN to encrypt your data when it is transmitted over the internet

Cost

IoT devices can be expensive to purchase and deploy. The cost of IoT networks can be prohibitive for small businesses and individuals. Some of the things you can do to reduce the cost of IoT include:

- Purchase devices in bulk
- Use open source software to manage your IoT network
- Use cloud-based services to store and analyze your IoT data

Standardization

There is no single standard for IoT devices. This can make it difficult to connect and interoperate devices from different manufacturers. Some of the things you can do to address the lack of standardization include:

- Use open standards whenever possible
- Work with your devices' manufacturers to develop standards for your specific use case

2.1.6 Future Trends and Innovations in IoT Devices

These are just a few of the future trends and innovations in IoT devices. As IoT technology continues to develop, we can expect to see even more innovative and groundbreaking applications for IoT devices in the years to come.

The rise of 5G

5G is the next generation of cellular network technology. It offers much faster speeds and lower latency than 4G LTE, which will make it possible for IoT devices to transmit data more quickly and reliably.

The growth of edge computing

Edge computing is a distributed computing paradigm that brings computing resources closer to the end user. This can improve performance and reduce latency for IoT applications.

The development of new sensors

New sensors are being developed that can measure a wider range of physical quantities, such as temperature, pressure, humidity, light, motion, and sound. This will enable IoT devices to collect more data about the environment and to perform more sophisticated tasks.

The use of artificial intelligence (AI) and machine learning (ML)

AI and ML are being used to improve the performance of IoT devices. For example, AI can be used to identify patterns in data and to make predictions. ML can be used to train devices to perform specific tasks.

The development of new standards

There is a need for new standards to ensure that IoT devices can interoperate with each other. These standards will need to address issues such as security, privacy, and interoperability.

2.1.7 LEOs/GEO vs IoT

A LEO satellite can be used as a cloudlet to provide low-latency connectivity to IoT devices. This is because LEO satellites have a much lower latency than GEO satellites.

This can be beneficial for applications that require real-time data transfer, such as autonomous vehicles and industrial automation. A geosynchronous satellite (GEO) can be considered a "cloud" in the sense that it can provide connectivity to ground-based IoT devices in a wide area. However, it is important to note that GEO satellites have a much higher latency than terrestrial networks, so they are not preferable for applications that require real-time data transfer. 2.2 show the height of Satellite Orbit.

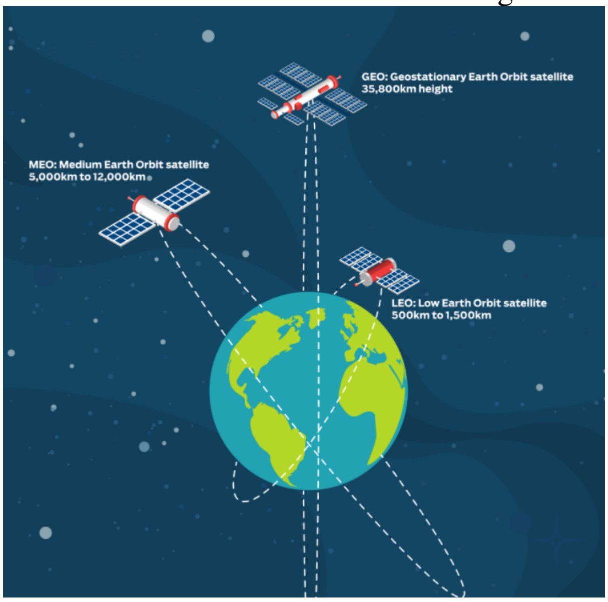

Figure 2.2: **Satellite Internet**

Here are some of the benefits of using a LEO Satellite as a cloudlet and GEO Satellite as a CLoud:

- **Low latency**: LEO satellites 2.3 have a much lower latency than GEO satellites. This means that data can be transferred to and from the satellite much faster
- **Global coverage**: LEO as well as GEO Satellites can provide global coverage, which means that IoT devices can be connected to the cloudlet or cloud no matter where they are located
- **Reliable connectivity**: LEOs/GEO Satellites can provide reliable connectivity, even in remote areas where there is no other infrastructure available

Here are some of the challenges of using a LEO satellite as a cloudlet and GEO as a cloud:

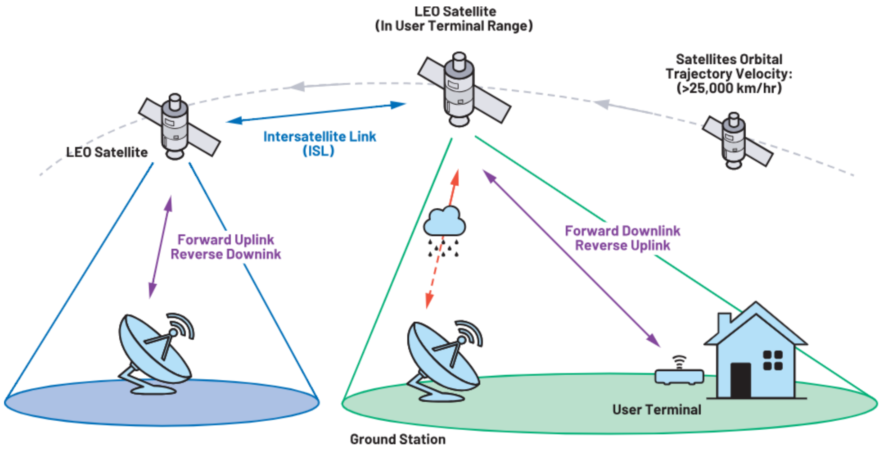

Figure 2.3: **LEO satellite as a cloudlet**

- **Cost**: LEO satellites can be expensive to deploy and operate.
- **Power consumption**: IoT devices that connect to LEO satellites can consume more power, as they need to transmit data over longer distances.
- **High latency**: GEO satellites have a much higher latency than terrestrial networks. This means that data can take longer to transfer to and from the satellite.
- **Limited bandwidth**: LEOs satellite as well as GEO Satellite can have limited bandwidth, which can be a problem for applications that generate a lot of data.

Overall, LEO satellites is good option for providing cloudlet services to IoT devices. GEO satellites can be a good option for providing connectivity to IoT devices in remote areas where data is not available at LEO Satellite. However, it is important to note that GEO satellites have a much higher latency than terrestrial networks, so they are not preferable for applications that require real-time data transfer.

2.2 Task Offloading

Task offloading is a technique used to improve the performance of IoT devices by offloading some of the processing tasks to a remote server. This can be done by using a proxy server or a cloudlet.

In the context of IoT devices connected to LEO/GEO satellite networks, task offloading can be used to improve the performance of the network by reducing the amount of data that needs to be transmitted over the network. This can be done by offloading computationally intensive tasks to a remote server, such as image processing or data analytics. There are a number of benefits to using task offloading in IoT devices connected to LEO/GEO satellite networks. These benefits include:

Improved performance

Task offloading can help to improve the performance of IoT devices by reducing the latency and bandwidth requirements. Latency is the time it takes for data to travel from the IoT device to the remote server and back. Bandwidth is the amount of data that can be transferred over the network in a given amount of time. By offloading computationally intensive tasks to a remote server, IoT devices can reduce the latency and bandwidth requirements, which can improve the performance of the IoT device.

For example, consider an IoT device that is collecting data from a sensor and sending the data to a remote server. If the IoT device is not powerful enough to process the data locally, it can offload the processing task to the remote server. This can reduce the latency of the IoT device, as the data does not need to be sent back and forth between the IoT device and the remote server.

Increased reliability

Task offloading can help to increase the reliability of IoT devices by reducing the load on the network. When an IoT device sends data to a remote server, it can put a load on the network. If the network is overloaded, it can cause latency and dropped packets. By offloading computationally intensive tasks to a remote server, IoT devices can reduce the load on the network, which can improve the reliability of the IoT device.

For example, consider an IoT device that is collecting data from a sensor and sending the data to a remote server. If the network is overloaded, it can cause latency and dropped packets. This can cause the IoT device to lose data or to experience delays in processing data. By offloading the processing task to the remote server, the IoT device can reduce the load on the network, which can improve the reliability of the IoT device.

Reduced costs

Task offloading can help to reduce the costs of operating an IoT network by reducing the amount of bandwidth that is required. The cost of operating an IoT network can be high, as it requires the purchase of IoT devices, the deployment of a network, and the maintenance of the network. By offloading computationally intensive tasks to a remote server, IoT devices can reduce the amount of bandwidth that is required, which can reduce the costs of operating an IoT network.

For example, consider an IoT network that is collecting data from a large number of sensors. If the IoT devices are not powerful enough to process the data locally, it can be expensive to send the data to a remote server. By offloading the processing task to the remote server, the IoT devices can reduce the amount of bandwidth that is required, which can reduce the costs of operating the IoT network.

2.2.1 How task offloading is being used in S-IoT

Here are some examples of how task offloading is being used in IoT devices connected to LEO/GEO satellite networks:

- **Smart cities**: Task offloading is being used in smart cities to improve the efficiency of city services, such as transportation and waste management. For example, task offloading is being used to process data from traffic cameras and sensors to improve traffic flow and reduce congestion.

- **Industrial automation**: Task offloading is being used in industrial automation to improve the efficiency of industrial processes. For example, task offloading is being used to process data from sensors in manufacturing plants to improve the quality of products and reduce waste.

- **Healthcare**: Task offloading is being used in healthcare to improve the quality of care and reduce costs. For example, task offloading is being used to process data from medical devices to improve the diagnosis and treatment of diseases.

Task offloading is a promising technology that has the potential to revolutionize the way IoT devices are used. By offloading computationally intensive tasks to a remote server, IoT devices can improve their performance, reliability, and cost-effectiveness.

2.2.2 Categories of task offloading

Full offloading

In full offloading, the entire task is executed on the remote server. This can be beneficial for tasks that are computationally intensive or that require a lot of data storage. However, full offloading can also introduce latency and reduce the responsiveness of the IoT device.

Partial offloading

In partial offloading, only a portion of the task is executed on the remote server. This can be beneficial for tasks that require both local and remote processing. Partial offloading can help to improve the performance of the IoT device while also reducing the amount of data that needs to be sent to the remote server.

Hybrid offloading

In hybrid offloading, a combination of full and partial offloading is used. This can be beneficial for tasks that have different processing requirements at different times. Hybrid offloading can help to improve the performance of the IoT device while also reducing the amount of data that needs to be sent to the remote server.

The best category of task offloading to use depends on the specific needs of the IoT device and the application. In our case we use full offloading as in far flung areas there is no telecom infrastructure so we completely rely on resource computation. If the task is computationally intensive, full offloading may be the best option. However, if the task is not computationally intensive, partial or hybrid offloading may be a better option.

2.2.3 Opportunistic communication for traffic offloading

Efficient offloading of mobile data traffic is also possible via opportunistic communication. Mobile data traffic, such as weather forecasts, sports news, and movie trailers, can be delivered to targeted users who can then distribute the content via Wi-Fi, Bluetooth, or D2D communication link [25].

2.3 Satellites

Satellites are designed for communication. They are used for mobile applications, such as communication with ships, cars, airplanes, handheld terminals, TV, and radio transmission. They are responsible for providing these services to a specific location (region) on Earth. The bandwidth and power of these satellites are determined by the desired footprint size, the complexity of the traffic control protocol methods, and the cost of the ground stations.

The signals of a satellite are most effective when they are focused on a specific location. When the region is concentrated, the emissions are confined to the specific area, limiting interference with adjacent systems. This results in increased spectrum efficiency. It is important to design satellite antenna patterns to optimally cover the selected geographical area.

Satellites should be designed with their short- and long-term utility in mind over their lifetime. If the satellite drifts from its orbit due to external influences, the earth station (ES) should be able to control it [26].

There are many different satellites that can be used for connection with IoT devices. Some of the most common satellites include:

- **Iridium**: Iridium is a constellation of 66 satellites that provides global coverage. Iridium is ideal for IoT devices that need to be able to connect no matter where they are located.

- **Inmarsat**: Inmarsat is a constellation of 11 satellites that provides global coverage. Inmarsat is a good choice for IoT devices that need to be able to connect in remote areas.

- **Globalstar**: Globalstar is a constellation of 48 satellites that provides global coverage. Globalstar is a good choice for IoT devices that need to be able to connect in areas where there is no terrestrial cellular coverage.

- **ORBCOMM**: ORBCOMM is a constellation of 38 satellites that provides global coverage. ORBCOMM is a good choice for IoT devices that need to be able to connect in areas where there is no terrestrial cellular coverage and where data usage is low

2.3.1 Configuration of a Satellite Communication System

The satellite system consists of three segments: the space segment, the control segment, and the ground section [26]. Details are as follows:

- **Space Segment**. The space segment consists of one or more operational and reserve satellites arranged in a constellation.

- **Control Segment**. The control segment comprises of all ground infrastructure for the monitoring and controlling of satellites, often known as tracking, telemetry, and command (TTC) stations, and for the management of satellite traffic and associated resources for communication networks.

- **Ground Segment**. The ground segment includes all traffic ES. These stations can range in size from a few centimeters to tens of meters, depending on the sort of service being considered.

2.3.2 Role of Satellites in 5G Networks

Satellites can play a vital role in 5G networks by extending coverage, providing backhaul, and supporting new applications. As 5G networks continue to evolve, satellites will become an increasingly important part of the 5G ecosystem.

Here are some additional details about the role of satellites in 5G networks:

Satellites can extend the coverage of 5G networks to rural and remote areas

This is important for applications that need to be available in these areas, such as telemedicine and connected vehicles. For example, Inmarsat is a global satellite communications company that is providing 5G services to maritime and aviation customers.

Satellites can provide backhaul for 5G networks

Backhaul is the connection between the core network and the edge network. By providing backhaul, satellites can help to reduce congestion and improve the latency of 5G networks. For example, OneWeb is a low-earth orbit (LEO) satellite constellation that is providing 5G services to rural and remote areas.

Satellites can support new applications that require high-speed, low-latency connectivity

These applications need a reliable and high-speed connection to the internet, and satellites can provide this connection. For example, Viasat is a satellite communications company that is providing 5G services to residential and business customers.

2.3.3 Remote and Rural Connectivity

Geostationary (GEO) satellites have traditionally been used to address the ”last mile” issue. This role could expand in terms of both scale and scope with the growth of low-earth orbit (LEO) satellite constellations, which provide more locations where links can be established. 5G networks will enable an exponentially increasing number of connected devices, including mobile phones, a wide range of IoT devices, and billions of sensors. These devices will be used for a variety of applications, such as interstate travel, air travel, sea travel, agriculture, and remote surgery.

While satellites need line of sight to connect directly to a device, which limits their usefulness in densely populated areas, the potential for massive machine-type communications (MMTC) and the fact that most of these devices will be dispersed over large geographic areas will increase the need for data collection and dissemination across 5G networks.

By using the extensive satellite coverage made possible by the proliferation of LEOs, and by integrating satellites with terrestrial networks through novel network architectures, satellites can offer a significant solution to this challenge. One of the main advantages of this approach is that LEOs, unlike GEOs, can now provide a true interactive experience, a level of connectivity that has not been available in rural and isolated areas until now.

The integration of satellite systems into 5G networks can help to connect rural areas where installing fiber optic cable is neither practical nor economically feasible. This will improve the quality of life for people in these areas and make it easier for businesses to operate there.

Chapter 3

SYSTEM MODEL AND PROBLEM FORMULATION

3.1 System Model

Figure 3.1 depicts a three-tiered architecture consisting of Internet of Things (IoT) devices, cloudlet, and cloud. Here, LEO and GEO satellites are performing the functions of cloudlet and cloud, respectively. We assume that IoT devices are located in far flung/remote areas where telecommunication infrastructure is not available. These IoT devices are equipped with sensors to collect the data from the surrounding and transmit data to third party for storage, data fusion, and computation. Since, these IoT devices lack storage, and computation capabilities, however, LEO and GEO satellites are equipped with plenty of on-board storage, and computation capabilities. Hence, LEO satellite as cloudlet and GEO as cloud offer the services like storage, and computation to the IoT devices in the far flung areas void of telecommunication infrastructure.

Lets consider a system with time slots and indexed as $t \in \mathbf{T} = \{0, 1, 2, 3, ...\}$. Lets a set of IoT devices denoted by $\mathbf{I}(t)$ where $i(t) \in \mathbf{I}(t) = \{1, 2, 3, ..., I(t)\}$ are operating in the time slot t and this set of IoT devices are served when $J(t)$ number of LEO-cloudlets where $j(t) \in \mathbf{J}(t) = \{1, 2, 3, ..., J(t)\}$ fly over the $I(t)$ IoT devices in far flung area. These LEO-cloudlets are inter-connected via microwave links to share the traffic load of $I(t)$ IoT devices with fairness. Moreover, $J(t)$ LEO-cloudlets have a high capacity microwave link with the GEO-cloud. The GEO-cloud will share the work load in case the LEO-cloudlet $j(t)$ can't entertain the storage, and the computation request from a IoT device $i(t)$. Thus, there are two different modes of communication and discussed separately in sub-section 3.1.2.

3.1.1 Resource allocation model

Few binary variables to show IoT device $i(t) \in \mathbf{I}(t)$ admission, association, and availability of LEO-cloudlet are defined below:

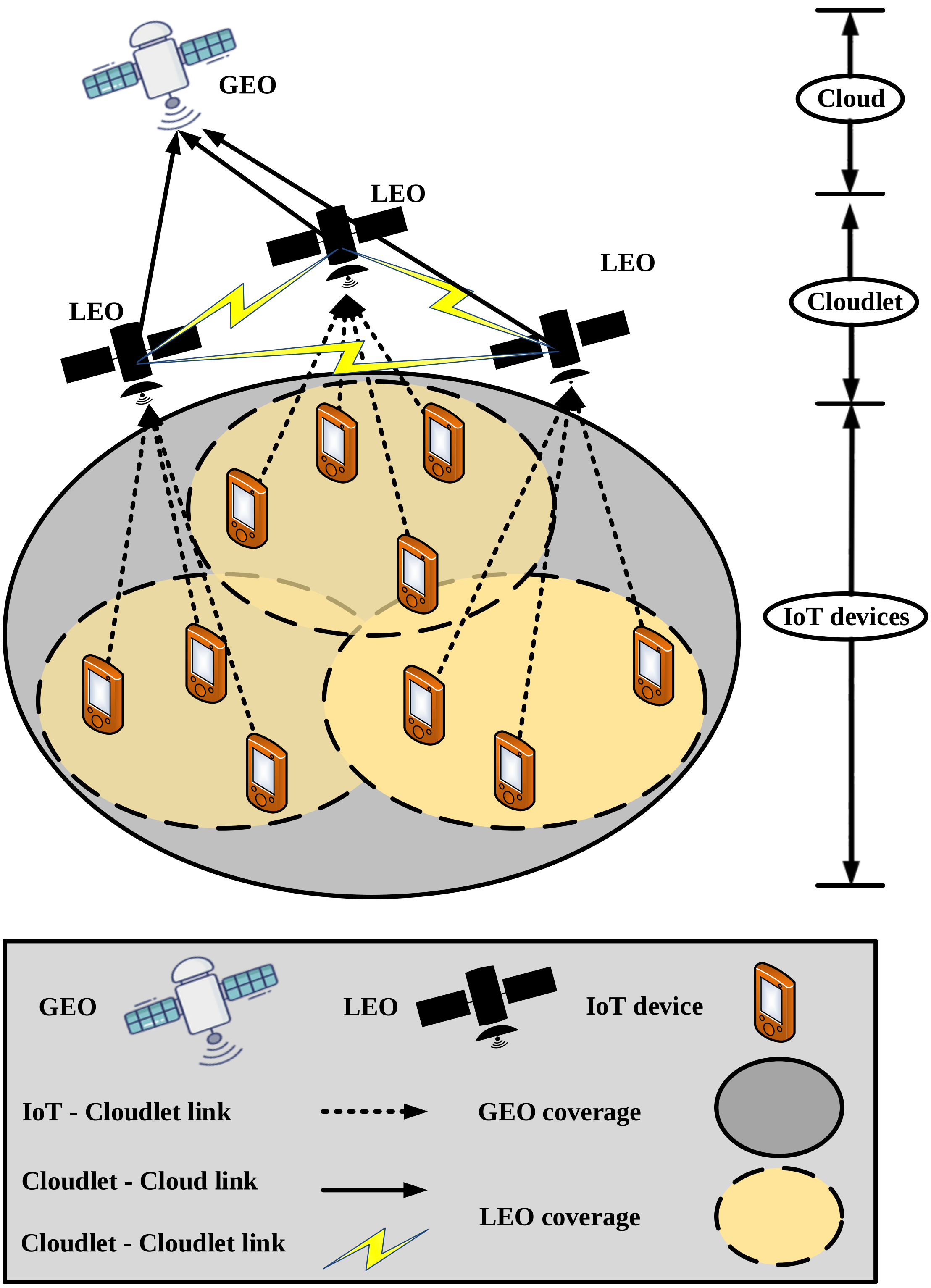

Figure 3.1: **System Model - GEO and LEO hybrid satellite network**

- **definition-1:** Let the $0/1$ indicator to show wether a IoT device $i(t) \in \mathbf{I}(t)$ is admissible or not is given below:

$$x_i(t) = \begin{cases} 1, & \text{IoT device is admissible} \quad (3.1a) \\ 0, & \text{Otherwise} \quad (3.1b) \end{cases}$$

- **definition-2:** Let the $0/1$ indicator to show wether a IoT device $i(t) \in \mathbf{I}(t)$ is associated with LEO-cloudlet $j(t) \in \mathbf{J}(t)$ or not is given below:

$$y_{i,j}(t) = \begin{cases} 1, & \text{IoT device is associated} \quad (3.2a) \\ 0, & \text{Otherwise} \quad (3.2b) \end{cases}$$

- **definition-3:** Let the $0/1$ indicator to show wether a LEO-cloudlet $j(t) \in \mathbf{J}(t)$ is available to fulfill request of the IoT device $i(t)$ or not is given below:

$$z_{i,j}(t) = \begin{cases} 1, & \text{LEO-cloudlet is available} \quad (3.3a) \\ 0, & \text{Otherwise} \quad (3.3b) \end{cases}$$

In this context, it is observed that a LEO-cloudlet denoted by $j(t) \in \mathbf{J}(t)$ has the capability to offer its services to multiple IoT devices. However, an IoT device represented by $i(t) \in \mathbf{I}(t)$ is restricted to associate with only a single LEO-cloudlet, namely $j(t) \in \mathbf{J}(t)$. This association of IoT devices should be such that fairness is maintained while distributing the traffic load among all LEO-cloudlets. Mathematically, the fairness is ensured using Jain's fairness index [27] as below:

$$\alpha_{i,j}(t) = \frac{\left(\sum_{j(t) \in \mathbf{J}(t)} \left(\sum_{i(t) \in \mathbf{I}(t)} y_{i,j}(t) \right) \right)^2}{J(t) \left(\sum_{j(t) \in \mathbf{J}(t)} \left(\sum_{i(t) \in \mathbf{I}(t)} y_{i,j}(t) \right)^2 \right)}, \quad (3.4a)$$

$$0 \leq \alpha_{i,j} \leq 1), \quad (3.4b)$$

where $\alpha_{i,j}(t)$ in (3.4a) is the user fairness index (UFI) and it's value ranges between zero and one as shown in (3.4b). The value of UFI is one when the distribution/ association of $I(t)$ IoT devices traffic load to the $J(t)$ LEO-cloudlets follow the optimum fairness.

Every IoT device $i(t) \in \mathbf{I}(t)$ can transmit data file to the LEO-cloudlet $j(t) \in \mathbf{J}(t)$ using it's power within upper limit of P_i. Mathematically, the range of allocated power with in the upper limit is given below:

$$0 \leq p_{i,j}(t) \leq P_i, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.5}$$

Every IoT device $i(t) \in \mathbf{I}(t)$ can associate and transmit data to a LEO-cloudlet $j(t) \in \mathbf{J}(t)$ [28]. The signal in the UL suffers path loss, attenuation due to rain, and attenuation due to atmospheric gasses when a IoT device $i(t) \in \mathbb{I}(t)$ associates and transmits data to LEO-cloudlet $j(t) \in \mathbf{J}(t)$. The channel gain between a IoT device and a LEO-cloudlet in the UL is given by [29].

$$h_{i,j}(t) = \frac{G_i^{\text{Tx}} G_j^{\text{Rx}}}{\xi_{i,j}^{PL}(t)\xi_{i,j}^{Rain}(t)\xi_{i,j}^{Gas}(t)}, \tag{3.6a}$$

$$\xi_{i,j}^{PL}(t) = \left(\frac{4\pi f_c s_{i,j}(t)}{\upsilon}\right)^2, \tag{3.6b}$$

$$\xi_{i,j}^{Rain}(t) = J_r \Re^{\mu_r} L_e, \tag{3.6c}$$

$$\xi_{i,j}^{Gas}(t) = \frac{A_w A_o}{sin\theta_{i,j}(t)}, \tag{3.6d}$$

where G_i^{Tx} and G_j^{Rx} are the antenna gains of the Internet-of-Things device and the low-Earth-orbit cloud node, respectively. Attenuation due to free-space path loss, rain, and atmospheric gases are denoted by $\xi_{i,j}^{PL}(t)$, $\xi_{i,j}^{Rain}(t)$, and $\xi_{i,j}^{Gas}(t)$, respectively. f_c is the carrier frequency, and $s_{i,j}(t)$ is the separation between the Internet of Things node $i(t) \in \mathbf{I}(t)$ and the low Earth orbit cloud node $j(t) \in \mathbf{J}(t)$. The υ denotes the velocity of light. The coefficients J_r and μ_r change with the frequency. The effective path length of a wave in rain is denoted by L_e, while the intensity of rainfall is denoted by $\Re$. A_w and A_o are the absorptions due to water vapours and oxygen, respectively [30]. $\theta_{i,j}(t)$ is the elevation angle between IoT device $i(t) \in \mathbf{I}(t)$ and LEO-cloudlet $j(t) \in \mathbf{J}(t)$ [31].

Attainable uplink data rate $\psi_{i,j}(t)$ from IoT device $i(t) \in \mathbf{I}(t)$ to the LEO-cloudlet $j(t) \in \mathbf{J}(t)$ is calculated as follows, in accordance with shannon's capacity theorem:

$$\psi_{i,j}(t) = b_{i,j}(t)log_2\left(1 + \Phi_{i,j}(t)\right), \tag{3.7a}$$

$$\Phi_{i,j}(t) = \frac{p_{i,j}(t)h_{i,j}(t)}{I_{i',j}(t) + \sigma^2}, \tag{3.7b}$$

$$I_{i',j}(t) = \sum_{j(t)\in\mathbf{J}(t)} y_{i',j}(t)p_{i',j}(t)h_{i',j}(t), \tag{3.7c}$$

where $i' \neq i$, $y_{i,j}(t) = 1$ when IoT device $i(t) \in \mathbf{I}(t)$ associates with the LEO-cloudlet $j(t) \in \mathbf{J}(t)$, and $y_{i,j}(t) = 0$ otherwise. The channel bandwidth is denoted by $b_{i,j}(t)$, while the signal to interference and noise ratio is represented by $\Phi_{i,j}(t)$. The noise is denoted by σ^2, and the interference from IoT device $i'(t) \in \mathbf{I}(t)$ to LEO-cloudlet $j(t) \in \mathbf{J}(t)$ in the UL is represented by $I_{i',j}(t)$. The resource blocks are allocated to a IoT device $i(t) \in \mathbf{I}(t)$ by LEO-cloudlet $j(t) \in \mathbf{J}(t)$ as per the requirement of quality of service (QoS). For a given data rate QoS and resource block fairness index (RFI), the following mathematical expressions can be used to determine the necessary number of resource blocks:

$$r_{i,j}(t) = \left\lceil \frac{Q_{i,j}(t)}{\psi_{i,j}(t)} \right\rceil, \tag{3.8a}$$

$$\gamma_{i,j}(t) = \frac{\sum\limits_{j(t)\in\mathbf{J}(t)} r_{i,j}(t)}{\sum\limits_{j(t)\in\mathbf{J}(t)} y_{i,j}(t)}, \tag{3.8b}$$

$$\beta_{i,j}(t) = \frac{\left(\sum\limits_{j(t)\in\mathbf{J}(t)} \left(\sum\limits_{i(t)\in\mathbf{I}(t)} \gamma_{i,j}(t)\right)\right)^2}{J(t)\left(\sum\limits_{j(t)\in\mathbf{J}(t)} \left(\sum\limits_{i(t)\in\mathbf{J}(t)} \gamma_{i,j}(t)\right)^2\right)}, \tag{3.8c}$$

$$0 \leq \beta_{i,j}(t) \leq 1, \tag{3.8d}$$

To fulfill the data rate requirement of $Q_{i,j}(t)$, the number of resource blocks required is denoted by $r_{i,j}(t)$ in (3.8a). $\gamma_{i,j}(t)$ in (3.8b) is the normalized number of resource block by associated IoT devices with a LEO-cloudlet. $\beta_{i,j}(t)$ in (3.8c) is the RFI and it's value ranges between zero and one shown in (3.8d). The value of RFI is one when the allocation of resource blocks to IoT devices follow optimum fairness.

3.1.2 Task offloading model

In this cellular environment, there are two modes to fulfill the data storage, and computation requests by the $I(t)$ IoT devices,i.e., LEO-cloudlet mode or GEO-cloud mode. LEO-cloudlet mode is the first choice of the IoT device since involves little latency due to less distance between IoT device and LEO-cloudlet. Second choice is the GEO-cloud mode if the data storage, and computation request by the IoT device $i(t) \in \mathbf{I}(t)$ is not fulfilled by the LEO-cloudlet $j(t) \in \mathbf{J}(t)$. The detail of two modes is given below:

1. **LEO-cloudlet mode:** Let the IoT device $i(t) \in \mathbf{I}(t)$ is operating in the far flung area and records two data files $f^{s}_{i,j}(t)$ and $f^{c}_{i,j}(t)$ from the surrounding environment. The $f^{s}_{i,j}(t)$ and $f^{c}_{i,j}(t)$ are the data files to be stored, and computed, respectively, by the IoT device $i(t) \in \mathbf{I}(t)$ to the LEO-cloudlet $j(t) \in \mathbf{J}(t)$. The Ω^{LEO}_{s} and Ω^{LEO}_{c} are storage and computation capacity of the LEO-cloudlet, respectively. The storage and computation tasks need to be performed by LEO-cloudlet $j(t) \in \mathbf{J}(t)$. These tasks are scheduled, queued, and transmitted to be accomplished in available N time windows. Latency experienced while completing these tasks is given below:

$$l^{\text{LEO}}_{i,j,q}(t) = \tau(N-1), \tag{3.9a}$$

$$l^{\text{LEO}}_{i,j,m}(t) = \frac{f^{\text{s}}_{i,j}(t) + f^{\text{c}}_{i,j}(t)}{\psi_{i,j}(t)}, \tag{3.9b}$$

$$l^{\text{LEO}}_{i,j,\rho}(t) = \frac{s_{i,j}(t)}{\upsilon}, \tag{3.9c}$$

$$l^{\text{LEO}}_{i,j,c}(t) = \eta\left(\frac{f^{\text{c}}_{i,j}(t)}{\Omega^{\text{LEO}}_{c}}\right), \tag{3.9d}$$

$$l^{\text{LEO}}_{i,j,T}(t) = l^{\text{LEO}}_{i,j,q}(t) + l^{\text{LEO}}_{i,j,m}(t) + l^{\text{LEO}}_{i,j,\rho}(t) + l^{\text{LEO}}_{i,j,c}(t), \tag{3.9e}$$

where $l^{\text{LEO}}_{i,j,q}(t)$ is the queue delay, $l^{\text{LEO}}_{i,j,m}(t)$ is the transmission delay, $l^{\text{LEO}}_{i,j,\rho}(t)$ is the propagation delay, $l^{\text{LEO}}_{i,j,c}(t)$ is the computing delay, and $l^{\text{LEO}}_{i,j,T}(t)$ is the total delay occur while completing the tasks of the IoT device $i(t) \in \mathbf{I}(t)$. The η is the number of CPU cycles required to compute the data at LEO-cloudlet and Ω^{LEO}_{c} is computing ability of the LEO-cloudlet in cycles/second. The $s_{i,j}(t)$ is the distance between IoT device $i(t) \in \mathbf{I}(t)$ and LEO-cloudlet $j(t) \in \mathbf{J}(t)$. The τ is the length of a time window, N is the total time windows.

2. **GEO-cloudlet mode:** GEO-cloud is contacted if the request by IoT device $i(t) \in \mathbf{I}(t)$ to store and compute the data files is not entertained by the LEO-cloudlet $j(t) \in \mathbf{J}(t)$. LEO-cloudlet $j(t) \in \mathbf{J}(t)$ sends the request to store and compute the data files to GEO-cloud. As the distance involved between LEO-cloudlet and GEO-cloud is very much high, so propagation delay involved will add too much latency to fulfill the request of IoT device $i(t) \in \mathbf{I}(t)$. In this case, the propagation delay [32] involved in storing and computing the requested data files is given below:

$$l^{\text{GEO}}_{i,j,\rho}(t) = \frac{s^{\text{GEO}}_{j}(t)}{\upsilon}, \tag{3.10a}$$

$$l^{\text{GEO}}_{i,j,c}(t) = \eta \left(\frac{f^{\text{c}}_{i,j}(t)}{\Omega^{\text{GEO}}_{c}} \right), \tag{3.10b}$$

$$l^{\text{GEO}}_{i,j,T}(t) = l^{\text{GEO}}_{i,j,\rho}(t) + l^{\text{GEO}}_{i,j,c}(t). \tag{3.10c}$$

The propagation delay $l^{\text{GEO}}_{i,j,\rho}(t)$ is distance dependent where $s^{\text{GEO}}_{j}(t)$ is the distance between LEO-cloudlet $j(t) \in \mathbf{J}(t)$ and GEO-cloud, and Ω^{GEO}_{c} is computing ability of the GEO-cloud in cycles/second. Using Eq. (3.9) and (3.10), the maximum latency experienced in this communication environment is given below:

$$l_{i,j}(t) = z_{i,j}(t) l^{\text{LEO}}_{i,j,T}(t) + (1 - z_{i,j}(t))\, l^{\text{GEO}}_{i,j,T}(t), \tag{3.11}$$

where $l_{i,j}(t)$ is the maximum delay which can be caused to a IoT device while completing its tasks.

3.2 Energy consumption model

The transmission energy and circuit energy are the two categories which are considered in the optimization technique for energy consumption model in the UL. Circuit energy includes the circuit components, i.e., amplifiers, convertors, and processing units etc. The transmission energy is the transmitter energy used while sending the data in the UL. The circuit energy and the transmission energy are denoted by P_c and $p_{i,j}$, respectively [33]. Mathematically, the total energy consumed by the IoT device $i(t) \in \mathbf{I}(t)$ to send data to the LEO-cloudlet $j(t) \in \mathbf{J}(t)$ is given below:

$$P_{total} = P_c + p_{i,j}. \tag{3.12}$$

The EE is calculated as follows based on the proportion of transferred data to energy used:

$$EE = \frac{\psi_{i,j}}{P_{total}}, \tag{3.13}$$

where the units of $\psi_{i,j}(t)$ and P_{total} are bits per second and watts, respectively. As a result, the unit of EE (Energy Efficiency) is expressed as bits per second per watt.

3.2.1 Problem Formulation with Mathematical Modeling

For the network depicted in Fig. 3.1, we now formulate the joint admission control, association of IoT devices, and allocation of power problem. Fairness in the assignment of $I(t)$ IoT nodes to $J(t)$ LEO-cloudlets is also a factor in this dilemma. Allocating chunks of spectrum to IoT devices in the network is done in a fair manner. To begin, we will define the objective function and the limitations.The ultimate segment of the paper entails the formulation of the mathematical model pertaining to the issue at hand. The goal function and its constraints are described below.

- **Objective function:** Using (2), (3.5), (3.7), (3.12), and (3.13), EE maximization/optimization is the objective of this research work and defined below:

$$EE = \frac{\sum_{j(t)\in\mathbf{J}(t)} \sum_{i(t)\in\mathbf{J}(t)} y_{i,j}(t)\psi_{i,j}(t)}{P_c + \sum_{j(t)\in\mathbf{J}(t)} \sum_{i(t)\in\mathbf{I}(t)} p_{i,j}}. \tag{3.14}$$

- **IoT device association:** Using (2), the constraints that ensures association of IoT device $i(t) \in \mathbf{I}(t)$ with just one LEO-cloudlet $j(t) \in \mathbf{J}(t)$ is given below:

$$\sum_{j(t)\in\mathbf{J}(t)} y_{i,j}(t) \leq 1 \, \forall \, i(t) \in \mathbf{I}(t). \tag{3.15}$$

- **Power allocation:** If the Internet-of-Things device $i(t) \in \mathbf{I}(t)$ is allowed into the network, it will receive the power allocation $p_{i,j}(t)$. The following constraint ensures that power is allocated to each admitted IoT device using (1) and (3.5).

$$0 \leq x_i(t)p_{i,j}(t) \leq P_i, \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t), \tag{3.16}$$

- **Achieved data rate versus QoS data rate:** Another QoS requirement is the minimum data rate required to complete the offloading tasks if IoT device $i(t) \in \mathbf{I}$ is admitted in the network . In order to guarantee a certain level of quality of service, the minimum data rate required to do so is constrained by (1), (3.5), (3.6), and (3.7).

$$\psi_{i,j}(t) \geq x_i(t)\Psi_{i,j}, \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t), \tag{3.17}$$

- **Achieved data rate versus QoS latency:** Another QoS requirement for the admitted IoT device is that achieved data rate should be such that maximum latency threshold is not compromised. The constraint to guarantee an adequate data rate for quality of service is stated here using (1), (3.5), (3.6), and (3.7).

$$\psi_{i,j}(t) \geq x_i(t) \left(\frac{f^{\mathrm{s}}_{i,j}(t) + f^{\mathrm{c}}_{i,j}(t)}{D_{i,j}(t)} \right), \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t), \tag{3.18}$$

- **Latency:** One of the quality of service (QoS) requirement is the minimum latency in accomplishment of task offloading to the LEO-cloudlet. Using (3), (3.9), (3.10), and (3.11), the constraint to ensure QoS minimum latency is given below:

$$l_{i,j}(t) \leq x_i(t) L_{i,j}, \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t), \tag{3.19}$$

- **LEO-cloudlet storage:** The constraints that ensures sum of data size of files to be store at LEO-cloudlet $j(t) \in \mathbf{J}(t)$ is with in its storage capacity is given below:

$$\sum_{i(t) \in \mathbf{I}(t)} z_{i,j}(t) f^{\mathrm{s}}_{i,j}(t) \leq \Omega^{\mathrm{LEO}}_s \, \forall \, i(t) \in \mathbf{I}(t). \tag{3.20}$$

- **Fairness in IoT device association:** The distribution of $I(t)$ IoT devices traffic load in terms of association with $J(t)$ LEO-cloudlets should follow fairness to avoid over loading of a LEO-cloudlet. Using (3.4), the constraint to ensure fairness in distribution IoT devices traffic is given below:

$$\alpha_{i,j}(t) \geq x_i Q_{\mathrm{UFI}}, \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t). \tag{3.21}$$

- **Fairness in RBs allocation:** The distribution of $I(t)$ IoT devices traffic load should follow fairness to avoid overloading and underloading of $J(t)$ LEO-cloudlets. Using (3.8), the constraint to ensure fairness in distribution RBs is given below:

$$\beta_{i,j}(t) \geq x_i Q_{\mathrm{RFI}}, \, \forall \, i(t) \in \mathbf{I}(t), \, j(t) \in \mathbf{J}(t). \tag{3.22}$$

Objective function and constraints defined in (3.14) - (3.22) helps in formulating a mathematical model to achieve latency aware resource allocation, i.e., fairness in IoT device association and resource blocks allocation etc and task offloading in GEO-LEO Satellite Networks.Notations chart sheet provides a concise overview of the annotations and representations commonly employed when posing a problem. To achieve throughput maximization in GEO-LEO satellite networks, the mathematically problem with objective function $\mathbb{U}$ is given below:

$$\max_{y,p} \quad \frac{\sum\limits_{j(t)\in\mathbf{J}(t)} \sum\limits_{i(t)\in\mathbf{I}(t)} y_{i,j}(t)\psi_{i,j}(t)}{P_c + \sum\limits_{j(t)\in\mathbf{J}(t)} \sum\limits_{i(t)\in\mathbf{I}(t)} p_{i,j}} \tag{3.23a}$$

$$\text{s.t.} \sum_{j(t)\in\mathbf{J}(t)} y_{i,j}(t) \leq 1 \,\forall\, i(t) \in \mathbf{I}(t), \tag{3.23b}$$

$$0 \leq x_i(t)p_{i,j}(t) \leq P_i,\, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.23c}$$

$$\psi_{i,j}(t) \geq x_i(t)\Psi_{i,j},\, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.23d}$$

$$\psi_{i,j}(t) \geq x_i(t)\left(\frac{f^{\mathrm{s}}_{i,j}(t) + f^{\mathrm{c}}_{i,j}(t)}{L_{i,j}(t)}\right), \forall\, i(t) \in \mathbf{I}(t),\; j(t) \in \mathbf{J}(t), \tag{3.23e}$$

$$l_{i,j}(t) \leq x_i(t)L_{i,j},\, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.23f}$$

$$\sum_{i(t)\in\mathbf{I}(t)} z_{i,j}(t)f^{\mathrm{s}}_{i,j}(t) \leq \Omega^{\mathrm{LEO}}_s \,\forall\, j(t) \in \mathbf{J}(t), \tag{3.23g}$$

$$\alpha_{i,j}(t) \geq x_i Q_{\mathrm{UFI}},\, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.23h}$$

$$\beta_{i,j}(t) \geq x_i Q_{\mathrm{RFI}},\, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t). \tag{3.23i}$$

Each IoT device $i(t) \in \mathbf{I}(t)$ is not allowed to associate with more than one LEO-cloud $j(t) \in \mathbf{J}(t)$ is ensured by constraint (3.23b). The power allocated to an admitted IoT device $i(t) \in \mathbf{I}(t)$ in the UL transmission should be within maximum power available is ensured by constraint (3.23c). The achieved data rate of an IoT device should be more than minimum QoS data rate requirement is ensured by constraint (3.23d). Similarly, the achieved data rate of an IoT device should be such that data transmitted take time less than QoS latency is ensured by constraint (3.23e). QoS maximum threshold for latency is ensured by constraint (3.23f). Sum of the data files to be stored at a LEO-cloudlet should be within the storage capacity of a LEO-cloudlet is ensured by constraint (3.23g). The fairness in the IoT devices traffic offloading is ensured by constraint (3.23h). The fairness in allocation of resource blocks among IoT devices is ensured by constraint (3.23i).

3.2.2 Alternate Technique

Numerator and denominator concave and convex functions are present in the problem stated in (3.23). The real valued functions $\psi_{i,j}(t)$, and $p_{i,j}(t)$ are defined on the subset of R^n, making this a classic Concave Fractional Programming (CFP) issue. In order to change this CFP problem into a concave optimization problem, we make use of a technique known as the Charnes Cooper Transformation (CCT) [34]. The optimization problem can be transformed into a concave one by substituting $p_{i,j}(t) = \left(\frac{u_{i,j}(t)}{v}\right)$. The comparable concave optimization problem is presented after making the necessary substitutions in (3.23).

$$\max_{y,p} \quad v \sum_{j(t)\in\mathbf{J}(t)} \sum_{i(t)\in\mathbf{J}(t)} y_{i,j}(t) b_{i,j}(t) log_2 \left(1 + \frac{u_{i,j}(t)h_{i,j}(t)}{v\left(I_{i',j}(t)+\sigma^2\right)}\right), \tag{3.24a}$$

$$\text{s.t.} \sum_{y(t)\in\mathbb{Y}(t)} \beta_{x,y}(t) \leq 1 \, \forall\, x(t) \in \mathbb{X}(t), \tag{3.24b}$$

$$0 \leq x_i(t) u_{i,j}(t) \leq v P_i, \, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24c}$$

$$y_{i,j}(t) b_{i,j}(t) log_2 \left(1 + \frac{u_{i,j}(t)h_{i,j}(t)}{v\left(I_{i',j}(t)+\sigma^2\right)}\right) \geq x_i(t)\Psi_{i,j}, \quad \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24d}$$

$$y_{i,j}(t) b_{i,j}(t) log_2 \left(1 + \frac{u_{i,j}(t)h_{i,j}(t)}{v\left(I_{i',j}(t)+\sigma^2\right)}\right) \geq x_i(t)\left(\frac{f^{\mathrm{s}}_{i,j}(t)+f^{\mathrm{c}}_{i,j}(t)}{L_{i,j}(t)}\right), \, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24e}$$

$$l_{i,j}(t) \leq x_i(t) L_{i,j}, \, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24f}$$

$$\sum_{i(t)\in\mathbf{I}(t)} z_{i,j}(t) f^{\mathrm{s}}_{i,j}(t) \leq \Omega^{\mathrm{LEO}}_s \, \forall\, j(t) \in \mathbf{J}(t), \tag{3.24g}$$

$$\alpha_{i,j}(t) \geq x_i Q_{\mathrm{UFI}}, \, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24h}$$

$$\beta_{i,j}(t) \geq x_i Q_{\mathrm{RFI}}, \, \forall\, i(t) \in \mathbf{I}(t),\, j(t) \in \mathbf{J}(t), \tag{3.24i}$$

$$P_c v + \sum_{j(t)\in\mathbf{J}(t)} \sum_{i(t)\in\mathbf{I}(t)} u_{i,j}(t) = 1. \tag{3.24j}$$

Hence, the issue expounded in (3.24) pertains to the category of predicaments recognized as conventional MINLP predicaments. Associating IoT devices with LEO-cloudlets and determining how much power each IoT device receives in the UL [35] is a sophisticated and difficult NP-hard task. The optimization issue in (3.24) is combinatorial in nature. To overcome this difficult issue, we could, for example, use an algorithm based purely on forceful methods. The brute force approach is predicated on a comprehensive search, wherein each alternative is systematically examined and resolved until the optimal solution is attained. If you want to find the best possible answer, you'll have to solve a problem with a search space that grows exponentially with the number of connected devices, or $2^{|I|}$. Moreover, the sophistication of the algorithm increases with the number of emulated IoT devices. To get to the $\epsilon = 10^{-3}$ optimal solution, the alternative is to use a simpler procedure, namely, outer approximation.

Chapter 4

PROPOSED ALGORITHM

The problem in (3.24) is a MINLP problem with a mix of linear, non-linear and binary variables. The OAA divides the MINLP problem in (3.24) into two sub-problems. These sub-problem are given below:

- Sub-problem NLP.
- Sub-problem MILP.

The two sub-problems at hand are not complicated and OAA achieves optimum solution within specific iterations [36, 37].

4.1 Overview of the ϵ-Optimal Algorithm

Assume that both the objective function and the limitations of the problems in (3.24) are represented by Θ and $\Pi_{\text{24b-24j}}$. Binary variables are symbolized by $\mathbf{T}$, $\mathbf{T} = \{x_i, y_{i,j}\}$, $\mathbf{N} = \{u_{i,j}\}$ and $\mathbf{M} = \mathbf{T} \cup \mathbf{N}$. For the Problems mentioned above in (3.24), the following four prepositions are valid:

1. The set $\mathbf{N}$ is nonempty, convex, and compact.
2. Both Θ and $\Pi_{\text{24b-24j}}$ are convex in $\mathbf{N}$ for some constant $\mathbf{M}$.
3. Differentiation can be performed for Θ and $\Pi_{\text{24b-24j}}$ for a specific $\mathbf{M}$.
4. In order to make a MINLP problem amenable to a precise solution, one must first fix the $\mathbf{M}$.

4.1.1 First Stage

To transform MINLP issues like those outlined in (3.24) into NLP problems, it is necessary to fix $\mathbf{M}$ at $\mathbf{M}^k$ in the preliminary phase. The UB of the best possible solution is the answer to the NLP problem. The natural language processing difficulty is as follows:

$$\min_{\mathbf{N}} \quad -\Theta(\mathbf{M}^k, \mathbf{N}) \tag{4.1a}$$

$$\text{s.t.} \;\; \Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}) \leq 0 \tag{4.1b}$$

4.1.2 Second Stage

By applying the solution to the NLP problem stated in (4.1), we can obtain the binary variables of $\mathbf{M}$ at $\mathbf{M}^k$. The (3.24) MINLP problems are transformed into the MILP problem using the results from the first stage. The MILP problem can be summarised as follows:

$$\min_{\mathbf{M}} \min_{\mathbf{N}} \quad -\Theta(\mathbf{M}^k, \mathbf{N}) \tag{4.2a}$$

$$\text{s.t.} \;\; \Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}) \leq 0 \tag{4.2b}$$

(4.2) can also be written as:

$$\min_{\mathbf{M}} \quad -\varpi(\mathbf{M}) \tag{4.3}$$

such that

$$\varpi(\mathbf{M}) \;\; = \min_{\mathbf{N}} \;\; -\Theta(\mathbf{M}^k, \mathbf{N}) \tag{4.4a}$$

$$\text{s.t.} \;\; \Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}) \leq 0 \tag{4.4b}$$

(3.24) projected onto $\mathbf{M}$-space presents the difficulty described in (4.3). For every $\mathbf{M}^k$, the constraints for the NLP issue stated in (4.1) hold, hence the projection problem may be expressed as follows:

$$\min_{\mathbf{M}} \min_{\mathbf{N}} \quad -\Theta(\mathbf{M}^k, \mathbf{N}^k) - \nabla\Theta(\mathbf{M}^k - \mathbf{N}^k)\begin{pmatrix}\mathbf{N} - \mathbf{N}^k \\ \mathbf{M} - \mathbf{M}^k\end{pmatrix} \tag{4.5a}$$

$$\text{s.t.} \;\; \Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}^k) - \nabla\Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}^k)\begin{pmatrix}\mathbf{N} - \mathbf{N}^k \\ \mathbf{M} - \mathbf{M}^k\end{pmatrix} \leq 0. \tag{4.5b}$$

The issue in (4.5) can be rewritten as follows by substituting ς for another variable:

$$\min_{\mathbf{M},\mathbf{N},\varsigma} \ \varsigma \tag{4.6a}$$

$$\text{s.t.} \ \ \varsigma \geq -\Theta(\mathbf{M}^k, \mathbf{N}^k) - \nabla\Theta(\mathbf{M}^k - \mathbf{N}^k)\begin{pmatrix} \mathbf{N} - \mathbf{N}^k \\ \mathbf{M} - \mathbf{M}^k \end{pmatrix} \tag{4.6b}$$

$$\Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}^k) - \nabla\Pi_{\text{24b-24j}}(\mathbf{M}^k, \mathbf{N}^k)\begin{pmatrix} \mathbf{N} - \mathbf{N}^k \\ \mathbf{M} - \mathbf{M}^k \end{pmatrix} \leq 0 \tag{4.6c}$$

4.1.3 Iterative Approach of the ϵ-Optimal Algorithm

The MILP problem provides an optimal LB in equation (4.6). A MILP issue [38] is solved using the branch and bound approach. Specifically, the MILP problem is motivated by the solution to the NLP issue at M^k [39, 40] once the objective function, Θ, and the constraints function, $\Pi_{\text{24b-24j}}$, are linear. The ϵ-optimal algorithm takes an iterative approach, which entails the following phases:

1. During the iterative process towards an ϵ-optimal solution, the lower bound (LB) progressively rises, while the upper bound (UB) gradually decreases

2. Once the discrepancy between the lower bound (LB) and upper bound (UB) diminishes to a magnitude smaller than ϵ, the solution is deemed optimal

3. In the event that the disparity surpasses the threshold of ϵ, the binary variables $\mathbf{M}$ are revised to $\mathbf{M}^{k+1}$. Consequently, the nonlinear programming (NLP) and mixed-integer linear programming (MILP) problems are readdressed in subsequent iterations to derive updated lower bound (LB) and upper bound (UB) values

4. The iterative process of updating the lower bound (LB) and upper bound (UB) persists until the discrepancy between them diminishes below the threshold of ϵ, signifying the achievement of the optimal solution

5. The diagram depicting the procedural steps of the ϵ-optimal algorithm is showcased in Figure 4.1.

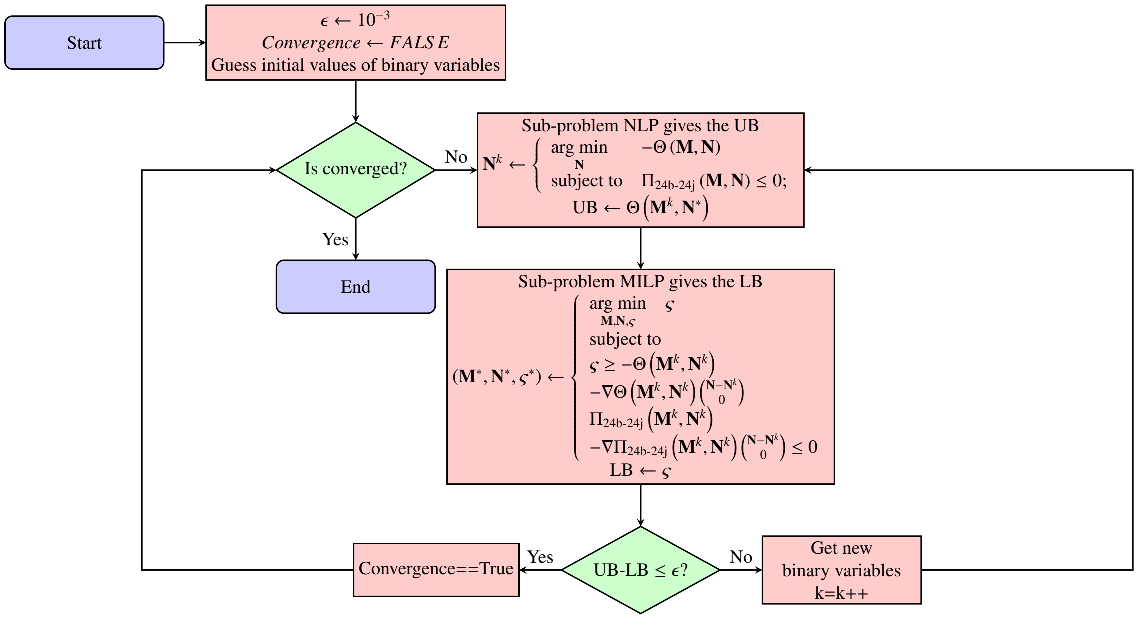

Figure 4.1: **Flow chart - outer approximation algorithm**

4.2 Algorithm Convergence and Optimality

The ϵ-optimal algorithm converges linearly, as stated by [36, 39]. The objective and constraints functions, i.e., Θ and $\Pi_{\text{24b-24j}}$, are convex when the binary variables $\mathbf{M}$ are fixed at $\mathbf{M}^k$. The ϵ-optimal algorithm [38] uses the branch and cut technique to quickly find the best solution (within $\epsilon = 10^{-3}$ steps) when all four preconditions are met. The ϵ-optimal algorithm guarantees that the result lies within the ϵ-bound of the optimal solution for any $\epsilon > 0$. The validity of the assertion holds true for lower magnitudes of ϵ. In the scenario of the given binary variable $\mathbf{M}$, denoting the optimality of $\mathbf{N}$ as per (4.6), one potential solution can be outlined as follows:

1. If $\varsigma \geq \Theta(\mathbf{M}^k, \mathbf{N}^k) \rightarrow viable\ solution$
2. Otherwise $\varsigma \leq \Theta(\mathbf{M}^k, \mathbf{N}^k) \rightarrow not\ a\ viable\ solution$

So, it's possible that there is no such thing as an unsolvable value of $\mathbf{M}^k$ for the MILP issue described in (4.6). Henceforth, the ϵ-optimal algorithm converges within a finite number of iterations, ensuring optimal outcomes as long as $\mathbf{M}$ remains constant. This can be attributed to the convexity of both the objective and constraint functions. A comprehensive proof of convergence for the OAA algorithm is provided in [36].

For Eq. (4.7), an exhaustive search algorithm (ESA) is capable of finding the optimal solution; however, it entails exponentially greater processing time. The computational complexity of ESA can be expressed using the S-IoT notation for complexity $\mathcal{C}$ and the number of users u as follows:

$$\text{Ç}_{ESA} = 2^{2u} \tag{4.7}$$

On the other hand, OAA with an infinite number of iterations [37] will eventually lead you to the ϵ-optimal algorithm. Below is a simplified representation of the computational complexity of the OAA:

$$\text{Ç}_{OAA} = \frac{u^2 \kappa}{\omega} \tag{4.8}$$

in the given context, the variable κ represents the complete count of constraints, while ω denotes the highest allowable deviation of the ϵ-optimal approach from the value of the global optimum. In the case of OAA, you may be certain that you will be provided with a solution that is optimal for ϵ, however in the case of ESA, this is not the case. The increasing difficulty of the computations performed by OAA and ESA is illustrated in the reference figure 4.2.

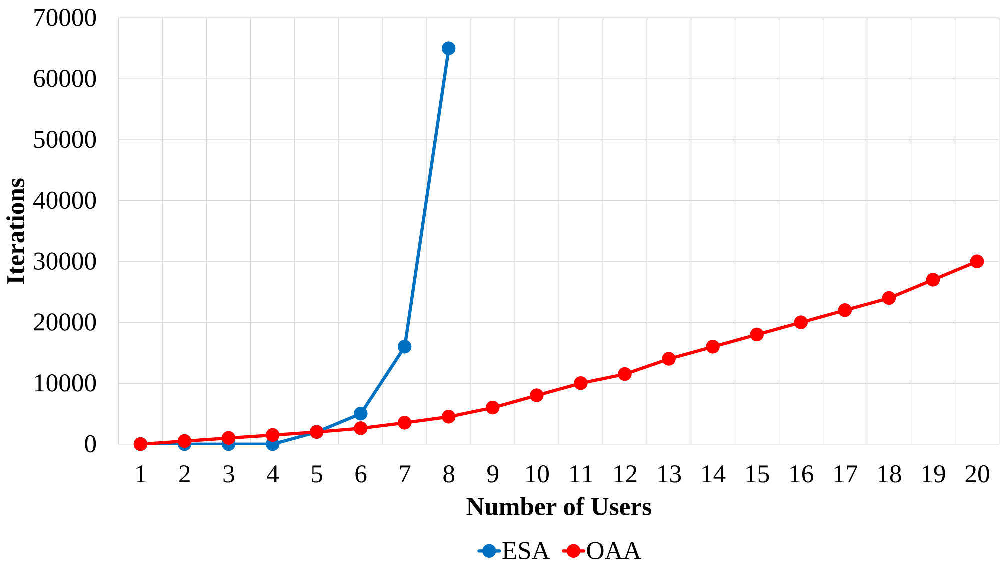

Figure 4.2: **Impact of User Count on Computational Complexity: OAA vs ESA.**

4.3 Computational Complexity Analysis of the ϵ-Optimal Algorithm

Calculating complexity sometimes involves the usage of flops [1] [41]. In the first stage of the epsilon-optimal algorithm, you are going to need to add five flops. In order to solve the NLP problem, simply add $4IJ\Upsilon$ and $2IJ$ flops. An extra $2IJ\Upsilon$ and $4IJ\Upsilon$ flips are required to solve the MILP problem. When examining the NLP and MILP problems concurrently, the algorithm incurs a total of two floating-point operations (flops). Incorporating additional binary values results in an additional four flops. The complexity of the ϵ-optimal algorithm can be quantified in terms of the number of flops required for its completion.

$$E = 5 + 2IJ + 4IJ\Upsilon + 4IJ\Upsilon + 2IJ\Upsilon + 4, \tag{4.9a}$$

$$E = 9 + 2IJ + 10IJ\Upsilon, \tag{4.9b}$$

$$E \approx 2IJ + 10IJ\Upsilon. \tag{4.9c}$$

The complexity of the ϵ-optimal algorithm can be expressed using Big O notation as $O(I \times J) + O(I \times J \times \Upsilon)$. Here, I represents the number of unlimited connected IoT devices, J represents the number LEO cloudlet, and Υ represents the number of constraints in the problem.

[1]Counting the amount of floating-point operations, or "flops," is one way to measure complexity. Additionally, one flop is added whenever division or multiplication is performed. When adding two flops together, complex addition is used, but when adding four flops together, complex multiplication is used. Multiplying a matrix of dimensions $l \times m$ by a matrix of dimensions $m \times o$ yields $2lmo$ flops. The logical operator and the assignment operator both increase the number of flops by one. The $log_2(x)$ operation takes two flip-flops to complete

Chapter 5

SIMULATION WITH RESULTS ANALYSIS

The simulation results obtained showcase the performance of the proposed strategy in addressing the fractional programming with respect to the energy efficiency (EE) of S-IoT. These results also offer valuable insights into the convergence behavior of the proposed algorithm. To carry out the outer approximation, the Basic open-source nonlinear mixed integer programming solver BONMIN [34] is employed.

The key performance parameters to show the advantages of the proposed strategy are as follows:

- Number of IoT associated
- Fairness in IoTA
- RB allocation
- Fairness in RB allocation
- Average throughput achieved
- Channel and throughput comparison
- Effect of rain
- EE effected by Movement of Satellite
- QoS EE achieved

5.1 Simulation Setup

The simulation utilized various system parameters, as listed in 5.1. Throughout the simulations, the maximum power for LEO (Low Earth Orbit) and GEO (Geostationary Orbit) Satellites was set to 33 dBm and 37 dBm, respectively. The maximum radius of LEOs and GEO was set to 1000 Km, and 42000 km respectively. The minimum required data rates ranged from 0.2 Mbps to 1.0 Mbps. The minimum allowed number of users was set to 3, while the maximum allowed number of users was 50, incremented by 5. A total of 160 Resource Blocks (RBs) were available for allocation to the users. Additional parameters included a zero mean Gaussian random variable set to 10 dB. The total circuit power (Pc) was set to 10^{-6} Watts, and the maximum allowable latency was set to 5 ms. These parameters were essential for conducting the simulations and evaluating the performance of the system.

Table 5.1: **System Parameters**

Parameter	**Value**
P_l	33 dBm
P_g	37 dBm
R_j^{d}	{0.2,0.4,0.6,1.0} Mbps
R_j^{u}	{0.2,0.4,0.6,1.0} Mbps
HL	1,000 Km
HG	37,786 Km
T_{RB}	160‘
G	50
$b_{i,j}$	0.1 Mbps
$\xi_{i,j}(t)$	10 dB
P_c	-30 dBm
$l_{x,y}(t)$	5 ms
f_{l}^c	10^9 cycle/s
f_{g}^c	5×10^9 cycle/s
f_{l}^s	2 Gbps
f_{g}^s	50 Gbps
Min IOTs	3
Increment	5
Max IOTs	50

5.2 Results With In-depth discussions

In this section, we present the results derived from our simulations, showcasing the efficacy of the proposed algorithm in attaining equitable admission control, IoT association, power allocation, and maximized energy efficiency (EE). Furthermore, we conduct a comprehensive performance comparison, contrasting the fairness-oriented approach with a non-fairness-based implementation [33, 34] in terms of IoT association, EE, and throughput. Our evaluations are carried out within the context of a hybrid geostationary Earth orbit (GEO)/low Earth orbit (LEO) satellite network.

5.2.1 IoT Association

Figure 5.1 presents a graph depicting the correlation between the number of IoT devices and the associated IoT devices in the satellite network, considering both fairness-based and non-fairness-based approaches. The term IoTA represents the total count of available IoT devices compared to the number of IoT devices associated with the satellite network, including both LEO and GEO satellites. The graph clearly demonstrates that as the number of IoT devices increases, there is a proportional increase in both fairness-based and non-fairness-based IoTA. This suggests that with the expansion of the devices associated within the network, the likelihood of their association with any available LEO/GEO satellite network also increases.

Furthermore, the graph reveals that the IoTA values for the fairness-based and non-fairness-based approaches are closely aligned, exhibiting only a marginal difference in the overall average number of associated devices. However, the fundamental distinction lies in the equitable distribution of associated devices among the available satellites in each scenario. In the fairness-based IoTA approach, the association of devices with a specific LEO satellite takes into consideration the fair distribution of the load across the available satellite network. Conversely, in the absence of fairness-based IoTA, the association of devices with a particular satellite does not consider the criterion of fair load distribution.

The graph 5.1 also depicts multiple satellites, including LEOs and GEO, each with different orbital velocities and QoS rates ranging from 0.2 to 1 Mbps. The findings clearly indicate that the number of IoT devices connected to GEO satellites is significantly lower compared to other LEO satellites. This discrepancy may be attributed to factors such as the long propagation, processing, and transmission delays involved in communicating with GEO satellites. Additionally, task offloading may occur when LEO satellites are unable to handle certain requests, resulting in those requests being directed to GEO satellites. Consequently, GEO satellites exhibit fewer associations with IoT devices compared to LEO satellites.

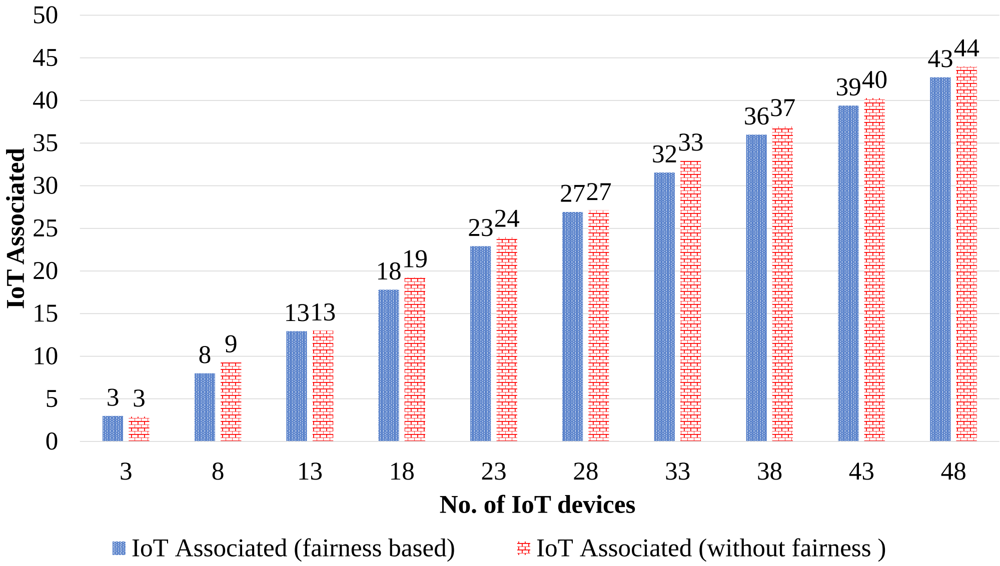

Figure 5.1: **IoT devices vs IoT Devices Associated in hybrid GEO/LEO Satellite Network.**

Graph 5.2 shows a comparison made between research work in [15] and [16] represents a previous scenario or condition, while curve of proposed with additional parameters represents an improved or optimized scenario. The improved curve shows a more efficient and effective allocation of resources, resulting in a higher number of IoT devices being associated with the network. This improvement suggests that the system has been enhanced to better handle the increasing number of IoT devices and accommodate their connectivity requirements.

The improved curve also indicates that the system has implemented better strategies for IoT device association, such as optimized algorithms or resource allocation techniques. These enhancements have contributed to a more efficient utilization of available resources, enabling a greater number of IoT devices to be successfully associated with the network.

5.2.2 IoT Fairness

Figure 5.3 showcases a plot that illustrates the fairness-based IoT Association (IoTA) as a function of different Quality of Service (QoS) rate requirements. The QoS rate requirements range from 0.2 to 1.0 Mbps, and the plot focuses on the association of

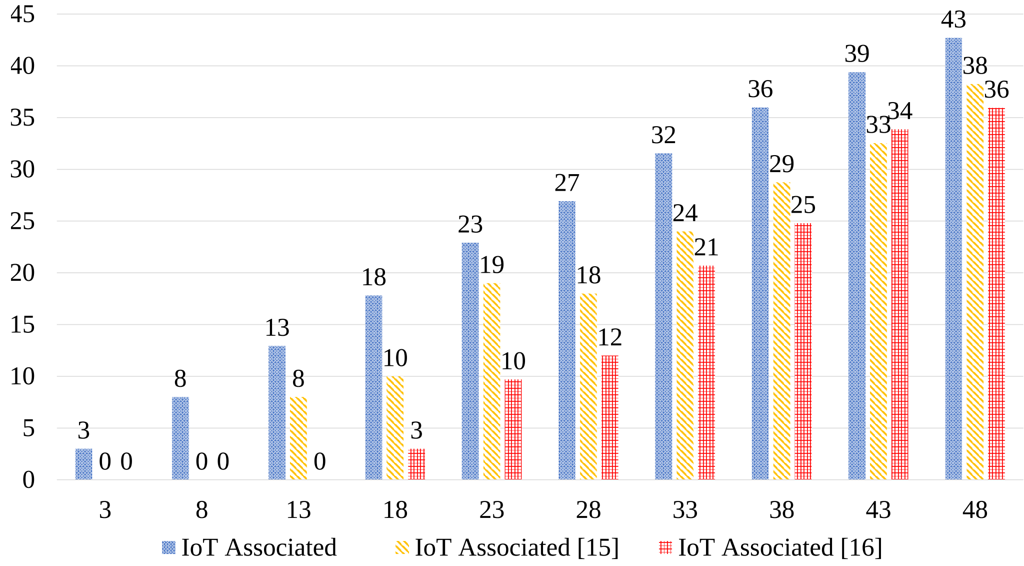

Figure 5.2: **IoT devices vs IoT Devices Associated in comparison to paper 15 and 16.**

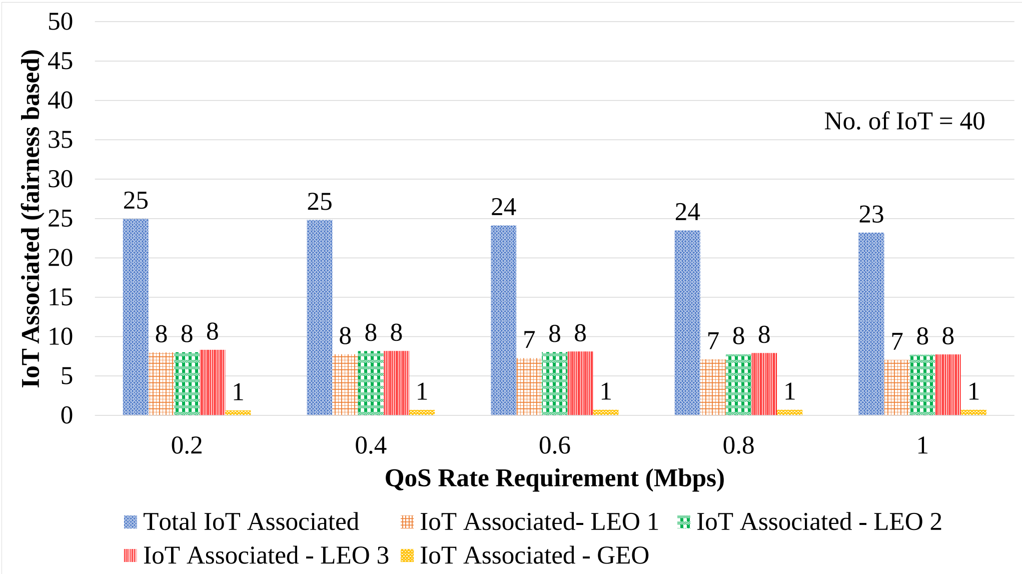

Figure 5.3: **QoS Rate Requirement vs IoT Devices Associated (fairness based).**

devices with both LEOs and GEO satellite networks. Analyzing the plot, it becomes apparent that when the QoS rate requirement is set to 0.2 Mbps, there is an equitable distribution of devices among the available LEO satellites. Each LEO satellite accommodates a similar number of associated devices, indicating a fair allocation across the LEO satellite network. As the QoS rate requirement gradually increases from 0.2 to 1.0 Mbps, the plot demonstrates a consistent trend similar to what was observed for the 0.2 Mbps data rate.

Furthermore, the plot reveals that the number of devices connected to the GEO satellite is comparatively lower than those associated with the LEOs. This can be attributed to the fact that the LEO satellites primarily handle the requests generated by IoT devices, fulfilling the majority of them. Only a few requests that cannot be accommodated by the LEOs are redirected to the GEO satellite. It should be noted that this allocation is influenced by factors such as increased delays and response times associated with the GEO satellite. Overall, the dominant association in IoTA is observed with the LEO satellites, regardless of the data rate requirement, indicating their prominent role in facilitating IoT device connections. This trend holds true for both low and high data rates. Moreover, Figure 5.3 demonstrates a marginal decrease in the overall number of associated devices as the Quality of Service (QoS) rate requirement progressively increases from 0.2 to 1.0 Mbps. This reduction in the IoTA performance indicates that the system associates a lower number of devices at higher data rates in comparison to lower data rates.

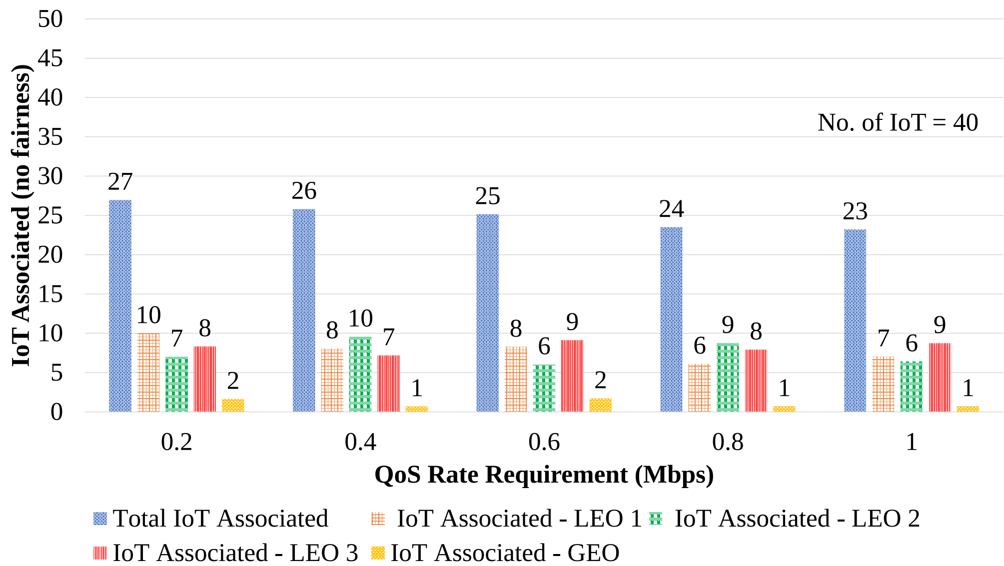

Figure 5.4: **QoS Rate Requirement vs IoT Devices Associated (Without fairness).**

In figure 5.4, Uneven distribution of devices can result in congestion in certain areas or on specific satellite beams, leading to performance degradation and potential service disruptions. Unfair distribution of IoT devices may result in some devices receiving a disproportionately higher share of network resources, such as bandwidth or processing capabilities. This can lead to congestion, increased latency, and degraded performance for devices that receive inadequate resources. Consequently, the overall network efficiency and user experience may suffer.

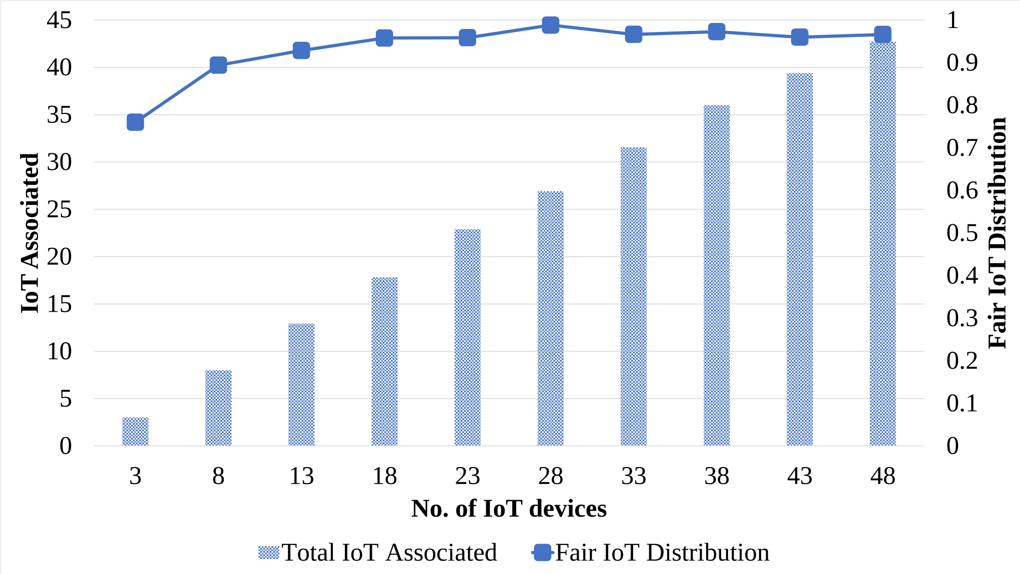

Figure 5.5: **IoT Devices vs IoT Devices Fairness.**

Figure 5.5 illustrates a graph depicting the relationship between the number of IoT devices and two factors: IoTA (IoT Association) and IoT fairness (IoTF). IoTA represents the total number of devices associated with the network, while IoTF represents the fairness observed during the association process. The graph shows that as the number of associated devices increases, the fairness also increases. Additionally, as the number of IoT devices is further increased, the IoTF value tends to 1, signifying a higher level of uniform fairness among the associated devices. This is demonstrated in Figure 7. The increase in fairness can be attributed to the larger pool of available devices, resulting in a higher IoTA. Consequently, the system can allocate these associated devices more fairly among the available satellite resources. Conversely, when the number of devices is low, the distribution of devices among the available satellites becomes challenging. Fairly distributing these devices in the LEO/GEO satellite network becomes more difficult. Consequently, the efficiency of fairness in device association is enhanced as the number of devices increases, in contrast to scenarios with a smaller number of devices.

Figure 5.6 showcases a comprehensive plot that illustrates the correlation between the number of IoT devices, IoT Association (IoTA), and IoT Fairness (IoTF) index at various Quality of Service (QoS) rate requirements. The QoS rate requirements considered are 0.2 Mbps, 0.4 Mbps, 0.6 Mbps, 0.8 Mbps, and 1.0 Mbps. The range of

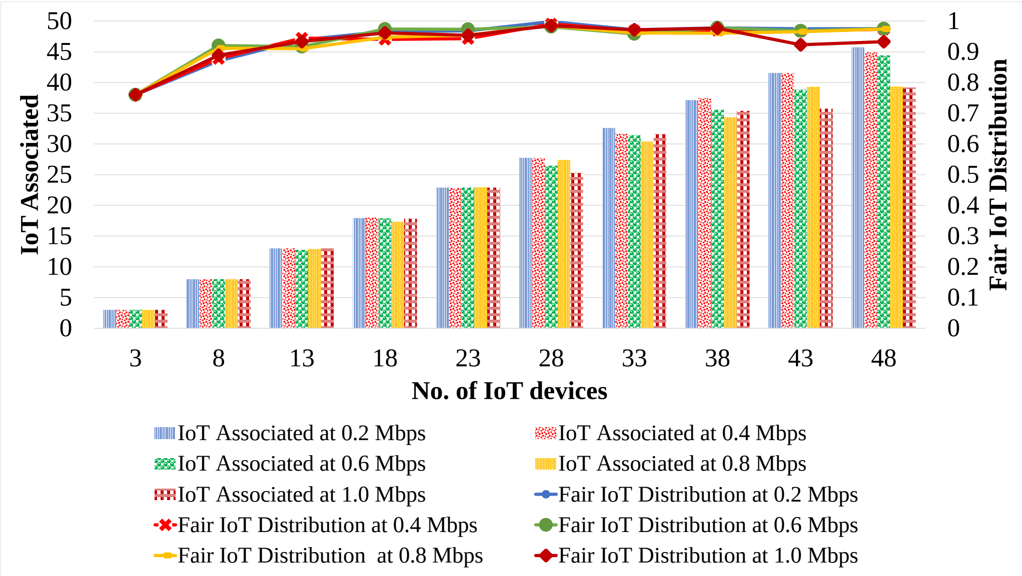

Figure 5.6: **IoT Devices Associated vs IoT Devices at different QoS rate requirements**

IoT devices analyzed spans from 3 to 50, with a step size of 5, providing a thorough examination of system behavior across different connected IoT device. Upon examination of Figure 5.8, it becomes apparent that as the number of users increases, there is a corresponding increase in IoTA for all QoS rate requirements. This observation aligns with the expectation that a larger number of devices would result in a greater number of associations within the system. Importantly, despite the decrease in IoTA as the QoS rate requirement increases, the fairness in associating devices with available LEOs and GEO satellites remains relatively consistent across all QoS rate requirements, including 0.2 Mbps, 0.4 Mbps, 0.6 Mbps, 0.8 Mbps, and 1.0 Mbps. This observation indicates that the system maintains a fair distribution of associations among the available satellite resources, regardless of the specific QoS rate requirement. These findings further validate the results obtained in Figure 5.6 and Figure 5.7, supporting the consistency and robustness of our research outcomes.

5.2.3 RB Fairness

Graph 5.7 provides insights into the fairness distribution of IoT devices among RBs. Fairness distribution refers to the equitable allocation of resources among devices, ensuring that each device receives a proportional share based on its requirements and the available resources. The analysis reveals that the fairness distribution remains relatively

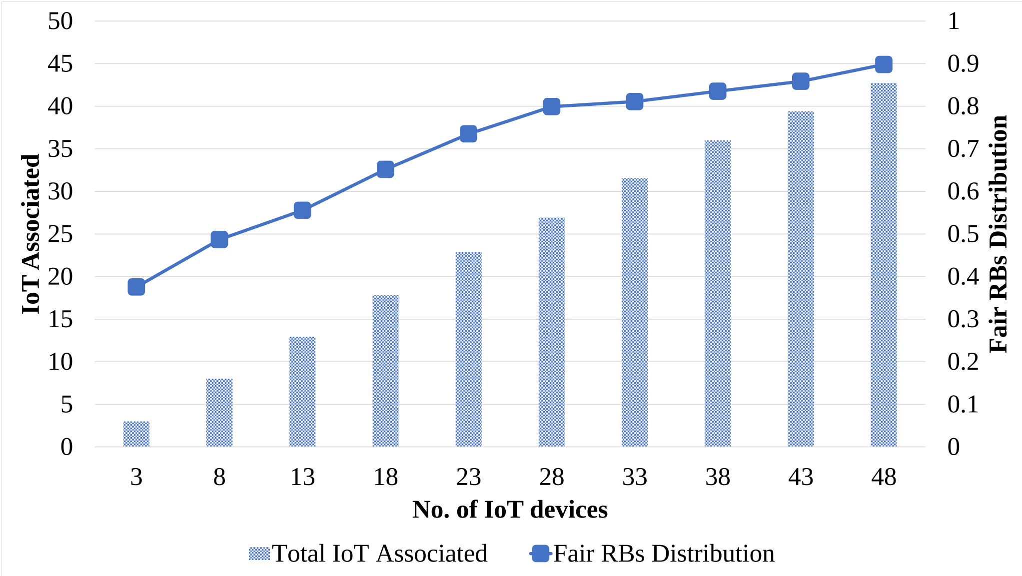

Figure 5.7: **IoT Devices vs IoT Devices Associated and RB (Fairness Distribution)**

consistent with respect to number of devices associated to it. Regardless of the number of IoT devices, the graph illustrates a stable distribution pattern, suggesting that the system maintains fairness in allocating RBs to devices. This finding is significant as it demonstrates the system's ability to ensure equitable resource utilization and avoid concentration or overloading of RBs on specific devices.

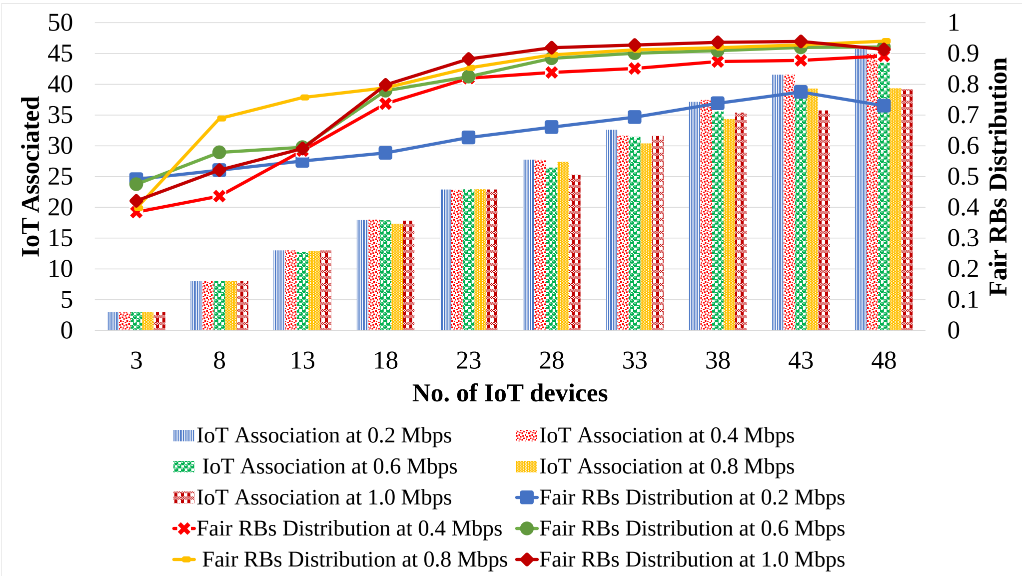

Figure 5.8: **IoT Devices vs IoT Devices Associated and RB at different QoS rate requirements.**

Figure 5.8 showing the analysis delves into the impact of different QoS rate requirements on the association of devices with RBs. The QoS rate requirement represents the minimum acceptable data rate for each IoT device, influencing the allocation of RBs.

The graph demonstrates that as the QoS rate requirement increases, the number of devices associated with RBs experiences a slight decrease. This observation suggests that higher data rate demands impose constraints on resource availability, resulting in a slightly lower number of devices being associated with RBs. Despite the variation in the number of devices associated with RBs across different QoS rate requirements, the graph illustrates that the system maintains a fair distribution of RBs among the IoT devices. Fairness distribution ensures that each device receives a proportionate share of RBs based on its requirements and the available resources. This observation indicates that the system effectively manages resource allocation to maintain fairness, irrespective of the specific QoS rate requirement.

5.2.4 RB Allocation

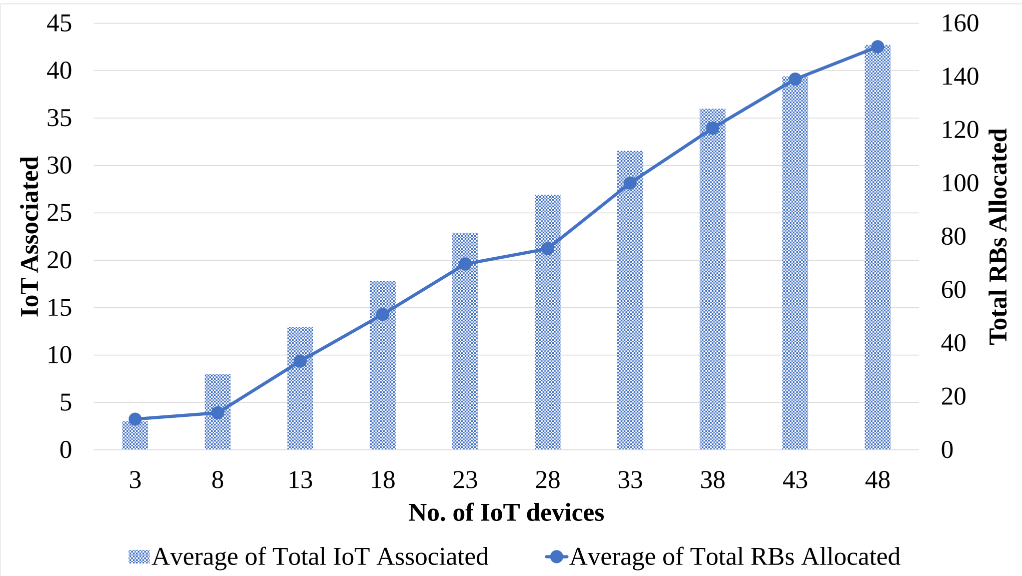

Figure 5.9: **IoT Devices vs IoT Devices Associated and Allocated RBs.**

The graph 5.9 illustrates the resource block RBs allocation to the IoT devices. RB allocation represents the distribution of available RBs among the devices. It is evident from the graph that as the number of IoT devices increases, the allocation of RBs also increases. This observation demonstrates that the system effectively manages RB allocation to accommodate the growing demand and ensure adequate resource provisioning for the associated devices.

Figure 5.10 showing the analysis delves into the impact of different QoS rate requirements on the association of devices with RBs. The QoS rate requirement represents the

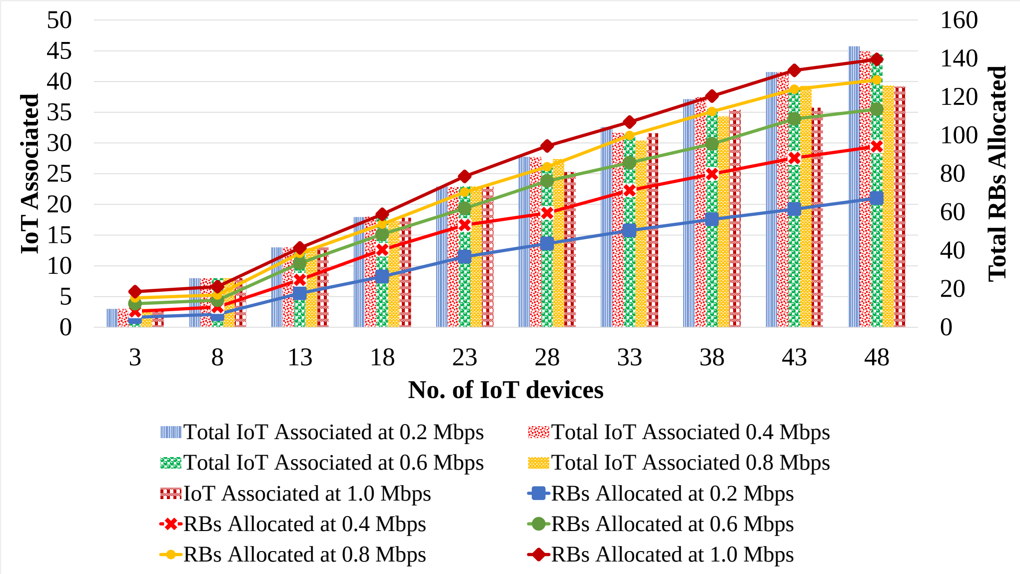

Figure 5.10: **IoT Devices vs IoT Devices Associated and RB Fairness at various QoS rate requirements.**

minimum acceptable data rate for each IoT device, influencing the allocation of RBs. The graph demonstrates that as the QoS rate requirement increases, the number of devices associated with RBs experiences a slight decrease. This observation suggests that higher data rate demands impose constraints on resource availability, resulting in a slightly lower number of devices being associated with RBs. Despite the variation in the number of devices associated with RBs across different QoS rate requirements, the graph illustrates that the system maintains a fair distribution of RBs among the IoT devices. Fairness distribution ensures that each device receives a proportionate share of RBs based on its requirements and the available resources. This observation indicates that the system effectively manages resource allocation to maintain fairness, irrespective of the specific QoS rate requirement.

Figure 5.11 depicts a graph illustrating the correlation between the QoS rate requirement of IoT devices and two metrics: IoT association and RB (Resource Block) allocation. The graph reveals an inverse relationship between IoT association and the QoS rate requirement, while RB allocation shows a direct relationship with higher QoS rate requirements. The graph depicted in Figure 5.11 provides clear evidence of the inverse relationship between the QoS rate requirement of IoT devices and the IoT association. It is anticipated that higher data rates demand greater power for maintaining satisfactory

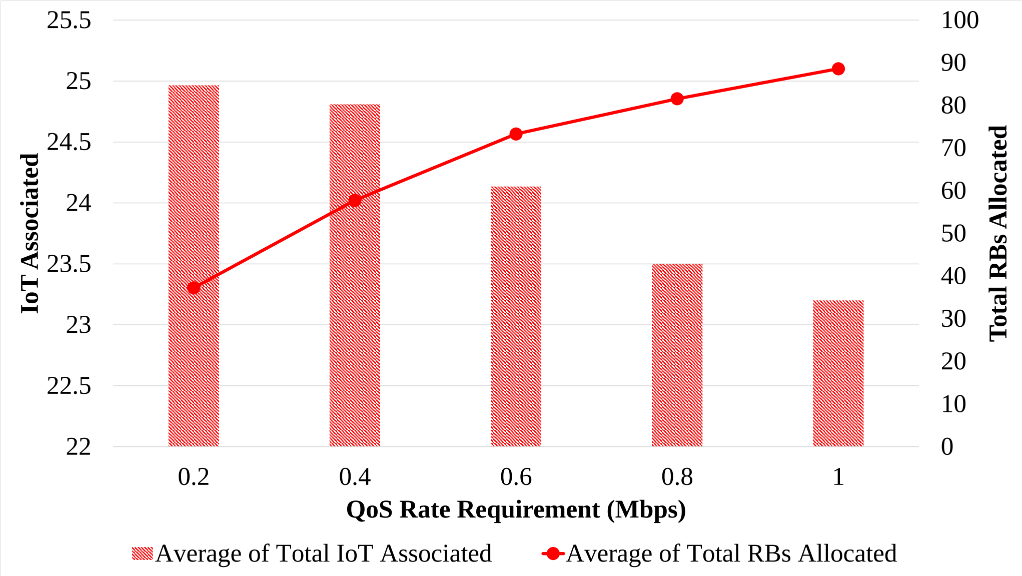

Figure 5.11: **QoS rate requirement vs IoT Devices Associated and Allocated RBs.**

performance. Consequently, the power required for a user to establish association with a specific LEO/GEO satellite also increases at higher data rates. Consequently, the IoT association decreases as the QoS rate requirement escalates. Conversely, the allocation of RBs demonstrates a positive trend, showing an increase as the QoS rate requirement rises. This means that higher data rates demand a larger allocation of RBs or spectrum resources to meet the increased transmission needs. Therefore, RB allocation at higher data rates is greater than at lower data rates.

5.2.5 Throughput

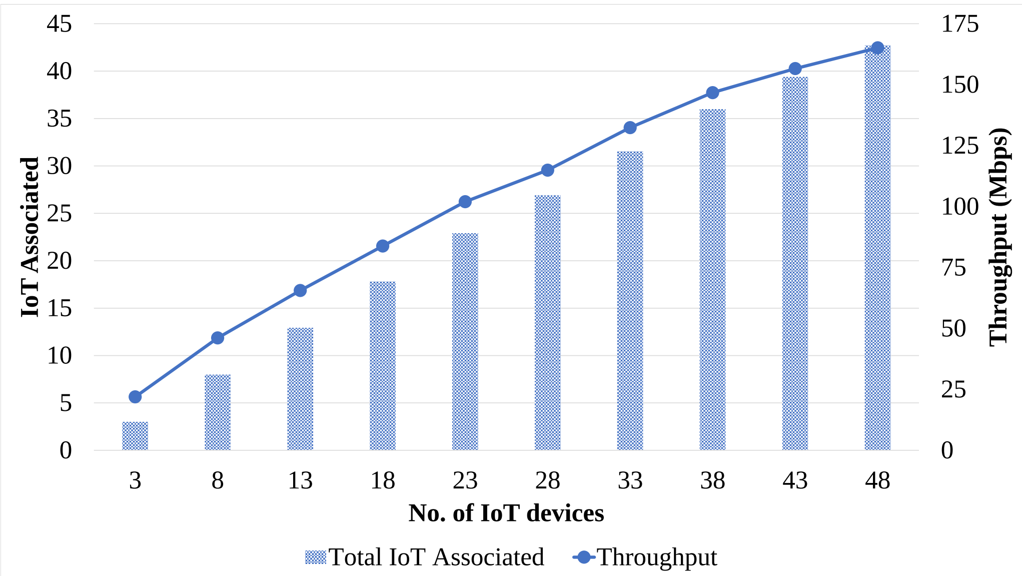

Figure 5.12: **IoT Devices vs IoT Devices Associated and Throughput.**

The graph 5.12 showcases the relationship between the number of devices associated with the network and the resulting throughput. Throughput represents the rate at which data is transmitted through the network and is a crucial performance metric for IoT applications. The graph illustrates that as the number of associated devices increases, the throughput also tends to increase. This observation suggests that the network can efficiently handle the data transmission demands of a larger device population, leading to higher overall throughput. As the number of IoT devices grows, the network demonstrates its ability to scale and maintain higher throughput levels. This scalability is essential for ensuring that the network can handle the increasing data traffic and meet the performance requirements of IoT applications. By efficiently managing resources such as bandwidth, transmission power, and scheduling, the network can ensure that data is transmitted more effectively, thereby increasing throughput. This optimization takes into account factors like channel conditions, traffic patterns, and QoS requirements.

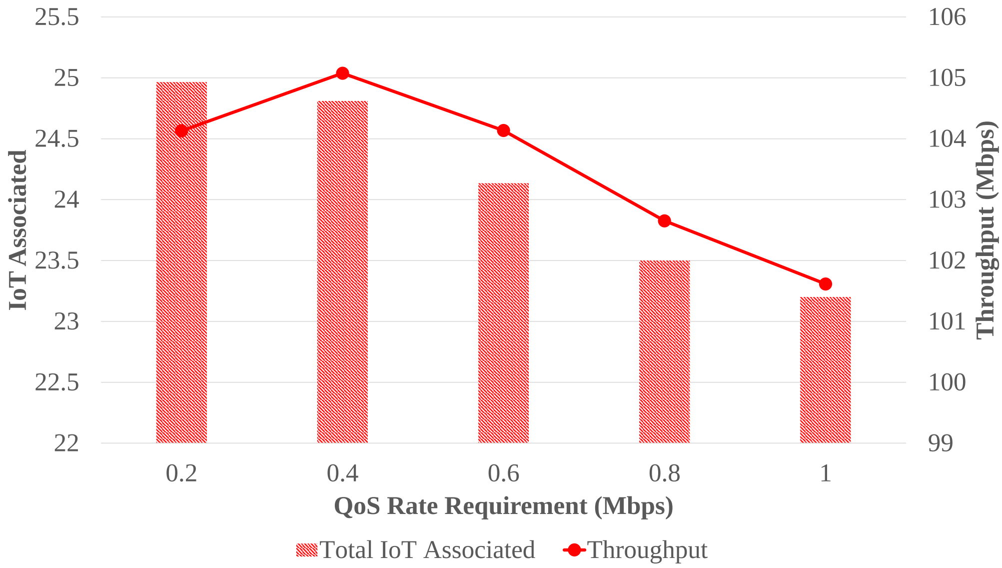

Figure 5.13: **QoS rate requirement vs IoT Devices Associated and Throughput.**

We have conducted an analysis considering the Quality of Service (QoS) rate requirement, which represents the minimum acceptable data rate for each IoT device. Figure 5.13 presents a graphical representation depicting the relationship between the number of IoT devices, IoT association (IoTA), and throughput for various quality of services rate requirements: 0.2 Mbps, 0.4 Mbps, 0.6 Mbps, 0.8 Mbps, and 1.0 Mbps.

The behavior of IoTA observed in the graph aligns with the previously discussed results, as the increase in number of devices demonstrates a consistent pattern across all QoS rate requirements. This indicates that the number of IoT associations increases proportionally with number of devices, regardless of specific QoS rate requirement.

Furthermore, Figure 5.13 illustrates the variations in throughput across various QoS rate requirements. It is noteworthy that the highest throughput is attained when the QoS rate requirement is at its lowest. However, as the QoS rate requirement increases, there is a gradual decrease in throughput. Nevertheless, it is important to emphasize that regardless of the specific QoS rate requirement, there is a general upward trend in throughput as the number of IoT devices increases.

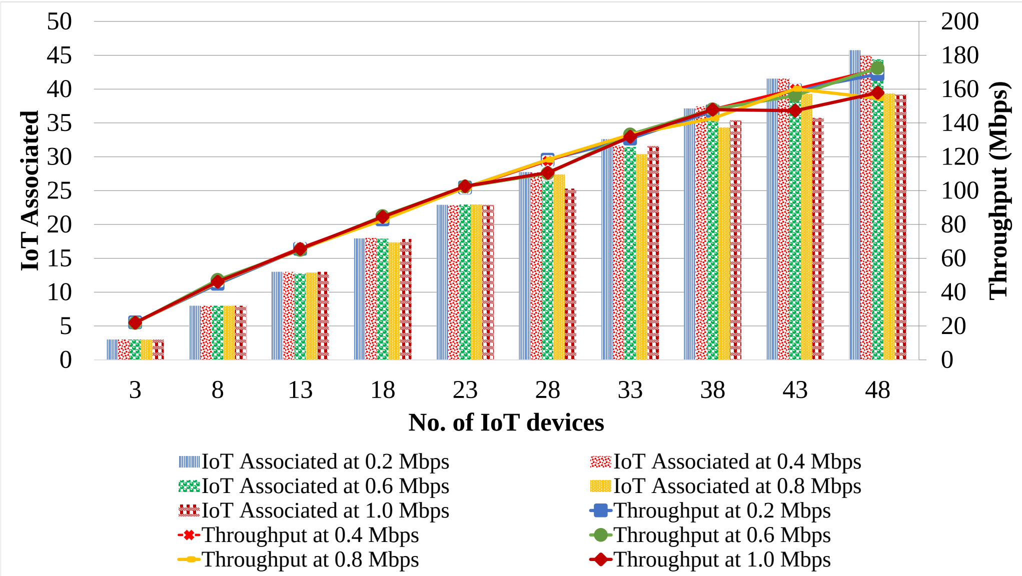

Figure 5.14: **QoS rate requirement vs IoT Devices Associated and Throughput.**

The graph presented in Figure 5.14 illustrates the relationship between the Quality of Service (QoS) rate requirement and both the number of IoT devices associated and the throughput. The QoS rate requirement, spanning from 0.2 Mbps to 1.0 Mbps, signifies the minimal data rate that each associated IoT device must meet to ensure satisfactory performance. Firstly, as the QoS rate requirement increases, there is a noticeable decrease in the number of IoT devices associated with the network. This trend suggests that higher data rate demands impose stricter criteria for device association, resulting in a reduced number of devices meeting the required threshold. Conversely, the graph demonstrates a positive correlation between the QoS rate requirement and the network throughput. As the QoS rate requirement rises, the network's ability to deliver data at the specified rate improves, leading to higher throughput. This relationship aligns with expectations, as a higher QoS rate requirement necessitates increased network capacity and efficiency to meet the demand for faster data transmission.

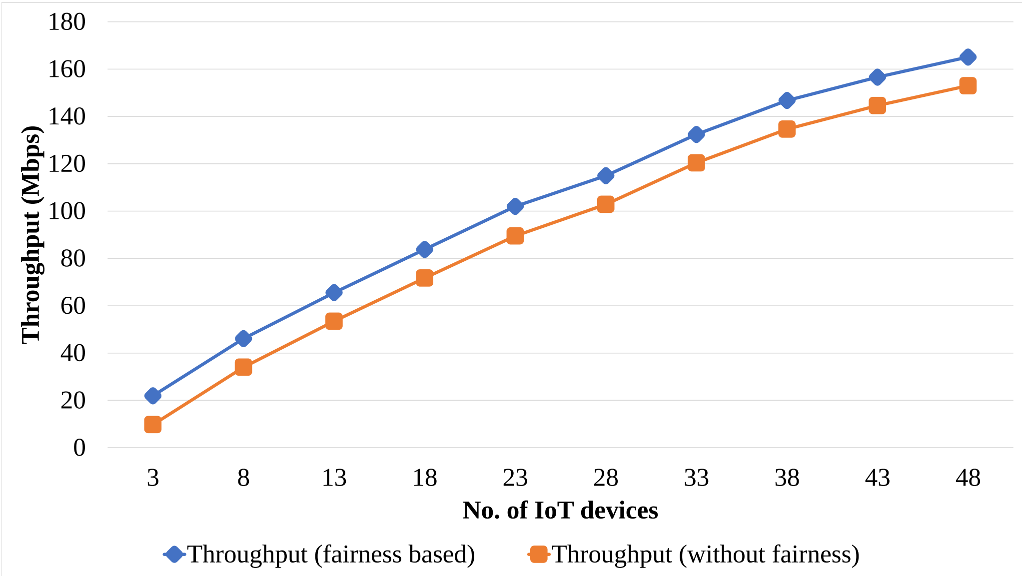

Figure 5.15: **IoT Devices vs and Throughput (both fairness-based and without fairness).**

In Figure 5.15, ist we show that there is no consideration for fairness among the IoT devices, and each device competes for network resources independently. As the number of IoT devices increases, the overall throughput of the system may initially increase this is because more devices are actively utilizing the available network resources, resulting in higher data transmission rates. Secondly, fairness mechanisms are employed to ensure equitable distribution of resources among the IoT devices. Fairness-based approaches typically aim to allocate network resources proportionally or provide equal opportunity for devices to transmit data. In comparison to the without fairness scenario, where each device can potentially monopolize resources, the fairness-based approach may result in a lower throughput per device. This is because resources are shared more fairly, and devices may experience reduced transmission rates to ensure fairness across the network. Fairness mechanisms can improve the stability and overall performance of the network by preventing individual devices from dominating the resources. This can lead to more consistent and predictable performance, albeit at potentially lower individual throughput.

5.2.6 Throughput with and without Rain

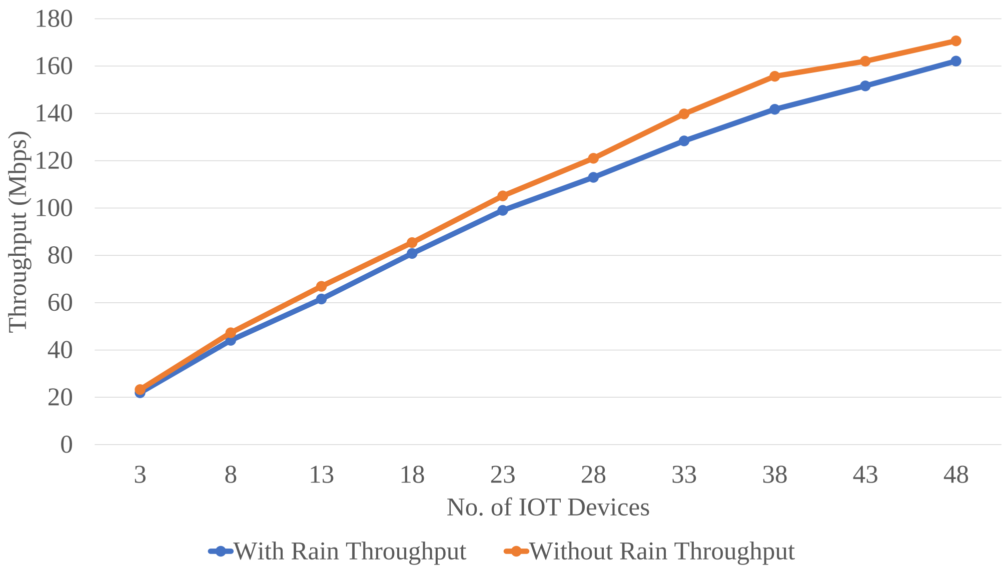

Figure 5.16: **Throughput (With and Without Rain).**

Figure 5.16 show the behaviour of throughput with and without rain as described in eq 3.6c. When IoT devices connected to LEO/GEO Satellite and its rainy environment than it is clearly observed from curve that throughput will decrease meanwhile having no rain throughput will increase obviously. Rain will only effect throughput when multiple devices wants to fetch their required data computation from network due to probability factor as less devices connected to network may not experience any specific change. In clear weather conditions, IoT devices can typically transmit data with higher signal strength and experience lower latency, ensuring smoother communication with the satellite network. The absence of rain reduces the chances of signal attenuation or signal loss, resulting in better overall connectivity. As raindrops fall through the signal path, they can cause signal absorption, scattering, and reflection, leading to signal degradation. The signal attenuation can result in a decrease in signal strength, increased noise, and a higher bit error rate (BER), affecting the quality and reliability of the connection.

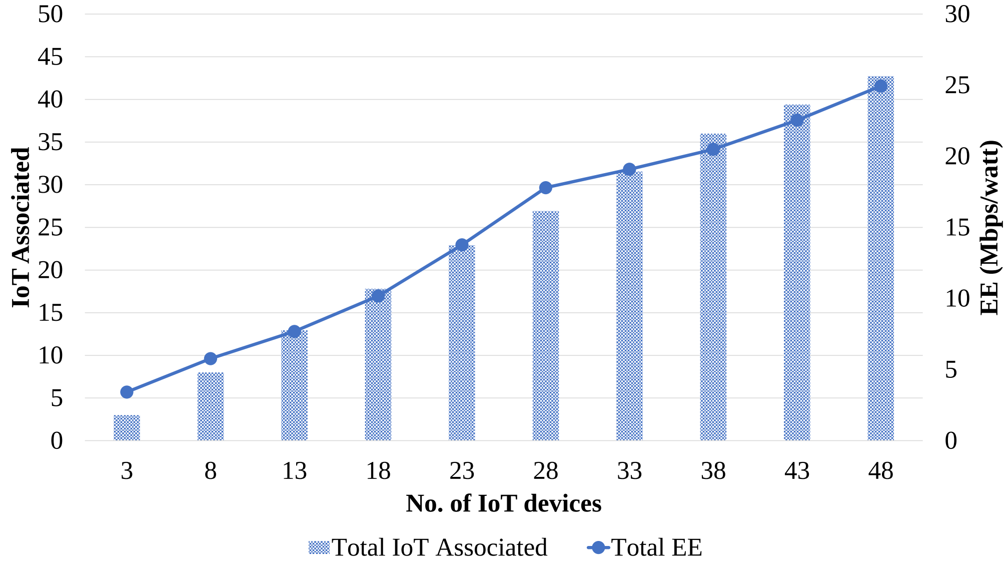

Figure 5.17: **IoT Devices vs and IoT Associated and Energy Efficiency.**

5.2.7 EE

The graph 5.17 depicts the relationship between the number of IoT devices and two key factors: the number of IoT devices associated and their corresponding energy efficiency. The x-axis represents the number of devices, ranging from 3 to 50, while the y-axis indicates the number of associated devices and their energy efficiency. It is evident that as the number of devices rises, the energy efficiency of the network gradually improves. This improvement can be attributed to the aggregation and optimization of resources across a larger device population. The upward trend in energy efficiency can be seen as a result of efficient resource allocation and utilization strategies. With a greater number of devices, there is an increased opportunity to consolidate data processing and storage, reducing redundant energy consumption. This optimization enables better utilization of available resources, resulting in improved energy efficiency across the network.

Graph 5.18 shows comparison between IoT devices associated vs EE with EE as per anthers described in [15] and [16]. Curve [15] and [16] represents a previous scenario or condition with no IoT admission, processing and queening delay factors. Also no fair IoT distribution as well as RB. The improved curve demonstrates a higher level of energy efficiency compared to the previous scenario. This improvement indicates that the system has implemented strategies to optimize energy usage and enhance the

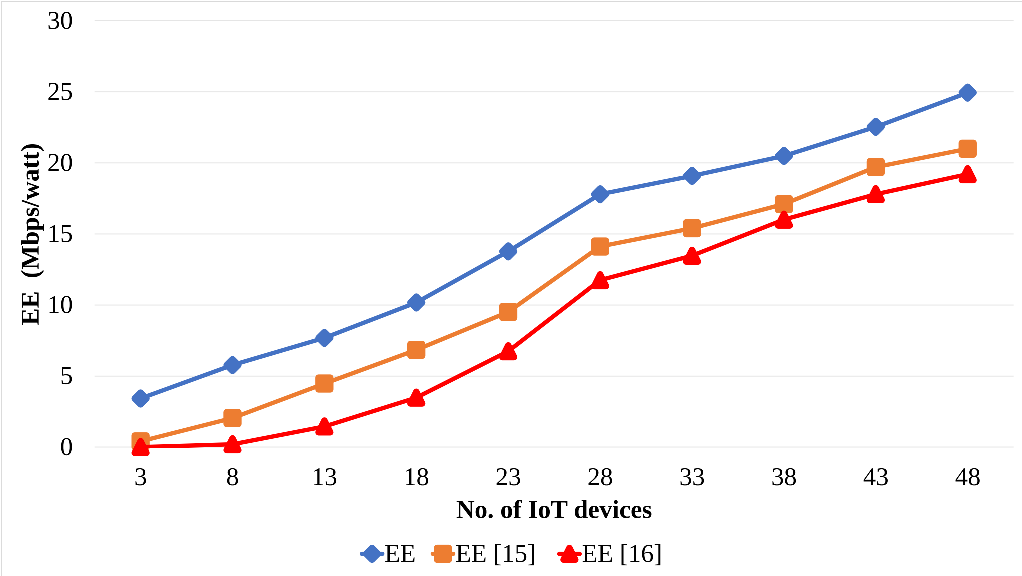

Figure 5.18: **IoT Devices vs and IoT Associated and Energy Efficiency in comparison to paper 15 and 16.**

overall energy efficiency of the network. The improved curve suggests that the system has employed energy-efficient algorithms, power management techniques, or resource allocation strategies to ensure the optimal utilization of energy resources. These enhancements have resulted in a more efficient allocation of energy among the associated IoT devices, leading to improved energy efficiency.

Furthermore, the improved curve indicates that the system has achieved a better balance between IoT device association and energy efficiency. It demonstrates that a greater number of IoT devices can be successfully associated with the network while maintaining or even improving energy efficiency.

The graph 5.19 illustrating the relationship between IoT device rain intensities and energy efficiency reveals a consistent trend: as rain intensities increase, both energy efficiency and IoT association decrease. Notably, the trend exhibits a significant decline in energy efficiency at extremely high rain intensity levels, particularly at 100 mm/hr. Rainfall leads to signal attenuation, scattering, and interference, which in turn degrades the quality and reliability of wireless channel. As rain intensity increases, these detrimental effects intensify, resulting in a decrease in energy efficiency as more energy is required to overcome the challenges posed by the degraded communication environment. Moreover, the decrease in IoT association can be attributed to the impact of rain

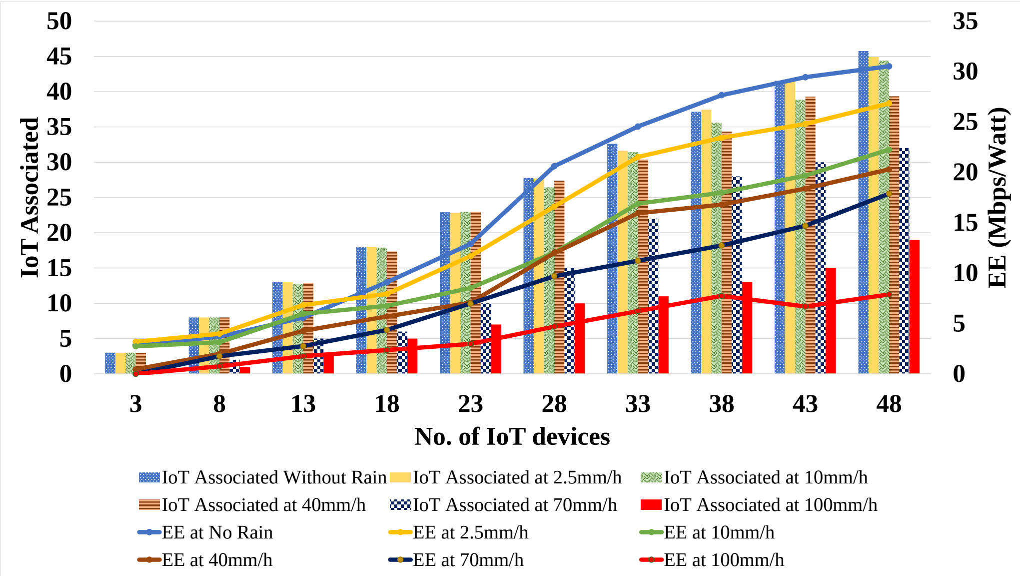

Figure 5.19: **IoT Devices vs IoT Devices Associated and Energy Efficiency (without rain and different intensities of rain.**

intensities on connectivity. As rainfall becomes heavier, it hampers the transmission of data, causing increased packet loss and disruptions in communication. Consequently, IoT devices may struggle to establish and maintain stable connections, leading to a reduction in the number of successful IoT associations.

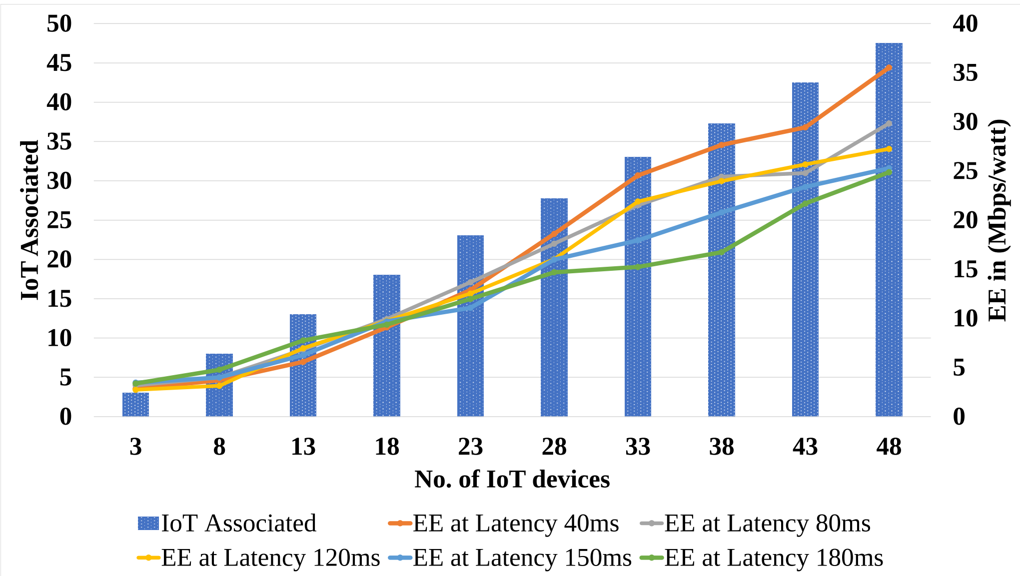

Figure 5.20: **IoT Devices vs IoT Devices Associated and Energy Efficiency (at different latencies).**

The graph 5.20depicting the relationship between IoT device latency and energy efficiency reveals a clear trend: as latency increases, both energy efficiency and IoT association decrease. When latency increases, it signifies a delay in transmitting and receiving data between IoT devices and the network. This delay leads to increased energy consumption as devices have to remain active for longer durations, waiting for responses or acknowledgments. Consequently, energy efficiency decreases as more energy is consumed per unit of data transmitted. higher latency negatively affects IoT association. Latency delays the exchange of information, causing delays in processing commands and receiving feedback. This can result in a reduced number of successful associations between IoT devices.

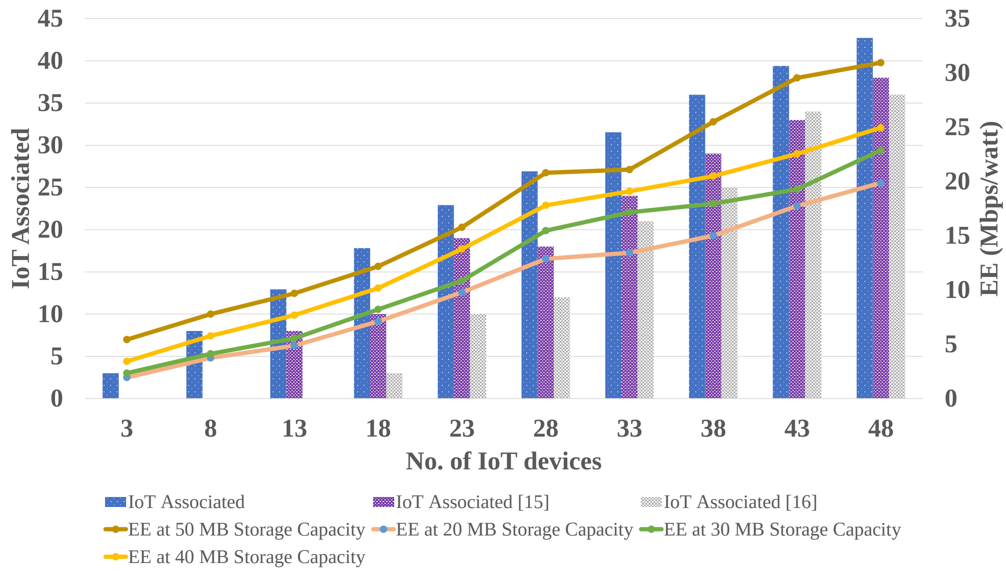

Figure 5.21: **IoT Devices vs IoT Devices Associated and Energy Efficiency (at different Storage values).**

The graph 5.21 shows the relationship between IoT device storage values and energy efficiency uncovers a compelling trend: as storage increases, so does energy efficiency, accompanied by a boost in IoT association. Devices with more storage capacity can locally store and process more data. It reduces data transmission frequency to and from the network, resulting in reduced energy consumption. It can efficiently store and retrieve data as needed, reducing the need for frequent communication and increasing energy efficiency. Moreover, the increase in storage capacity positively impacts IoT association that allows devices to store more data locally, enabling them to operate autonomously and maintain continuous functionality even when network connectivity is intermittent or temporarily unavailable. It increases the likelihood of successful IoT associations as devices can maintain operations and synchronize data when network connectivity is restored.

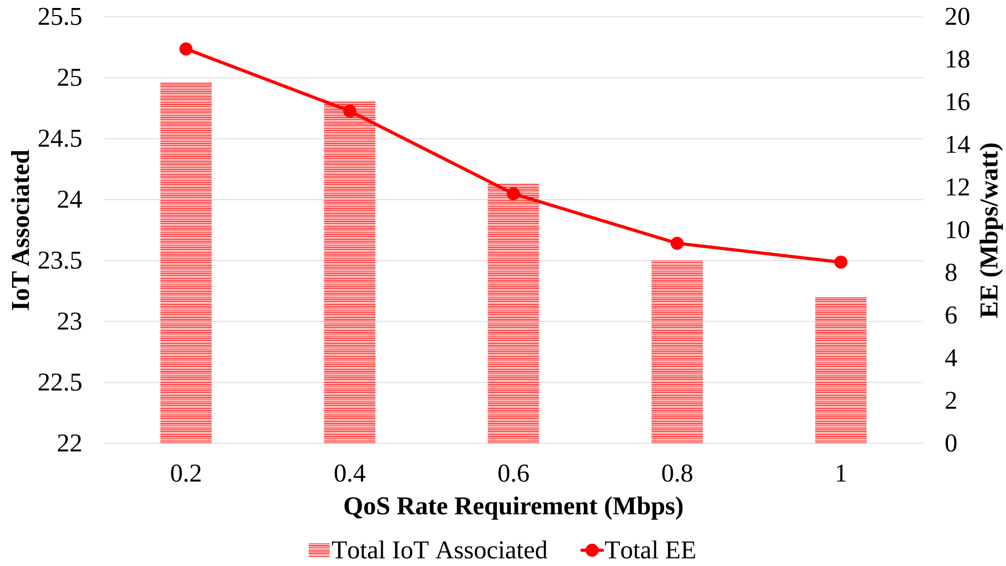

Figure 5.22: **QOS Rate Requirement vs Energy Efficiency.**

Additionally, the graph 5.22 indicates that the rate of energy efficiency improvement appears to slow down as the number of devices continues to increase. This observation suggests that there may be diminishing returns in terms of energy efficiency gains beyond a certain device threshold. It is crucial to carefully balance the benefits of device association with the associated energy consumption to maintain a sustainable and efficient IoT network.

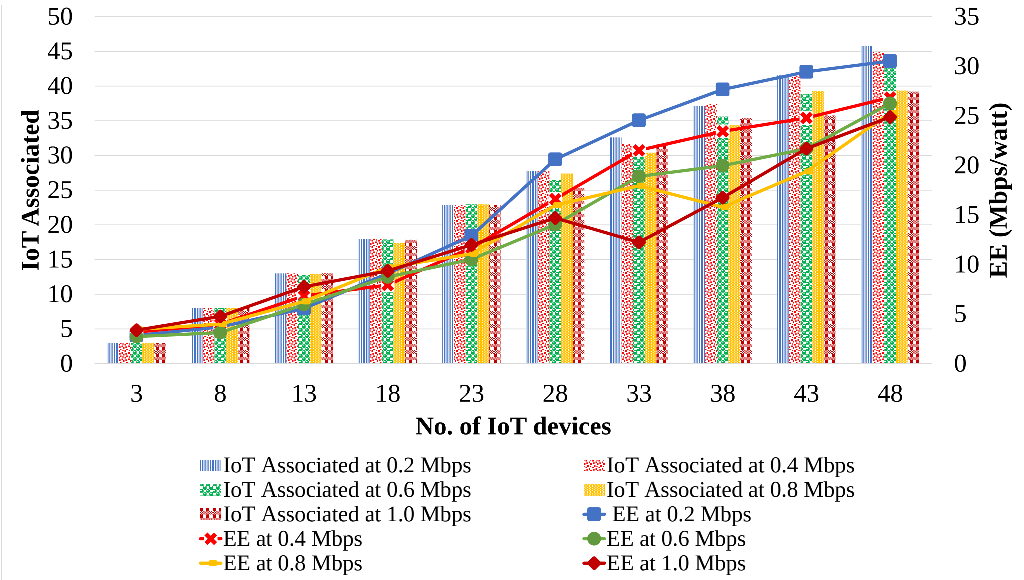

Figure 5.23: **IoT Devices vs IoT Associated and EE at QOS Rate Requirement.**

The graph 5.23 shows the variation in energy efficiency at different QoS rate requirements. Figure 22 displays a graph illustrating the relationship between the number of IoT devices, IoT Association (IoTA), and Energy Efficiency (EE) at various Quality of Service (QoS) rate requirements, including 0.2 Mbps, 0.4 Mbps, 0.6 Mbps, 0.8 Mbps, and 1.0 Mbps. The graph demonstrates that EE reaches its maximum when the QoS rate requirement is at its minimum, specifically at 0.2 Mbps. However, as the QoS rate requirement escalates to 0.6 Mbps and 1.0 Mbps, there is a noticeable decrease in energy efficiency (EE). Nonetheless, regardless of the quality of service rate requirement, EE shows an increasing trend with a rise in the number of devices. These findings are consistent with the results presented in Figure 5.17 and Figure 5.22, reinforcing the validity and consistency of our observations.

5.2.8 EE and RBs Allocation

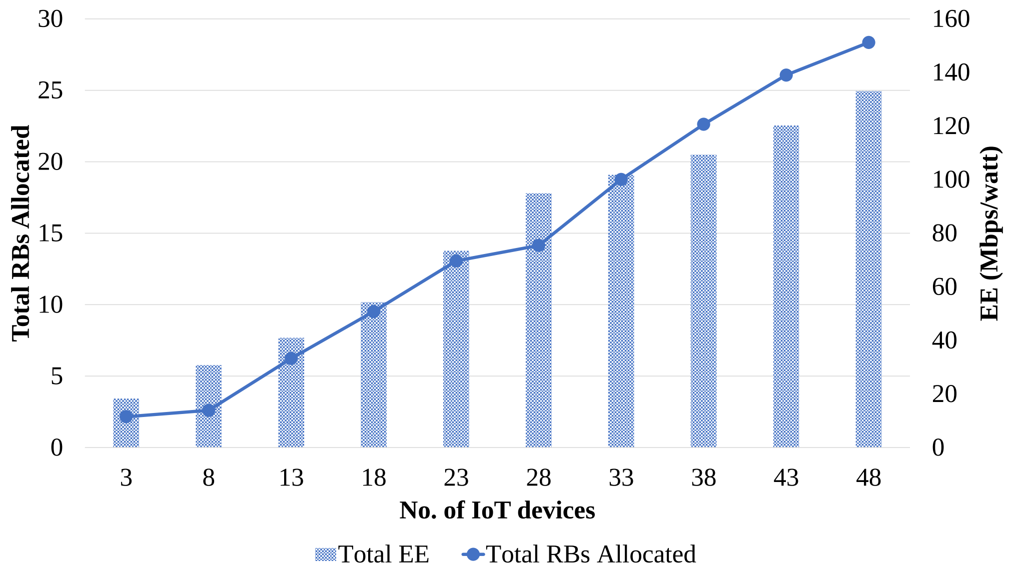

Figure 5.24: **IoT Devices vs EE and RB Allocation.**

Analyzing the graph depicted in Figure 5.24, it becomes apparent that with the proliferation of IoT devices, discernible patterns and trends emerge in both energy efficiency (EE) and resource block (RB) allocation. Firstly, focusing on Energy Efficiency, it can be observed that EE generally experiences a gradual increase as the number of IoT devices rises. This implies that, on average, the network becomes more energyefficient when accommodating a larger number of IoT devices. This positive correlation between the number of devices and energy efficiency is indicative of improved resource utilization and optimized transmission strategies.

On the other hand, RB Allocation refers to the allocation of available resource blocks, which are fundamental units of wireless communication, to the IoT devices. The graph demonstrates that RB Allocation follows a similar pattern as Energy Efficiency. As the number of IoT devices increases, there is an accompanying increase in the allocation of resource blocks. This indicates that the network is effectively managing its resources to meet the demands of a growing number of devices. A higher allocation of resource blocks facilitates better connectivity, improved data transmission rates, and enhanced overall network performance. The graph also provides insights into how different allocation strategies impact energy efficiency and vice versa. This knowledge can guide the development of resource allocation algorithms and protocols that optimize both EE and RB Allocation, leading to improved network performance and sustainability.

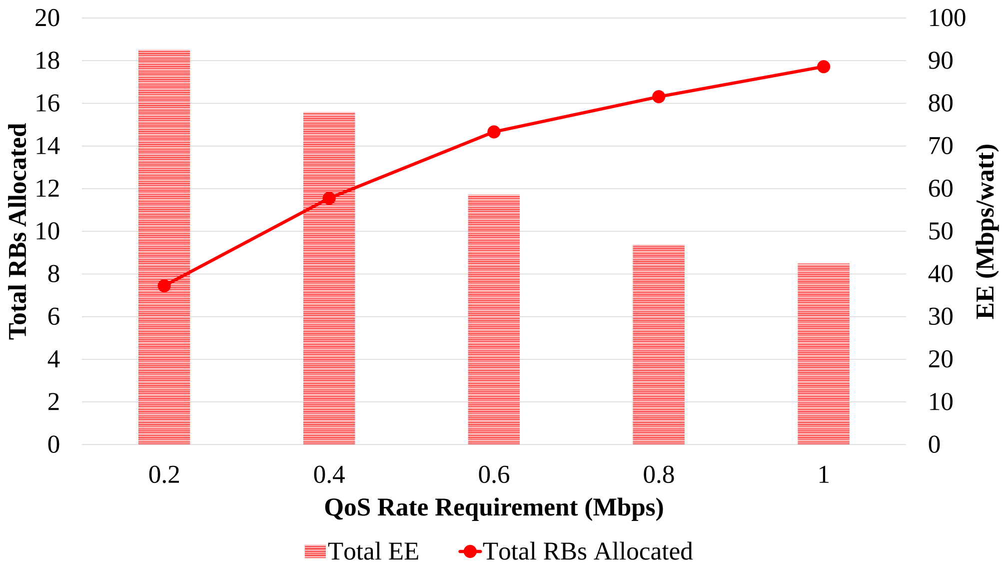

Figure 5.25: **QoS Rate Requirement vs EE and RB Allocation.**

The graph 5.25 depicting the relationship between QoS, EE, and RBs allows us to evaluate the impact of QoS requirements on energy efficiency and resource allocation. The analysis of EE in relation to QoS and RBs enables us to assess the tradeoffs between energy consumption and network performance. By optimizing EE, we can enhance battery life, reduce energy costs, and promote sustainable IoT deployments.

It has been observed that as the Quality of Service (QoS) rate requirement for devices escalates, the allocation of Resource Blocks (RBs) to associated devices also experiences a corresponding upsurge. However, in this particular scenario, Energy Efficiency (EE) tends to undergo a decrement. This intricate interplay between QoS, RB allocation, and EE has been duly substantiated in the graphical representation denoted as Figure 5.21, wherein the conspicuous trend of elevated EE for lower data rates and its gradual decline for higher data rates becomes evident. This phenomenon can be ascribed to the augmented power consumption necessitated by the maintenance of heightened data rates, as corroborated by the empirical evidence delineated in Figure 5.24. Conversely, the allotment of RBs to associated devices tends to be meager for lower data rates but gradually intensifies for higher data rates, thereby aligning with the discernible patterns unveiled in Figure 5.13.

Chapter 6

CONCLUSION

This work focuses on the exploration of joint admission control, IoT association, and power distribution in hybrid satellite-assisted Internet of Things (S-IoT) networks. The primary objective is to ensure fairness in IoT association and spectrum resource allocation while maximizing energy efficiency (EE). The underlying problem, a Convex Fractional Programming (CFP) conundrum, is deftly transformed into a concave optimization dilemma through the deft utilization of the Charnes-Cooper Transformation (CCT). The proposed Outer Approximation Algorithm (OAA) is then employed to solve the concave optimization problem and obtain the epsilon ϵ optimum solution, with ϵ set to 10^{-3}. The effectiveness of the ϵ-optimum solution obtained through OAA is evaluated by considering various system parameters, including IoT association (IoTA), IoT fairness (IoTF), resource block (RB) fairness, and energy efficiency (EE). The results show that both IoT fairness and RB fairness increase as the number of associated devices increases. Additionally, EE demonstrates an upward trend with an increase in the number of users. However, EE decreases as the Quality of Service (QoS) rate requirement increases.

Chapter 7

FUTURE WORK

Here are some possible future work and extensions of our thesis title ”Energy Efficient Resource Allocation and Task Offloading in Satellite Assisted Internet of Things Networks”:

Consider the impact of mobility on resource allocation and task offloading:

As IoT devices move around, their communication and computing needs will change. This can lead to challenges in terms of resource allocation and task offloading. Future work could investigate how to dynamically allocate resources and offload tasks to ensure that IoT devices can continue to operate efficiently even when they are mobile.

Explore the use of machine learning to improve resource allocation and task offloading:

Machine learning can be used to learn the behavior of IoT devices and the environment in which they operate. This information can then be used to improve the accuracy of resource allocation and task offloading decisions. Future work could investigate how to use machine learning to improve the performance of satellite assisted IoT networks.

Consider the use of multiple satellites to improve resource allocation and task offloading:

Using multiple satellites can increase the available computing resources and provide more options for task offloading. Future work could investigate how to use multiple satellites to improve the performance of satellite assisted IoT networks. These are just a few of the many possible future work and extensions of the this thesis. As the field of satellite assisted IoT continues to develop, there will be many opportunities for researchers to make significant contributions.

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APPENDICES

APPENDIX A

Charnes-Cooper transformation for fractional programme

In a fractional programme (FP), objective function is ratio of two functions that are nonlinear in general. if $f(z), g(z)$ and $k_m(z)$ where $\mathcal{M} = \{1, 2, 3....M\}$ defined on set $S \subset R^n$, having real values, a fractional programme is defined as

$$\begin{aligned} &\max_{z \in S} \ \frac{f(z)}{g(z)} \\ &\text{subject to:} \\ &C1 : h_m(z) \leq 0 \end{aligned} \tag{1}$$

If g(z) is positive and convex, f(z) is positive and concave, assuming S is convex set, then FP is called concave fractional programme (CFP). Charnes-Cooper transformation [43] use following variable transformations to reduce a CFP to a concave programme.

$$y = \frac{z}{g(z)} \tag{2}$$

$$t = \frac{1}{g(z)} \tag{3}$$

The equivalent concave problem for Eq. (4.4) can be written as

$$\begin{aligned} &\max_{\frac{y}{t} \in S} \ t f_o \frac{y}{t} \\ &\text{subject to:} \\ &C1 : h_m(z) \leq 0 \end{aligned} \tag{4}$$