Multi-objective Resource Optimization in Space-Aerial-Ground-Sea Integrated Networks

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Publications

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Abstract

Space-air-ground-sea integrated (SAGSI) networks are envisioned to connect satellite, aerial, ground, and sea networks to provide connectivity everywhere and all the time in sixth-generation (6G) networks. However, the success of SAGSI networks is constrained by several challenges including resource optimization when the users have diverse requirements and applications. We present a comprehensive review of SAGSI networks from a resource optimization perspective. We discuss use case scenarios and possible applications of SAGSI networks. The resource optimization discussion considers the challenges associated with SAGSI networks. In our review, we categorized resource optimization techniques based on throughput and capacity maximization, delay minimization, energy consumption, task offloading, task scheduling, resource allocation or utilization, network operation cost, outage probability, and the average age of information, joint optimization (data rate difference, storage or caching, CPU cycle frequency), the overall performance of network and performance degradation, software-defined networking, and intelligent surveillance and relay communication. We then formulate a mathematical framework for maximizing energy efficiency, resource utilization, and user association. We optimize user association while satisfying the constraints of transmit power, data rate, and user association with priority. The binary decision variable is used to associate users with system resources. Since the decision variable is binary and constraints are linear, the formulated problem is a binary linear programming problem. Based on our formulated framework, we simulate and analyze the performance of three different algorithms (branch and bound algorithm, interior point method, and barrier simplex algorithm) and compare the results. Simulation results show that the branch and bound algorithm shows the best results, so this is our benchmark algorithm. The complexity of branch and bound increases exponentially as the number of users and stations increases in the SAGSI network. We got comparable results for the interior point method and barrier simplex algorithm to the benchmark algorithm with low complexity. Finally, we discuss future research directions and challenges of resource optimization in SAGSI networks.

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Chapter 1

Introduction

Wireless communication technologies have played a critical role in the evolution of modern connected societies. Advances in wireless systems have significantly changed the way people access and exchange information, from earlier analog mobile systems to more sophisticated digital systems [1]. Multi-dimensional heterogeneous networks can be more tightly integrated using cutting-edge technologies such as low-power vast area networks, wireless sensing, improved location tracking, millimeter-wave (mmWave), wireless backscatter networking, and software-defined radios in beyond fifth-generation (B5G) and sixth-generation (6G) networks. Future wireless networks will face deployment, coverage, and capacity constraints due to traditional terrestrial networking technology. Despite significant advances in wireless networks, the evolving smart infrastructure, efficient technologies, and diverse wireless applications (e.g., autonomous vehicles, virtual and augmented reality, remote surgery, and holographic projection) make the launch of space-air-ground-sea integrated (SAGSI) networks in 6G inevitable [2].

Airborne users frequently imagine a positive online experience while flying. Current data communication techniques used in space and ground communications cannot ensure aerial users' quality-of-service (QoS). They consume a lot of energy to execute content requests due to high propagation delays and restricted network coverage [3]. We need more resources for highly reliable connectivity in all the network layers in future SAGSI networks. Similarly, in [4], the authors stated that the demand for Internet-based services such as web services and video streaming on airplanes is growing. Offering Internet-based services in the air increases the challenge of providing cost-effective solutions, which is already a challenge in core networks. Provisioning and managing Internet-based services entails considering routing and placement concerns in the core network and new link connections, such as air-to-ground connections from satellites and direct air-to-ground links. The authors of [5] argued that the ever-growing power of quantum computers poses a severe security risk to SAGSI networks. Fortunately, information-theoretic security may be achieved via quantum key distribution to provide secure communications. SAGSI networks are more flexible and reliable than traditional wireless networks, with better coverage and high-quality seamless connectivity. To fully utilize the advantages of heterogeneous networks, SAGSI networks connect space-based, air-based, ground-based, and maritime networks. However, because of the heterogeneity, time-varying, and self-organizing properties of SAGSI networks, the deployment and utilization still face significant challenges [6]. Research efforts in [7], such as air-to-ground link connections and direct air-to-ground links, need to be considered as developed solutions to overcome the heterogeneous nature of SAGSI networks and apply to all the network layers for high-speed, seamless communication. Hence, SAGSI networks are vital for today's communication.

In SAGSI networks, satellites and space stations play an essential role. Satellites use solar energy, making them energy sustainable, and as they orbit around the globe, they have wide coverage. Aerial networks are also essential in SAGSI networks for various industrial, mission-critical, and emergency applications. An efficient airborne ad-hoc network can be quickly developed using miniature balloons and fixed-wing high-altitude flying aircraft. With the emergence of underwater networks [8] leveraging standard platforms, ground networks can be further extended [9]. Recently, SAGSI networks have been deployed for cross-region, cross-airspace, and cross-sea integrated SAGSI networks to achieve seamless global coverage [9]. As SAGSI networks mature, they will play a significant role in cyberspace, interactivity, intelligence, and connectivity [10]. In [11], the authors noted that the energy resources of satellites, unmanned aerial vehicles (UAVs), and gadgets are limited due to low battery capacity and inconsistent energy supply, which reduces network lifetime and results in service disruption in SAGSI networks. There are significant hardware differences among communication systems, which makes it challenging to communicate between them. The authors of [12] proposed a SAGSI Internet of vehicle (IoV) edge-cloud architecture based on network function virtualization (NFV) and software-defined networking (SDN) to handle various communication networks (satellite, air, and terrestrial networks) and computing resources in IoV. They also developed an optimization model based on the specifications of the SAGSI-service IoV.

Key parameters must be optimized to meet the technical needs of SAGSI networks. Moreover, efficient management of resources can help provide better services to heterogeneous resource-constrained devices and a wide range of applications. For example, a gamer wearing a lightweight virtual reality headset to play interactively engaging games requires a fast data rate and low latency. Autonomous vehicles on the road, or UAVs, require high-throughput, high-reliability, and low-latency connectivity. Hence, it is important to investigate different requirements that must be considered while managing and optimizing resources in SAGSI networks to improve the quality, reliability, and deployability of SAGSI networks. Several radio resource management schemes have been developed for SAGSI networks while considering different objectives and constraints, including but not limited to optimizing throughput [13, 14], latency [14, 15], energy consumption [16], network cost [17], outage probability [18], task scheduling [19,20], caching [21], and performance coverage [22]. The constraints faced include power/energy [23], capacity [24], security [12], QoS [25, 26], quality-of-experience (QoE), mobility [15, 27], trajectory [28], central processing unit (CPU) cycle frequency [29], delay [30], location [31], time and radio resources [32, 33].

1.1 Architecture, Use Cases and Requirements

Fig. 1.1 illustrates the SAGSI network's architecture that includes mainly four types of networks, namely, space, aerial, ground, and sea networks. Each network has different communication chan-

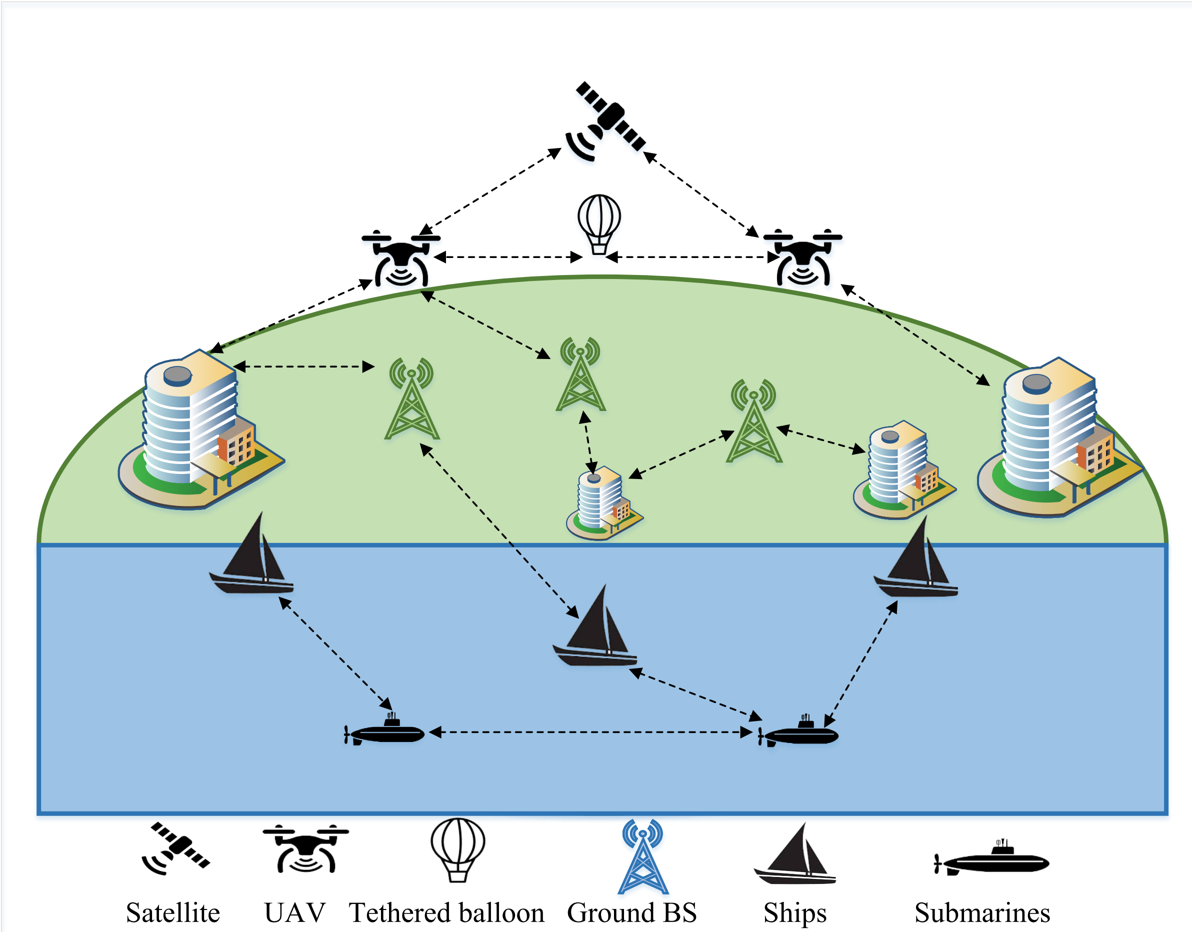


Figure 1.1: An illustration of SAGSI network's architecture.

nel models and components that communicate within and with integrated networks. For example, the ground network consists of base stations (BSs) and user equipment (UE). These components use the terrestrial infrastructure of ground networks, which can be either in short-range, medium-range or long-range communication. Similarly, aerial networks include UAVs to connect BSs and UAVs. HAPs are also part of aerial networks. In the space network, UAVs are connected to satellites. Aerial networks also provide internetwork communications between UAVs and tethered balloons, another component of future aerial networks. In this architecture, the sea network, ships, and submarines are the significant components of the network, and they are connected to both BSs and UAVs. SAGSI networks will address the challenges of connecting billions of devices with diverse QoS requirements, increasing traffic volume, and providing reliable connectivity all the time and everywhere. For instance, enhanced mobile broadband (eMBB) addressed human-centric applications for high-data-rate access to mobile services and multi-media content. With a peak

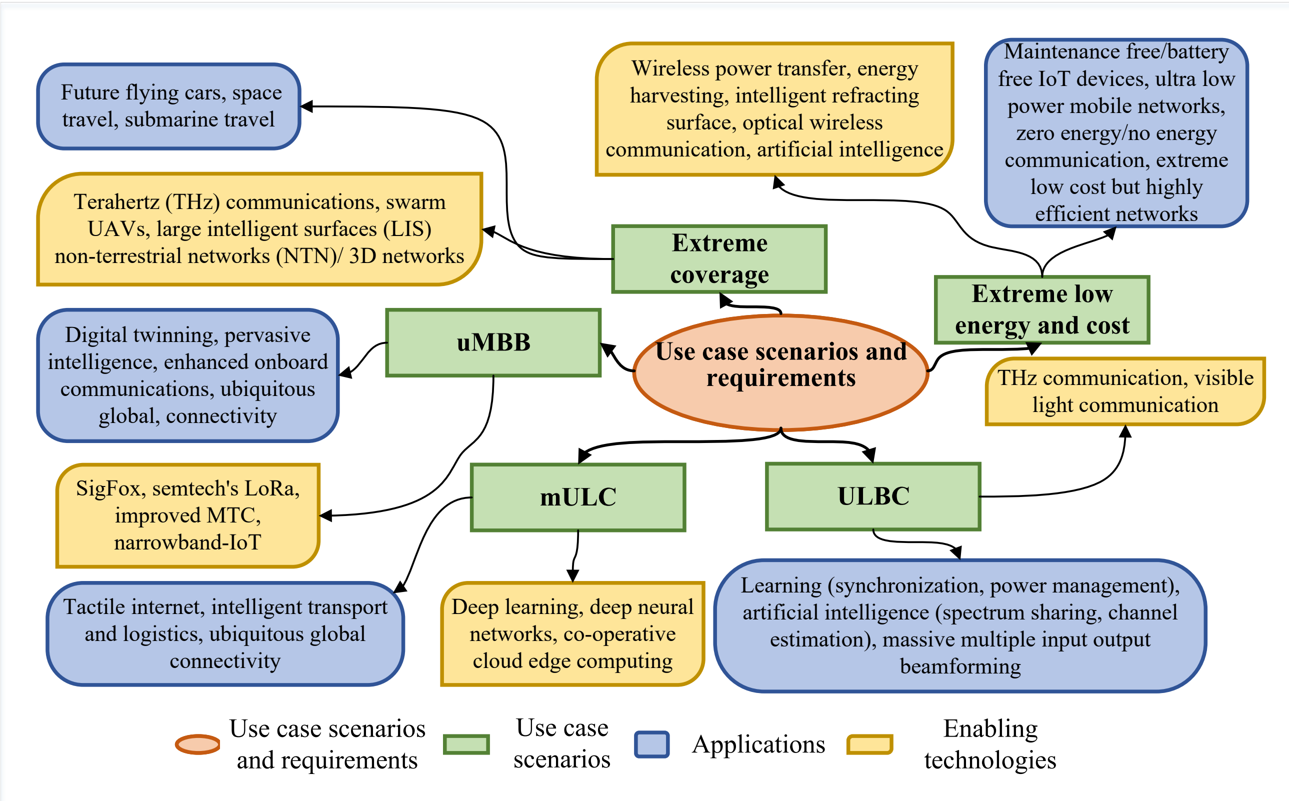


Figure 1.2: Use cases, applications, and enabling technologies for SAGSI networks. uMBB: Ubiquitous mobile broadband; mULC: Massive ultra-reliable low latency communication; ULBC: Ultra-reliable low latency broadband communication.

data rate of 10 to 20 Gbps, or 10,000 times more traffic, and support for macro and small cells with a high mobility range of roughly 500 km/h, eMBB can be characterized as a scenario [7]. Another aspect of future SAGSI networks is the support of massive machine-type communications (MTC), over 100 times more devices per unit area than existing networks [34]. Massive MTC also provides a 10-years battery life and supports asynchronous access [7]. At the same time, the ultra-reliability and low latency communication (URLLC) scenario provides ultra-responsive connections. It offers less than 1 ms air interface latency and 5 ms E2E latency between UE and BS [35]. It guarantees 99.9999 percent availability and ultra-reliable connectivity. The authors of [36] claimed that URLLC offers high-speed mobility while offering low to medium data rates (50 kbps to 10 Mbps). A combination of eMBB, massive MTC, URLLC, extreme low energy and cost, and extreme coverage results in various scenarios which support use cases and applications in SAGSI networks, as Fig. 1.2 shows.

1.1.1 Ultra-reliable low-latency broadband communication (ULBC)

The ultra-reliable low-latency broadband communication (ULBC) is a use case scenario with eMBB and URLLC requirements. ULBC enables mission-critical connectivity for emerging applications requiring high dependability, latency, and availability, including industry 5.0, the smart grid, and autonomous cars. Holographic communication, extended reality, tactile Internet, multi-sense experiences, and pervasive intelligence are some application areas for ULBC. As an illustration, holographic communication-based immersive gaming and multi-sensory experiences require both broadband and ultra-reliable low-latency communication as service requirements [37]. The enabling technology for ULBC is terahertz (THz) communication which offers high capacity, allowing wide spectrum channels and very high-speed data. Furthermore, THz communications can achieve high data rates via visible light communication. Recently, the idea of using artificial intelligence (AI) and ML in the physical and medium access control (MAC) layers has been put up, this can also be an application scenario for ULBC [38]. ML can help with synchronization, power management, modulation, and coding methods. Additionally, effective spectrum sharing, channel prediction, and adaptive and real-time operations might benefit from ML. Additionally, massive multiple-input multiple-output (MIMO) uses numerous inputs and outputs to meet the data throughput, reliability, and latency requirements. However, such solutions must be improved further to achieve the goals of future wireless networks. As a result, more sophisticated algorithms must be created to identify the areas where ULBC can efficiently share the spectrum [7]. The UAV network is convinced that a significant component of B5G and 6G networks are desired to accommodate multiple types of service requirements simultaneously. However, how to converge different types of services onto a common UAV network without deploying an individual network solution for each type of service is challenging [39].

1.1.2 Massive ultra-reliable low-latency communication (mULC)

Massive ultra-reliable low-latency communication (mULC) is an emerging use case scenario wherein users need high reliability and low latency and consists of many devices. Hence, mULC combines massive MTC and URLLC. Applications covering this use case scenario include tactile Internet, intelligent transport and logistics, and ubiquitous global connectivity. Enabling technologies that can help the mULC scenario are deep learning-based transmission prediction, which is an emerging solution for reducing latency [37]. Data-driven deep learning systems can predict user demands and time-varying channel states in advance, resulting in lower transmission delay. To improve operation latency, model-driven deep learning can train deep neural networks and replace standard techniques with accelerated online deep neural networks. Distributed and cooperative processing, based on local and cooperative operations on edge devices, are other important strategies for reducing operation latency. Several challenges are associated with dependability such as lower frequency means it can penetrate into different medium easily, however, if frequency rises blockages may occur between transmitters and receivers. Re-configurable meta-surfaces can control the propagation of the environment during communications to increase dependability. Cooperative mobile edge computing (MEC) [36] is another enabling technology for mULC, which supports the underlying network. A tightly connected hybrid cloud and MEC strategy are required for coordinated and load-balanced operations. The cloud assists the MEC (and vice versa) in meeting the heterogeneous service requirements of essential mULC. A cooperative hybrid strategy can address issues associated with delay-sensitive and delay-tolerant equipment [40]. In a shared resource block, the mULC can be thought of as employing power-domain non-orthogonal multiple access (NOMA). Devices that are both delay-sensitive and tolerant can share a sub-carrier. In addition, sub-carrier and transmission power distribution can be combined to increase the number of successfully connected IoT devices that can meet QoS requirements. An appealing radio access network slicing approach for mULC services might also be adaptive resource coordination for crucial MTC devices [36].

1.1.3 Ubiquitos mobile broadband (uMBB)

The requirements of eMBB and massive MTC are combined in ubiquitous mobile broadband (uMBB). Applications under this scenario include increased onboard communications, pervasive global networking, digital twinning, and pervasive intelligence [37]. Orthogonal frequency division multiple access (OFDMA), enhanced antenna techniques, reverse link sector capacity optimization, adaptive interference management mechanism, and effective reverse link control design are examples of enabling technologies [41]. Two primary technologies can be used as enablers, out of which one is improved MTC, and the second is narrowband IoT [42]. Numerous 6G-enabled applications, such as the IoVs, can benefit from the upgraded MTC's high mobility and high bandwidth data rates (up to 1 Mbps) [43].

1.1.4 Extreme low energy

Devices in SAGSI networks are expected to use sophisticated signal-processing algorithms. They also must deal with big data, which requires a lot of processing and energy. As a result, energy is a concern in SAGSI networks. Zero energy is a major driving force behind future SAGSI networks that will enable many IoT devices to maintenance-free and battery-free operations. Wireless power transfer (WPT), energy harvesting, and intelligent reflecting surface (IRS) are enabling technologies for low energy consumption. Enabling technologies for low cost also use visible light communication, which is part of optical wireless communication technologies. Existing network infrastructures do not support energy harvesting, owing to the inefficiency of electronic circuitry in converting captured energy into electric current [7]. As a result, the future communication network can facilitate effective energy harvesting. Energy-harvesting circuits should also enable the self-powering of devices, enabling off-grid operations, durable IoT devices, and longer standby intervals. The authors looked at the energy-harvesting methods typically employed in the IoT context [44]. They concluded that some energy harvesting methods could use small-size piezovoltic cells or piezoelectric devices to supply considerable energy for an extended period. Other energy harvesting methods, in contrast, depend on specific cycles such as day and night, working days and weekends, and require vast circuits for capturing the energy. According to the authors of [45], intelligent energy management may be essential for enabling energy efficiency for IoT gadgets that communicate. For instance, obtaining energy from intentionally created or naturally occurring environmental resources can eliminate the need for batteries in IoT networks. Nowadays, IoT systems offer energy harvesting techniques so that they can be self-sustainable up to some extent. Also, novel waveforms and modulations with low peak-to-average power ratios are necessary to reduce power usage [46].

1.1.5 Extreme coverage

The coverage expansion is intended to reach regions not currently covered by the traditional mobile communication system, such as space, the ocean, and the sky. Non-terrestrial networks using geostationary satellites, low earth orbit (LEO) satellites, and HAPs are a potential option for offering high-quality communication services in locations the typical mobile communication network cannot reach. In addition, the digital divide in rural and urban areas is another motivation behind the extreme coverage use case scenario; people who do not have access to the Internet can be easily marginalized politically, socially, and economically. Furthermore, the disadvantages of lack of connectivity access are readily amplified for network's overall performance elderly, disadvantaged communities, and the disabled affected by it. Despite this, as the number and capacity of undersea fiber cables have lately increased, information and communication technologies infrastructure and solutions have advanced dramatically in the previous century. This has increased investments in terrestrial fiber capacity. Logistics services such as home delivery using UAVs is a compelling use case, and unmanned or highly complex operations in primary industries such as agriculture, forestry, and fisheries are examples of prospective use cases. Applications use cases include future flying cars, space travel, and submarine travel. For extreme coverage, enabling technologies include THz communication, swarm UAVs and IRS [7].

1.2 Motivation and Objectives

Efficient resource management is necessary in SAGSI networks to ensure uninterrupted connectivity for various devices. Optimizing SAGSI networks can improve energy efficiency, resource utilization, and user association, bridging the digital divide in remote areas and enabling seamless connectivity for various devices and applications. Network resource optimization can enhance the design and deployment of future SAGSI networks, leading to enhanced network performance and user experience. Moreover, exploring optimization algorithms such as the branch and bound algorithm adds to the body of knowledge in network optimization techniques. Ultimately, this thesis aims to contribute to advancing efficient and reliable wireless connectivity by benefiting users, industries, and society.

The objective is to design a resource management scheme while considering energy efficiency, resource utilization, user association, and prioritizing users in the SAGSI networks. The goal is to optimize the network's performance by deploying UAVs at optimal locations with high user density. This optimization problem considers data rate, power, and available resource constraints.

1.3 Thesis Contributions

The following are the main contributions of this thesis:

- We offer a thorough analysis of SAGSI networks from resource optimization studies that have been looked into during the previous five years.

- We examine the creation of numerous anticipated new applications and how the capabilities of upcoming 6G networks will make it possible to put these applications into use.

- We propose two cutting-edge use case scenarios essential for SAGSI networks in 6G, including low energy, cost, and extensive coverage.

- We review efforts in SAGSI networks and research activities in a 6G environment from a resource optimization perspective. To the best of our knowledge, this is the first time such a review has been done.

- We mathematically formulate the problem of optimizing user association in a SAGSI network. Considering the complexities introduced by different channel models for each communication layer, we addressed the challenge of maximizing energy efficiency while accommodating constraints on data rate, power, resource demand, and the total number of resources available.

- We solve the formulated problem using three different algorithms: branch and bound algorithm (BBA), interior point method (IPM), and barrier simplex algorithm (BSA).
- We compare the simulation results in which the optimal results obtained using the BBA are considered as benchmarks. Through this analysis, we evaluated the effectiveness and efficiency of each method in achieving efficient user association and energy efficiency within the context of a SAGSI network.

1.4 Organization of Thesis

The rest of the thesis is organized as follows: Chapter 2 provides a background and literature review on resource optimization in SAGSI networks. This chapter includes a detailed review of existing surveys and a comprehensive discussion on optimization categories in different domains and layers of SAGSI networks. In contrast, non-radio resource management is out of the scope of our work. We discuss the solutions and techniques for joint optimization problems and performance metrics and measurements used in the literature to access the solutions discussed. Chapter 3 provides the system model and optimization problem for optimizing user association with and without urgent priorities while maximizing the system's energy efficiency, resource utilization, and user association. Chapter 4 presents simulation results obtained using three algorithms (BBA, IPM, and BSA) while considering various scenarios in network configuration. The simulation results of IPM and BSA are compared with the BBA in terms of associated users to BSs and UAVs, and satellites. Finally, the thesis concludes, and future research directions are highlighted in Chapter 5.

Chapter 2

Literature Review

Many recent surveys are available related to SAGSI networks such as [1, 37, 42, 47–53]. Some authors considered two layers (e.g., ground and air), whereas some considered three layers (e.g., space, air, and ground). However, only a few have targeted all the layers of an integrated network, and one such work is [50]. Hence, in this survey, we consider all the layers of the integrated network to understand how resources can be managed in all the layers and how it is possible to communicate securely while transmitting in a heterogeneous network. For instance, the authors of [47] presented a survey on 6G wireless communications networks and focused primarily on key performance indicators in SAGSI networks. The authors presented a detailed review of 6G networks, their key performance indicators, and novel use cases, such as holographic communication and industrial automation. The potential 6G requirements, challenges, and trends are also highlighted, e.g., green 6G and three-dimensional (3D) coverage. While the authors of [54] reviewed the essential technologies that can be used in 6G networks. The core performance parameters covered in this survey were essential factors in developing 6G networks. In contrast to the survey in [47], we considered all the above aspects briefly, with our primary objective being resource management in SAGSI networks.

The authors of [37, 42, 52, 53] reviewed the development of 6G networks, including use cases, requirements, technologies, architectures, and future challenges. In [37], the authors explored the need for 6G by describing critical drivers, the disruptive use cases, and the fast rise of mobile traffic. The authors suggested an architecture for 3D coverage incorporating both terrestrial and non-terrestrial networks. They showed how, under 6G deployment scenarios, the average data consumption would rise from 5 GB in 2020 to 250 GB in 2030. The authors argued that 6G networks would be a radio-optical system, an intelligent connected platform, and an integrated space-air-ground network. The authors of [42] explored the recent trends driving 6G, discussed emerging applications (e.g., smart grid, industry 5.0, collaborative robots, and intelligent healthcare), presented a vision and requirements of 6G, and summarized projects such as Google Loon which uses how to deliver reliable Internet connections to remote and rural regions using aerial networks (e.g., UAVs or balloons). They also highlighted low-coverage, medium-coverage, and high-coverage surveys on 6G networks.

In [52], the authors analyzed the development status of the SAGSI network, including the development of satellite communication and key technologies for integrating space-air-ground networks. They discussed, how SAGSI networks are applied in 6G. However, for their successful implementation, the technology supporting the network architecture, mobility management, resource allocation, and load balancing still must address specific significant issues. In [53], the authors proposed a vision toward architecture based on intelligent communication environments with its layered approach and discussed future research directions in 6G networks. The authors presented a taxonomy of 6G wireless systems, use cases, emerging machine learning (ML) schemes, and communication and computing technologies. They investigated resource management in SAGSI networks and all the previously listed factors to implement integrated networks successfully. In [48], the authors focused on heterogeneity in SAGSI networks and studied the current literature on spectral efficiency. The unique features of heterogeneous networks are identified, including system capacity, ultra density, reduced uncovered areas, reduced link loss and delays, and improved spectral efficiency. In contrast to their work, we focus on additional resource parameters including system capacity and delay minimization to improve the overall performance of SAGSI networks.

The authors of [49] focused their research on the tactile Internet of things (IoT) and extensively reviewed architectures, protocols, algorithms for radio resource optimization, and non-radio resource allocation techniques. The authors evaluated the performance of tactile Internet based on different use cases from distinct application domains. Since we investigated every aspect of SAGSI networks and all potential use cases, requirements, and applications, our work differs from theirs. Non-radio resources, however, are outside of the scope of this paper. The authors of [1] provided an overview of aerial radio access networks. They proposed an architecture that swiftly sets up a flexible access infrastructure on demand and uses airborne components like UAVs and satellites. They also explored system models where mobility, energy consumption, transmission propagation, and communication latency are all real-world phenomena. In [51], the author's focus was on end-to-end (E2E) network optimization using ML. They looked at four topics from an optimization point of view, ML for network access, ML for network routing, ML for controlling network congestion, and adaptive streaming control.

The authors of [32] focused on space-air-ground networks, and they presented an overview of the most recent state-of-the-art results on resource allocation applications. They demonstrated the benefits of a single-use scenario comprising integrated space high-altitude platforms (HAPs), ground networks, and non-radio resource scheduling policies by exploiting deep neural networks. In [50], the authors reviewed existing SAGSI networks and their architectures and discussed the characteristics of SAGSI networks and potential challenges. The authors highlighted the security requirements of SAGSI networks, emphasizing the differences among typical networks. They discussed security threats, attack methodologies, and countermeasures for SAGSI networks. The authors of [55] discussed the technical issues related to post-disaster networks, including the physical and networking challenges that must be addressed. They focused on the networking layer while discussing integrated space-air-ground designs, routing, and delay-tolerant/software-defined networks. At the physical layer, they reviewed the literature on channel modeling, coverage and capacity, radio resource management, localization, and energy efficiency. They also presented interesting simulation results demonstrating how to apply ad-hoc network designs in emergencies. The authors also reviewed ML techniques for optimizing the network.

We reviewed available technologies that are potential candidates for deployment in SAGSI networks. From all the discussions above and Table 2.1, we found that all the state-of-the-art surveys address only one part of the overall development of SAGSI networks in 6G. Most existing surveys discuss enabling technologies, applications, and performance indicators. However, none of the works we discussed above focused on resource optimization in SAGSI networks. In contrast to existing surveys, we comprehensively review all the resource management aspects of SAGSI networks.

2.1 Radio Resource Optimization

Resource optimization aims to ensure efficient network design and performance of the SAGSI network while satisfying constraints. Factors that impact SAGSI network performance include latency, availability, packet loss, network jitter, and network utilization. Consequently, if we can optimize network resources, we can significantly improve the networks' quality and overall performance. The key aspects of resource optimization in SGAINs include throughput, energy consumption, delay, task offloading and resource utilization, network operation cost, outage probability, the average age-of-information, CPU cycle frequency, task scheduling, the network's overall performance, intelligent surveillance, SDNs, performance degradation, the convergence of 6G and IoTs and relay communication, which we explain next.

2.1.1 Throughput and capacity maximization

Throughput and capacity maximization is one of the main goals of recent research on resource optimization for SAGSI networks which falls under the ULBC use case scenario to ensure higher data rates and maximize the capacity of network. In [56, 57], the authors considered UAV association in SAGSI networks. In these papers, the authors tried to improve the throughput and capacity of SAGSI networks in association with UAVs. In particular, the authors of [56] considered a SAGSI network association supported by a UAV. The authors developed an optimization

Table 2.1: Existing surveys on SAGSI Networks
RMF: Resource management focused; SAG: Space-air-ground integrated network; HET: Heterogeneity of Network; APP: Applications; CS: Core Services; ET: Enabling Technologies; UC: Use cases.

Ref.	**Year**	6G	**RMF**	**SAG**	**APP**	**CS**	**ET**	**UC**	**Remarks**
[47]	2021	✓	✗	✗	✓	✓	✓	✓	Reviewed the need for 6G, use cases, enabling technologies, challenges and future directions.
[37]	2021	✓	✗	✗	✓	✓	✓	✓	State-of-the-art analysis is presented and provided a comprehensive survey of related works.
[48]	2021	✗	✓	✗	✗	✗	✗	✗	Emphasized on the heterogeneous nature but in 5G networks.
[54]	2021	✓	✗	✗	✓	✓	✓	✓	A comprehensive review of the future evolution of 6G networks is presented.
[49]	2021	✓	✗	✗	✓	✓	✓	✓	Reviewed existing architectures and algorithms for tactile Internet.
[50]	2021	✓	✗	✓	✗	✗	✓	✗	Reviewed main security issues, challenges in SAGSI networks.
[42]	2021	✓	✗	✗	✓	✓	✓	✓	Reviewed a broad-range of 6G concepts including standardization.
[1]	2021	✓	✗	✗	✓	✓	✓	✓	Reviewed 6G infrastructure with a focus on radio access networks.
[51]	2021	✓	✗	✗	✓	✗	✗	✗	Reviewed 6G networks with a focus on machine learning (ML) enabled end-to-end (E2E) communications.
[52]	2021	✓	✗	✓	✓	✗	✗	✗	A short review on current developments in SAGSI networks is presented.
[53]	2020	✓	✗	✗	✗	✗	✓	✓	Reviewed 6G taxonomy, Q-learning and federated learning-based transceivers.
Our Survey	-	✓	✓	✓	✓	✓	✓	✓	We present a comprehensive survey on SAGSI networks from a resource optimization perspective in 6G networks.

problem to maximize overall UAV network capacity while satisfying power, altitude, QoS, interference from macrocell and satellite networks, and sub-channel allocation constraints. It is a convex optimization problem that optimizes sub-channel and power control. The proposed approach is a two-stage joint hovering altitude and power control system. Stage 1 entails joint sub-channel and power control while considering a fixed altitude, utilizing the Lagrangian dual decomposition method. Stage 2 consists of the optimal hovering altitude of each UAV based on the results obtained from Stage 1. The performance of the proposed work is evaluated in terms of the probabilities of violating the interference limit, spectral efficiency (bps/Hz), and probability of satisfying the capacity requirement concerning QoS. The scalability of the proposed work needs to be evaluated, and only a limited area and number of UAVs have been considered. Moreover, the algorithm's complexity needs to be considered for its practicality.

The authors of [57] considered the inevitable cross-tier interference in SAGSI networks. The objective is to provide joint optimization for power and altitude. The constraints include power, safety, and hovering altitude, QoS guarantee, interference, and sub-channel allocation. The problem defined is a concave-convex optimization problem. This problem is solved via the Lagrange dual decomposition and concave-convex process approach, followed by a low-complexity greedy search algorithm. The performance of the proposed work is evaluated in terms of spectral efficiency, probabilities of satisfying the capacity requirements, and probabilities of violating the interference limit. The altitude of UAVs is limited to 200m to 400m in simulations. In [58], the authors proposed to boost the distributed throughput of SAGSI networks, the authors developed a solution to optimize the access and backhaul lines jointly. They assumed that LEO satellites would provide backhaul connectivity while space BSs and UAVs would provide downlink service for ground clients. To choose the best BSs approaches, reinforcement learning algorithms are utilized. To distribute resources between the space BSs and the UAVs and to enhance the 3D trajectories of the UAVs, they proposed two techniques based on the multi-armed bandit and satisfaction algorithms. Average throughput and user outages are used to gauge how effective the suggested processes were.

The authors of [33] achieved flexible, dependable, and scalable network resource management for SAGSI vehicular networks, and a software-defined architecture was considered. Mobility management, QoS-aware resource allocation, and energy efficiency are just a few of the restrictions considered. To achieve the trade-off between signaling overhead and system status acquisition in various scenarios, the authors proposed a hybrid and hierarchical SAGSI control architecture. The placement of the material, the caching parameter, and the content delivery are all optimized. The proposed work's effectiveness is assessed using the average throughput per vehicle and the execution time of the SDN control algorithm. In [59], the authors highlighted that conventional offloading techniques are insufficient for dynamic SAGSI networks. Thus, they looked at SAGSI networks' reinforcement learning-based traffic offloading while considering node mobility, an extensive and frequent change in network traffic and link condition. The energy, queue capacity, and power consumption limits are considered for the traffic offloading problem. The authors proposed a double-deep Q-learning algorithm with an improved delay-sensitive replay memory mechanism to educate the node to select the offloading approach based on adjacent nodes and primary data. The authors also developed a unified data-gathering system utilizing the hello package and offline training to aid the suggested offloading technique. The performance of the suggested task is evaluated in terms of network throughput, drop rate, average latency, training loss, and value estimation.

In [60], the authors proposed combining the ground-to-space transmission technique with a HAP-reserved transmission scheme to improve terrestrial communication and conserve transmission power. They maximized the overall throughput and optimal probability of the network. The constraints on the number of ground users and the competition of users with feasibility are considered in the mixed integer non-linear programming problem (MINLP). The authors proposed a transmission control strategy wherein the user determines the transmission scheme, i.e., switches between the ground-air-space link transmission and the ground-to-space link transmission with a probability. They emphasized maximizing the throughput and obtained the optimal probability that a user selects the ground-air-space transmission scheme. The authors evaluated the performance of the proposed work in terms of normalized throughput. However, the performance is limited by the number of users and the probability of users accessing the network.

Intelligent reflecting surfaces can offer an energy-efficient and cost-effective solution to achieve high spectral efficiency in SAGSI networks by intelligently reconfiguring signal propagation using passive reflecting elements. Meanwhile, there is a growing demand for high-throughput geostationary satellite communications to provide broadband services in inaccessible or poorly covered areas. The authors of [61] proposed a satellite communication network where a satellite transmits signals to a ground mobile terminal using multicarrier communications. The signal delivery from the satellite to the ground mobile terminal is assisted by intelligent reflecting surfaces, which shift the signal phase smartly toward the ground terminal to enhance the effective gain. The intelligent reflecting surfaces are mounted on a high building with multiple reconfigurable passive elements and a smart controller. Power allocation and phase shift design are jointly optimized to maximize the system's channel capacity. The joint optimization problem is non-convex, which is difficult to solve through traditional convex optimization methods. Therefore, the authors proposed an epsilon-optimal algorithm based on mesh adaptive direct search algorithm to obtain an efficient solution. Simulation results obtained with this approach demonstrate the benefits of intelligent reflecting surfaces-assisted satellite communication in terms of system channel capacity.

In [62], the authors aimed to improve the data throughput of ground users by integrating ground BS with air stations (such as balloons). Several constraints have been considered: bandwidth, power, association, HAP- and tethered balloon placement, access link associations, user QoS constraints, back-hauling bandwidth, and peak power. The solution proposed is access link optimization and back-hauling optimization. The performance is evaluated in terms of the average uplink data rate and average downlink data rate. In [19], the authors considered a SAGSI network for supporting maritime communications, where the LEO satellite constellations, passenger airplanes, terrestrial BSs, and ships serve as the space-air-ground-sea layers, respectively. The objective is to use a distributed topology rather than a quasi-predictable network topology. The constraints include minimum throughput and a minimum lifetime of the path. The challenge is constrained minimum delay routing. The proposed solution is a complete Pareto solution that uses single and multiple objective routing instead of all Pareto-optimal routes rather than delay-throughput pair. The authors evaluated the proposed work using latitude, E2E throughput, coverage ratio, and path lifetime. It uses a distributed operating system and takes advantage of the somewhat predictable network topology.

Table 2.2: Throughput and Capacity Maximization

Reference	**Objective**	**Constraints**	**Problem Type**	**Solution**	**Remarks**
[56]	Sub channel and power control jointly; hovering altitude.	Power, altitude, QoS, interference, and subchannel allocation.	Convex optimization.	Two-stage joint hovering altitude and power control, joint subchannel and power control using Lagrangian dual decomposition method while considering the fixed altitude.	500 m $\times$ 500 m area with ten macrocells and 10 satellite users. The coverage radius of each UAV is 50m and users are randomly distributed in each coverage area. The complexity of the algorithm was not discussed.

[58]	Average throughput of system.	QoS aware resource allocation, determine the feasible region in the 3D space for the UAVs locations, set of available power levels for the BSs.	A multi-armed bandit problem which is an association problem.	Utilized a method in which each BS aims at satisfying its reward function: i) backhaul links: BS-satellite association and ii) access links: learning-based algorithms.	Storage or cache capacities are not discussed in this work.
[33]	Resource management, content placement, caching and content delivery.	Mobility management, QoS aware resource allocation and energy efficiency.	Joint optimization of resource utilization.	Hybrid and hierarchical SAGVN control architecture.	Cross-layer network security is not considered.
[59]	To improve overall network throughput and average delay.	Energy, power consumption and capacity of network.	Traffic offloading.	Double deep Q-learning algorithm with improved delay sensitive replay memory algorithm.	The proposed algorithm solely depends on Hello packet protocol, we cannot comment on its performance for other topologies.
[60]	Ground-air-space transmission scheme.	Number of ground users and their competition.	MINLP.	Integration of two transmission techniques.	Only feasible when total users on the ground are less than 80 and probability is between 0.1 and 0.7.

[57]	Joint subchannel and power control, hovering altitude.	Power, safety and hovering altitude, QoS guarantee, interference and subchannel allocation.	Concave-convex.	Two-stage joint optimization algorithm for uplink resource allocation.	Altitude of UAVs has a limited range of 200 to 400 meters.
[62]	Access link optimization and backhaul optimization.	Bandwidth and power constraints, association, back-hauling bandwidth and rate, station and user peak powers, access link associations, and user QoS.	A linear and convex optimization problem for solving the associations and power allocations.	Integrating the ground BSs. Ground BSs with higher altitude stations.	Simulation results are limited to an area of 70 by 70 km.
[19]	Complete Pareto front out of all Pareto-optimal routes.	Path lifetime.	Multi-objective routing problem.	Single objective routing and multiple objective routing.	The dataset trained here is random and generated within a window of six hours, the increase or decrease of time window may impact dataset training/testing and latency.

Lessons learnt: Table 2.2 presents a summary of the main lessons learned from the works discussed above.

- Physical location and frequency planning should be more widely researched with various optimization approaches in SAGSI networks.
- In [24], the authors concluded that there exists a trade-off among throughput, UAV deployment cost, and queueing states.

- The authors of [33] did not consider maximizing throughput, cross-layer network security. Storage or cache can enhance the work done in [58], and the datasets used in [19] were very limited and randomly generated.

2.1.2 Energy consumption

The devices involved in SAGSI networks are generally resource-constrained in terms of battery life. The question of extending these devices' life becomes a significant concern. This requires efforts in two areas: i) energy efficiency, which will minimize energy consumption, and ii) energy self-supply, which will provide new energy to devices in SAGSI networks [63]. This section reviews the current literature on different aspects of energy consumption in SAGSI networks.

With the increasing use of renewable energy sources in power systems, there is a need for fast and reliable connections between renewable energy sources components and equipment to ensure the delivery of quality power. In [64], the authors explored the potential of SAGSI networks to accelerate the use of RES by providing faster and more stable data bandwidth. The applications of SAGSI networks in RES include the point-to-point energy trade market, vehicular networks, wireless energy transfer, energy management systems, smart grids, self-healing, smart batteries, and AI-based weather forecasting. The authors of [64] discussed the advantages and challenges of implementing SAGSI network in RES sectors, as well as practical applications and potential implementations. Their discussion highlights that, although SAGSI network can help improve renewable energy sources' security, connectivity, integration, and sensory data processing, it still faces various technical limitations, such as incompatibility issues with older devices, higher power consumption, and operating cost. Further, future research should address these limitations to ensure the cost-effectiveness and compatibility of 6G in RES. Additionally, the authors also highlighted that the SAGSI network in the RES sector needs intensive development to address security and privacy issues, hardware support, and ultra-fast communications with low latency.

The authors of [4] examined the best offloading strategy and the distribution of communication and computing resources for a satellite performing while energy is minimized in SAGSI networks.

In [25, 65, 66], the author's considered UAVs network energy or power consumption, its efficiency, and management in SAGSI networks. In [65], the authors explained that the exponentially growing UAV communications demand is dramatically increased by UAV applications, which causes a dearth of spectrum resources for UAVs. Here, energy is a restriction, and sue at hand is the lack of spectrum resources for UAVs, which requires semi-definite programming, relaxation, and convex optimization. The authors proposed a cooperative networking architecture UAV-swarm-aided SAGSI network to address this problem. The performance measures are in terms of potential applications of UAV communications.

In [25], the authors proposed an intelligent UAV-assisted fault diagnosis technique which uses data from buoys and UAVs to identify preliminary faults using a Cubature Kalman filter-based radial bias function neural network server, it uses data from buoys and UAVs to identify preliminary faults. The authors used deep reinforcement learning (DRL) algorithm for the data collection path and deep deterministic policy gradient on B5G-MEC servers for energy efficiency. The fault status of each buoy is determined by the collective decision made by diagnosis centers resulting in a high aggregation ratio and low energy cost. The QoS was improved while the performance was evaluated using metrics such as test error, multi-fault classification, aggregation ratio, and energy cost. In [66], the authors considered remote IoT networks as an effective approach for providing services to smart devices, which are often remote and dispersed over in a wide area. Since the ground BS deployment is difficult, and the power consumption of smart devices is limited in remote IoT networks, the hierarchical space-air-ground architecture is required for these scenarios. They investigated the energy-efficient resource allocation problem in a two-hop uplink communication with UAV relays. They solved two sub-problems optimally with different algorithms. They discussed the power constraints as a major issue for 6G networks whereas the problem type they defined is a non-convex MINLP. Their algorithms were evaluated based on the number of smart devices and energy efficiency.

In [12], the authors proposed solutions to efficiently manage several communication networks (satellite, air, and terrestrial networks) and computation resources in the IoV. They proposed a

SAGSI-IoV edge-cloud architecture based on SDN and NFV. They developed an optimization model based on the service requirements of the SAGSI network and proposed an improved algorithm. Constraints on service delays, resource use, energy consumption, and security are considered. The proposed model was evaluated based on how often the task failed and how much energy is consumed. In [16], the authors considered the gateway selection problem to minimize the transmission energy. Toward this end, they formulated the issue of inter-segment gateway selection as a constrained optimization problem. They proposed two algorithms, i.e., an optimal enumeration algorithm and a simulated annealing-based algorithm. They considered the link capacity constraint with the problem type as a constrained optimization problem, and they evaluated the performance based on the average transmission energy consumption of the system.

Lessons learnt: Table 2.3 presents a summary of the main lessons learned from the works reviewed above.

- Energy consumption and power utilization can be optimized using different algorithms such as those described in [16] and [66]. However, there is still much work to be done to satisfy the heterogeneous nature of SAGSI networks.
- The basic hardware differences in different layers of the SAGSI network must still be addressed for optimal usage of energy resources as [12] describes.
- The authors did not explain how angle-based diversity selection enhances their work [12] whereas the scalability of [66] needs to be evaluated while considering computational complexity.

Table 2.3: Energy Consumption

Reference	Objective	Constraints	Problem Type	Solution	Remarks

[12]	Energy efficiency of SAGSI-IoV edge-cloud architecture.	Service delays, resource use, energy consumption, and security.	Edge-cloud resource scheduling.	Solution includes i) population initialization, ii) reproduction, iii) update strategy for convergence.	Limited discussion on the angle-based diversity selection.
[65]	QoS guarantee energy efficiency.	Energy consumption.	Semi-definite programming and convex.	Cooperative networking architecture UAV-swarm-aided SAGSI network.	Only the energy consumption of UAVs is considered here.
[16]	Minimizing transmission energy.	Capacity.	Inter-segment gateway selection.	An optimal enumeration algorithm. and a simulated annealing-based algorithm.	They used 10 nodes with a communication distance of less than one km.
[25]	Energy cost and aggregation ratio.	QoS.	Linear indiscernibility.	Intelligent fault-diagnosis algorithm.	They compared different algorithms with proposed one for energy cost.
[66]	System energy efficiency.	Power constraints.	Non-convex MINLP.	Two sub-problems are solved using different algorithms.	Computational complexity is very high when adding up the complexity of all algorithms in their work.

2.1.3 Delay minimization

In SAGSI networks, guaranteed QoS for particular traffic types (e.g., delay-sensitive traffic) is challenging mainly because of the limited resources of different network layers [67]. Next, we review recent works on delay minimization in SAGSI networks.

The authors of [68] proposed power systems impose stringent security and delay requirements on computation offloading, which cannot be satisfied by existing power IoT networks. They addressed this challenge by combining blockchain, space-air-ground integrated power IoT and ML. A consensus message is broadcasted using LEO satellites to reduce the block creation delay, and UAVs provide variable coverage enhancement. Specifically, they proposed a semi-distributed learning-based secure and low-latency electromagnetic interference-aware compute offloading algorithm to minimize the total queuing delay over the long term. They also proposed the federated deep actor-critic-based electromagnetic interference-aware algorithm, a task-offloading algorithm. Performance is evaluated based on queuing delay of task offloading and task computation versus time. The constraint observed in their work is security. We observe that the area (400m by 400m) is too small for delay optimization with 12 power IoT devices distributed evenly and four ground BSs, two UAVs, and one LEO satellite.

Deep learning techniques are used in [19, 59, 69, 70] for optimizing delay issues in SAGSI networks. In [69], the authors investigated the problem of IoT task offloading for the SAGSI network scenario wherein computing resources are shared by IoT devices cooperatively. They formulated the task offloading problem to minimize the processing delay of all tasks, considering the tasks of each IoT device, UAV mobility, and computing power difference between the UAV and the LEO satellite. Next, they formulated the problem as a Markov decision process (MDP) linear programming. They proposed a curriculum learning-multi-agent deep deterministic policy gradient approach to learn the near-optimal offloading strategy. The performance was evaluated using metrics such as transmission delay, the number of IoT devices and the value of the UAV utility function. The computational complexity should have been discussed in their work. The authors of [70] proposed a task scheduling scheme to minimize offloading and computing delay while considering the UAV energy capacity and the task processing delay. They formulated online scheduling as an integer non-linear optimization problem and developed a risk-sensitive DRL algorithm. The algorithm evaluates the risk, which measures the energy consumption that exceeds the UAV energy capacity constraint. The algorithm finds the optimal delay parameter and each state's risk. The authors measured the performance by calculating how much energy is consumed and how much delay can be expected. The authors should have discussed the computational complexity of their scheme.

The authors of [59] proposed a double Q-learning algorithm with a delay-sensitive replay memory algorithm in SAGSI networks to minimize the network delay. The authors considered constraints such as the high mobility of nodes, frequently changing network traffic, and link state. They used performance metrics such as signaling overhead, dynamic adaptivity, packet drop rate and transmission delay. When the UAV's speed increases from 5m per second to 30m/second there is a decrease in the packet drop rate but also a decrease in the throughput which is not feasible for network optimization. The authors of [19] proposed a deep learning-aided multi-objective routing algorithm for heterogeneous service requirements in SAGSI networks. The distributed algorithm exploits the quasi-predictable network topology. The constraints considered are E2E delay, E2E throughput and path lifetime. The problem defined is a multi-objective optimization problem. They called the algorithm aeronautical ad-hoc networking. The authors evaluated the performance in terms of the average performance of max E2E delay. The authors of [71] considered the optimization of energy and delay simultaneously. They proposed a task scheduling scheme to minimize the offloading and computing delay of all tasks while considering the constraint of UAV energy capacity. The authors proposed a distributed, robust latency optimization algorithm for the mixed integer linear problem (MILP). They evaluated the performance using metrics such as energy consumed and delay.

The authors of [72] described how frequent link errors and dynamic connections in SAGSI networks worsen data failure and computation slowdown and constrain the improvement of AI service efficiency. They proposed a novel coded storage and computation architecture with artificial intelligence services, which can offer reliable storage and flexible computation offloading to accelerate distributed ML. The constraints observed are energy constraints, fault tolerance, mobility, and location. The problems identified include data failure and computation slowdown. The performance measures used include average offloading delay, average retrieval delay and block rate/congestion rate. In SAGSI networks, UAV delay optimization is the main concern in [15, 59, 73]. Radio resource allocation and bidirectional offloading configuration are jointly optimized in [74]. The formulated optimization problem is non-convex and considered constraints on the sum of radio resources and the stability of the queue. The authors solved the problem in two steps: i) optimization of bidirectional offloading configuration with known radio resource allocation and ii) optimization of radio resource allocation using the brute-force search method. They concluded that performance depends on average delay, broadcasting capacity, and task arrival rate and analyzed the average delay of network using queuing theory.

In [73], the authors elaborated on the prominent future of SAGSI network architecture to support the demands of IoT applications. They considered a UAV to collect the data from IoT devices within the coverage range. Then a decision can be made at the UAV using local processing or offloading to the nearby BS or the far-away satellite. Constraints considered included QoS, energy resources, and uncertainty of the system dynamics. The problem type is linear programming. The authors proposed a stochastic policy for task offloading, where multiple devices are computing tasks to be processed. The performance was measured using energy consumption, delay, task drop, and arrival rates. In [15], the authors minimized the maximum computation delay among IoT devices by scheduling association control, task allocation, transmission power and bandwidth allocation, UAV computation resource, and deployment position. The constraints involved include resources, delay, and bandwidth for this convex optimization problem. They also proposed an efficient algorithm whose convergence is further proved. The performance evaluation is measured using metrics such as maximum computation delay versus computation capability of IoT devices, UAV, and cloud computation capability.

Lessons learnt: Table 2.4 the main lessons learnt from the research works discussed above.

- Blockchain, ML, AI, and deep learning are promising solutions for all kinds of delay problems in SAGSI networks [68], [72], [19].
- The quality of service and overall delay of SAGSI networks depend heavily on each other due to their versatile and heterogeneous nature [73].

- The author's work is valid for only a limited area of 400m by 400m [68]. Similarly, in [69] there is no discussion of computational complexity.

Table 2.4: Delay Minimization

Reference	Objective/optimization	Constraints/parameters	Problem Type	Solution	Remarks
[68]	Security and queuing delay.	Long-term security.	Joint optimization of task offloading and resource allocation.	A learning-based interference-aware computation offloading algorithm and the federated deep actor-critic-based interference-aware algorithm.	Their work is valid for a limited area of 400 m $\times$ 400 m.
[69]	Delay.	Average time of a task.	MDP linear programming.	A curriculum learning-multi-agent deep deterministic policy gradient approach.	No discussion on computational complexity.
[71]	Average offload delay (total latency) and energy.	Noise spectral density (parameter), UAV capacity, BS capacity, cloud capacity.	MILP.	Distributed robust latency optimization algorithm.	The UAV switches the BS if the BS capacity reaches to a critical value.

[70]	Minimize time average task processing delay.	UAV capacity and task processing delay.	Integer non-linear optimization problem.	Delay-orientated IoT task scheduling scheme.	The authors did not discuss the complexity of the proposed scheme.
[72]	Average retrieval delay and average offloading delay.	AI service efficiency, data failure, and computation slowdown.	Intelligence incorporation in the network.	Coded storage-and-computation architecture with AI services.	Proposed architecture can be used for distributed networks to improve node slowdown and node failure.
[59]	Global delay of network.	High dynamics or location changes.	Mix-integer non-convex optimization problem.	A double Q-learning algorithm with improved delay-sensitive replay memory algorithm.	Increase in UAVs speed from 5m per second to 30m/second; a decrease in the packet drop rate and throughput.
[74]	Average delay and overall QoS.	Sum of radio resources and stability of queue.	Non-convex.	Heuristic algorithm.	The work demonstrated the trade-off between broadcast resources and unicast resources.
[73]	Delay aware IoT task scheduling.	QoS, energy resources and uncertainty of system dynamics.	Linear programming.	Stochastic policy.	UAV trajectory is fixed in this work.
[15]	UAV position optimization and resource scheduling.	Resources, delay and bandwidth.	Convex optimization.	Alternating optimization algorithm.	Resource sharing in SAGSI networks with mixed cloud edge computing.

[19]	Delay.	E2E delay, E2E throughput and path lifetime.	Multi-objective optimization.	Proposed aeronautical ad-hoc networking.	A real scenario of the Atlantic Ocean is considered, and it is not clear how the algorithm will behave when applied to any other locations.

2.1.4 Task offloading, task scheduling, and resource allocation/utilization.

Task scheduling, task offloading, and resource utilization must be appropriate for the overall resource management of SAGSI networks. Hence, in this section, we review different aspects of resource allocation, resource utilization by different task scheduling techniques and task offloading schemes available in the literature.

In [30], the authors proposed a learning-based queue-aware task offloading and resource allocation algorithm. The constraints observed here are queuing delay and short-term decision-making. The problem type is a joint optimization problem and is divided into three sub-problems: i) device-side task splitting and resource allocation; ii) task offloading; and iii) server-side resource allocation. The performance metrics observed are energy consumption, convergence performance and queue blockage delay. In [75], the authors maximized the achievable rate of vehicles on the ground by jointly optimizing the transmit power and the UAV trajectory. They considered constraints related to UAVs which included energy, transmission, and mobility. The authors decomposed the non-convex formulated problem into two sub-problems to find the trajectory and transmit power allocation. They derived the closed-form expressions for the transmit power allocation for the given UAV trajectory. On the other hand, they calculated the UAV trajectory using the successive convex approximation technique for the sub-problem with the given power allocations. The performance measures used were the ground vehicle's sum rate and the maximum transmit power.

In [76], the objective was to minimize the system's power consumption. The problem type defined is mix-integer non-convex programming. They proposed an algorithm which divides the problem into two sub-problems to find a near-optimal solution with low computational complexity. The solution uses two algorithms, the optimal sub-channel selection and power control algorithm, and the joint resource allocation and HAP deployment algorithm. The constraints observed in their work are smart devices' power constraint, HAPs power constraint, sub-channel allocation constraint, and HAP deployment constraint. The performance metric used is system power consumption. Although the authors discussed computational complexity, they assumed a square search space, it is not clear if the computational complexity increases or decreases when the search space is not limited to a square.

In [76], the author's objective was to minimize the system's power consumption. The problem type defined is mix-integer non-convex programming. To discover a close-to-optimal solution with little computing cost, they created a method that splits the problem into two more minor problems. The optimal sub-channel selection and power control method and the combined resource allocation and HAP deployment algorithm are the two algorithms used in the solution. The limitations seen in their research include the power limitations of intelligent devices, the power limitations of HAPs, the limitation of sub-channel allocation, and the limitation of HAP deployment. System power consumption is used as a performance parameter. The authors did not discuss when the computational complexity grows or reduces if the search space is not restricted to a square, even though the authors' discussion of computational complexity was based on a square search space.

In [31], the authors highlighted the limited storage capacity of the space-air network. The servers in the air also do not have the storage capacity to handle the data uploaded by the edge server. Thus, the coordination of storage resources in SAGSI networks must be investigated. They proposed a storage resource management algorithm based on distributed DRL in which the resource management process is modeled as an MDP. The network attributes of storage resources are extracted in each physical edge domain to develop a training environment. The authors proposed a radio resource management framework for SAGSI networks based on distributed DRL. The constraints are the location constraint of the request node mapping and resource allocation.

The problem is how to coordinate the storage resources of SAGSI networks. The performance was evaluated based on time, revenue rate, requests from users, and acceptance rate. They claimed that the algorithm is flexible in dealing with the changes in resource conditions. However, they do not provide any information about the resource conditions their proposed algorithm is flexible.

In [77], the authors reviewed edge computing research on SAGSI networks. They proposed a framework of edge computing-enabled SAGSI networks to provide several services for vehicles in remote areas. The objective is to minimize task completion time and satellite resource usage. The authors proposed a pre-classification scheme to reduce the action space's size. They developed a deep imitation learning-driven offloading and caching algorithm to enable real-time decision-making. The problem defined here is a fine-grained offloading and caching problem as a multi-label classification process which can also be defined as a reinforcement learning scenario or MDP. The authors considered energy supply and time constraints as well as trajectory optimization. The performance is measured in terms of accuracy and task completion time. It will be a challenge to modify the hardware on a large scale and the hardware cost will likely increase.

The authors of [78] optimized the planning of the service function chains under limited heterogeneous resources to map them on physical networks while considering the trade-off between resource utilization of both communication and computation. The service function chain (SFC) planning problem is formulated as an integer non-linear programming problem. They also proposed a heuristic SFC planning algorithm to reduce the computational complexity and a new metric, aggregation ratio, to observe the trade-off between communication and computation resource consumption. The algorithms proposed are heuristic SFC planning for the SAGSI network algorithm, service flow routing algorithm, and virtual network functions (VNFs) placement algorithm. The constraints observed are computation resource constraints and communication resource constraints. The performance was measured based on the computation resource consumption, bandwidth resource consumption, resource costs per completed service request, and the number of service requests. Moreover, they used a single hop delay of 10-15ms, if and only if nodes are distributed uniformly. The impact on the delay is not clear if nodes are not distributed uniformly.

In [79], the authors proposed an integrated space-air-ground network that can achieve ubiquitous network coverage and can be effective in an emergency communication scenario. The authors discussed the network constraints in their work. The problems identified include network updates and on-demand network optimization. Therefore, they introduced network-slicing technology to the wireless communication part of the integrated space-air-ground network to solve the problems faced by the current power communication network. They analyzed the current state of the power communication network and proposed a space-air-ground integrated network architecture based on network slicing.

The authors of [80] investigated the efficient data delivery and task management in SAGSI networks. They developed a SAGSI model to reduce the number of satellite attitude adjustments and increase the task scheduling time, which satellites, UAVs, and ground stations introduce. Then, the scheduling problem in SAGSI is formulated as an MDP to maximize the sum of priorities of successfully scheduled tasks under some constraints. The constraints are switch time and storage capacity. The problem defined is task scheduling which is non-convex. Next, the authors proposed an adaptive particle swarm optimization intelligent coordinated scheduling algorithm to adjust the global and local search capabilities dynamically. In their proposed algorithm, three task scheduling processes: collection, storage and transmission are considered jointly for resource interaction, and the global and local search capabilities of particles, and are coordinated dynamically with adaptive inertia weight. Furthermore, the authors developed a two-criterion resource allocation method for less scheduling conflict, and the scheduling order is determined based on the task's priority and deadline. The performance is measured in terms of sum priority and the number of tasks.

In [81], the authors proposed an offloading scheme that addressed the co-existing requirements of heterogeneous devices by offloading the traffic effectively to the suitable segment of SAGSI networks. The constraints considered are the offloaded eMBB and URLLC traffic vectors, the bandwidth resources allocated to the micro BSs, and the trajectory of UAVs. The problem is formulated as a multi-objective non-convex problem. Specifically, the URLLC traffic is offloaded to the UAV and terrestrial links to satisfy its stringent latency requirements. The algorithm proposed is deep deterministic policy gradient reinforcement learning. The results emphasized the integration of different segments of SAGSI networks to address heterogeneous QoS requirements. The performance was measured regarding the number of UAVs and the eMBB availability as a function of the number of UAVs. In [82], the authors surveyed state-of-the-art results on SAGSI networks. The performance SAGSI networks is affected by the limited resource at each network layer. Thus, it is crucial to integrate systems efficiently, optimize protocols, and manage resources in SAGSI networks. The authors presented a comprehensive literature review from a network design and resource management perspective to analyze performance and optimization in SAGSI networks.

The research results discussed above mainly focused on task scheduling, task offloading, resource allocation, and utilization in different layers of SAGSI networks using different algorithms and techniques. However, computational complexity is a major issue in many of these techniques. The number of devices used is limited, which can make their practical deployments hard to achieve where we often have many devices connected to networks. Interoperability (among different layers of networks) is also a major challenge that was not fully discussed. Moreover, flexibility, security, and optimization of task scheduling, offloading, allocation, and utilization are areas that need further research to demonstrate the efficacy of these techniques and algorithms.

Table 2.5 summarizes the results of the works we have reviewed above.

- For different segments or slices of SAGSI networks, we must have a universal task scheduling and task offloading technique, then it would be easy to reap the maximum benefit from resource utilization.
- Reinforcement learning and deep learning are optimal techniques which must be considered for task scheduling and task offloading [31] and [81].

Table 2.5: Task offloading, task scheduling, and resource utilization

Reference	Objective/optimization	Constraints/parameters	Problem Type	Solution	Remarks
[30]	Long-term time average energy consumption and Joint optimization.	Queuing delay and short-term energy consumption.	Lyapunov optimization problem.	Queue-aware task offloading and resource allocation algorithm.	Tested on a very limited area of 1km $\times$ 1km.
[75]	Maximize the vehicle's achievable data rate by jointly optimizing transmit power and UAV trajectory.	UAV energy, UAV power transmission, UAV mobility.	Non-convex.	Successive convex approximation technique, alteration algorithm.	Jointly optimize transmit power and UAV trajectory.
[76]	Minimize system power consumption.	Smart devices power, HAPs power, sub-channel allocation, HAP deployment.	Mix-integer non-convex programming problem.	Optimal sub-channel selection and power control algorithm, joint resource allocation and HAP deployment algorithm.	It is unclear if the computational complexity increases or decreases if the search space is not limited to a square.

[31]	Storage capacity of SAGSI network.	Location, bandwidth demands, delay, and data rate.	MDP.	A SAGSI storage resource management algorithm based on distributed DRL.	They do not provide enough details on the resource conditions and did not specify how the algorithm is flexible which is claimed in work.
[78]	Optimize the planning of SFCs under limited heterogeneous resources and map them onto physical networks, considering the balance of resource utilization of both communication and computation.	Computation resource constraints and communication resource constraints.	Integer non-linear programming problem.	Aggregate ratio, heuristic SFC planning algorithm, service flow routing algorithm, VNFs placement algorithm.	Nodes are distributed uniformly with a delay of 10, 15ms, and if the distribution of nodes is not uniform, the delay behavior is unexpected.
[79]	Proposed an architecture to fulfill different demands of bandwidth, delay, and data rate.	Network constraint.	Network update and network optimization.	Integrated SAGSI network architecture using slicing technology.	Network slicing technology is emerging technique for different resource optimization techniques in SAGSI networks.
[80]	Data delivery and task management.	Switching time between two satellites and storage capacity.	Non-convex.	Adaptive particle swarm optimization intelligent coordinated scheduling algorithm.	For tasks with same priorities, tasks are chosen based on early deadlines.

[81]	Better QoS.	The offloaded eMBB and URLLC traffic vectors, the bandwidth resources allocated to the micro BSs, and the trajectory of UAVs.	Multi-objective non-convex problem.	Deep deterministic policy gradient reinforcement learning algorithm.	Proposed offloading approach enhanced the network's availability and reduced the latency in SAGSI networks.
[82]	State-of-the-art comprehensive survey of existing research focusing on network design, resource allocation, performance analysis, and optimization.	Integrates all three network segments.	Best performance for traffic delivery.	Review on SAGSI networks from network design and resource allocation.	Shed light on three segments of heterogeneous networks.

2.1.5 Network operation cost, outage probability, and average age-of-information

Resource management in different areas of SAGSI networks is vital. Areas such as network operational cost, the level of outage expected, and the average age of information must be optimized very carefully. This section discusses the related works in this area and identifies the lesson learnt.

The authors of [23] considered UAV-assisted WPT in SAGSI networks to provide power to IoT devices to satisfy their QoS, safety, and stability requirements. The authors developed an architecture for SAGSI power IoT for task offloading and resource scheduling. They also proposed an online algorithm to minimize the network operation cost by jointly optimizing task assignment, local and UAV computing resources, and association control. Here, the constraints are the moving nature of satellites (geographical environment) and the energy of power IoT devices. The optimization problem is decomposed into three sub-problems and solved separately using Lyapunov optimization. Moreover, the authors analyzed the proposed algorithm in terms of stability and sustainability. They also discussed the trade-off between network stability and operation cost. They evaluated the performance in terms of the sum queue backlog of the powered IoT devices, average energy consumption, and cost.

In [83], the authors calculated the routing path and data center deployment to satisfy the QoS requirements of the passengers with minimum cost. Hence, adapting the service location is an important task due to flight movements. In their work, they formulated two MILPs for the problem of joint service placement and routing: i) static and ii) mobility-aware in SAGSI networks to minimize the total cost. They compared static and mobility-aware approaches using comprehensive evaluations in a realistic European-based SAGSI network. The constraints in this work are the number of service requests, capacity limit, the sum of assigned traffic, QoS in terms of delay, and flow conservation. The performance measures include average total cost which includes deployment and service costs, and the average number of total migrations. In [18], the authors viewed the SAGSI networks in terms of cooperative communications and introduced relay networking to model the SAGSI system from the cooperative perspective, wherein the cooperating HAP and BS assist the transmission from GEO to UE. The approximated and asymptotic closed-form expressions for outage probabilities of each link were derived as well as the outage probability of the SAGSI system. They also proposed sub-optimal solutions with low complexity whose efficiency was verified by Monte Carlo simulations. The problem defined here is the spatial distribution of HAP. Based on the constructed framework of SAGSI, they analyzed the outage performance and approximated the outage probability as well as the asymptotic outage probability in closed form. Mobility and location changes are the major constraints. The performance metrics are outage and error analysis for both single hop and double hop, asymptotic analysis of signal-to-noise ratio (SNR) for both uplink and downlink scenarios.

In [84], the authors proposed covert wireless uplink communication in SAGSI vehicular networks by hiding the transmission behavior in public channels. They minimized the outage probability by jointly optimizing the transmit power and the improper Gaussian signaling. They derived the optimal transmit power by considering the constraint on the QoS of the system using the Gaussian signaling scheme. The authors evaluated the performance based on the data transmission efficiency, outage probability, noise uncertainty and maximum available transmit power. The authors of [85] investigated the optimal actions that minimize the long-term average age-of-information. The authors considered the parameter characterizing the event of channel erasure, following an independent and identically distributed Bernoulli distribution. The authors used the age-of-information to capture the timeliness of the status updates. The authors proposed two hybrid automatic repeat request (HARQ) schemes, and an incremental redundancy HARQ scheme to mitigate errors during transmissions. To minimize the long-term average age-of-information, they formulated an MDP, and prove that the optimal transmission policies for the classical HARQ scheme and the incremental redundancy HARQ scheme behave differently in threshold structures (relative values iteration is an algorithm used for finite values and the finite number of iterations). The problem type is the age-oriented optimization problem, and the performance metrics are the length of information redundancy and re-transmission times. They did not discuss the complexity of their proposed system and scheme.

The authors of [86] studied the age-of-information of vehicular status updates in SAGSI networks for intelligent transportation systems. They proposed a model to predict the vehicular communication link and transmit it in advance to the receiver. The parameters of the proposed system model are arrival rate and propagation delay. The authors found that prediction has more advantages in short-range compared to long-range communications. The performance of the average age-of-information is improved using an MDP framework to find a switching strategy for the prediction policy. The algorithm developed as a solution is the value iteration method. Further, to improve the age-of-information performance, they developed an MDP framework whose performance depends on prediction time (how much delay is expected) and the average age-of-information.

The difference between bandwidth and data rate needs resource management for QoS requirements. Storage or caching also have some interdependent bandwidth and delay requirements and needs to be optimized at a low cost. Another important resource to be optimized according to SAGSI requirements is CPU cycle frequency which is again very important and is related to transmission frequencies in wireless communications. This section reviewed recent research on data rate difference and bandwidth discrepancy, storage, and CPU cycle frequency.

In [87], the authors used a time-expanding graph to deal with the periodic motion of LEO satellites in SAGSI networks. The time-expanding graph represents the resources and task flow transmission processes. The objective was to maximize the total amount of data received by the data center on the ground while considering resource constraints and flow restrictions. The formulated MILP is solved using a brute-force algorithm and Benders decomposition-based algorithm to obtain an optimal solution with less complexity. For the scalability of the proposed system, the authors proposed an acceleration algorithm based on an approximation algorithm and unit-flow shortest path algorithm. The performance is measured based on energy capacity, iterations, number of users, total received data, and storage capacity. They found that the distance between HAPs and LEO satellites is much larger than the distance from the users to HAPs, the reduced distance between HAPs and LEO satellites has a slight effect on the network performance.

In [26], the authors investigated fair resource allocation and resource auction strategies. The difference between the allocated and the required data rate is maximized while considering constraints on QoS of users, sub-channel and power. Their proposed solution uses a civil aircraft-augmented SAGSI network architecture. They proposed a sub-channel allocation algorithm, a service-oriented fair iteration algorithm, and a resource auction iteration algorithm. The problem defined is convex-relaxation and logarithmic approximation. Sub-channel and power allocation are jointly optimized using the service-oriented fair iteration algorithm. They used performance measures such as user density, number of users, and sum rate. The network capacity is saturated when the number of users exceeds 250.

The authors of [72] proposed a novel coded storage and computation architecture, which can offer reliable storage and flexible computation offloading to accelerate distributed ML. Energy and mobility are the major constraints while performance measures are average offloading delay, average retrieval delay, and block rate or congestion rate. The authors of [33] proposed AI-based engineering solutions to facilitate efficient network slicing, mobility management, and cooperative content caching and delivery. Resource allocation is a challenge or constraint, while performance measures are time, average throughput, and the number of vehicles. In [29], the authors proposed an online resource scheduling scheme that jointly optimizes CPU cycle frequency, power control, and UAV trajectory planning. Their objective was to maximize the long-term time-averaged total system computation rate. The constraints here are CPU cycle frequency, network stability and sustainability of the remote IoT devices, energy sustainability, and network sustainability. The problem formulated is a nonlinear stochastic optimization problem that is non-convex. The main problem is decoupled into three subproblems using Lyapunov optimization. They also proposed an online algorithm, namely joint optimization of CPU cycle frequency, allocation, power control, and UAV trajectory in remote IoT networks, to obtain the optimal CPU cycle frequency, power control, and UAV trajectory planning. The performance metrics used include the average computation rate and the cumulative density function (CDF) on different voltages. In [88], the authors discussed a healthcare IoT system in SAGSI networks based on cellular technology, where the channel state information may not be perfect. A healthcare IoT device receives RF energy from the small cell BS in this system. Then it transmits physiological status updates to the corresponding small BS promptly. The authors formulated a distributionally robust optimization problem to minimize the average age of information (metric to measure the freshness of the data) under energy harvesting and information transmission probability constraints. To efficiently solve the NP-hard problem, the authors proposed a low-complexity iterative algorithm that decomposes the optimization problem into two subproblems. Simulation results obtained show a tradeoff between the age of information and energy consumption in the healthcare IoT system.

Lessons learnt: Table 2.6 summarizes the main lessons learnt from the works discussed above.

- Co-operative channel models can reduce the outage probability in SAGSI networks [18].

- Long-term average age-of-information can be improved by using intelligent transportation systems [86]. To minimize the average time for network operation cost, WPT can be used in SAGSI networks for task offloading and resource scheduling [23].
- Storage resource management is vital for SAGSI networks [72].
- If the data rate difference of task offloading and task scheduling of tasks can be efficiently managed, the performance of system can be improved significantly [26].

Table 2.6: Network operation cost, outage probability, and average age of information

Reference	**Objective/optimization**	**Constraints/parameters**	**Problem Type**	**Solution**	**Remarks**
[23]	The battery capacity of power IoT devices.	Geographical environment and energy of power IoT.	Stochastic optimization problem.	Matching game-based association optimization algorithm; Improved queue awareness-based greedy UAV computing resource allocation algorithm.	Joint task offloading is performed in the WPT-enabled network.

[83]	To minimize total cost of network.	Number of service requests, capacity limit, sum of assigned traffic, QoS in terms of delay, flow conservation.	Two MILPs for the problem of joint service placement and routing.	Joint service placement and routing: i) static and ii) mobility aware. The mobility-aware approach can utilize direct air-to-ground and satellite connections to satisfy the passenger service requests cost-effectively compared with static approach.	Joint service placement and routing in SAGSI networks.
[18]	Optimization of spatial distribution of HAPs.	Mobility and location changes.	Spatial distribution of HAPs.	Cooperative communications and relay communication to model and construct the framework of SAGSI networks for different outage scenarios.	Outage performance analysis of integrated networks.

[84]	Data transmission efficiency and outage probability.	QoS of host communication system, covertness requirement, and maximum power budget.	Joint transmit power and improper Gaussian signaling factor optimization problem.	The optimal solution was derived strictly for the transmit power with a Gaussian signaling scheme. Then, with the approximate outage probability of the host system, the optimal transmit power and circularity coefficient factor pair were jointly designed for an improper Gaussian signaling scenario.	Improper Gaussian signaling performs better in outage probability but needs more power, and it needs to be clarified how much trade-off is needed between power utilization and outage probability.
[85]	Find the optimal actions that minimize the long-term average age-of-information.	Assumed event of channel erasure occurs, which follows an independent and identically distributed Bernoulli distribution parameter.	MDP.	Two HARQ schemes and an incremental redundancy HARQ scheme were developed to mitigate transmission errors.	The complexity of the system and the proposed schemes have not been discussed.

[86]	Minimize the long-term average information age.	Arrival rate and propagation delay.	MDP.	Value iteration method whose prediction is more advantageous for short-range communications.	Prediction policy for in-time status updates in SAGSI networks.
[87]	Cooperative HAP and LEO satellite schemes.	Multiple resource and flow restrictions.	MILNP.	Benders decomposition-based algorithm, acceleration algorithm, unit-flow shortest path algorithm, approximation algorithm.	The authors did not discuss how the performance could be affected for longer distances between HAP and LEO.
[26]	To minimize the difference between the allocated and required data rate of users.	QoS of user, subchannel and power constraints.	Convex-relaxation and logarithmic approximation.	Subchannel allocation algorithm, service-oriented fair iteration algorithm and resource auction iteration algorithm.	Network growth is very slow if the number of users exceeds 250.
[72]	A new paradigm to enhance intelligent services in space-air-ground integrated networks.	Energy constraint.	Data failure and computation slowdown.	Coded storage-and-computation architecture.	For distributed ML they considered coded storage and computation architecture.

[33]	Resource management efficiency.	Network constraint.	Resource management problems.	They considered a case study and discussed the results.	Optimal resource management strategies are proposed in this work.
[29]	Sustainable device operation and enhanced computational capability.	CPU cycle frequency, network stability and sustainability of remote IoT devices, energy sustainability and network sustainability constraint.	Non-linear stochastic (non-convex).	An online algorithm, joint optimization of CPU cycle frequency, allocation, power control and UAV trajectory in remote IoT networks.	This work increases long-term time-averaged total system computation rate while satisfying network stability and sustainability.

2.1.6 Joint optimization

Joint optimization refers to a resource management technique where multiple parameters are considered simultaneously to improve the performance of SAGSI networks. In this section, we review recent efforts which jointly optimized the network components to achieve high efficiency from the network.

In [89], the authors maximized the system sum rate by considering the proportional rate and sustainability of ground nodes. They formulated two optimization problems to jointly optimize power control, time allocation, and UAV trajectory while maximizing the sum rate. The constraints defined here are energy-neutral, information casualty, and proportional rate. They adopted decode and forward (DF) and amplify and forward (AF) protocols. The authors solved the non-convex problems using two near-optimal iterative algorithms with successive convex approximation and alternating optimization methods. The performance of DF and AF algorithms depends on satisfying the proportional rate and the sustainability of the ground network.

The authors of [90] formulated a non-convex problem to optimize the time slot division, sub-channel allocation, power control and UAV deployment to maximize the system sum rate. Hence, they applied alternating optimization and successive convex approximation techniques to transform the non-convex problem into a solvable form. The constraints defined here are distance, power, and manufacturing cost for batteries. Next, the authors proposed a near-optimal multi-variable alternating iterative algorithm to obtain a resource allocation scheme for the overall problem. The performance measures are sum rate, transmit power and harvested energy.

In [91], the authors formulated a channel model usage problem. The authors considered parameters such as link parameters, turbulence parameters whereas for their simulations they considered parameters such as wavelength, HAP altitude, LEO altitude, variance of background noise and receiver noise bandwidth. In this research, the authors dealt with free space optics (FSO) RF technologies for uplink SAGSI networks by utilizing UAV such as HAP as a relay station for achieving better reliability. In this context, they proposed single-hop satellite communication and SAGSI-based dual hop satellite communication system models for uplink with hybrid FSO/RF links. The authors investigated the performance of proposed system models using analytical and simulation results. They used performance metrics such as outage and error analysis of both single hop and two hops, asymptotic analysis of SNR for both uplink and downlink scenarios. In [92], the authors focused on providing a reliable, asynchronous, and fully distributed approach that associates nodes across the layers so that the total end-to-end rate of the assigned agents is maximized. The problem is modeled as a multi-sided many-to-one matching game. The constraints are network constraints. The authors proposed a randomized matching algorithm with low information exchange. The algorithm showed an efficient and stable association between nodes in adjacent layers. The performance is measured in terms of sum rate, final association with the multi-sided algorithm and the number of users.

In [22], the authors proposed a novel approach to address the optimization problem of gateway selection, bandwidth allocation, and UAV deployment to maximize the system's spectral efficiency. Here the problem defined is non-convex MINLP. Although the space-air-ground IoT systems bring about several benefits, they also need to overcome many challenges due to the high mobility, unreliable satellite links, and limited resources. Specifically, when multiple UAVs act as relays for cross-tier communications to transfer the collected data from the ground network layer to the satellite layer, how to select an appropriate number of UAVs as gateways to improve system spectral efficiency remains a challenge. Most existing works utilize all UAVs as relay nodes and neglect the spectrum allocation. Constraints can be considered as limited power, bandwidth, and resource allocation. The authors proposed a Dinkelbach method-based iterative algorithm as their solution by alternately adopting simulated annealing and successively convex programming technologies. They also proposed another algorithm called a simulated annealing-based gateway selection algorithm and joint optimization of gateway selection, UAV deployment, and bandwidth allocation. They evaluated the performance using metrics such as spectral efficiency, and the number of UAVs and IoT devices on the ground.

Marine IoT systems have increased significantly with the development of aerial and space vehicles in the SAGSI network. Marine IoT systems can assist in environmental protection, military surveillance, and sea transportation. However, the unpredictable climate changes and the extreme channel conditions of maritime networks make it difficult to collect and process a large amount of maritime data efficiently and reliably. To address this issue, the authors of [93] proposed a hybrid LEO and UAV edge computing method in SAGSI networks for marine IoT systems. This system uses two edge servers mounted on UAVs and LEO satellites to process the collected data in real-time. The aim is to minimize the total energy consumption of the battery-constrained UAV by jointly optimizing the communication and computation bit allocation along with the UAV path planning under latency, energy budget, and operational constraints. The proposed methods are developed for three different cases according to the accessibility of the LEO satellite: always on, always off, and intermediate disconnected, using successive convex approximation strategies. The numerical results obtained show that significant energy savings can be achieved by optimizing the bit allocation and UAV path planning for all cases of LEO accessibility compared to partial optimization schemes that design only the bit allocation or UAV trajectory.

Lessons learnt: Table 2.7 summarizes the main lessons from the research works discussed above.

- We can improve the system's sum rate by jointly optimizing the time slot division, subchannel allocation, power control and UAV relays deployment [90].

- Spectral efficiency can be improved by optimizing the overall bandwidth and channel model usage [22, 91].

Table 2.7: Joint optimization

Reference	**Objective/optimization**	**Constraints/parameters**	**Problem Type**	**Solution**	**Remarks**
[89]	Maximize the system sum rate.	Energy neutral, information causality, and proportional rate constraints.	Non-convex.	DF protocol and AF protocol.	DF and AF protocols are used for WPT.
[90]	Maximize the system sum rate by jointly optimizing the time slot division, sub-channel allocation, power control, and UAV relay deployment.	Distance, power, and manufacturing cost for batteries.	Non-convex MINLP.	Multi-variable alternating iterative resource allocation algorithm.	WPT and wireless information transfer are shown by different links. Furthermore, the authors argued that improving the link cannot improve data rate.

[91]	Integrating free space optics and RF in SAGSI networks using UAVs, HAP, and LEO.	Link parameters, turbulence parameters.	Channel model improvement.	Single-hop satellite communication and SAGSI network-based dual-hop satellite communication system models for uplink satellite communication with hybrid FSO/RF links.	Link between HAPS and satellites is not very sensitive, the authors considered weak turbulence and minor pointing errors, which is not the case in real life.
[22]	Joint optimization problem of gateway selection, bandwidth allocation, and UAV deployment to maximize the system spectral efficiency.	Limited power, bandwidth, and resource allocation.	Non-convex MINLP.	A Dinkelbach method-based iterative algorithm and joint optimization of gateway selection, UAV deployment, and bandwidth allocation.	Spectral efficiency has been improved in the across-tier network.
[92]	To maximize total E2E transmission data rate of the assigned agents.	Network constraints.	Many-to-one matching game problem.	Multi-sided algorithm.	Association is discussed in a heterogeneous network with matching game theory.

2.1.7 Overall performance of network and performance degradation

Like all other factors, we must focus on the overall performance of SAGSI networks. If we optimize multiple resources, the overall performance of networks will be increased in multiple areas. Similarly, in contrast, if few resources are not managed properly, it will lead to a state where the performance of SAGSI networks degrades. In this section, we review the available literature on performance degradation and the overall performance of SAGSI networks.

In [94], the authors investigated THz ultra massive MIMO-based aeronautical communications and proposed an effective channel estimation and tracking scheme, which can solve the performance degradation problem. The constraint considered is space constraint. The problem type can be generalized as performance degradation. An initial aeronautical link is established based on the rough angle estimates acquired from the navigation information. The delay-beam squint at the transceiver can be substantially reduced by using a grouping true-time delay unit module (GTTDU). The solution developed comprises three algorithms. First, the prior-aided iterative angle estimation algorithm is used to estimate azimuth/elevation angles. These angles are used to find the precise beam alignment and refine the GTTDU module to eliminate the delay-beam squint further. Second, the authors proposed the prior-aided iterative Doppler shift estimation algorithm. An initial aeronautical link is established based on the angle estimates acquired from the navigation information. Third, the authors developed an algorithm for data transmissions to track the beam-aligned effective channels based on a data-driven decision.

In [95], the authors proposed heterogeneous network switching algorithms which usually use fixed weights of attributes (such as delay) to make decisions. Here, the problem defined is switching between networks, non-convex in nature as the constraints include network quality indicators (NQI). In their work, the authors proposed the Monte Carlo-MDP algorithm to balance the network load of multiple networks. It can dynamically adjust the access networks of users in the system while considering the users' service requirements and network differences. The Monte Carlo method is used to improve the convergence speed of the MDP algorithm. The performance measures used include the number of users and the system's utilization. In [27], the authors proposed an architecture called civil aircrafts augmented space-air-ground integrated vehicular networks. The main goal of the sky access platforms' deployment with UAVs is to provide maximum communication coverage under the constraints of QoS. The problem defined is resource allocation in hybrid networks. The proposed network architecture is novel in three main aspects: a normal network architecture, collaboration with multiple SAPs, and service-oriented fair allocation. Although civil aircraft augmented-SAGSI networks can bring out many benefits, it also faces issues due to their high mobility and cross-layer characteristics.

In [96], the authors explored providing QoS guarantees to vehicles. They proposed an architecture called QoS guaranteed access assistance to serve vehicles. The parameters considered include a set of access assistants, deployment cost and several BSs, satellite stations, and the maximum number of vehicles. The problem defined is non-convex. The access assistance uses a virtualized layer that consists of the logical resources of ground infrastructure for deployment. After deploying access assistance, vehicles can obtain network services to meet QoS requirements. The authors proposed three algorithms: basic deployment, deep Q-learning-based on-demand deployment, and cost-effective access assistant deployment. They evaluated performance of the algorithms in terms of the success rate of autonomous driving requests.

In [10], the authors analyzed the development of the mobile communication network of high-speed railways, and discussed the SAGSI network architecture and the application scenarios (in high-speed railways) along with the network structure. At the same time, the authors also discussed the communication services, existing problems, and key technologies in the SAGSI networks. They also studied the use of AI technologies in enabling the efficient resource utilization of smart railways communication in SAGSI networks. The performance measures used were throughput, transmission delay, reliability, and security. The authors of [97] aimed to improve the performance of SAGSI networks which remains a significant challenge. The authors proposed an AI technique to optimize SAGSI networks because AI shows promise in many applications. First, they analyzed several main challenges of SAGSI networks and discussed how AI can solve these problems. Then, they considered the satellite traffic balance as an example and proposed a deep learning-based scheme to improve traffic control performance. They used performance metrics such as network throughput and packet loss in their performance evaluation tests.

In [28], the authors proposed the framework of a SAGSI network wherein drones act as relays to upload data from smart devices to low earth orbit satellites. Considering many smart devices, the authors tried to maximize the system capacity by jointly optimizing smart devices connection scheduling, power control, and UAV trajectory, where joint optimization is a non-convex optimization problem. The formulated problem is a mixed integer non-convex optimization problem, which is challenging to solve directly. The constraints considered are UAV trajectory, safety, coverage, and LEO satellite capacity. Hence, the authors proposed an efficient iterative algorithm to solve the above-mentioned non-convex optimization problem by applying variable substitution, successive convex optimization techniques, and the block coordinate descent algorithm. The algorithms presented in their work are resource allocation algorithms for joint smart device connection scheduling, power control, and UAV trajectory design. Specifically, they alternately iterate smart device connection scheduling, power control, and UAV trajectory design to obtain the maximum system capacity. They evaluated the performance of their algorithms based on the number of smart devices and the system's maximum capacity. In [98], the authors highlighted that the emergence of advanced applications such as smart cities, healthcare, and virtual reality requires more demanding requirements from SAGSI networks. These requirements include improved secrecy, greater integrity, non-repudiation, authentication, and access control.

Lessons learnt: Table 2.8 presents the main lessons learned from the past works we have reviewed above.

- AI is playing a significant role in performance improvement and QoS requirements [10, 97].
- By balancing the varying network load and optimized trajectory, we can increase the network's overall performance, the number of users and resource utilization [28, 95].

Table 2.8: Overall Performance of Network and Performance Degradation

Reference	Objective/optimization	Constraints/parameters	Problem Type	Solution	Remarks
[94]	Solution of performance degradation.	Triple delay-beam-doppler squint effects.	Performance degradation problem.	Prior-aided iterative angle estimation and iterative doppler shift estimation algorithms; a channel tracking algorithm based on data-driven decision-directed.	Computational complexity is too high and needs improvements.
[95]	Switching algorithm in heterogeneous networks.	Network quality indicators.	Non-convex MDP.	Monte Carlo-MDP.	Optimal performance refers to when the number of users is 120, which is far less in actual practice.
[96]	IoVs access decisions to satisfy QoS requirements.	Set of access assistants, deployment cost, several BSs, satellite stations, and a maximum number of vehicles.	Non-convex.	Basic deployment, deep Q-learning based on-demand deployment and cost-effective access assistant deployment.	Basic deployment and on-demand deployment schemes are adapted and based on this cost-effective deployment is observed.

[27]	Sky access platform deployment related to UAVs.	QoS and power constraints.	Resource allocation in hybrid networks.	CAA-SAGSI networks.	Deployment of this network is difficult and expensive.
[10]	Application trend of SAGSI networks in HSRs.	Worked in high-speed railways.	Updated research work available in integrated network development and high-speed railways.	Application scenarios of AI technologies in enabling efficient resource utilization.	Resource allocation and coverage were not considered.
[97]	To improve the overall performance of SAGSI network	Several main challenges solved by AI in SAGSI networks.	Applications of SAGSI networks.	A deep learning-based scheme to improve traffic control.	Future research directions should also include cost-effectiveness.
[28]	Improve performance of SAGSI network.	UAV trajectory constraints, safety constraints, coverage constraints, and LEO satellite capacity constraints.	Non-convex MINLP.	Resource allocation algorithm for joint smart device connection scheduling, power control, and UAV trajectory design.	With the increase in the number of intelligent devices, demand for the number of UAVs will increase to increase the capacity of systems with low complexity.

2.1.8 Software-defined networking (SDN)

SDN and NFV are important areas of SAGSI networks as they are the agile and flexible way to visualize and validate our architectures afterward and how they will perform in a virtual setting while considering different layers of SAGSI networks. There are several research efforts in this area where several authors [6,99–104] proposed different architectures and discussed their validity and performance. We review such works here from a resource management perspective.

In [99], the authors proposed a software-defined SAGSI network architecture with a layered structure to support seamless, cost-effective, and efficient vehicular services. The resource in each segment of SAGSI networks is sliced using network slicing to obtain service isolation. A resource pool is created for all available resources and is hierarchically managed to offer vehicular services. The parameters used in their proposed architecture are LEO altitude (1414 km), period 114 130 min, inclination angle 0 degrees, altitude of HAP 20 km and minimum elevation angle 10 degrees and radius of Earth is 6371 km. The problem is a bipartite one-to-many matching one. They evaluated the performance of their architecture using the maximum number of satellite beams and the number of HAPs.

In [6], the authors proposed a cross-domain virtual network embedding (VNE) algorithm to solve the multi-domain VNE problem (which is a decision-making problem to show whether the virtual node is embedded in the physical layer) in the SAGSI network. They modeled the different network segments and their attributes based on the user needs and the actual situation of the SAGSI networks. A DRL algorithm is trained based on the extracted network attributes. The probability of each underlying node being embedded can be derived through training. The VNE algorithm which is based on DRL is better than the one based on heuristic methods. In [101], the authors discussed the use of mmWave and UAVs and studied channel effects in new scenarios. ML algorithms could enhance the performance of SAGSI networks using mmWave. The authors considered parameters such as channel, bandwidth characteristics of radio wave propagation, and each path of multiple signals. The authors proposed a cloud-based modular simulation system to support emerging applications and technologies in B5G networks. The performance measures used include average received power, frequency, number of UAVs, delay spread, and angle spread arrival. The delay in the received signals increases when the density of UAVs increases. This is because the reflection, scattering, and diffraction effects increase when the density increases resulting in high angular spread thereby resulting in a higher system delay.

The authors of [100] pointed out that NFV and SDN are complementary and promising technologies that reduce the function provisioning cost and coordinate the heterogeneous physical resources in the SAGSI networks. The authors investigated the online dynamic VNF mapping and scheduling in SAGSI networks, considering the dynamicity of IoV services or mobility which is a constraint. The VNF live migration, re-instantiation, and rescheduling are enabled to enhance the service acceptance ratio and profit of the service provider. Considering the heterogeneity of SAGSI network nodes, the authors modeled the migration cost and additional delay incurred by VNF live migration and re-instantiation. Next, they jointly optimized the dynamic VNF mapping and scheduling as a MILP problem with specified cost and delay models. They proposed two Tabu search-based algorithms: i) VNF remapping and rescheduling algorithm and ii) pure VNF rescheduling algorithm to obtain suboptimal solutions efficiently. The authors evaluated the performance in terms of service providers' profit, service acceptance ratio, and QoS satisfaction level. With a small service arrival rate, physical resources are adequate to support the new services. Therefore, there is little room for improvement in the proposed remapping and rescheduling strategies when the network load is light.

The authors of [102] proposed a SAGSI network architecture where satellites can provide seamless coverage. UAVs can enhance the data processing capacity to support terrestrial IoT services. The constraints observed in their work are resource constraints and UAV operation time (due to limited battery) constraint. The problem can be defined as resource allocation in SAGSI networks. To support the edge computing functionalities of SAGSI networks, they proposed two novel frameworks for satellites and UAVs called intelligent enhanced satellites and intelligent enhanced UAVs, respectively. These presented three typical application scenarios wherein SAGSI networks can support and specify the application domain of each segment. The performance measure used is data rate of the proposed system. In [104], the authors identified the role of network reconfiguration in SAGSI networks to coordinate heterogeneous resources and studied how the NFV and SFC can improve mission offloading. The number of successfully served mission requests is maximized while bandwidth and computation cost are minimized. The major constraint is the physical network's resource capacity, bandwidth, and computation resources. Here, the problem is a non-linear integer programming one. The solution provided is reconfiguration in SAGSI networks via NFV and SFC. The performance metrics used are the average number of offloaded missions, number of missions, cost per completed mission. SFC should also be planned by jointly considering the possible threats such as jamming and eavesdropping. Mitigating security threats can also be the key motivation for mission offloading.

In [103], the authors highlighted that diversifying large numbers of static small cells faces many fundamental challenges such as the deployment cost, energy consumption and control. This motivated the authors to develop the SAGSI network, a programmable, scalable, and flexible framework to integrate space, air, and ground resources for matching dynamic traffic demands with network capacity supplies. First, they presented a comprehensive review of state-of-the-art literature available in SAGSI networks. Then, they described the conceptual architecture of SAGSI networks and emphasized its benefits. Next, they presented four typical application cases of SAGSI networks. Here the constraints are limited network capacity supplies. The performance measures are normalized throughput versus moving cell involvement factor and service success probability for a new request versus normalized active loads. The proposed architecture has many deployment issues, including data acquisition, data integrity, privacy and security, and energy efficiency. The authors of [105] proposed integration of MEC with the control of SDN-autonomous underwater vehicle navigation systems (AUVNS) to improve the system's performance. Specifically, they suggested upgrading the control plane of the SDN-AUVNS to support multi-tier edge computing. The artificial potential field theory [106] is used to construct the network controlling model and develop an underwater tracking model for SDN-AUVNS. This model is used to track underwater pollution equipotential lines of specific concentrations. To provide accurate path planning for equipotential line tracking, the authors used the linearizability mechanism to optimize and revise the control input for the SDN-AUVNS. Finally, the authors proposed a fast united control algorithm that schedules the SDN-AUVNS to intelligently track underwater pollution equipotential lines.

Lessons learnt: Table 2.9 presents a summary of the main lessons learned from the research works we have reviewed above.

- SDN, NFV, and SFC enable more effective use of bandwidth resources and system capacity [100, 104].

- ML algorithms are highly effective in SDN networks with resource management and QoS requirements [97].

- A concept of software-defined space-air-ground integrated moving cells, a programmable, scalable, and flexible framework to integrate space-air-ground resources for meeting the dynamic traffic demands with network capacity supplies is significant. However, it has several limitations [103].

Table 2.9: Software Defined Networking

Reference	**Objective/optimization**	**Constraints/parameters**	**Problem Type**	**Solution**	**Remarks**
[99]	The motivations and challenges for the integration of space-air-ground networks.	LEO altitude (1414 km), period 114 130 min, inclination angle 0 degrees, altitude of HAP 20 km and minimum elevation angle 10 degrees, and radius of the earth is 6371 km.	Bipartite one-to-many matching problem.	Software-defined integrated vehicular networks.	For successful integration of different layers of networks, all research challenges should be solved to incorporate SDN features.

[6]	Model SAGSI networks heterogeneous resource orchestration, VNE.	Binary variable to show whether the virtual node is embedded into the physical layer.	Decision-making problem.	They built a feature matrix based on network attributes extracted from the SAGSI network and used it as the agent training environment.	The VNE algorithm based on the ML method is better than the one based on heuristic methods.
[100]	NFV and SDN are used to reduce the function provisioning cost and coordinate the heterogeneous physical resources in the SAGSI networks.	Mobility, cost, and delay.	MINLP.	Tabu search-based algorithms, a slackness-based algorithm.	When the network load is light, the room for further performance improvement is limited.
[101]	Proposed different SAGSI network paradigms, including its composition and network architecture.	Channel and bandwidth characteristics of radio wave propagation and each path of multiple signals.	Multilayer satellite networks.	The scattering characteristics of UAVs on mmWave are investigated using mmWave 3D imaging, and the authors also examined the signal frequency shift. A future cloud-based modular simulation system for SAG IoT applications is proposed.	The latency in receiving signals likewise increases as the density of UAVs rises. The effects of reflection, scattering, and diffraction on the signal grow increasingly significant as the number of UAVs rises.

[102]	Space-air-ground enabled edge computing architecture.	Resource constraints and volume constraints.	Resource allocation in space-air-ground edge-enabled networks.	Intelligent enhanced satellites and intelligent enhanced UAVs are two revolutionary frameworks for satellites and UAVs.	Security issues are still significant concerns, according to their research.
[103]	To create a programmable, scalable, and adaptable framework to combine space, air, and ground resources for balancing dynamic traffic needs.	Coverage of network.	-	Software-defined space-air-ground integrated moving cells in different application scenarios.	Many deployment issues are there, e.g., like data acquisition integrity and privacy.
[104]	Reduce bandwidth and computing costs to increase the number of mission requests that can be successfully processed.	The physical network's resource capability, including its bandwidth and computing resources.	Non-linear integer programming problem.	NFV and SFC network reconfiguration in space, air, and ground integrated networks.	Security and privacy issues are a major concern here.

2.1.9 Intelligent surveillance and relay communication

Intelligent surveillance and relay communication are a major concern of systems (e.g., military and healthcare systems), which are highly sensitive from a security and reliability point of view in SAGSI networks. Next, we review recent works focused on intelligent surveillance and relay communication from a resource management perspective.

In [107], the authors proposed a passive location estimator for moving aerial targets using multiple satellites. The proposed estimator first filtered direct wave signals in the channel using a bandpass filter and then the direct path and multipath interference are suppressed using a sequence cancellation algorithm. Then, the fourth-order cyclic cumulant cross-ambiguity function of the signals in the reference channels and the four-weighted fractional Fourier transform fourth-order cyclic cumulant cross-ambiguity function of signals in the surveillance channels are derived. The performance measures used are normalized mean square error and SNR. In [20], the authors developed a new communication structure. The parameters considered in that work include radio frequency between the high-altitude platform (HAP) and the UAV and the between each HAP and UAV. The problem is stable matching between HAPs and UAVs (by using stable marriage matching). In a stable marriage matching the authors proposed a matching HAP and UAV using the Gale-Shapley algorithm [20]. The authors evaluated the performance using metrics such as the number of UAVs and the average evaluation score of random matching and matching with the Gale-Shapley algorithm.

Lessons learnt: Table 2.10 summarizes the main lessons learnt which include:

- If we want to incorporate intelligence in SAGSI networks, there will be an increase in the computational complexity of the overall system due to surveillance data processing [107].
- The stable marriage algorithm in SAGSI networks provides reliable results for stable communications [20].

Table 2.10: Intelligent Surveillance and Relay Communication

Reference	Objective/optimization	Constraints/parameters	Problem Type	Solution	Remarks
[107]	Intelligent surveillance of moving target location parameters.	Mobility.	Estimation of location parameters.	Utilizing several satellites, time difference of arrival and frequency difference of arrival are computed, as well as the distance between the target and the receiver and the velocity of the moving aerial object.	Computational complexity is high due to matrix operations.
[20]	Proposed a new communication structure.	RF and distance between HAP and UAV.	Stable marriage algorithm.	The Gale-Shapley algorithm.	They assumed 100 to 500 HAPs and 500 to 2500 UAVs, which is not a practical approach, usually the number of UAVs is less than the number of HAPs.

2.2 Summary

SAGSI networks are regarded as the most beneficial designs to meet the requirements of future applications. In this literature review, we reviewed resource optimization strategies in SAGSI networks. We found that each optimization domain is crucial to efficiently using communication and computing resources in SAGSI networks. We categorized and thoroughly analyzed resource optimization's relevant aspects, including throughput, capacity, delay, energy, SDN, overall performance, and joint optimization. The resource optimization of categories is studied from the viewpoint of how a problem is solved for an optimization problem under certain constraints, assessed to what extent researchers are successful in achieving their objective, and criticized their work where it has some room for improvement. Moreover, we also pour our thoughts into lessons learned from each resource (s) category. We discussed numerous issues in research and possible solutions for SAGSI networks. Based on this review, we concluded that the dependability and coverage of SAGSI networks would significantly improve if we could efficiently optimize radio resources like bandwidth, energy, power, etc. We also identified the significant results of many recent related works on SAGSI networks and enabling technologies such as blockchain, AI/ML, and NOMA in SAGSI networks.

Chapter 3

Multi-objective Optimization in SAGSI Networks

In this chapter, we address the optimization of SAGSI networks by formulating a multi-objective problem that focuses on energy efficiency, resource utilization, and priority-based user association. These objectives are crucial in enhancing the overall network performance and ensuring a satisfactory user experience. We employ advanced optimization techniques to balance energy consumption, efficient resource allocation, and prioritized user association. We also discuss the key factors that affect energy efficiency and resource utilization and the challenges of prioritizing user association in a dynamic network environment.

3.1 Related Work

Researchers have investigated multi-objective optimization to optimize multiple network parameters simultaneously. These studies have demonstrated the potential to enhance network performance and reduce latency in SAGSI networks. This section discusses some of the latest studies in this field. However, there is still a need for more research in this area to improve further the efficiency and effectiveness of SAGSI networks in 6G. In [108], the authors proposed an analytical framework to evaluate the outage probability of energy efficiency in IRS-assisted wireless communication systems. The limitations of the proposed model for complex real-world scenarios and network dynamics are not discussed. The study assumed ideal channel conditions without considering practical impairments such as fading and interference. Similarly, in [109], the authors proposed a robust model for addressing uncertainty in user traffic demand and developed a heuristic approach. The scalability of the proposed method for large-scale instances remains a limitation. The evaluation mainly compared existing approaches without considering other metrics such as computational complexity or convergence analysis.

In [110] proposed storage resource management algorithm based on distributed deep reinforcement learning shows promising results. However, the practical challenges of deploying and training the deep reinforcement learning model in a real-time, dynamic network environment should be discussed. The algorithm's scalability concerning network size and complexity needs to be addressed. In [111], the authors proposed an alternating optimization approach to minimize energy consumption and meet delay constraints; however, the study needs a comprehensive analysis of the algorithm's convergence properties and computational complexity. Additionally, the evaluation mainly focused on energy consumption, and the trade-offs with other performance metrics, such as throughput and fairness, are not extensively explored. Authors of [112] proposed a data access scheme for civil aircraft-enabled SAGSI network, which shows energy consumption reduction and processing delay improvement. However, the limitations of the reinforcement learning-based approach, such as training time, exploration-exploitation trade-offs, and model convergence, still need to be addressed. The evaluation focused on reducing energy consumption without considering other key performance indicators.

In [113], the joint optimization algorithm for user association, power allocation, and UAV trajectory demonstrated improved energy efficiency. The algorithm's computational complexity and scalability are not discussed. The evaluation mainly focused on energy efficiency improvement, and the trade-offs with other performance metrics, such as throughput and latency, should be more extensively analyzed. In [114], the authors proposed a hybrid offloading scheme to minimize energy consumption, the evaluation is limited to comparing energy consumption with benchmark schemes, and the trade-offs with other performance metrics, such as latency and reliability, should be more extensively discussed. The scalability of the proposed algorithm for large-scale networks needs to be addressed. In [115], a deep reinforcement learning-based offloading method is proposed to show energy-saving and computation efficiency effectiveness. The challenges of training deep learning models in resource-constrained IoT devices or the scalability of the proposed approach to handle large-scale networks should be discussed. Similarly, in [116], the ANFCQGSOR protocol shows improvement in clustering and routing for vehicular ad hoc networks (VANETs), the study lacks a comprehensive analysis of the protocol's scalability, overhead, and robustness in dynamic and highly mobile vehicular environments. The evaluation primarily focuses on performance comparison with existing techniques without discussing the limitations or potential challenges of the proposed protocol.

To overcome the abovementioned limitations, we propose a framework for multi-objective optimization to improve network performance and user experience. The goal is to achieve high energy efficiency, effectively utilize available resources, and prioritize user association based on their requirements. Integrating multiple objectives into a unified framework presents a novel approach to network optimization. The research findings can guide network operators, engineers, and policymakers in making informed decisions and designing efficient SAGSI networks.

3.2 System Model and Problem Formulation

We consider the SAGSI network that consists of N number of users. The SAGSI network consists of three layers: ground, aerial, and space layers represented L_1, L_2, and L_3, respectively. The number of BSs on the ground layer is denoted by M_1, the number of UAVs in the aerial layer is denoted by M_2, and the number of satellites in the space layer is represented by M_3. We assume that *n-th* user can be associated with either BS or UAV or satellite at a given time, i.e., all three layers of the SAGSI network are available to users. However, we do not consider the connections of BSs to UAVs and satellites or vice versa in this thesis. For the sea network, we are considering

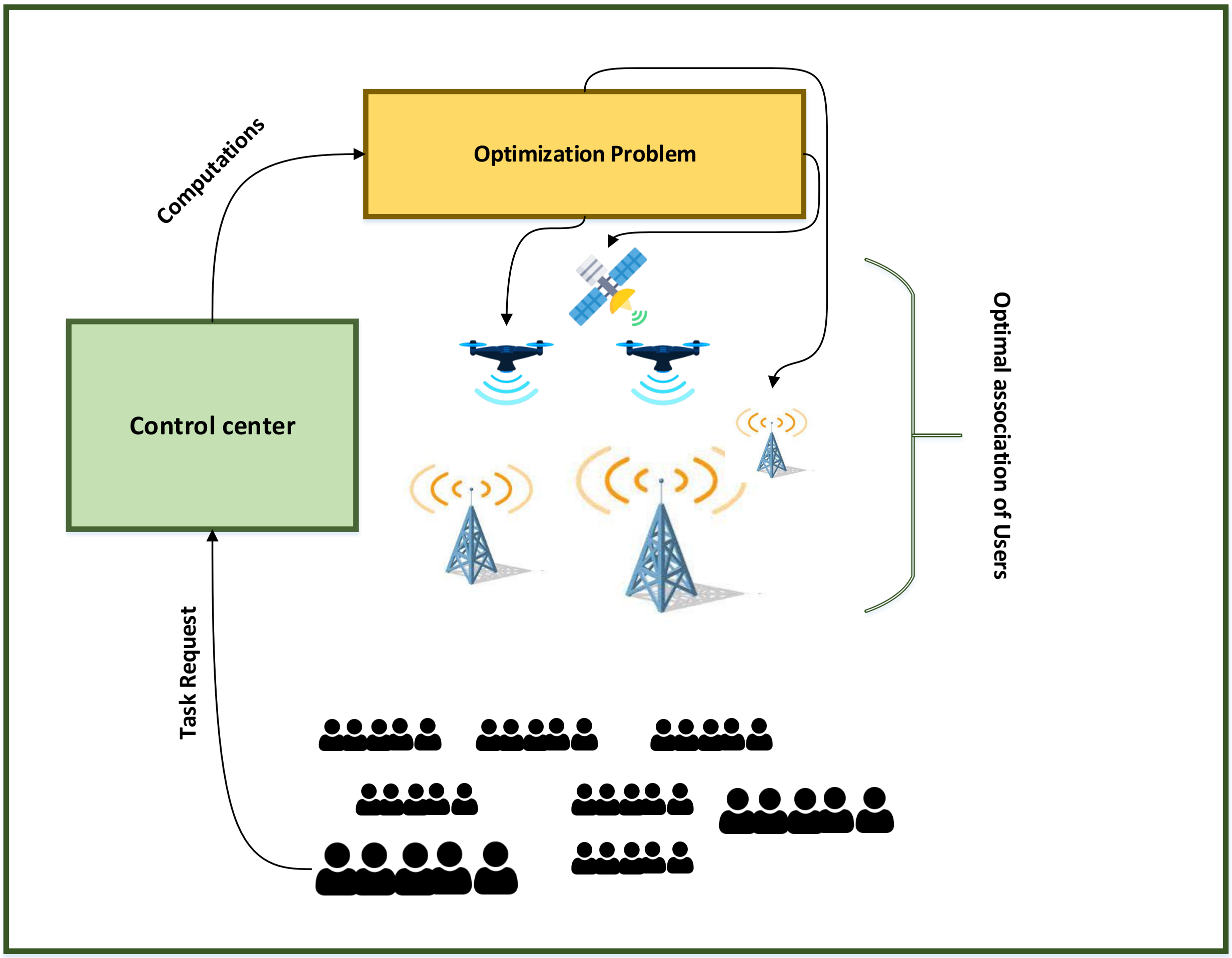


Figure 3.1: An illustration of the system model for SAGSI networks.

only seashore BSs that cover a certain distance over the sea, whereas deep sea stations are not considered in our work. Fig. 3.1 illustrates the system model for SAGSI networks.

We assume the users have low-power devices with limited communication and computation resources. The *n-th* user can offload its task T_n represent data size in bits to *m-th* station of *l-th* layer for computation. The association of *n-th* user with *m-th* station (which can be on the ground with layer L_1, in the air with layer L_2 or in space with layer L_3) of *l-th* layer is represented by a binary variable as:

$$a_{n,m,l} = \begin{cases} 1 & \text{if associated with } \textit{m-th} \text{ station of } \textit{l-th} \text{ layer} \\ 0 & \text{Otherwise.} \end{cases} \tag{3.1}$$

When *n-th* user offloads a task T_n to the *m-th* station of *l-th* layer, communication resources are needed. The data rate of *n-th* user can be calculated as:

$$R_{n,m,l} = W_{n,m,l} log_2 \left(1 + \frac{P_n g_{n,m,l}^2}{\sigma^2}\right), \forall n,\ m,\ l, \tag{3.2}$$

where $g_{n,m,l}^2$ is the channel gain, P_n is the transmission power of *n-th* user, $W_{n,m,l}$ is the channel bandwidth, σ^2 is the power of Gaussian noise at *n-th* user. The channel gain $g_{n,m,l}^2$ depends on the network layer in which it is operating. We use the Hata model for the ground layer considering the urban scenario [117]. We use the 2-ray reflection model for the aerial communication [118]. For the space layer, we use the Friis transmission equation, which is used for space communication in literature [119].

The energy efficiency of the SAGSI network can be defined as the ratio of the total data rate to transmit power of the system. This can be written as:

$$E_{n,m,l} = \frac{\sum\limits_{l}\sum\limits_{m}\sum\limits_{n} R_{n,m,l}}{\sum\limits_{n} P_n}. \tag{3.3}$$

We consider the utilization of computational resources denoted by η_{uti}, which is the ratio of the number of computational resources required to the total resources provided by the system as:

$$\eta_{uti} = \frac{\sum\limits_{n}\sum\limits_{m}\sum\limits_{l} a_{n,m,l} T_n}{\sum\limits_{m}\sum\limits_{l} f_{m,l}}, \tag{3.4}$$

where $f_{m,l}$ represents resources available by *m-th* station of *l-th* layer.

We define a utility function to maximize energy efficiency, resource utilization, and priority-based user association as:

$$U = \omega_1 a_{n,m,l} E_{n,m,l} + \omega_2 \eta_{uti} + \omega_3 \beta_n \sum_n \sum_m \sum_l a_{n,m,l}, \tag{3.5}$$

where β_n is the priority of each user, which is defined based on their residual energy. For illustration purposes, the task's priority generated by *n-th* user varies from 1 to 4 (1 is for lowest priority, and 4 is the highest priority). ω_1, ω_2, and ω_3 are weights associated with energy efficiency, resource utilization, and use association, respectively. By adjusting these weights, we can emphasize particular objectives over others, depending on the specific requirements and priorities of the users. This multi-objective approach allows us to find a balanced solution that maximizes the overall system performance.

We formulate a multi-objective optimization problem to maximize energy efficiency, resource utilization, and user association with users' priority while optimizing user association. The optimization problem can be written as:

$$\begin{aligned}
&\max_{a} : U, \\
&\text{Subject to:} \\
&C1 : P_n \leq P_n^{MAX}, \quad \forall\, n \\
&C2 : R_{n,m,l} \geq R_n^{MIN}, \quad \forall\, n, m, l \\
&C3 : \sum_m \sum_l a_{n,m,l} \leq 1, \quad \forall n \\
&C4 : \sum_n a_{n,m,l} T_n \leq f_{m,l}, \quad \forall m, l \\
&C5 : \sum_n a_{n,m,l} \leq \gamma_{m,l}, \quad \forall m, l \\
&C6 : a_{n,m,l} = \{0, 1\} \quad \forall n,
\end{aligned} \tag{3.6}$$

where C_1 depicts the transmit power of *n-th* user is less than the maximum transmit power P_n^{MAX}. C_2 ensures that offloading data rate of *n-th* user must meet the minimum data rate requirement R_n^{MIN}. C_3 restricts that *n-th* user can only be associated with maximum one station of *l-th* layer. C_4 is the resources the user requests should be less than or equal to resources available by the network. C_5 restricts the number of connections associated with *m-th* station of *l-th* layer should be less than the maximum limit $\gamma_{m,l}$, where $\gamma_{m,l}$ is the maximum number of users served by *m-th* station of *l-th* layer. C_6 ensures that the user can be connected or not connected at a given time. The decision variable $a_{n,m,l}$ is binary and constraints are linear. Thus, the problem is a binary linear programming problem.

3.3 Solution Approach

The *n-th* user can request a task T_n to the control center in the proposed framework. The control center then run the optimization problem in (3.6) to assign *m-th* station from *l-th* layer to *n-th* user based on the task requirements, channel conditions, and resource availability. We solve the optimization problem using the branch and bound algorithm (BBA), interior point method (IPM), and barrier simplex algorithm (BSA). The results obtained using BBA are considered as a benchmark to evaluate the performance of IPM and BSA.

3.3.1 Branch and bound algorithm (BBA)

The BBA is a powerful optimization technique to solve combinatorial problems with integer variables. This algorithm combines branching and bounding to explore the solution space and find the optimal solution efficiently. In the branch phase, the algorithm divides the problem into smaller subproblems by branching on specific variables, creating a tree-like search structure. The bounding phase involves estimating an upper bound on the objective function value for each subproblem. Using linear programming relaxation, the algorithm can tighten these bounds and prune branches guaranteed to lead to suboptimal solutions. The BBA also incorporates cutting planes and valid inequalities that refine the bounds. By iteratively applying these branching, bounding, and cutting techniques, the algorithm systematically explores the solution space, reducing it until the optimal solution is found.

To solve the optimization problem in (3.6) with BBA, we input the number of users, the number of stations (BSs, UAVs, and satellites), calculated data rates from three different channel models (ground, air, and space), and input that value to BBA optimizer; we also input the values of transmit power, several resources needed, a total number of available resources from the system, and the range of priorities which users can have from 4 being the highest priority and 1 as the least priority. The algorithm returns the optimal user association $a_{n,m,l}$ and the system's utility.

3.3.2 Interior point method (IPM)

The IPM algorithm explores the interior of the feasible region to find the solution. The algorithm iteratively solves a series of barrier subproblems by adding logarithmic barrier terms to the original objective function and constraints. These barrier terms guide the algorithm toward the feasible interior region while preserving the convexity of the problem. The IPM utilizes Newton's method to solve the barrier subproblems, iteratively updating the solution and moving toward the optimal solution. The algorithm converges to the solution when the duality gap, which measures the difference between the primal and dual objective function values, becomes sufficiently small.

We provide several inputs to tackle our optimization problems using the IPM. We input the number of users and the number of stations encompassing BSs, UAVs, and satellites. Additionally, we calculate data rates for three different layers, which become input to the IPM optimizer. Furthermore, we incorporate parameters such as transmit power, the required number of resources, and the total number of available resources within the system. These parameters play a vital role in the optimization process. Additionally, we define a priority range for users, with values ranging from 1 (least priority) to 4 (maximum priority). Once we have all the required inputs, we execute the IPM algorithm to determine the system's user associations $a_{n,m,l}$ and overall utility.

3.3.3 Barrier Simplex Algorithm (BSA) (Gurobi)

Gurobi Optimizer is a powerful mathematical optimization software designed to solve complex optimization problems. Gurobi is known for its high-performance capabilities, efficiency, and versatility, making it a popular choice among researchers, practitioners, and organizations across various sectors. It is mainly known for its exceptional performance on large-scale, real-world problems, where it can handle millions of variables and constraints with remarkable speed and accuracy. We used the academic version of Gurobi, which offers various solution techniques, including BSA. We solve the problem in (3.6) using BSA. We input the number of UEs, the number of stations (BSs, UAVs, and sattelites), and the calculated data rates obtained from three distinct channel models: ground, aerial, and space. Additionally, we input values such as transmit power, the number of required resources, and the total number of available resources within the system. Moreover, we specify a range of user priorities, where 4 represents the highest priority and 1 represents the lowest priority. Once we have all the necessary inputs, we execute the BSA to determine the optimal user associations $a_{n,m,l}$ and the system's overall utility.

3.3.4 Complexity Analysis

We can solve the problem using BBA; however, the computational complexity is high. The worst-case complexity of the BBA algorithm is equal to exhaustive search [120]. The time complexity of the BBA algorithm depends on the branching factor, the number of feasible solutions, and the pruning strategy. The computation complexity of BBA algorithm is $O(2^{N+NM})$. The computation complexity of the IPM depends on the problem size, the number of variables and constraints, and the convergence rate. In practice, IPM has a polynomial time complexity of $O((N+M)^{3.5}\log(1/\epsilon)$, where ϵ denotes the precision accuracy [121]. The BSA algorithm has a polynomial time complexity of $O((N+M)^3$ [122]. Table 3.1 compares these algorithms. We can conclude that the complexity of the BBA algorithm is increasing exponentially as we increase the number of users and stations. In contrast, the IPM algorithm has less complexity than BBA for increasing the number of users and stations; while BSA (Gurobi) has similar complexity as of IPM.

Table 3.1: Complexity comparison of BBA, IPM, and BSA algorithms

Parameters	**BBA Algorithm**	**IPM Algorithm**	**BSA Algorithm**
$N = 2$, $M = 6$	262,144	324,000	320,000
$N = 2$, $M = 8$	16,777,216	576,000	570,000
$N = 3$, $M = 6$	16,800,000	576,000	569,530
$N = 3$, $M = 8$	4.2950e+09	1,024,000	1,022,000

3.3.5 Summary

This chapter focused on optimizing user association and resource allocation in an integrated SAGSI network, considering multiple layers such as BSs, UAVs, and satellites. Users send their task requests to the control center, which assigned associations and allocated resources based on task requirements and channel conditions. We formulated an optimization problem to optimize network performance and applied the BBA, IPM, and BSA to solve the optimization problem. BBA is considered as a benchmark to evaluate the performance of the other two algorithms.

Chapter 4

Simulation Results

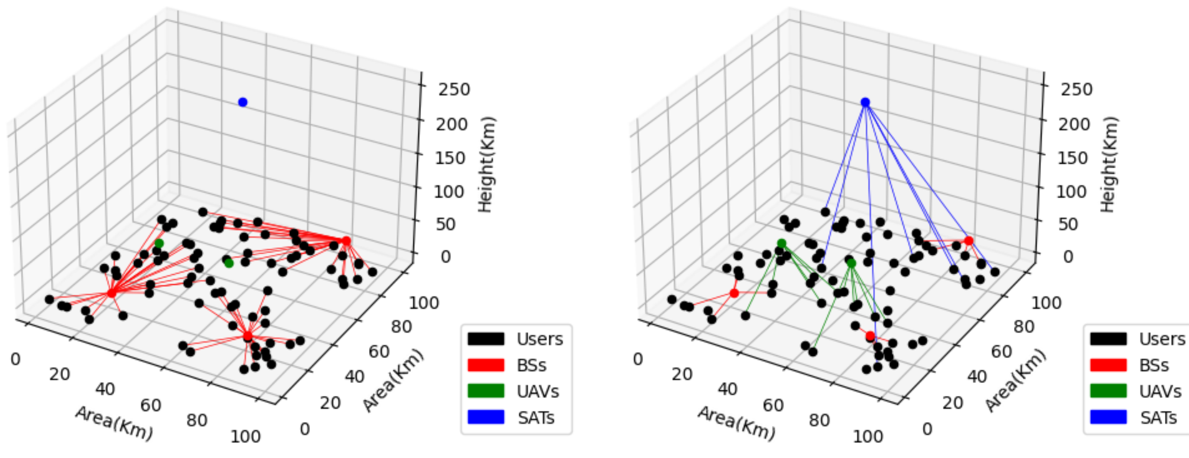
This chapter presents the simulation results to evaluate the performance of the proposed multi-objective framework for the SAGSI network. We evaluate the performance of the proposed framework using BBA, IPM, and BSA. The BBA provides optimal results with high computation complexity compared to the other two algorithms. Thus, the results obtained using the BBA algorithm are used as a benchmark to evaluate the performance of the IPM and BSA. We consider a SAGSI network with the number of users varying from $N = 10 - 100$, the number of BSs is $M_1 = 4$ in layer L_1, the number of UAVs is $M_2 = 3$ in layer L_2, and the number of satellites is $M_3 = 2$ in layer L_3. The objective of assigning BSs, UAVs, or SATs for the task T_n is to maximize network energy efficiency, resource utilization, and priority-based user association. The detailed simulation parameters are given in Table 4.1.

Fig. 4.1 shows user association with BSs (red dots), UAVs (green dots), and satellites (blue dots) for $N = 20 - 100$, $M_1 = 3$, $M_2 = 2$, and $M_3 = 1$. We consider an area of 100km $\times$ 100km and a height of up to 250km. Fig. 4.1(a) shows the user association based only on distance. For example, all the users are associated with the closest available BSs. Fig. 4.1(b) represents the optimal association in which users are associated with UAVs and satellites based on the optimization problem in (3.6). When resources are unavailable on the ground layer, users can be associated with UAVs; when UAVs cannot fulfill resources demand, users will be associated with satellites. To op-

Table 4.1: Simulation parameters.

Parameter	Value
Number of users (N)	$20 - 100$
Number of BSs (M_1)	3
BSs frequency	900 MHz [123]
BSs bandwidth	20 MHz
BSs noise floor	-90 dBm
BSs height	5m
BSs transmit power	23 dBm [124]
Number of UAVs (M_2)	2
UAVs frequency	2.4 GHz [125]
UAVs bandwidth	20 MHz
UAVs noise floor	-90 dBm
UAVs height	100m
UAVs transmit Power	23 dbm [126]
Number of satellites (M_3)	1
Satellite frequency	4 GHz [127]
Satellite bandwidth	20 MHz
Satellite noise floor	-90 dBm
Satellite height	20000m
Satellite transmit power	36 dBm [128]
User equipment height	1.65 meters

timize the placement of UAVs, we use the K-mean clustering algorithm to determine the optimal coordinates for the UAVs. We obtained the cluster centers as the UAV coordinates by clustering the UE coordinates into a specified number of clusters equal to the number of UAVs. Once the UAV coordinates are determined, we update the locations of UAVs in the system. The height of the UAV is set to a constant value of 100m. From Fig. 4.1, we can conclude that optimal association is more effective than distance-based association methods in certain situations. The optimal association considers factors beyond the distance between entities, such as cost, efficiency, feasibility, and other relevant constraints. This broader perspective can lead to more accurate and significant associations. In complex scenarios involving multiple entities and constraints, optimal association methods can provide more precise and robust solutions.



(a) (b)

Figure 4.1: User association with BSs, UAVs, and satellites for $N = 80$, $M_1 = 3$, $M_2 = 2$, and $M_3 = 1$ (a) distance-based association and (b) optimal association.

4.1 Number of associated users versus the total number of users

Fig. 4.2 shows the number of associated users versus the total number of users. We consider the number of BSs $M_1 = 3$, the number of UAVs $M_2 = 2$, and the number of satellites $M_3 = 1$. We evaluate the performance of BBA, IPM, and BSA for users varying from 10-80. For $N = 10$, the number of resources users request is deficient compared to system resources, so all the users are associated. For $N = 20$, the same trend is observed as BSs can fulfill the requirements of user demands. For $N = 30$, all three algorithms started associating users with UAVs, and this trend carried on as users grew to 40; when $N = 50$, the maximum capacity of BSs and UAVs reached, so users started associating with satellites, and this trend went on until 80 UEs. Comparing the three algorithms, we can infer that the BBA algorithm prioritizes stable associations with BSs and gradually incorporates UAVs into the user associations. On the other hand, the IPM demonstrates a more dynamic behaviour, adjusting the associations with UAVs and satellites based on specific requirements and resource availability. The observed patterns highlight the algorithms' differences, showcasing each approach's strengths and trade-offs.

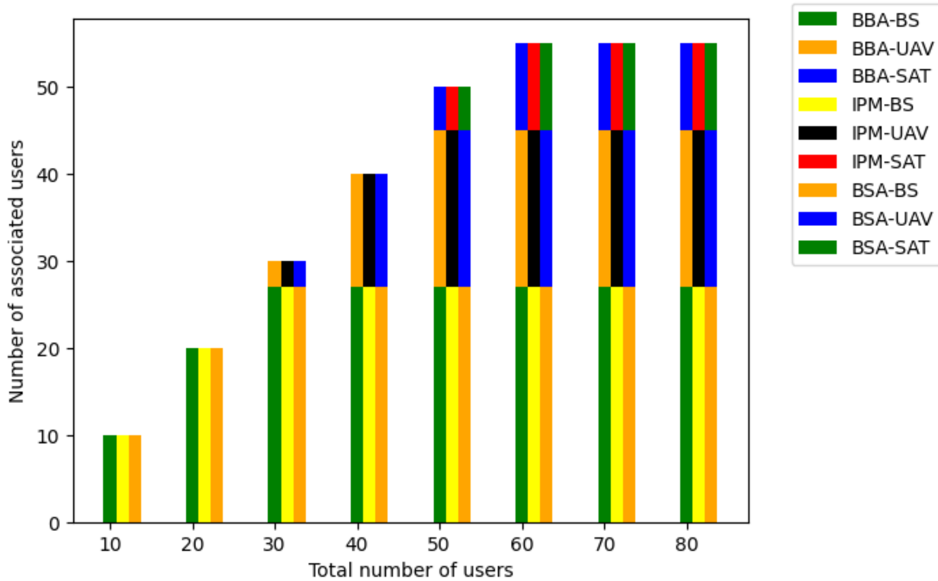


Figure 4.2: Number of associated users versus the total number of users.

4.2 Capacity utilized versus total number of users

Fig. 4.3 shows the capacity utilized versus the total number of users. We consider the number of BSs $M_1 = 3$, the number of UAVs $M_2 = 2$, and the number of satellites $M_3 = 1$. When the number of users $N = 10$, all users are using the capacities of BSs. The number of resources users request is deficient compared to system resources compares the capacity utilization for three algorithms BBA, IPM, and BSA. When the total number of users varies from 10-80, we see consistent capacity utilization of resources with all three algorithms. We analyzed the capacity utilization patterns for each algorithm. For BSs utilization, all three BBA, IPM, and BSA exhibit similar trends, with a gradual increase in capacity utilization when the number of users increased. This suggests that all three algorithms effectively allocate users to BSs, UAVs, and SATs to meet their demands. While all three algorithms effectively utilize BSs, the IPM and BSA also demonstrate greater adaptability and efficient utilization of UAVs and SATs. These findings highlight that all three algorithms optimize resource allocation and meet user demands in a dynamic network environment.

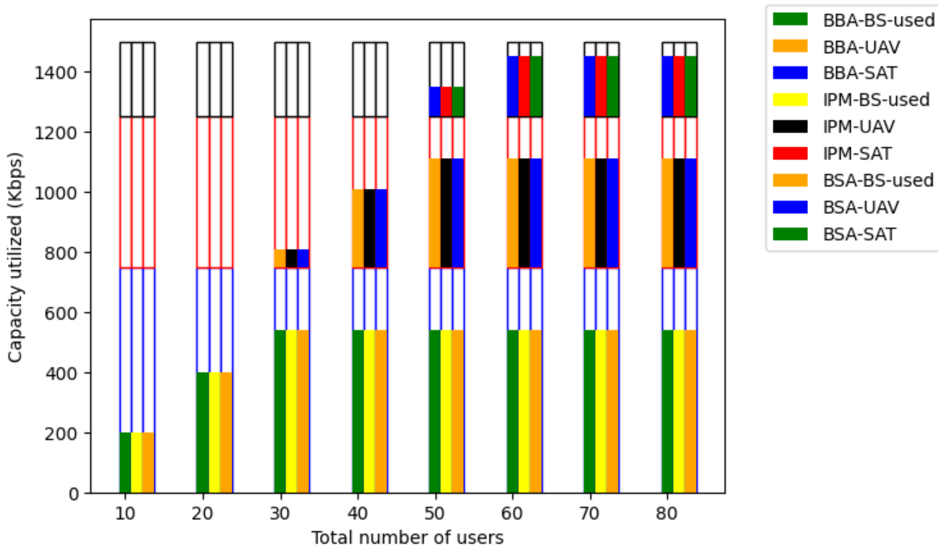


Figure 4.3: Capacity utilized versus the total number of users.

4.3 Task priority

Fig. 4.4 number of connected users with priority versus the total number of users. For illustration purposes, the task priorities range from 1 to 4, with 4 being the highest priority. We consider 25% users in each priority level. By examining the distribution of task priorities, we can assess how the system handles the different priority levels. The graph provides insights into the utilization and allocation of resources based on priority considerations. It helps evaluate the system's ability to handle high-priority tasks effectively and ensures that essential tasks receive attention. The second last bar representing priority 1 tasks in the task priority graph signifies that these tasks are the least prioritized and may experience compromises or reduced resource allocation compared to higher-priority tasks. Similarly, the last bar shows the compromise of level 2 priority while serving priority levels 3 and 4. This visualization underscores the need for careful resource management and decision-making to appropriately address critical and high-priority tasks while acknowledging the trade-offs associated with lower-priority tasks.

By examining the graphs collectively, we gain valuable insights into the system's performance regarding task prioritization, user association, and capacity utilization. These findings contribute to a comprehensive understanding of the system's effectiveness in balancing multiple objectives,

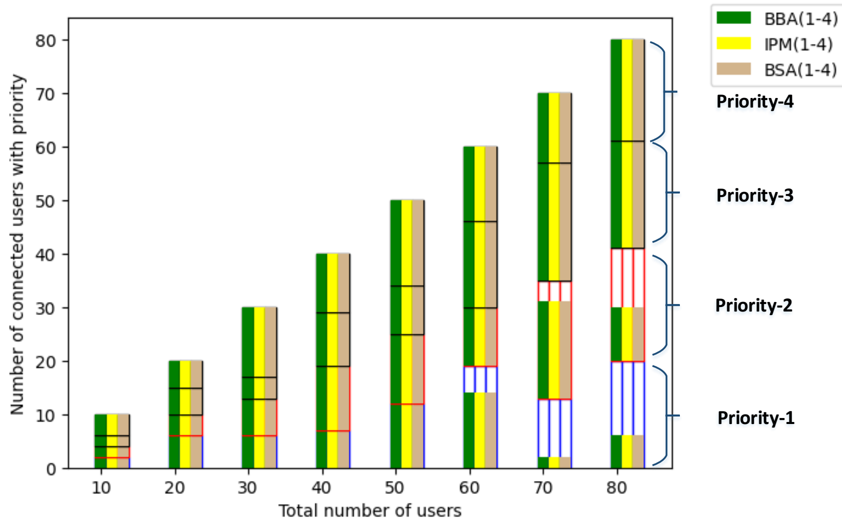
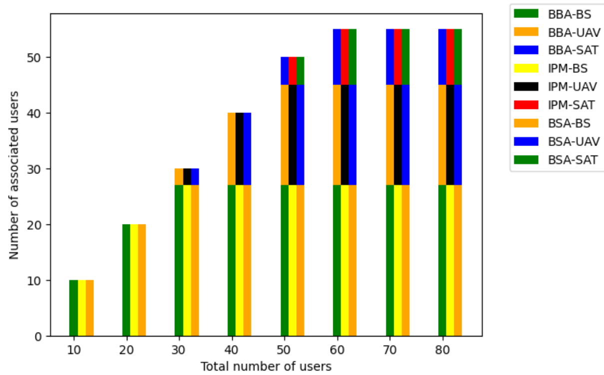


Figure 4.4: Number of connected users with priority versus total number of users.

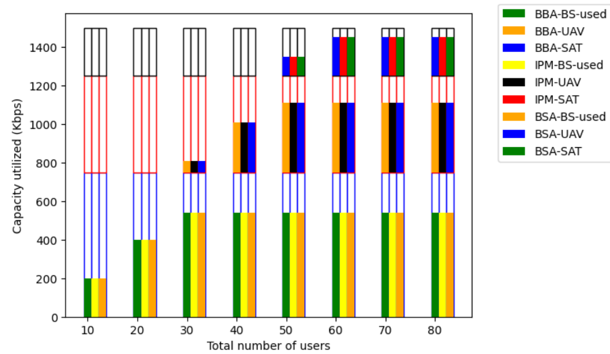
managing task priorities, and optimizing resource allocation to meet user requirements and achieve desired performance outcomes.

4.4 Energy Efficiency

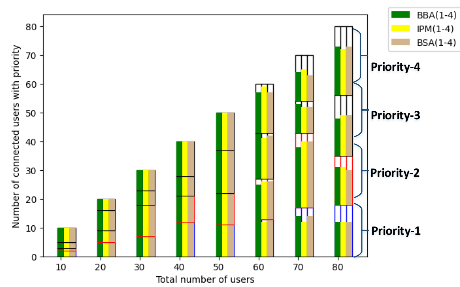
Figs. 4.5(a)-(c) show the performance of the proposed framework when $\omega_1 = 1$ (energy efficiency), $\omega_2 = 0$ (resource utilization), and $\omega_3 = 0$ (association with priority). The energy efficiency analysis focuses on how effectively the system utilizes energy resources while meeting the desired performance requirements. The results represent energy efficiency and showcase the relationship between energy efficiency and system performance metrics, such as the number of users or tasks. It provides insights into the system's ability to optimize energy consumption while maintaining satisfactory performance levels. Fig. 4.5(a) depicts the number of associated users versus the total number of users and provides insights into the system's capacity to establish connections. As the total number of users increases, the number of associated users also rises, indicating that the framework can effectively accommodate a growing user population while prioritizing energy efficiency. At the same time, three bars illustrate three algorithms (BBA, IPM, and BSA). Fig.



(a)



(b)



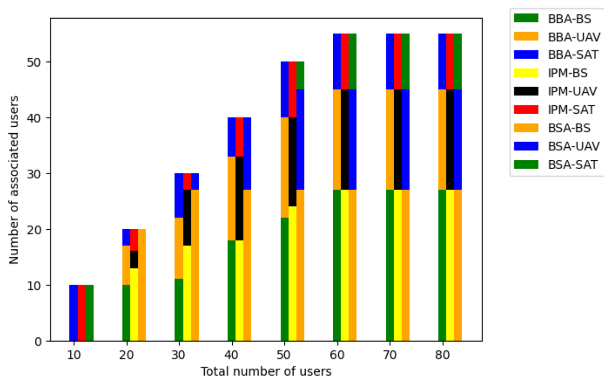
(c)

Figure 4.5: Performance of the proposed framework for only energy efficiency when $\omega_1 = 1$, $\omega_2 = 0$, and $\omega_3 = 0$ (a) number of associated users versus the total number of users, (b) capacity utilized versus the total number of users, and (c) number of connected users with priority versus the total number of users.

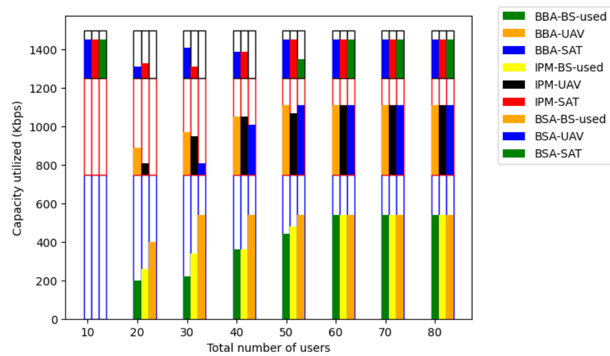
4.5(b) shows the capacity utilized versus the total number of users, demonstrating the efficient utilization of available resources. As the number of users increases, the capacity utilization remains relatively stable, indicating that the proposed framework can effectively allocate resources to meet the demand while optimizing energy efficiency. Fig. 4.5(c) shows the number of connected users with priority versus the total number of users, highlighting the framework's ability to prioritize users based on their specific requirements. As the total number of users increases, the number of connected users with priority also increases, indicating the system's capability to cater to the needs of critical users while still maintaining energy efficiency as a primary objective. Overall, the results presented in Figs. 4.5 provide evidence of the proposed framework's effectiveness in achieving energy efficiency goals. The framework demonstrates the ability to handle increasing users while maintaining efficient resource utilization and prioritizing critical connections. These findings emphasize the framework's potential to balance energy efficiency and other objectives, showcasing its value in practical applications where energy optimization is crucial.

4.5 Resource Utilization

Figs. 4.6 presents the outcomes of evaluating the proposed framework, specifically focusing on resource utilization as the sole objective while assigning zero weights to energy efficiency and association with priority $\omega_1 = 0$ (energy efficiency), $\omega_2 = 1$ (resource utilization), $\omega_3 = 0$ (association with priority). Fig. 4.6(a) shows the number of associated users versus the total number of users and provides insights into the framework's ability to establish connections while prioritizing resource utilization. As the total number of users increases, the number of associated users also rises, indicating that the framework effectively accommodates a larger number of users while maximizing resource utilization as the primary objective. Fig. 4.6(b) depicts the capacity utilized versus the total number of users, demonstrating the efficient allocation of resources. As the number of users increases, capacity utilization also increases, indicating that the proposed framework optimizes resource allocation to meet the growing demand while focusing on resource utilization. Fig. 4.6(c) illustrates the number of connected users with priority versus the total number of users, highlighting the framework's ability to connect users with priority while emphasizing resource utilization. As the total number of users increases, the number of connected users with priority also increases, showcasing the framework's capability to cater to critical users while ensuring efficient resource utilization. However, we can see that all three algorithms cater to priorities with different association patterns. In summary, the results presented in Figs. 4.6 demonstrate the effectiveness of the proposed framework in maximizing resource utilization as the sole objective. The framework can handle increasing users while optimizing resource allocation and prioritizing connections based on user requirements.



(a)



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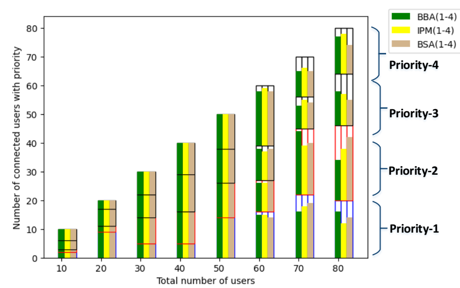
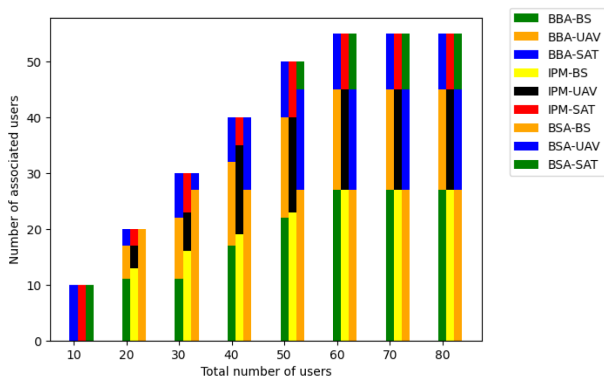


(c)

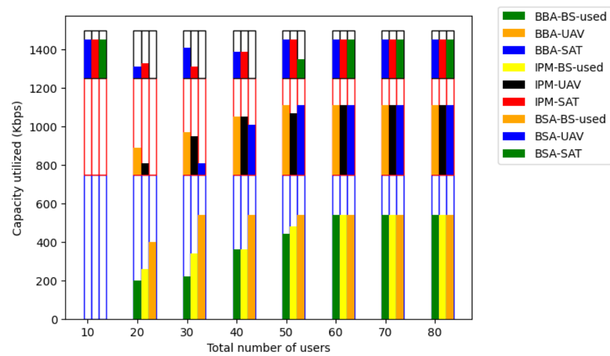
Figure 4.6: Performance of the proposed framework for resource utilization when $\omega_1 = 0$, $\omega_2 = 1$, and $\omega_3 = 0$ (a) number of associated users versus the total number of users, (b) capacity utilized versus the total number of users, and (c) number of connected users with priority versus total number of users.

4.6 Task Priorities

Figs. 4.7 shows the performance of the proposed framework with a focus on user association with priority as the primary objective and zero weights assigned to energy efficiency and resource utilization, i.e., $\omega_1 = 0$ (energy efficiency), $\omega_2 = 0$ (resource utilization), $\omega_3 = 1$ (association with priority). It helps in understanding how tasks with varying priorities are allocated resources and the impact of task prioritization on the system's overall performance. Fig. 4.7(a) shows the number of associated users versus the total number of users and provides insights into the framework's ability to establish connections with priority users. As the total number of users increases, the number of associated users also rises, indicating that the framework effectively prioritizes connections



(a)



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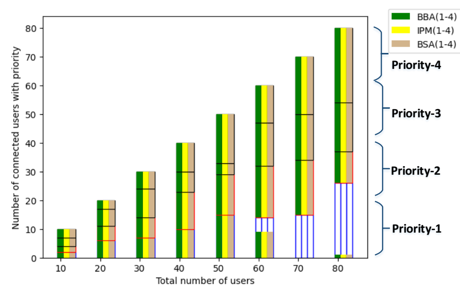

(c)

Figure 4.7: Performance of the proposed framework for task priority when $\omega_1 = 0$, $\omega_2 = 0$, and $\omega_3 = 1$ (a) number of associated users versus the total number of users, (b) capacity utilized versus the total number of users, and (c) number of connected users with priority versus total number of users.

with users requiring special attention while disregarding energy efficiency and resource utilization. Fig. 4.7(b) shows the capacity utilized versus the total number of users and does not emphasize resource utilization in this scenario. Therefore, capacity utilization remains constant or exhibits no significant trend with the increasing number of users, as the primary objective is focused on association with priority rather than resource optimization. Fig. 4.7(c) illustrates the number of connected users with priority versus the total number of users and highlights the framework's capability to connect and cater to priority users. As the total number of users increases, the number of connected users with priority also increases, demonstrating the framework's ability to prioritize specific users while overlooking energy efficiency and resource utilization; only users with the least

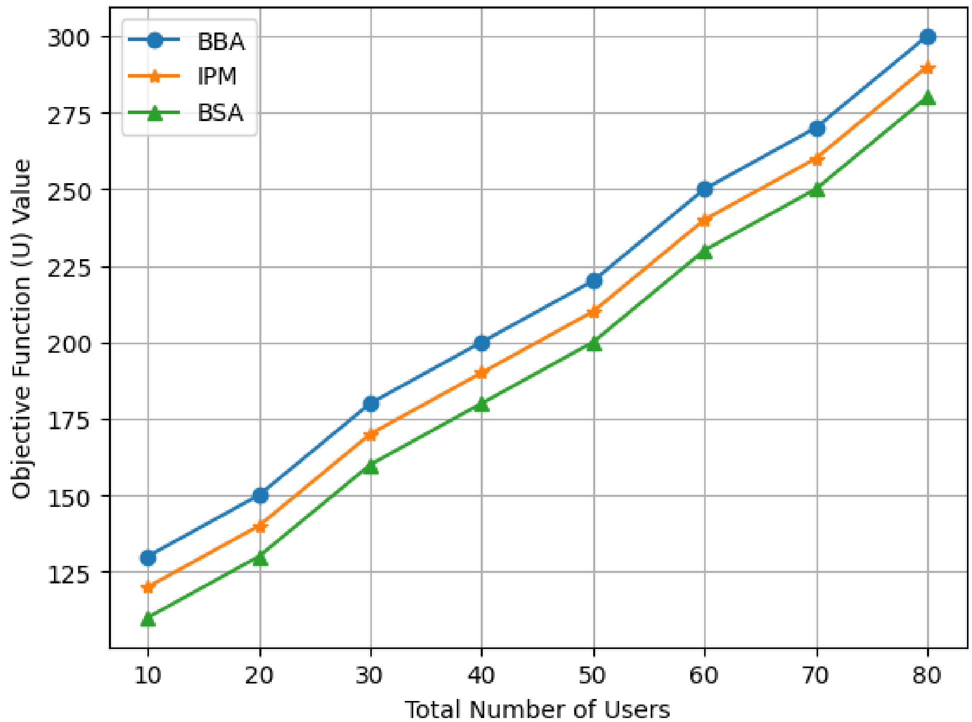

Figure 4.8: Utility or Objective function of the proposed framework for resource utilization when $\omega_1 = 1$, $\omega_2 = 1$, and $\omega_3 = 1$.

priority are compromised, as we can see in last three bars of all three algorithms (BBA, IPM, and BSA). In conclusion, the results presented in Figs. 4.7 highlight the effectiveness of the proposed framework in achieving association with priority as the primary objective.

Fig. 4.8 shows the overall utility given in (3.5) (which comprised of energy efficiency, resource utilization, and number of associated users) versus the total number of users. It is observed that when the number of users increases, the objective function's values may exhibit almost the similar trend for BBA, IPM, and BSA; our objective function utility is increasing. We considered $\omega_1 = 1$, $\omega_2 = 1$, and $\omega_3 = 1$ whereas all other simulation parameters are given in Tabel 4.1. The relationship between the total number of users and the corresponding accurate function values is crucial for optimizing system design and decision-making.

4.7 Summary

This chapter presented the simulation results of implementing the proposed framework for user association in a wireless network. The performance of three algorithms, BBA, IPM, and BSA, was evaluated based on several metrics, including energy efficiency, resource utilization, and task priorities. The BBA demonstrated a stable association pattern with BSs while gradually incorporating UAVs over iterations. The IPM exhibited a dynamic behaviour, adjusting associations with UAVs and satellites based on specific requirements and resource availability. The BSA showed similar association patterns as the BBA but with slight variations in the associations with UAVs. Overall, the simulation results highlighted the strengths and trade-offs of each algorithm, providing insights into their performance and suitability for different system requirements and constraints. We learned that our benchmark algorithm BBA shows the best results but with higher complexity, it's relatively inexpensive in terms of time if the number of users and stations is less, but as we increase our number in iterations, its complexity is very high. Hence, IPM and BSA, are equally good with less complexity.

Chapter 5

Conclusion and Future Work

5.1 Conclusions

SAGSI networks and designs have strong potential to meet the requirements of future applications. In this thesis, we reviewed resource optimization strategies in SAGSI networks. We found that each optimization domain is crucial to the efficient use of communication and computing resources in SAGSI networks. We categorized and thoroughly analyzed resource optimization's relevant aspects such as throughput, capacity, delay, energy, SDN, overall performance, and joint optimization. We studied the resource optimization categories from the perspective of how a problem can be solved for an optimization problem under certain constraints, and we evaluated the extent to which researchers have been successful in achieving their objectives and we identified areas where we need further improvements and research. Moreover, we summarized the lessons learned from each resource category.

We discussed numerous research issues and possible solutions for SAGSI networks. Based on this review, we concluded that the dependability and coverage of SAGSI networks would improve significantly if we could efficiently optimize the resources of these networks. We also identified the significant results of many recent related works on SAGSI networks along with enabling technologies such as blockchain, AI/ML, and NOMA in SAGSI networks. We then mathematically formulate an optimization problem that combines energy efficiency, resource utilization, and task priorities to optimize the performance of our system. Through extensive simulations and analysis, we evaluated the system's performance regarding associated users, capacity utilization, task priorities, and utility achieved.

The results demonstrated the effectiveness of our objective function in achieving a balance between energy efficiency, resource utilization, and task priorities, ultimately improving the overall system performance. By incorporating the priority of users in the objective function, we also observe the impact of different priorities on the overall system performance. The results of our analysis demonstrate the effectiveness of our objective function in achieving a balance between energy efficiency, resource utilization, and task priorities. This balanced approach ensures that higher-priority tasks are efficiently handled while maximizing the overall system performance. Overall, by incorporating the concept of user priority and exploring both individual and multi-objective optimization approaches, we effectively manage and allocate resources based on the importance of tasks, leading to improved system performance and the satisfaction of user requirements.

5.2 Challenges and Future Research Directions

Next, we discuss open research challenges and future research directions based on recent works we have reviewed and analyzed. In SAGSI networks, we must resolve the issues and challenges of integrated networks. In [1], the authors argued that intelligent radio, very high spectrum utilization, and network stability should exist. Security and privacy issues and simulation tools should also be improved and updated according to the current needs of QoS and QoE standards. In [53], the authors stated that a few areas must be investigated to reap the benefits of SAGSI networks in 6G. These areas include adaptive ML, scalable and reliable blockchain, intelligent service, self-sustaining 6G networks, modeling for THz and mmWave communication, zero energy enabled 6G, routing schemes for 6G enabled nano-IoT and bio-IoT and meta-learning enabled 6G [50]. All these research areas have their challenges and show promise for the successful implementation of SAGSI networks in 6G. Adaptive ML-enabled 6G is one of these topics. The authors of [50] also identified security as one of the challenges that must be addressed in SAGSI networks. In [49], the authors stated that tactile Internet and SAGSI networks are novel topics which must be investigated in the future. They also pointed out that future research works must focus on algorithms, architectures, protocols, and intelligent prediction schemes for SAGSI networks.

The authors of [129] developed AI systems based on deep learning and big data analytics which require significant communication and computation resources resulting in increased latency, energy consumption, network congestion and also raised privacy concerns in training and inference processes. The authors of [130] and [131] described the evolution of device-to-device (D2D) communication. However, challenges related to radio resource optimization, interference minimization, mobility, security, and trust must be addressed to take full advantage of D2D networks. The authors of [132] analyzed and designed a security framework for multiple networks coexisting together. For example, such networks can result in high-security threats compared to standalone networks which can handle unknown and out-of-network accesses. In [133] proposed that the routing strategy needs to be updated timely according to the time-varying topology due to satellite links' high dynamics and delay. SDNs are considered for efficient operation and management of complex networks. SDN can implement reliable, centralized control, and secure automation solutions for traditional and future networks [134]. For example, the complexity of future networks needs security automation using SDN to overcome delays caused by security operations. Thus, this is a potential area for future research.

In [48], the authors proposed new network scenarios in SAGSI networks, communication security, spectrum efficiency, deep heterogeneous structures, and energy efficiency. Interestingly, they also emphasized that new deep learning, ML techniques, and optimal transmit power schemes have great potential to improve SAGSI network efficiency. In [7] the authors discussed research directions covering six main domains: ultimate mobile experience, hyper-intelligent networking, harmonized networks, extreme global network coverage, sustainable networks and ultimate security, privacy, and trust. All research opportunities mentioned above, research directions, and challenges have been described in the most recent works done SAGSI networks in 6G. Interoperability and complexity are significant challenges in designing and implementing integrated SAGSI networks. These networks require seamless and reliable communication among multiple nodes that operate in diverse environments, such as terrestrial, aerial, and underwater domains. Achieving interoperability in such heterogeneous networks is critical due to the differences in communication protocols, hardware and software architectures, and network topologies. Moreover, the complexity of these networks arises from the need to integrate various technologies, including satellite communication, airborne networks, terrestrial cellular networks, and underwater communication, into a cohesive and efficient system. In [135], the authors argued that the SAGSI network architecture faces new challenges at the network layer that are not present in traditional terrestrial communication systems.

These challenges include network design and optimization, data transmission between different networks, and interoperability of hardware devices. One of the primary challenges is ensuring that the network can support mobility and has the necessary emergency networking and dispatch capabilities to deal with unexpected situations. This is particularly important when reliable and uninterrupted communication is critical, such as in emergency response scenarios. Therefore, SAGSI networks must be designed and optimized to ensure that they can provide seamless communication in dynamic and complex environments.

Additionally, the network should be capable of providing reliable and secure data transmission between different networks, despite differences in protocols, hardware, and topology. Achieving interoperability of hardware devices is also a crucial challenge that must be addressed to ensure seamless communication across the network. Similarly, the authors of [136] provided a comprehensive and systematic overview of the complexities of SAGSI networks in disaster management applications, including hardware-based, network-based, protocols-based, and security-based complexities. They also highlighted the challenges associated with disaster management systems and the need to address them to ensure reliable and effective disaster management. The findings of this study have significant implications for disaster management practitioners and researchers, as the authors provided a better understanding of the challenges and opportunities associated with utilizing SAGSI networks in disaster management applications.

After reviewing the literature available, next, we point out some limitations and relevant research concerns from all the above discussions:

- Security standards and architectures still need to be defined for SAGSI networks which means these networks would be vulnerable to attacks on any layer of integrated networks.
- Managing seamless 3D mobility intelligently while moving up in the layers, in air or space or down the ground level or deep in ocean or submarine level remains an open challenge.
- How to achieve global coverage while optimizing power losses and improve system efficiency is another challenge [7].
- Smart energy management and resource management is key to the success of SAGSI networks.
- Being backward compatible with previous generations of cellular networks is very important for 6G integrated networks. Thus, we need flexible network topologies and backward compatibility with legacy networks.
- We must develop a global-level optimization mechanism to increase the collaborative utilization of available resources at different layers in SAGSI networks.
- A system is required to generate standard and good-quality datasets for learning tasks with different properties, densification, and channel modeling.
- The hybrid centralized-distributed AI solutions are needed to efficiently use the computing capabilities of the cloud servers and massive IoT devices at the network edge in SAGSI networks.
- Gadget-free communication is only possible if we integrate sensors and interfaces into the environment to provide seamless communication in SAGSI networks in 6G.

- The interoperability of hardware devices and communication protocols remains a critical future research direction and challenge in developing SAGSI networks.

- The increasing complexity of SAGSI networks remains a significant challenge in the design and optimization of SAGSI networks.

5.3 Limitations of Proposed Framework and Potential Improvements

We highlight some limitations in the proposed framework at the end of the thesis as follows:

- The objective function in the proposed framework combines energy efficiency, resource utilization, and task priorities. However, it may need to be more accurate in the complexities of real-world scenarios. Future research can explore more sophisticated objective functions, additional factors, and constraints.

- The proposed framework focused on optimizing user association. However, in practical scenarios, there may be multiple parameters that can be optimized to improve the system's performance.

- The current analysis relies on simplified resource utilization metrics, such as capacity utilization. Future research can explore more comprehensive and accurate resource utilization metrics considering various resources, interdependencies, and quality-of-service requirements.

Following are possible directions to improve the proposed framework in future:

- Develop an adaptive objective function that dynamically adjusts its weights or parameters based on the system's operating conditions, user demands, and environmental factors. This would allow the system to adaptively prioritize energy efficiency, resource utilization, and task priorities based on real-time conditions.

- Explore combining machine learning techniques, such as reinforcement learning or genetic algorithms, to optimize the objective function. These approaches can learn and adapt the system's behaviour over time, leading to more efficient resource allocation and improved performance.
- Investigate the impact of network dynamics on the objective function, such as user mobility, varying traffic patterns, and changing network conditions. Dynamic factors can help enhance the objective function's adaptability and robustness in real-world scenarios.
- Conduct extensive scalability analysis to assess the objective function's performance as the system size and complexity increase. Investigate the trade-offs between computational complexity and optimization performance to ensure the objective function remains efficient and effective for large-scale deployments.

Addressing these limitations and exploring future research directions can further refine the objective function, leading to more effective resource allocation, improved system performance, and enhanced user satisfaction in dynamic and resource-constrained environments.

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