



Design and Resource Optimization of Sparse Code Multiple Access-Assisted Communication Systems

By

**Saumya Chaturvedi
PhD18104**

under the supervision of

**Prof. Vivek Ashok Bohara
Prof. Anand Srivastava**

Department of Electronics and Communication Engineering
Indraprastha Institute of Information Technology-Delhi

July, 2024



Design and Resource Optimization of Sparse Code Multiple Access-Assisted Communication Systems

By

Saumya Chaturvedi

submitted

in partial fulfillment of the requirements

for the award of the degree of

Doctor of Philosophy

to the

Indraprastha Institute of Information Technology-Delhi

Okhla Industrial Estate, Phase III

New Delhi, India - 110020

July, 2024

*To the fond memories of all the people, the ones who changed
the way I saw the world, gave me confidence, and whose
influence I will never forget ...*



Indraprastha Institute of Information Technology-Delhi
Okhla Industrial Estate, Phase III
New Delhi-110020, India
July-2024

Certificate

This is to certify that the thesis titled **Design and Resource Optimization of Sparse Code Multiple Access-Assisted Communication Systems** being submitted by **Saumya Chaturvedi** to the Indraprastha Institute of Information Technology-Delhi, for the award of the degree of **Doctor of Philosophy**, is an original research work carried out by her under our supervision. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted in part or full to any other university or institute for the award of any degree/diploma.

Prof. Vivek Ashok Bohara

Prof. Anand Srivastava

Department of Electronics and Communication Engineering
Indraprastha Institute of Information Technology, Delhi
New Delhi-110020
July 2024



Indraprastha Institute of Information Technology-Delhi
Okhla Industrial Estate, Phase III
New Delhi-110020, India
July-2024

Declaration

This is to be certified that the dissertation entitled **Design and Resource Optimization of Sparse Code Multiple Access-Assisted Communication Systems** being submitted by **Saumya Chaturvedi** to the **Indraprastha Institute of Information Technology-Delhi**, for the award of degree of **Doctor of Philosophy**, is a bonafide work carried out by me. This research work has been carried out under the supervision of **Prof. Vivek Ashok Bohara** and **Prof. Anand Srivastava**.

The study pertains to this dissertation has not been submitted in part or in full, to any other University or Institution for the award of any other degree.

Saumya Chaturvedi
PhD student
Dept. of ECE
IIIT-Delhi, India

Acknowledgements

I would like to express my appreciation to my academic supervisors **Prof. Vivek Ashok Bohara** and **Prof. Anand Srivastava** for giving me the opportunity to work on this thesis and enlighten my PhD journey through their continuous support, active monitoring, and timely feedback. They provided me with a perfect platform and ecosystem to showcase my abilities, providing unwavering encouragement and support at every stage.

Dr. Zilong Liu accepted the role of being my mentor and guided me in my research. I would thank him for his patience and for making it easy to ask the dumb questions. I really appreciate his openness and support to my research topic. I am very grateful to **Prof. Pei Xiao** for giving me a clear understanding of the domain-specific things which were essential for completing this work. I thank them for their co-operation, enthusiasm, highest priority to research, and patience throughout my PhD journey.

The work in this thesis wouldn't have been possible without the continuous support of advisors. I would like to thank them for providing excellent research facilities. I am grateful to the **Indraprastha Institute of Information Technology-Delhi** for providing excellent infrastructure, research environment and research-oriented course work.

I want to direct a big thank you to Tata Consultancy Services for providing me with a research fellowship under **TCS Fellowship** that helped me financially throughout my PhD. This partnership and working with industry has been a special part of my PhD time which nourished my research skills and brought a big positive change in me.

I would also like to extend my thanks to my professional colleagues from **Wirocomm Research Group** and **CoE Li-Fi** lab at IIIT-D. I would also like to express my sincere thanks to Ashutosh Vaish, Dil Nashin Anwar, Syed Asrar, Mansi Peer, Anand Singh, Mohd. Hamza, Gurinder Singh, Saswati Paramita, Akshita Gupta, Rana Kumar Jana, Rahul, Priyanka Singh, and Neetu R.R. for our discussions which enhanced my deeper understanding of concepts. I would like to thank Astha Verma, Neeraj Pandey, Nidhi Goyal, Amina Haroon, and Mitali Sinha for discussing several courses and their emotional support.

I am also grateful to many people from IIIT-D Khagendra, Neelanjna, Shubham, Kaynaat, Sachin, Vivek, Hanshita, Belal, Rashid for having cheerful and fruitful discussions. My gratitude also extends to the technical and admin support staff of IIIT-D, especially Mrs. Preeti, Mr. Raju Biswas, Mr. Imran, Mr. Vinod Prasad and Mr. Kapil for being extremely helpful in the fast resolution of all technical and admin related matters.

My family's support, love and cooperation have been enormous throughout my journey. I am thankful to my parents **Mrs. Saraswati Chaturvedi** and **Mr. H. P. Chaturvedi**, for their blessings, my brothers, especially Ashutosh, Anubhav and Dhruv, sister-in-law, my loving nephew Raghav and all the loved ones for their full support, not just during PhD but throughout my life.

Saumya Chaturvedi

Contents

Abstract	xi
1 Introduction	1
1.1 New Applications and Research Directions	3
1.2 Objectives and Contributions	4
1.2.1 Codebook Design and Multi-user Detection	4
1.2.2 Resource Allocation in SCMA-assisted Communication systems	5
1.3 List of Publications	6
1.3.1 Journal Papers	6
1.3.2 Conference Papers	6
1.4 Thesis organization	6
2 Introduction to Codebook Design and Decoding in SCMA	8
2.1 SCMA Encoding	8
2.1.1 System Model	8
2.1.2 SCMA Encoding and CB Design	9
2.1.2.1 Designing of Mother Constellation	10
2.1.2.2 Constellation Operators	11
2.2 Decoding	12
2.2.1 MAP Detection	13
2.2.2 Message Passing Algorithm	15
2.2.3 Illustration of MPA Decoding for 4×6 SCMA System	15
2.3 Literature survey and Motivation	20
2.3.1 SCMA for Visible Light Communications	20
2.3.2 SCMA with Reconfigurable Intelligent Surface	20
2.3.3 SCMA with Unmanned Aerial Vehicles Networks	21
2.3.3.1 Single UAV	21
2.3.3.2 Multiple UAVs	22

2.4	Objectives and Key Contributions	23
3	Low-Complexity Codebook Design for SCMA based Visible Light Communication	26
3.1	Introduction	26
3.1.1	Input-dependent Gaussian noise	26
3.2	Proposed Work	27
3.2.1	The SCMA-VLC Model	27
3.2.2	SCMA-VLC Decoding	29
3.3	CB Design and Optimization	29
3.3.1	The Problem Formulation	29
3.3.2	The Objective Function	32
3.3.3	Complexity Analysis	32
3.3.4	Theoretical BER	34
3.4	Results and Discussion	34
3.5	Conclusion	38
4	Resource Allocation in SCMA-Aided IRS System	39
4.1	System Model and Problem Formulation	39
4.1.1	Problem Formulation	40
4.2	Alternating Optimization	41
4.2.1	Factor graph matrix assignment	42
4.2.2	Power Allocation	43
4.2.3	Phase Optimization	44
4.2.4	Complexity Analysis	45
4.3	Results and Discussion	46
4.3.1	Sum-Rate Analysis for 4×6 SCMA Block	46
4.3.2	Sum-Rate Analysis for 5×10 SCMA Block	48
4.4	Conclusion	50
5	Sum-Rate Maximization of SCMA-Aided UAV System	52
5.1	System Model and Optimization Problem Formulation	53
5.1.1	System Model	53
5.1.2	UAV Energy Consumption Model and Channel Model	54
5.1.3	Problem Formulation	55
5.2	Proposed Solution	57

5.2.1	Problem 1 Solution	57
5.2.1.1	UAV Deployment Location	58
5.2.1.2	Designing UAV 3D Trajectory	59
5.2.2	Problem 2 Solution	61
5.2.2.1	Designing $\mathbf{F}$ for a given $\mathbf{P}$	61
5.2.2.2	Power Allocation	61
5.2.3	Complexity	62
5.3	Results and Discussion	63
5.3.1	Performance Analysis for 4×6 and 5×10 SCMA Block	63
5.3.2	Sum-Rate Analysis for Proposed UAV Trajectory	65
5.4	Conclusion	69
6	Resource Allocation for SCMA-Aided Multi-UAV Transmission System	70
6.1	System Model and Optimization Problem Formulation	70
6.1.1	System Model	70
6.1.1.1	Air-to-Ground (A2G) Channel Model	71
6.1.1.2	Data Transmission Model	72
6.1.2	Problem Formulation	73
6.2	Proposed Solution	74
6.2.1	Users clustering and UAVs deployment	74
6.2.2	Designing Factor graph matrix	75
6.2.2.1	CSI-based continuous Subchannel allocation (CCSA) scheme	75
6.2.2.2	SINR-based continuous Subchannel allocation (SCSA) scheme	76
6.2.2.3	CSI-based Flexible Subchannel allocation (CFSA) scheme	77
6.2.3	Power Allocation	77
6.2.4	Non-uniform Bandwidth allocation	78
6.2.5	Complexity	79
6.3	Results and Discussion	79
6.4	Conclusion	82
7	Summary and Future Work	83
7.1	Summary	83
7.2	Potential Future Research Directions	84

List of Figures

2.1	An illustration of 4×6 SCMA Encoding.	10
2.2	Four-rings star-QAM mother constellation with $d_v = 2$ and $M = 4$. . .	12
2.3	Factor graph of the 4×6 SCMA system corresponding to the FGM shown in (2.3).	17
2.4	Message Passing from FN to VN.	17
2.5	Message Passing from VN to FN.	18
3.1	The system model diagram of 4×6 SCMA with the proposed CBs at the transmitter in VLC channel.	28
3.2	SCMA constellations scatter plots with $J = 3, K = 4, P_e = 30, \varsigma^2 = 10$ (a)-(c): DR based constellation sets, (d)-(f): Log-sum-exp based constellation sets.	35
3.3	BER performance comparison for $J = 3$ between DR based CBs and Log-sum-exp CBs for $\sigma^2 = 0.01, M = 4$	35
3.4	BER performance comparison for $J = 4$ between SCMA DR based CBs, Log-sum-exp CBs and OMA scheme for $\sigma^2 = 0.01, M = 4$	36
3.5	SCMA constellations with $J = 4, K = 4, P_e = 30, \varsigma^2 = 10$ (a)-(d): DR based constellation sets, (e)-(f): Log-sum-exp based constellation sets. .	36
3.6	BER performance for (a) $J = 5$ (b) $J = 6$ for $\sigma^2 = 0.01$ and $M = 4$. . .	37
3.7	Theoretical and Simulated BER performance comparison for (a) $J = 3$ (b) $J = 4$ for $\varsigma^2 = 5, \sigma^2 = 0.01$ and $M = 4$	38
4.1	The system model of an IRS-aided SCMA system with J users.	40
4.2	The flow chart of the proposed AO-based method for solving problem (4.3).	42
4.3	Simulated IRS-assisted SCMA communication system consisting of an AP, J number of users and one N -element IRS.	47
4.4	Sum-rate versus transmit power for IRS-aided SCMA system with $K = 4, J = 6$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘ $\triangleright$ ’ denotes the proposed $\mathbf{F}$ using Algorithm 4	47

4.5	Sum-rate versus N for $J = 6$ and $K = 4$ with total transmit power = 30 dBm, where ‘+’ denotes the fix $\mathbf{F}$ and ‘▷’ denotes the proposed $\mathbf{F}$ using Algorithm 4	48
4.6	Sum-rate versus the horizontal distance between IRS and AP with total transmit power of 40 dBm, $J = 6, K = 4$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘▷’ denotes the proposed $\mathbf{F}$ using Algorithm 4	49
4.7	Sum-rate versus total power for IRS-aided SCMA system with $J = 10, K = 5$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘▷’ denotes the proposed $\mathbf{F}$ using Algorithm 4	49
4.8	Sum-rate versus N for $J = 10$ and $K = 5$ with total transmit power = 30 dBm, where ‘+’ denotes the fix $\mathbf{F}$ and ‘▷’ denotes the proposed $\mathbf{F}$ using Algorithm 4	50
5.1	A plot of the SCMA-assisted UAV system with UAV’s 3D trajectory from the predefined initial location to the final deployment location. . .	54
5.2	Proposed solution outline.	58
5.3	Sum-rate versus UAV transmit power for $K = 4$ and $J = 6$, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents proposed $\mathbf{F}$	64
5.4	Sum-rate versus number of users for UAV-SCMA system, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents the proposed $\mathbf{F}$	65
5.5	Sum-rate versus radius of circular field for 4×6 SCMA block, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents the proposed $\mathbf{F}$	66
5.6	CDF curves for 4×6 SCMA block at UAV transmit power of 30 dBm, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, dashed line represents static $\mathbf{F}$ as shown in (2.3), and solid line denotes optimized $\mathbf{F}$	66
5.7	Sum-rate versus UAV transmit power for $K = 5$ and $J = 10$, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, ‘+’ denotes the fixed $\mathbf{F}$ and ‘o’ denotes the proposed $\mathbf{F}$	67
5.8	CDF curves for 5×10 SCMA block at transmit power of 30 dBm, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, dashed line represents static $\mathbf{F}$ as shown in (5.22), and solid line denotes optimized $\mathbf{F}$	67
5.9	Performance of the proposed scheme with respect to the benchmark schemes 10 users.	68
5.10	CDF of average sum-rate for PD-NOMA and SCMA aided UAV trajectories.	68
6.1	Illustration of the considered scenario, where N UAV-BSs serve M ground users.	71
6.2	3D placement of five UAVs serving 50 users.	80

6.3	Sum-rate versus UAV transmit power (a) CCSA (b) SCSA (c) CFSA based FGM, ‘Uni’ denotes uniform, ‘Alloc’ denotes allocated power from Algorithm 8 and ‘Non-uni’ denotes the non-uniform bandwidth allocation from Algorithm 9. Subfigure (d) shows the sum-rate performance for proposed SCMA based schemes, static FGM, OMA and IF schemes.	81
6.4	CDF plot for multi-UAV SCMA network for (a) CCSA (b) SCSA (c) CFSA based FGM, (d) shows the CDF plot for proposed SCMA based schemes, static FGM, OMA and IF schemes.	82

ABSTRACT

The evolution of next-generation communication systems, driven by applications like smart cities, factories of future, and autonomous vehicles, has led to a surge in communication devices and applications facilitated by 5G-and-beyond networks. While legacy orthogonal multiple access (OMA) schemes struggle to meet the demands of these applications, non-orthogonal multiple access (NOMA) has gained prominence for its potential to provide more links, lower access latency, and higher spectral efficiency.

This thesis delves into the disruptive sparse code multiple access (SCMA) scheme proposed by H. Nikopour and H. Baligh, exploring its performance in various scenarios. Firstly, a novel codebook (CB) is designed for SCMA-based visible light communication (VLC) systems, addressing shot noise issues. An iterative algorithm optimizes the CB, and theoretical bit error rate (BER) expressions are derived, showing superior performance in simulations compared to existing literature.

The study extends to an intelligent reflecting surface (IRS)-aided downlink SCMA system for sum-rate maximization, considering constraints like minimum user data rate, total power, SCMA CB structure, and IRS channel coefficients. An alternating optimization (AO) algorithm tackles the non-convex joint optimization problem, demonstrating significant performance improvements over the IRS-aided SCMA system without IRS.

In the realm of unmanned aerial vehicles (UAVs), the report shifts focus to a SCMA-assisted UAV system. The objective is to optimize resource utilization and maximize the system data rate within energy constraints. We explore UAV 3D placement optimization, optimal UAV 3D trajectory computation, and spectral resource and transmit power allocation, showcasing the benefits of SCMA in enhancing communication systems through UAV assistance. Further, the investigation extends to SCMA with multiple UAVs, addressing challenges of inter-UAV and intra-UAV interference. The complexities involve equitable user allocation, frequency reuse-based subchannel assignment, and iterative algorithms for power and bandwidth allocation, presenting a comprehensive approach to optimize system performance in multi-UAV scenarios. In conclusion, this comprehensive study demonstrates the versatility and effectiveness of SCMA across diverse scenarios, ranging from VLC to IRS-aided systems and UAV-assisted networks, showcasing its potential to revolutionize next-generation communication systems.

Chapter 1

Introduction

The next-generation mobile communication systems are expected to support a wide range of vertical industries such as e-health, smart homes/cities, connected autonomous vehicles, and factories-of-future [1–5]. While this leads to ubiquitous, rapid, and intelligent data services, anytime and anywhere, the explosive growth of communication devices and applications arising from the 5G-and-beyond communication networks reinforces the threat of an increasingly congested spectrum.

Multiple access, as one of the core techniques of wireless communication, aims to enable two or more users to access the finite system resources simultaneously in an efficient manner. The conventional communication systems mostly rely on orthogonal multiple access (OMA) schemes where multiple users are mutually orthogonal in a certain domain. In the past cellular networks, there have been time division multiple access (TDMA), frequency division multiple access (FDMA), code division multiple access (CDMA), and orthogonal frequency-division multiple access (OFDMA) [6]. As an example, in TDMA, each user is given a distinct time slot, and no two users simultaneously share the same time slot. In every OMA scheme, the number of users being simultaneously served is at most that of the orthogonal resources. Thus, the OMA techniques may not meet the stringent requirements of next-generation mobile applications.

In recent years, non-orthogonal multiple access (NOMA) has attracted tremendous research attention with the major advantages in providing more communication links, lower access latency, and higher spectral efficiency compared to OMA [7,8]. In a NOMA system, two or more users are superimposed over an identical physical resource (e.g., power, frequency, time, or code) to provide an overloading factor larger than one. This strategic approach enhances the spectral efficiency of the system, effectively addressing the escalating requirements of mobile Internet and the Internet of Things (IoT) [9]. In general, there are two types of NOMA: power-domain NOMA (PD-NOMA) and code-domain NOMA (CD-NOMA).

PD-NOMA demonstrates its capability to accommodate numerous users sharing the same resource element (RE) by assigning distinct power levels according to their individual channel conditions. The receiver employs successive interference cancellation (SIC) to detect the transmitted signals effectively. It is shown in [10] that if both NOMA and OMA employ optimal resource allocation, NOMA can still outperform the conventional OMA. PD-NOMA is considered as a potential scheme for 5G and beyond

systems, especially for downlink scenarios [11]. On the other hand, CD-NOMA can be conceptualized as an extension of CDMA, where diverse codebooks or sequences are assigned to different users. Low density signature/spreading (LDS) is one of the early CD-NOMA techniques, which involves spreading each user's data across multiple resource elements (REs) in a sparse manner [12, 13]. Consequently, the multiuser interference pattern at the receiver forms a low-density graph, thereby mitigating the complexity associated with multiuser detection. In LDS, all users employ the repetition of quadrature amplitude modulation (QAM) constellations to spread the information over their pre-assigned REs. The sparsity inherent in LDS allows for the utilization of the widely employed message passing algorithm (MPA) for detection at the receiver [14].

In 2013, sparse code multiple access (SCMA) was proposed by H. Nikopour and H. Baligh as a disruptive CD-NOMA scheme [15]. Building upon the initial idea of low-density signature CDMA (LDS-CDMA) [12], several bits of every user are directly mapped to a sparse complex vector (codeword) which is drawn from its associated sparse codebook (CB) [16, 17]. For instance, in a scenario where each user is allocated two REs, LDS transmits the repetition of a single QAM symbol over both REs, while SCMA transmits distinct symbols over each RE. In SCMA, each transmission constitutes a component of a multi-dimensional constellation. Also, SCMA brings the “constellation shaping gain” that is not possible for LDS-CDMA. Unlike SIC based multiuser detection (MUD), SCMA carries out the decoding with the aid of MPA by exploiting the sparse structure of SCMA codewords. This allows SCMA to achieve a near-optimal bit error rate (BER) performance as well as a reduced complexity (compared that of the maximum-likelihood receiver).

There have been many studies in the literature to investigate the NOMA technique for the 5G and beyond networks [11, 18–20]. It was shown in [20], that the incorporation of dynamic power allocation and diversity order in PD-NOMA lead to an enhancement in the BER performance. Another important observation was that, considering fairness and BER optimization, SCMA still outperforms PD-NOMA in terms of uncoded and coded BER, as well as in the presence of channel estimation errors. In [19], resource allocation methods were proposed for both PD-NOMA based and SCMA based systems to maximize the sum rate. The numerical results revealed that the SCMA outperforms PD-NOMA, but the system complexity of SCMA is higher than PD-NOMA. Therefore, various low-complexity detection methods have been proposed for SCMA systems in static [21] and mobile environments [22, 23]. It was demonstrated in [24] that CD-NOMA exhibits superior robustness and is a favorable candidate for massive connectivity. SCMA outperforms LDS by exploiting the constellation shaping gain [15].

Given the appealing attributes of CD-NOMA, especially SCMA, it is imperative to comprehensively examine SCMA from diverse perspectives. Moreover, the enhanced performance of SCMA is mainly dependent on the meticulous design of sparsely structured codebooks, decoders and the strategic resource allocation. As such, the focus of this thesis is to unravel both the potential benefits and challenges associated with integrating SCMA into various configurations.

1.1 New Applications and Research Directions

This section presents a few promising directions for future SCMA research:

- *SCMA for Visible Light Communications:* Demands for data-intensive applications in future wireless applications have driven visible light communications (VLC) as a promising candidate to provide high-speed and secure indoor/outdoor wireless access across unlicensed spectrum [25–27]. SCMA has been employed to enhance the bandwidth efficiency in VLC systems. The VLC systems have the requirement of real and positive signal transmission. In [28–30], radio-frequency (RF) based multi-dimensional CBs have been used and made suitable changes so that they can be applied to the VLC system. The SCMA CBs have been designed specifically for VLC systems in [31–33].
- *SCMA with Intelligent Reflecting Surface:* IRSs have received significant attention from both academia and industry as it can smartly reconfigure the wireless propagation environment [34]. IRS improves the coverage performance of the wireless system by reflecting the incident signals after adjusting their phases and/or amplitudes in the desired direction [35]. The integration of IRS and SCMA was investigated in [36, 37] where IRS phase shifts are optimized, and a low-complexity decoder was designed to improve the system performance.
- *SCMA for UAV Communications:* UAVs are expected to play an essential role in the next-generation wireless communication systems [38]. UAV-assisted networks offer various advantages compared to the conventional communication systems that heavily rely on terrestrial base stations (BSs). The agile mobility and maneuvering prowess of UAVs empower them to establish direct line-of-sight (LoS) connections with a majority of communication devices [39]. Compared to terrestrial BSs, UAVs can be employed in a variety of environments with difficult geographical conditions. This can be made by designating a UAV as a mobile BS for rapid deployment to the target areas (e.g., hotspots or remote villages/forests) for real-time on-demand coverage. In [22], a multi-user high mobility system based on SCMA was proposed, and receivers were designed for both uplink and downlink systems. In view of this, SCMA technique can be studied for the UAV communication systems owing to their advantages of providing more concurrent communication links, reduced access latency, and higher spectral efficiency.
- *Grant Free SCMA:* With the deployment of massive number of wireless devices in various vertical industries (such as factory automation, autonomous driving, smart health care, etc.), massive machine-type communication (mMTC) has been attracting tremendous research attention over the past years. With mMTC, one aims to achieve both massive connectivity and low latency. Legacy communication systems are highly inefficient due to the significant signaling overhead and long handshaking latency imposed by the grant based scheduling [40]. Grant-free access has been extensively studied to make a difference where the active users contend the shared resources by directly transmitting to the BS. Grant-free SCMA allows users to transmit data in the preconfigured resources, which is called contention transmission unit (CTU), i.e., a combination of time, frequency, CB, and pilot. In [41], an acknowledgment feedback based user-to-CTU mapping was proposed for grant-free SCMA to decrease the collision probability.

Through our literature survey, we identified SCMA as a promising technique for providing massive connectivity with improved spectral efficiency. However, its application in various scenarios, such as VLC, UAV, and IRS communications, remains largely unexplored. Therefore, we have undertaken this research to investigate the potential of SCMA in these areas, with the overarching goal of enhancing system performance and efficiency across diverse wireless communication setups.

1.2 Objectives and Contributions

The primary aim of this thesis is to investigate the SCMA systems from two main perspectives:

1.2.1 Codebook Design and Multi-user Detection

CB designing is a key feature that distinguishes SCMA from other multiple access techniques, and designing CB plays an important role in the performance of the system. Since the behavior of CBs highly depends on the type of the channel, it is crucial to employ a constellation that is suitable for a certain application. Also, since the optimal maximum likelihood (ML) receiver for SCMA is too complex in most applications, one highly popular detection technique is MPA, which exploits the sparsity structure of SCMA. MPA is a near-optimal technique, where its performance improves with increasing the signal-to-noise-ratio (SNR) and the number of iterations. In Chapter 2, we introduce the CB designing and MPA based multi-user detection (MUD) scheme in SCMA. One of the key aspects in the design of SCMA systems is to deploy efficient multiuser detection schemes that recovers the transmitted data from each active user. We also provide overview of the low-complexity detection schemes proposed in the literature.

In recent years, visible light communication (VLC) has emerged as a reliable alternative to legacy radio-frequency (RF) based communication, especially for indoor scenarios. VLC offers various advantages such as unlicensed spectrum, free of electromagnetic interference, and ease of deployment using existing illumination infrastructure along with high-level security. To support multiple access in VLC, conventional OFDMA may not be employed as VLC has the requirement of real and positive signal transmission. To overcome the above drawback, direct current-biased optical OFDMA (DCO-OFDMA) and asymmetrically clipped optical OFDMA (ACO-OFDMA) have been studied. However, DCO-OFDMA suffers from deteriorated bit error rate (BER), and ACO-OFDMA suffers from reduced spectral efficiency. In Chapter 3, we present a novel CB design for SCMA based indoor VLC system, which suffers from shot noise. In particular, novel low-complex CB design technique has been proposed for SCMA-VLC system impaired by shot noise. This work emphasizes that the designing of specific CBs is required for the SCMA-VLC system. The proposed CBs are generated by optimizing the log-sum of exponentials of all rotated Euclidean distances (REDs) between the superimposed codewords. The proposed CBs provide improved BER performance as compared to CBs proposed in the existing literature along with reduced complexity. Further, the theoretical analysis of BER is also performed for the shot noise incorporated SCMA-VLC system.

1.2.2 Resource Allocation in SCMA-assisted Communication systems

Relatively fewer studies have been done on the resource allocation aspects than CB designing and MUD in SCMA. In general, the BS allocates uniform power to all the users without considering channel state information (CSI). Thus, it becomes important to allocate the resources depending on the system environment and required applications.

Chapter 4 delves into the resource allocation strategies for maximizing the sum-rate in an SCMA-assisted intelligent reflecting surface (IRS) downlink system. IRSs have attracted tremendous research attention owing to their potential of supporting intelligent and more efficient wireless communications. IRS, a planar array of cost-effective controllable passive elements, reflects signals intelligently. The proposed system model focuses on an SCMA-aided IRS system, addressing resource allocation optimization through an alternating optimization (AO) based iterative algorithm. The algorithm divides the main optimization problem into subproblems which are then solved iteratively. The key challenge is optimizing resource allocation across subchannels to mitigate multi-user interference and ensure fairness in minimum rate among users. We start with factor graph matrix (FGM) assignment using effective channel gains, followed by power allocation using Lagrange dual decomposition. Lastly, we address phase optimization considering constraints on IRS reflecting elements with the Riemannian Conjugate Gradient (RCG) algorithm.

UAVs are anticipated to play a vital role in advancing next-generation wireless communication systems, enhancing current setups dependent on terrestrial BSs. Their flexibility allows for direct LoS connections with numerous devices, particularly advantageous in delivering services in challenging geographical conditions. However, UAV-assisted networks face a limited energy problem. Chapter 5 focuses on a downlink SCMA-assisted UAV system, with the objective of optimizing resource utilization and maximizing the system data rate within energy constraints. Towards this direction, we first focus on the optimization of UAV 3D placement by maximizing the system sum-rate. Next, we compute an optimal UAV 3D trajectory from the given initial position to the final deployment location considering the available on-board energy. After arriving at the hovering point, spectral resources and transmit power at the UAV are allocated to each user to maximize the system sum-rate.

Chapter 6 focuses on investigating SCMA with multiple UAVs, addressing challenges associated with inter-UAV and intra-UAV interference that require sophisticated resource management for achieving desired QoSs. The challenges are: 1) In a multi-UAV scenario, user communication rates depend not only on desired signal strength but also on interference levels, necessitating a balance in UAV placement optimization. 2) Allocating a subset of total spectral resources to each UAV from the available network spectrum requires determining the optimal subset and allocating subchannels to mitigate high interference levels, posing a non-trivial task. 3) After subchannel allocation, optimizing power and bandwidth allocation to each subchannel for overall system performance improvement becomes complex due to coupled optimization variables. To address this optimization problem, we decompose it into four sub-problems, addressing them individually. We first present a modified K-means algorithm for equitable user allocation to UAVs. Subsequently, we propose three frequency reuse-based subchannel assignment schemes to mitigate inter-UAV and intra-UAV interference. Finally, itera-

tive algorithms are proposed for power and bandwidth allocation to each subchannel for ground users.

1.3 List of Publications

Thus far, our main contributions in this thesis, which are published or submitted for publication, are as follows:

1.3.1 Journal Papers

1. S. Chaturvedi, V. A. Bohara, Z. Liu, A. Srivastava and P. Xiao, "Resource Management for Sum-rate Maximization in SCMA-Assisted UAV System", *Veh. Commun.*, Dec. 2023.
2. S. Chaturvedi, V. A. Bohara, Z. Liu and A. Srivastava, "Sum-Rate Maximization of IRS-Aided SCMA System," *IEEE Trans. Veh. Technol.*, vol. 72, no. 8, pp. 10462-10472, Aug. 2023, doi: 10.1109/TVT.2023.3260976.
3. S. Chaturvedi, D. N. Anwar, V. A. Bohara, A. Srivastava and Z. Liu, "Low-Complexity Codebook Design for SCMA-Based Visible Light Communication," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 106-118, 2022, doi: 10.1109/OJCOMS.2022.3141800.
4. S. Chaturvedi, Z. Liu, V. A. Bohara, A. Srivastava and P. Xiao, "A Tutorial on Decoding Techniques of Sparse Code Multiple Access," *IEEE Access*, vol. 10, pp. 58503-58524, 2022, doi: 10.1109/ACCESS.2022.3178127.
5. S. Chaturvedi, Z. Liu, V. A. Bohara, A. Srivastava and P. Xiao, "Resource Allocation for SCMA-Assisted Multi-UAV Transmission Systems" submitted in *IEEE Transactions on Network Science and Engineering*.

1.3.2 Conference Papers

1. S. Chaturvedi, V. A. Bohara, Z. Liu and A. Srivastava, "Trajectory Design for Sum-Rate Enhancement in UAV-SCMA System," *Proc. IEEE 97th Veh. Technol. Conf. (VTC-Spring)*, 2023, pp. 1-6.
2. S. Chaturvedi, V. A. Bohara, Z. Liu, A. Srivastava and P. Xiao, "Resource Allocation for Sum-Rate Maximization in Multi-UAV SCMA Networks", in *Proc. IEEE GLOBECOM Workshops (GC Wkshps)*, 2023.

1.4 Thesis organization

The remainder of the thesis is structured as follows: Chapter 2 provides a detailed discussion of the SCMA scheme. Chapter 3 delves into SCMA codebook design for VLC systems and analyzes the BER of SCMA-VLC. Resource allocation schemes are

then explored in: 1) Chapter 4 for SCMA-assisted IRS systems, 2) Chapter 5 for SCMA-assisted UAV systems, and 3) Chapter 6 for SCMA-assisted multi-UAV systems. Finally, Chapter 7 provides a summary of the thesis and offers insights into potential future research directions.

Chapter 2

Introduction to Codebook Design and Decoding in SCMA

SCMA is a novel CD-NOMA scheme that is essentially an enhanced variation of low density signature/spreading (LDS) [12, 13]. Like with LDS, each RE is shared among only a subset of the active users, constituting a sparse structure, but SCMA users map their incoming bits to multidimensional constellations to spread their information instead of using the repetition of QAM over their pre-assigned REs. For instance, if each user is assigned to two REs, LDS transmits the repetition of one QAM symbol over both REs, whereas SCMA transmits a different symbol over each RE. Each SCMA transmission is a component of a multidimensional constellation.

2.1 SCMA Encoding

In this section, we discuss the basic principles of SCMA and the CB design, as it is one of the important issues of SCMA that affects the performance of the overall system.

2.1.1 System Model

Consider an uplink SCMA system in which J users transmit data to the base station (BS) using K REs (e.g., time- or frequency- slots). In SCMA, the data/input bits of user j is mapped to a complex codeword using the SCMA encoder. For instance, user j intends to transmit B coded bits $\mathbf{b}_j = [b_j^1, \dots, b_j^B]$, where $B = \log_2(M)$ and M is the modulation order. In SCMA, there is a CB defined for each user of size $K \times M$, and each column of this CB is called a codeword. Thus, for J users, the combined set of the CBs for all the users is denoted by Γ of size $K \times M \times J$. The SCMA encoder maps the input bits of symbol m , ($m = 1, \dots, M$) of the user j to a codeword $\mathbf{x}_j^m = \Gamma(:, m, j) = \mathbb{C}^{K \times 1}$.

Let $\mathbf{H}_j = \text{diag}[h_{1,j}, \dots, h_{K,j}]^T$ be the effective channel matrix for the j th user, where $h_{k,j}$ denotes the channel fading coefficient at the k th RE for the j th user. The

received signal at the BS is

$$\mathbf{y} = \sum_{j=1}^J \mathbf{H}_j \mathbf{x}_j^m + \mathbf{n}, \quad (2.1)$$

where $\mathbf{n} \in \mathbb{C}^{K \times 1}$ is the noise vector, each element of which is modeled by complex Gaussian distribution $\mathcal{CN}(0, \sigma^2)$. Due to the sparse nature of SCMA CBs, d_f out of J users overlap over each RE, and each user data is transmitted on $d_v < K$ REs. Let ξ_k be the set of users transmitting data over the k th RE and ζ_j be the set of REs on which the j th user has active transmission. By definition, the cardinalities of ξ_k and ζ_j are d_f and d_v , respectively. Thus, the received signal at the k th RE is given as

$$y_k = \sum_{j \in \xi_k} h_{k,j} x_{k,j}^m + n_k, \text{ for } k = 1, 2, \dots, K, \quad (2.2)$$

where $x_{k,j}^m$ denotes the codeword element transmitted by user j over the k th RE corresponding to symbol m , and n_k is the noise received at the k th RE. In this article, superscript m is neglected sometimes, in case the modulation symbol does not need to be specified.

– *Example:* Let us consider 4×6 SCMA block encoding having $K = 4$ REs and $J = 6$ users as shown in Fig. 2.1 with overloading factor $\lambda = J/K = 1.5$. The allotment of REs among users can be represented by a FGM, where each row corresponds to a RE, and each column corresponds to a user, respectively. The number of ones in a row is d_f , and the number of ones in a column is d_v . $\mathbf{F}_{kj} = 1$ denotes that user j has active transmission over the k th RE. For a 4×6 SCMA block, the FGM of order 4×6 corresponding to Fig. 2.1 is given below:

$$\mathbf{F}_{4 \times 6} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}, \quad (2.3)$$

Note that the number of users superimposing over one RE is 3, i.e., $d_f = 3$ and the number of non-zero values in every column is 2, i.e., $d_v = 2$.

2.1.2 SCMA Encoding and CB Design

The performance gain of SCMA over other NOMA schemes is strongly dependent on judiciously designed sparse CBs. The CB of each user has its own sparsity pattern. The SCMA CB design problem involves finding the optimum mapping matrix, $\mathbf{V}^*$, along with the optimum multidimensional constellation, $\mathbf{A}^*$, and may be defined as

$$\mathbf{V}^*, \mathbf{A}^* = \arg \max_{\mathbf{V}, \mathbf{A}} D(S(\mathbf{F}, \mathbf{A}; J, M, d_v, K)) \quad (2.4)$$

where D is the design criterion for the SCMA system, S , with J users and K REs. Albeit numerous families of CBs have been proposed in the literature, optimal CB design remains open. The current designs are mostly sub-optimal and are based on a multi-stage approach [42–46]. For the j th user, multi-dimensional CB, $\text{CB}_j = \Gamma(:, :, j)$ of size $K \times M$ can be expressed as

$$\text{CB}_j = \mathbf{V}_j \Delta_j \mathbf{A}_{\text{MC}}, \text{ for } j = 1, 2, \dots, J, \quad (2.5)$$

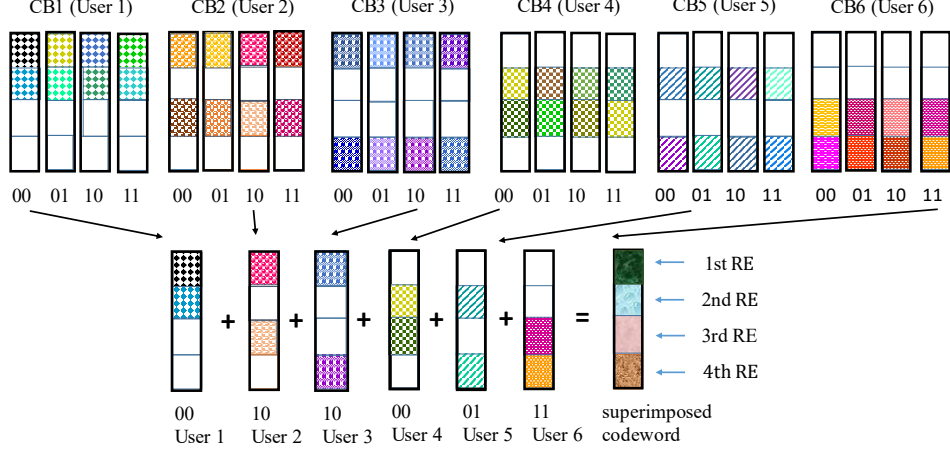


Figure 2.1: An illustration of 4×6 SCMA Encoding.

where $\mathbf{V}_j \in \mathbb{B}^{K \times d_v}$ denotes the binary mapping matrix, $\mathbf{A}_j = \Delta_j \mathbf{A}_{\text{MC}}$, $\mathbf{A}_{\text{MC}}$ denotes the multi-dimensional mother constellation and Δ_j refers to the constellation operator for the j th user. The mapping matrix is selected so that each user has active transmissions over a few fixed REs only. Each column of the factor graph $\mathbf{f}_j = \text{diag}(\mathbf{V}_j \mathbf{V}_j^T)$. The binary mapping matrices of six users corresponding to the FGM in (2.3) are given below

$$\mathbf{V}_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \mathbf{V}_2 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \mathbf{V}_3 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix},$$

$$\mathbf{V}_4 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \mathbf{V}_5 = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}, \mathbf{V}_6 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

$\mathbf{V}_1$ indicates that user 1's data is transmitted over the first and the second REs. Similarly, $\mathbf{V}_2$ indicates that user 2's data is transmitted over the first and the third REs, and so on. Once the mapping matrices are decided, the next step is to design the mother constellation $\mathbf{A}_{\text{MC}}$ and constellation operator, Δ_j .

2.1.2.1 Designing of Mother Constellation

The mother constellation matrix $\mathbf{A}_{\text{MC}} \in \mathbb{C}^{d_v \times M}$ represent each $\log_2(M)$ bits with a codeword of d_v elements. In general, the mother constellation is designed to possess good distancing properties. Also, to mitigate multi-user interference, dependency among the nonzero codeword elements is induced such that the receiver can recover the overlapping codewords from other REs. Several works were proposed to optimize the design of the mother constellation [42, 44, 47–52].

In [42], a mother constellation was designed such that the real and imaginary parts are independent, while the complex dimensions are still dependent. A shuffling ap-

proach was used, which reduces the detection complexity from M^{d_f} to $M^{d_f/2}$. In [44], constellation based on the rotation of QAM constellations was proposed. The approach was known as M-Bao, and feasible if $d_f \leq 3$. In [51], a low-projection mother constellation was proposed that employs lesser number of colliding constellation points over each RE, and also reduces the detection complexity. In [47, 52], constellation points of a given dimension in the mother constellation belong to the concentric rings. The codeword elements for the first dimension of the mother constellation are taken from a star-QAM constellation, then the codeword elements of other dimensions are generated by scaling and permuting the points of the first dimension. The objective was to minimize the pairwise error probability (PEP) between two superimposed codewords $\mathbf{s}_a, \mathbf{s}_b$ which is given by

$$\mathbb{P}(\mathbf{s}_a, \mathbf{s}_b | \mathbf{H}) = Q\left(\sqrt{\frac{\|\mathbf{H}(\mathbf{s}_a - \mathbf{s}_b)\|^2}{2N_0}}\right) \quad (2.6)$$

where N_0 is the noise variance. This approach is powerful because the PEP criteria is applied directly to the codewords of $\mathbf{CB}_j$, and this method can be extended for generating large CBs. In some works, the approach was to solve the optimization problem defined in (2.4) to generate the CBs. The problem in (2.4) is usually NP-hard and is difficult to solve [53]. Thus, the optimization problem is reformulated and solved using different optimization techniques [49, 50, 54]. In [55], CB design using maximum distance separable (MDS) codes was proposed which provides improved signal-space diversity. In [56], CB design based on Reinforcement Learning (RL) was proposed which are suitable for large-scale SCMA schemes.

2.1.2.2 Constellation Operators

Once the mother constellation is designed, constellation operators, Δ_j are applied to generate multiple CBs for different users. The operators should be designed to mitigate the multi-user interference and increase the decodability of the multi-user signals at the receiver. A constellation operator, Δ_j (as shown in (2.5)) may include either one or combination of phase rotation, complex conjugate, user power offset, and dimensional permutation [47, 57–59]. The main motive of applying constellation operators is to maintain uniquely decodable symbols for users to collide at the same RE. In [60], the optimization of the constellation operator was proposed to find the most appropriate permutation set, which has the maximum sum of the distances between the interfering codewords. In [61], a multistage optimization scheme was proposed to design low-projected multidimensional constellations. It should be noticed that the designing criteria D in (2.4) should not be compromised with the constellation operators.

Next, an example of SCMA CB design for $J = 6, K = 4, M = 4, d_v = 2$ based on M -dimensional star-QAM constellations is provided [47]:

- Step 1: Designing the mother constellation, $\mathbf{A}_{MC}$: The mother constellation is designed based on the four concentric rings star-QAM signaling constellation, as shown in Fig. 2.2.

$$|OA| = R_1, |OB| = R_2, |OC| = R'_1, |OD| = R'_2,$$

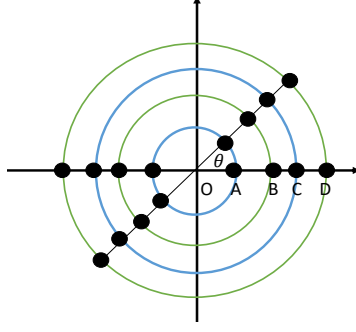


Figure 2.2: Four-rings star-QAM mother constellation with $d_v = 2$ and $M = 4$.

where $\alpha = \frac{R_2'}{R_2} = \frac{R_1'}{R_1}$ and $\beta = \frac{R_2'}{R_1'} = \frac{R_2}{R_1}$. Thus, the mother constellation, $\mathbf{A}_{MC}$, can be expressed as

$$\mathbf{A}_{MC} = \begin{bmatrix} \alpha R_1 & R_1 & -R_1 & -\alpha R_1 \\ -R_2 & \alpha R_2 & -\alpha R_2 & R_2 \end{bmatrix}. \quad (2.7)$$

where $R_1 = \sqrt{\frac{1}{2(\alpha^2 + \beta^2 + \alpha^2 \beta^2 + 1)}}$, assuming each user's CB energy is equal to one, and the value of $\alpha = 3, \beta = 1/0.62$ [47].

- Step 2: Constellation operators: The constellation operators for six users are as follows:

$$\Delta_1 = \begin{bmatrix} e^{i\theta_1} & 0 \\ 0 & e^{i\theta_2} \end{bmatrix}, \Delta_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$\Delta_3 = \begin{bmatrix} 0 & e^{i\theta_3} \\ e^{i\theta_1} & 0 \end{bmatrix}, \Delta_4 = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\theta_2} \end{bmatrix},$$

$$\Delta_5 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \Delta_6 = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\theta_3} \end{bmatrix}.$$

Traditionally, $\theta_1 = 0, \theta_2 = \pi/3$ and $\theta_3 = \frac{2\pi}{3}$. Then, the CB for first user is $\mathbf{CB}_1 = \mathbf{V}_1 \Delta_1 \mathbf{A}_{MC}$, and similarly CB for other users can be generated using (2.5).

2.2 Decoding

The process of extracting data from the noise corrupted received signal is called decoding, and there are two types of decoding, namely hard and soft decoding. In some communication systems, conventional hard decoding is used, where each decision is taken at the receiver based on a certain threshold value. For instance, a simple hard decoding receiver decides that if the received value is greater than the threshold value, it will be decoded as 1, and 0 otherwise. However, it is not verified how close or far is the received value to the threshold before making the decision. An alternative approach is to obtain the estimated sequence and its reliability level, where the latter

indicates the ‘confidence’ we have in that estimated sequence. Such a decoding approach is called soft decoding [62, 63]. In this way, more information can be extracted from the received data, and estimation/detection can be carried out in an iterative and improved manner.

2.2.1 MAP Detection

The objective of an optimal detector is to minimize the probability of error ($P(e)$) for the transmitted bit sequence, i.e., to minimize the mismatch between transmitted bits ($\mathbf{b}$) and estimated bits ($\hat{\mathbf{b}}$).

$$\min P(e) = \min P(\mathbf{b} \neq \hat{\mathbf{b}}). \quad (2.8)$$

Given all the possible observations $\mathbf{y}$ and the channel coefficient matrix $\mathbf{H}$, we have

$$P(e) = \int P(e|\mathbf{y})f(\mathbf{y})d\mathbf{y}, \quad (2.9)$$

where $P(e|\mathbf{y})$ indicates the probability of error given received vector $\mathbf{y}$ and $f(\mathbf{y})$ indicates the probability density function (PDF) of $\mathbf{y}$. It is noted from (2.9) that $P(e)$ is proportional to $P(e|\mathbf{y})$. Since $\mathbf{b}$ is the desired data,

$$P(e|\mathbf{y}) = 1 - P(\mathbf{b}|\mathbf{y}), \quad (2.10)$$

where $P(\mathbf{b}|\mathbf{y})$ denotes the probability of $\mathbf{b}$ given the vector $\mathbf{y}$. Thus, to minimize the probability of error, $P(\mathbf{b}|\mathbf{y})$ needs to be maximized and this detection scheme is termed as MAP detection. Using Bayes’ rule,

$$P(\mathbf{b}|\mathbf{y}) = \frac{f(\mathbf{y}|\mathbf{b})P(\mathbf{b})}{f(\mathbf{y})}, \quad (2.11)$$

where $f(\mathbf{y}|\mathbf{b})$ indicates the conditional PDF of $\mathbf{y}$ given $\mathbf{b}$ and $f(\mathbf{y})$ indicates the PDF of $\mathbf{y}$. Assuming the prior probabilities $P(\mathbf{b})$ are identical for different $\mathbf{b}$, so

$$P(\mathbf{b}|\mathbf{y}) \propto f(\mathbf{y}|\mathbf{b}). \quad (2.12)$$

Thus, the $\mathbf{b}$ which maximizes $f(\mathbf{y}|\mathbf{b})$ is chosen to minimize the probability of error and this detection scheme is called the maximum likelihood (ML) detection. In short, the MAP detection is equivalent to the ML detection when prior probabilities take the identical value.

MAP Detection in SCMA:

For an SCMA decoder, given $\mathbf{y}$ and the channel matrix $\mathbf{H}$ at the receiver, the detected multiuser codeword $\hat{\mathbf{X}} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_j]$ is given as

$$\hat{\mathbf{X}} = \underset{\mathbf{x}_j \in \mathbf{CB}_j, \forall j}{\operatorname{argmax}} p(\mathbf{X}|\mathbf{y}), \quad (2.13)$$

The transmitted codeword of each user can be estimated by maximizing its a-posteriori probability mass function (PMF). This can be calculated by taking the marginal of the joint a-posteriori PMF defined in (2.13).

- **Marginalization:** It is known that if $\mathcal{V}$ is a function of several variables, then $\mathcal{V}$ with respect to a specific variable can be obtained by carrying out marginalization with respect to that variable.

- *Example:* Let $\mathcal{V}(\alpha_1, \alpha_2, \dots, \alpha_j, \dots, \alpha_J)$ be a function (also called a global function) of J number of variables, then the marginalized function with respect to α_j variable is given as

$$\mathcal{V}(\alpha_j) = \sum_{\alpha_1} \cdots \sum_{\alpha_{j-1}} \sum_{\alpha_{j+1}} \cdots \sum_{\alpha_J} \mathcal{V}(\alpha_1, \dots, \alpha_J), \quad (2.14)$$

i.e., the summation with respect to all the variables except α_j . It can be written in a more compact form as

$$\mathcal{V}(\alpha_j) = \sum_{\sim \alpha_j} \mathcal{V}(\alpha_1, \alpha_2, \dots, \alpha_j, \dots, \alpha_J), \quad (2.15)$$

where $\sim \alpha_j$ denotes that the summation is performed with respect to all the variables of the global function except for α_j .

Similar to (2.15), the marginalization with respect to $\mathbf{x}_j$ in (2.13) leads us to symbol by symbol detection for the j th user which can be given as

$$\hat{\mathbf{x}}_j = \operatorname{argmax}_{\mathbf{x}_j \in \mathbf{CB}_j} \sum_{\sim \mathbf{x}_j} p(\mathbf{X}|\mathbf{y}). \quad (2.16)$$

Again using Bayes' rule, we have

$$\hat{\mathbf{x}}_j = \operatorname{argmax}_{\mathbf{x}_j \in \mathbf{CB}_j} \sum_{\sim \mathbf{x}_j} f(\mathbf{y}|\mathbf{X})P(\mathbf{X}). \quad (2.17)$$

For SCMA system, assume that the noise components corresponding to the K REs are identically distributed and independent of each other. As a result, we have

$$f(\mathbf{y}|\mathbf{X}) = \prod_{k=1}^K f(y_k|\mathbf{X}), \quad (2.18)$$

where $k = 1, \dots, K$ denotes the REs and y_k is the received signal at the k th RE. Consequently, (2.17) becomes

$$\hat{\mathbf{x}}_j = \operatorname{argmax}_{\mathbf{x}_j \in \mathbf{CB}_j} \sum_{\sim \mathbf{x}_j} \left(P(\mathbf{X}) \prod_{k=1}^K f(y_k|\mathbf{X}) \right), \quad \text{for } j = 1, \dots, J. \quad (2.19)$$

Solving the marginal product of functions (MPF) problem in (2.19) with brute force will lead to prohibitively high complexity and hence may be infeasible when the number of users is large. Thanks to the sparsity of SCMA CBs, we will show in the sequel that low-complexity MPA can be leveraged with the aid of *factor graph* to solve the MPF problem in (2.19) with near-optimal performance.

2.2.2 Message Passing Algorithm

MPA is an algorithm to conduct inference from graphical models by passing belief messages between the nodes. Now, we discuss how messages are passed across a factor graph, and the resultant inference obtained using MPA. In SCMA systems, each variable node (VN) denotes one data layer, and each function node (FN) denotes the likelihood function at the RE. Therefore, the total number of VNs equals the total number of users, and the total FNs equals the total REs present. Consider a factor graph having K FNs and J VNs. Message passing in a factor graph using MPA is an iterative process if the factor graph has cycles (closed loops) present in it. In every iteration, there are two steps. In Step 1, a belief message is passed from an FN to a VN, and in Step 2, the message is passed from a VN to an FN. MPA starts by passing messages from leaf nodes. A node has a degree (number of edges connected to it) d , then it will remain idle until messages have arrived on $d - 1$ edges.

Let $\eta_{j \rightarrow k}$ be the message sent from the VN j to the FN k and $\eta_{k \rightarrow j}$ be the message from the FN k to VN j . Let ζ_j and ξ_k be the set of nodes directly connected to VN j and FN k , respectively. Next, MPA can be carried out as follows:

1. Passing message from FN k to VN j :

$$\eta_{k \rightarrow j}(\mathbf{x}_j^m) = \sum_{\sim \mathbf{x}_j} \left(\psi_k \prod_{j' \in \xi_k \setminus \{j\}} \eta_{j' \rightarrow k}(\mathbf{x}_{j'}^m) \right), \quad (2.20)$$

where ψ_k is the likelihood function associated with FN k and $j' \in \xi_k \setminus \{j\}$ denotes all the VNs of ξ_k except j th VN. Also, $\eta_{j' \rightarrow k}(\mathbf{x}_{j'}^m)$ denotes the message from the VN j' to the FN k corresponding to symbol $\mathbf{x}_{j'}^m \in \mathbf{CB}_j$, $m = 1, \dots, M$.

2. Passing message from VN j to FN k :

$$\eta_{j \rightarrow k}(\mathbf{x}_j^m) = \prod_{k' \in \zeta_j \setminus \{k\}} \eta_{k' \rightarrow j}(\mathbf{x}_j^m), \quad (2.21)$$

where $k' \in \zeta_j \setminus \{k\}$ denotes the FNs in ζ_j except the k th FN. The message is normalized to ensure that the sum of all the probabilities is equal to one.

$$\eta_{j \rightarrow k}(\mathbf{x}_j^m) = \frac{\prod_{k' \in \zeta_j \setminus \{k\}} \eta_{k' \rightarrow j}(\mathbf{x}_j^m)}{\sum_{\mathbf{x}_j^l \in \mathbf{CB}_j} \prod_{k' \in \zeta_j \setminus \{k\}} \eta_{k' \rightarrow j}(\mathbf{x}_j^l)}. \quad (2.22)$$

The above algorithm uses the sum and product operations, and hence it is also called the sum-product algorithm. The detailed explanation of (2.20) and (2.21) is given in [14]. It is noted that (2.21) is simpler than (2.20) because there is no local function associated with a VN. After a few iterations, each bit's bit log-likelihood ratio (LLR) is calculated to estimate the bits transmitted by each user. The MPA for decoding of $K \times J$ SCMA system is summarized in **Algorithm 1**.

2.2.3 Illustration of MPA Decoding for 4×6 SCMA System

MPA is applied over the factor graph shown in Fig. 2.3 and messages are passed between the VNs and FNs in both the directions of the SCMA factor graph. It is noted

Algorithm 1: The Message Passing Algorithm

Inputs:
 J : Number of users.

 K : Number of REs.

 $\mathbf{CB}_j$: CB of j th user, $\forall j = 1, \dots, J$.

 $\mathbf{y}$: The received signal vector.

Output:

 Estimated value of bits for j th user, $\forall j = 1, \dots, J$.

Initialize:

 The prior probability of each codeword: $\eta_{j \rightarrow k}^0 = P(\mathbf{x}_j^m) = \frac{1}{M}, \forall j = 1, \dots, J, k \in \zeta_j$.

1: Step 1: Message passing along the nodes
for $t = 1$ **to** N_t **do**

a) Update Resource Node:

$$\eta_{k \rightarrow j}^t(\mathbf{x}_j^m) = \sum_{\sim \mathbf{x}_j} \left(\exp \left\{ \frac{-1}{N_0} \left\| y_k - \sum_{j \in \xi_k} h_{k,j} x_{k,j}^m \right\|^2 \right\} \prod_{j' \in \xi_k \setminus \{j\}} \eta_{j' \rightarrow k}^{t-1}(\mathbf{x}_{j'}^m) \right),$$

b) Update Variable Node:

$$\eta_{j \rightarrow k}(\mathbf{x}_j^m) = P(\mathbf{x}_j) \prod_{k' \in \zeta_j \setminus \{k\}} \eta_{k' \rightarrow j}^{t-1}(\mathbf{x}_j^m).$$

end
end
2: Step 2: Bit LLR

The final belief computed at each VN is:

$$I(\mathbf{x}_j^m) = \left(\frac{1}{M} \right) \prod_{k \in \zeta_j} \eta_{k \rightarrow j}(\mathbf{x}_j^m) \quad (2.23)$$

 The i -th bit LLR ($1 \leq i \leq \log_2(M)$) at j -th VN is

$$\begin{aligned} \text{LLR}(b_j^i) &= \log \frac{P(b_j^i = +1)}{P(b_j^i = -1)}, \\ &= \log \frac{\sum_{\mathbf{x}_j^m \in \mathbf{CB}_j | b_j^i = +1} I(\mathbf{x}_j^m)}{\sum_{\mathbf{x}_j^m \in \mathbf{CB}_j | b_j^i = -1} I(\mathbf{x}_j^m)}. \end{aligned} \quad (2.24)$$

 where, $\hat{b}_j^i = +1$ if $\text{LLR}(b_j^i)$ is positive otherwise $\hat{b}_j^i = -1$.

that the factor graph of the SCMA system contains cycles in it. Thus messages are passed between the nodes for some iterations until the termination criteria is achieved. The objective is to detect the symbols transmitted by each user, i.e., compute (2.19) using MPA, and this can be carried out in the following steps:

1. Initialization.
2. Passing of messages between FNs and VNs.
3. Termination and selection of codewords.

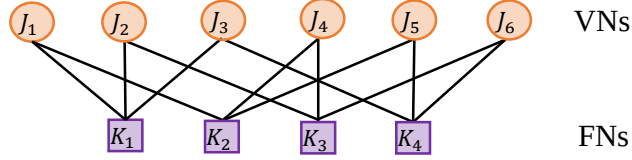


Figure 2.3: Factor graph of the 4×6 SCMA system corresponding to the FGM shown in (2.3).

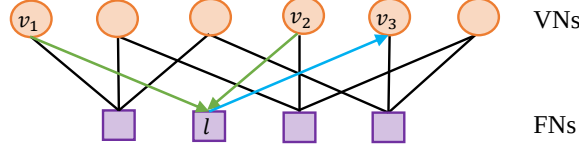


Figure 2.4: Message Passing from FN to VN.

The algorithm is discussed in a detailed manner for 4×6 SCMA system as follows:

- **Step 1: Initialization**

Assuming received vector $\mathbf{y}$ and channel coefficient matrix $\mathbf{H}$ are known at receiver, firstly the likelihood ratio is computed at each FN. Let us assume a FN l where data of three users corresponding to set $\xi_l = \{v_1, v_2, v_3\}$ superimpose. Therefore, the likelihood function at FN l becomes $\psi(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0)$, where, $\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3$ are the codewords transmitted by users belonging to set ξ_l , respectively. Assume the set of codeword elements allotted to user v on RE l is denoted as $\mathbf{CB}_{l,v}$. The likelihood function of FN l is given as

$$\psi(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0) = \exp \left(\frac{-1}{N_0} \|y_l - (h_{l1}x_{l,1} + h_{l2}x_{l,2} + h_{l3}x_{l,3})\|^2 \right),$$

$$\text{for } x_{l,1} \in \mathbf{CB}_{l,1}, x_{l,2} \in \mathbf{CB}_{l,2}, x_{l,3} \in \mathbf{CB}_{l,3}. \quad (2.25)$$

Here, $x_{l,v}$ denotes the codeword element transmitted by the v th user on the l th RE. In total, KM^{df} values are stored for function $f(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0)$. For an uncoded SCMA system, let us assume equal prior probability for each codeword, i.e., $P(\mathbf{x}_1) = P(\mathbf{x}_2) = P(\mathbf{x}_3) = \frac{1}{M}$. Therefore, the initial message passed from VN v_1, v_2, v_3 to the l th FN is

$$\eta_{v_1 \rightarrow l}^{\text{init}}(\mathbf{x}_1) = \eta_{v_2 \rightarrow l}^{\text{init}}(\mathbf{x}_2) = \eta_{v_3 \rightarrow l}^{\text{init}}(\mathbf{x}_3) = \frac{1}{M}. \quad (2.26)$$

- **Step 2: Passing of messages between FNs and VNs.**

- (i) **Message from FN to VN:**

Let us assume $\xi_l = \{v_1, v_2, v_3\}$, where v_1, v_2, v_3 denotes the three users connected to RE l , respectively. To pass the message from the FN to one user, information received on the FN from the other two users may be regarded as extrinsic information, as shown in Fig. 2.4.

Message passed from FN l to VN v_1 is given as

$$\eta_{l \rightarrow v_1}(\mathbf{x}_1) = \sum_{\mathbf{x}_2 \in \mathbf{CB}_2} \sum_{\mathbf{x}_3 \in \mathbf{CB}_3} \left(\psi(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0) \times \eta_{v_2 \rightarrow l}(\mathbf{x}_2) \eta_{v_3 \rightarrow l}(\mathbf{x}_3) \right), \text{ for } \mathbf{x}_1 \in \mathbf{CB}_1. \quad (2.27)$$

In (2.27), messages from the two VNs (i.e., $\eta_{v_2 \rightarrow l}(\mathbf{x}_2)$ and $\eta_{v_3 \rightarrow l}(\mathbf{x}_3)$) are multiplied with the local likelihood function of l th FN and then marginalized with respect to v_1 . Similarly, message passed from FN l to VNs v_2 and v_3 , respectively are

$$\eta_{l \rightarrow v_2}(\mathbf{x}_2) = \sum_{\mathbf{x}_1 \in \mathbf{CB}_1} \sum_{\mathbf{x}_3 \in \mathbf{CB}_3} \left(\psi(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0) \times \eta_{v_1 \rightarrow l}(\mathbf{x}_1) \eta_{v_3 \rightarrow l}(\mathbf{x}_3) \right), \text{ for } \mathbf{x}_2 \in \mathbf{CB}_2. \quad (2.28)$$

$$\eta_{l \rightarrow v_3}(\mathbf{x}_3) = \sum_{\mathbf{x}_1 \in \mathbf{CB}_1} \sum_{\mathbf{x}_2 \in \mathbf{CB}_2} \left(\psi(y_l | \mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, N_0) \times \eta_{v_1 \rightarrow l}(\mathbf{x}_1) \eta_{v_2 \rightarrow l}(\mathbf{x}_2) \right) \text{ for } \mathbf{x}_3 \in \mathbf{CB}_3. \quad (2.29)$$

Message passing from FN l to VN v_3 is shown graphically in Fig. 2.4. The message transmitted from FN l to VN v indicates the guess of what signal is received at FN l for all possible values of VN v .

(ii) Message from VN to FN:

Let us assume $\zeta_v = \{l_1, l_2\}$, where l_1 and l_2 are the FNs connected to VN v .

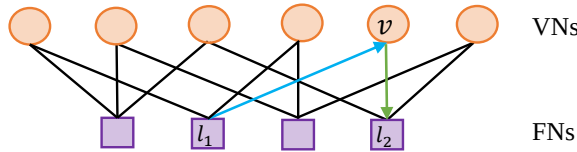


Figure 2.5: Message Passing from VN to FN.

Message sent from VN v to FN l_1 and l_2 , respectively are:

$$\eta_{v \rightarrow l_1}(\mathbf{x}_v) = \text{normalize}(P_a(\mathbf{x}_v) \eta_{l_2 \rightarrow v}(\mathbf{x}_v)), \quad \text{for } \mathbf{x}_v \in \mathbf{CB}_v, \quad (2.30)$$

$$\eta_{v \rightarrow l_2}(\mathbf{x}_v) = \text{normalize}(P_a(\mathbf{x}_v) \eta_{l_1 \rightarrow v}(\mathbf{x}_v)) \quad \text{for } \mathbf{x}_v \in \mathbf{CB}_v, \quad (2.31)$$

where P_a denotes the prior probability of user v and $\eta_{l_2 \rightarrow v}$ indicates the updates VN v received from the FN l_2 . Here, normalization is necessary to ensure that

each belief falls in the range of $[0,1]$. The normalization is conducted similar to (2.22) and so, (2.30) can also be written as

$$\eta_{v \rightarrow l_1}(\mathbf{x}_v) = \frac{P_a(\mathbf{x}_v)\eta_{l_2 \rightarrow v}(\mathbf{x}_v)}{\sum_{\mathbf{x}_v} \eta_{l_2 \rightarrow v}(\mathbf{x}_v)}, \quad \text{for } \mathbf{x}_v \in \mathbf{CB}_v.$$

The message from the VN v to FN l_2 is shown graphically in Fig. 2.5. Since the factor graph has cycles, the passing of messages between FNs to VNs is repeated for a few iterations. This continues until no considerable change is observed in the belief computed at each VN.

- **Step 3: Termination and selection of codewords.**

After repeating Step 2 for N_t number of iterations, the final belief is computed at each VN, which is the product of the prior probability and messages from the neighboring FNs of each VN.

$$I_v(\mathbf{x}_v) = P_a(\mathbf{x}_v)\eta_{l_1 \rightarrow v}(\mathbf{x}_v)\eta_{l_2 \rightarrow v}(\mathbf{x}_v), \quad \text{for } \mathbf{x}_v \in \mathbf{CB}_v. \quad (2.32)$$

The probability for each codeword is calculated at each VN, and the codeword with the highest probability becomes the estimated codeword for that user. This is one method of estimating the transmitted symbol for each user. Another method is to compute bit LLR from $I_v(\mathbf{x}_v)$. The i -th bit LLR for VN v is given as

$$\text{LLR}(b_v^i) = \log \frac{P(b_v^i = +1)}{P(b_v^i = -1)} = \log \frac{\sum_{\mathbf{x}_v | b_v^i = +1} I_v(\mathbf{x}_v)}{\sum_{\mathbf{x}_v | b_v^i = -1} I_v(\mathbf{x}_v)}, \text{ for } i = 1, \dots, B. \quad (2.33)$$

In case of $M = 4$, there are two bits per symbol. Let $\mathbf{CB}_v = \{\mathbf{x}_v^1, \mathbf{x}_v^2, \mathbf{x}_v^3, \mathbf{x}_v^4\}$ denote the four codewords corresponding to four symbols $\{s^1, s^2, s^3, s^4\}$ that can be sent by user v . Using (2.32), final belief corresponding to each of the four codewords is calculated. Then, the LLR of the first bit is given as

$$\text{LLR}(b_v^1) = \log \frac{P(b_v^1 = +1)}{P(b_v^1 = -1)} = \log \frac{I_v(\mathbf{x}_v^1) + I_v(\mathbf{x}_v^2)}{I_v(\mathbf{x}_v^3) + I_v(\mathbf{x}_v^4)}. \quad (2.34)$$

The ratio of the belief computed corresponding to codewords $\mathbf{x}_v^1, \mathbf{x}_v^2$ and $\mathbf{x}_v^3, \mathbf{x}_v^4$ gives the bit LLR of the first bit. Consequently, if $P(b_v^1 = -1) > P(b_v^1 = +1)$ or if $\text{LLR}(b_v^1) < 0$, then '1' is decoded for first bit of the symbol otherwise 0. Similarly, for the second bit, if $\text{LLR}(b_v^2) < 0$, then '1' is decoded for the second bit of the symbol. The bit LLR for the second bit is given as

$$\text{LLR}(b_v^2) = \log \frac{I_v(\mathbf{x}_v^1) + I_v(\mathbf{x}_v^3)}{I_v(\mathbf{x}_v^2) + I_v(\mathbf{x}_v^4)}. \quad (2.35)$$

In SCMA, MPA is an efficient decoding technique by exploiting the CBs sparsity. Using MPA, the receiver is able to attain near-optimum decoding performance with computation complexity $O(d_f M^{d_f})$. Several advanced MPA based detectors with lower computation complexity, followed by a few non-MPA based SCMA detectors have been proposed in the literature [64–68].

2.3 Literature survey and Motivation

In SCMA, the bits corresponding to each user are directly mapped to a codeword which is extracted from its associated CB, as discussed in the previous section. Thanks to its coding gain and constellation shaping gain, there is improvement in sum-rate and bit error rate (BER) [19, 20, 69]. Further, several low-complexity detection methods have been proposed for SCMA systems, both in static [21] and mobile environments [22, 23]. With the increasing demand for higher capacity and massive connectivity in future wireless applications, there is a strong interest in investigating the integration of SCMA with other communication systems to explore higher performance gains. This section presents the research objectives carried out in this thesis work based on SCMA, CB design and resource allocation in SCMA systems. In this thesis work, four research objectives have been discussed, which are presented in the following subsections. Each subsequent subsection contains a brief literature survey followed by the motivation for the respective research objective.

2.3.1 SCMA for Visible Light Communications

Literature Survey: Several research works incorporating SCMA in VLC (SCMA-VLC) systems have been presented in the literature. In [28], [29], experimental demonstration of SCMA-VLC system with overloading factor of 1.5 was reported. In [70], a hybrid power-domain SCMA was investigated for VLC, showing improved data rate at the cost of reduced transmission distance. In [30], color-domain SCMA was proposed for VLC for a large throughput gain over conventional white light SCMA system. All the above works used the predefined RF complex SCMA CBs and made suitable changes (such as Hermitian symmetry and DC-level shifting) so that they can be applied to the VLC system. The authors in [31] focused on SCMA constellation design for VLC system in the presence of thermal noise with six users and eight resource elements (REs). In [32] and [33], SCMA CB has been designed for three users with four REs considering the impact of varying shot noise in VLC systems. Although [31–33] have proposed SCMA CBs for different VLC systems, however, there is still a lack of literature on designing SCMA CBs with overloading factor greater than one while considering the presence of shot noise in VLC systems.

Motivation: Based on the above literature, there is no theoretical BER expression for shot noise incorporated SCMA-VLC system. As seen from the literature, most of the works related to SCMA-VLC either do use RF CBs, or they designed for low overloading factor with high complexity which does not fully utilize SCMA for VLC systems. Therefore, it is essential to design SCMA CBs for overloading factor greater than one and theoretical BER expression considering shot noise in the SCMA-VLC systems.

2.3.2 SCMA with Reconfigurable Intelligent Surface

Literature Survey: Several research works incorporating NOMA with IRS systems have been presented in the literature [71–79]. In [71], the sum-rate was maximized in an IRS-aided NOMA system by jointly optimizing the IRS phases and beamforming

at the base station (BS). In [72], the rate regions calculated for both OMA and NOMA techniques are characterized by the IRS reflection matrix. In [73, 74], the objective was to minimize the total transmit power by optimizing the active and passive beamforming. In [75], the required minimum transmit power was analyzed between NOMA and OMA schemes in the IRS-assisted system. The minimum signal-to-interference-plus-noise-ratio (SINR) was maximized in [76] by phase optimization and transmit power allocation, in case of single and multi-antenna scenario. [77] investigated the power allocation, channel assignment, and IRS reflection matrix to maximize the system throughput. In [78], the weighted sum-rate was maximized by optimizing the deployment of the IRS location, power allocation, and the reflection matrix in a NOMA system. [79] proposed a resource allocation framework for maximizing the sum-rate through optimized decoding order, user association, power allocation, and reflection matrix.

Motivation: It is noted that most of the above works were mainly focused on the integration of PD-NOMA with IRS. An IRS-aided SCMA system was firstly investigated in [80], in which a low-complexity decoder was proposed. [81] analyzed the symbol error rate, diversity order, and the sum-rate in an IRS-aided SCMA system. [82] maximized the received signal-to-noise-ratio (SNR) by optimizing the IRS coefficients. As SCMA is a type of NOMA technique, it faces inter-user interference. However, the previous works on IRS-aided SCMA systems [80–82] did not consider the effect of inter-user interference in their investigation. Thus, we have proposed to maximize the sum-rate in a downlink IRS-aided SCMA system by optimizing the FGM, power allocation, IRS reflection matrix, and choose the appropriate IRS deployment location.

2.3.3 SCMA with Unmanned Aerial Vehicles Networks

2.3.3.1 Single UAV

Literature Survey: Several research works based on the integration of NOMA with UAV systems are documented in the literature [83–98]. In [84], N. Zhao *et al.* worked on the security aspect of NOMA-UAV networks and proposed two secure transmission schemes by beamforming optimization and power allocation, respectively. Sun *et al.* [85] investigated a downlink cyclical NOMA-based UAV network and optimized UAV trajectory and multi-user communication scheduling to maximize the minimum user rate. In [86], the UAV 2D placement, admission control, and NOMA power allocation were optimized in order to maximize the number of users with a satisfied QoS experience. The uplink NOMA random access (RA) was studied in [87], in which the maximum stable throughput was characterized in terms of the UAV’s altitude and beamwidth. P. Qin *et al.* utilized UAVs for access and high altitude platform stations (HAPSs) for data backhaul to establish the air-ground integrated network (AGIN), and achieve uninterrupted coverage for remote Internet of Things (IoT) devices [88].

Within the context of *NOMA-assisted UAV systems*, several works investigate joint optimization of various optimization variables such as UAVs placement [84, 89, 90], UAVs trajectories [85, 88, 91, 92, 95–97], power allocation [84, 86, 88–91, 95, 96, 98] and subchannel allocation [88, 97]. They have worked to improve various performance objectives, including capacity [87, 89, 90, 92, 96], maximize the minimum user rate [91, 98], energy efficiency [88, 95], uplink energy minimization [97], and secrecy [84].

Motivation: It is noticeable from the above-mentioned literature that the NOMA-assisted UAV systems are more efficient in providing improved QoSs. However, most of these works focused on integrating PD-NOMA with the UAV systems. The performance of PD-NOMA in UAV communications, however, may not be guaranteed due to the following reasons: 1) A perfect SIC technique is often used at the receiver side, which may not be possible in complex wireless channels; 2) SIC depends on the accurate CSI in order to determine the right decoding order, but this may be difficult in view of the mobile UAVs; 3) The user pairing of PD-NOMA could consume a significant amount of system resources, especially in a dynamic moving environment. The PD-NOMA provides performance gains over OMA schemes when the user pair has distinctive channel conditions [99]. Thus, PD-NOMA requires additional constraints of user pairing and reordering in the optimization problem. However, SCMA does not need such stringent constraints. To the best of the author’s knowledge, there is no existing research in the literature on SCMA-assisted UAV systems focused on efficiently utilizing available resources and maximizing the system data rate. The proposed work ensures that all the end users receive appropriate QoS by optimizing the UAV 3D deployment and trajectory with energy constraints, as well as optimization of SCMA subcarrier and power allocation.

2.3.3.2 Multiple UAVs

Literature Survey: Within NOMA-assisted multi-UAV networks [100–113], researchers have delved into optimizing various factors, including user clustering and association [100, 101], scheduling [102], UAVs placement [100, 103–105], power allocation [100–102, 104, 105], UAVs trajectories [101] and subchannel assignment [104]. Various performance objectives have been improved, including capacity [100, 104–107, 113], energy efficiency [102, 108–110], uplink energy minimization [101] and delay [111]. In [108], energy efficiency (EE) was maximized in a network of UAVs employing NOMA. Specifically, multiple UAVs equipped with multiple antennas concurrently served as simultaneous power and information transmitters towards energy receivers and information receivers. The paper [102] formulated a max-min optimization problem and optimized scheduling, transmit power allocation and UAV trajectory. A multi-UAV coverage scheme was studied in [103], whereby the objective was to maximize the average UAV capacity and guarantee the users coverage. The authors in [101] studied the joint optimization of user pairing, UAVs’ trajectories, association between user and UAV, and power allocation for uplink NOMA-aided multi-UAV networks. In [104], system capacity was maximized in an uplink IoT multi-UAV NOMA systems through the joint optimization of subchannel assignment, transmit power for IoT sensors, and the altitudes of UAVs. In [105], the UAVs three-dimension (3D) deployment and power allocation of users were optimized to maximize the sum-rate. In [109], the study delved into the optimization of multiple UAVs 3D deployment, resource allocation, and UAV-users association within a NOMA-assisted mobile-edge computing (MEC) uplink network. In [110], an investigation was conducted into EE of UAV-enabled NOMA MEC framework. This framework deploys multiple UAVs as edge servers to offer computational assistance to the ground users.

Motivation: To the best of our knowledge, few research has been conducted on investigating the potential performance enhancements in multi-UAV networks networks

facilitated by SCMA. While SCMA renders the connectivity problem, high interference necessitates the sophisticated management of resources to obtain desired QoSs. The primary challenges can be identified as follows: 1) In a multi-UAV scenario, the communication rate experienced by each user is contingent not only upon the desired signal strength but also on the interference levels. The optimization of UAV placement necessitates achieving a balance between the desired signal strength, intra-UAV interference and inter-UAV interference. 2) Out of the total spectrum resources available in the network, a subset of total spectral resources is allocated to each UAV. Figuring out which subset, and then allocating the subchannels to each user in order to mitigate inter-UAV and intra-UAV interference is a non-trivial task. 3) After the subchannel allocation, the quantum of bandwidth that should be allocated to each subchannel in order to improve the overall system performance, as the optimization variables are coupled with each other is also worth addressing. Consequently, it is essential to methodically devise efficient algorithms to fully harness the benefits of incorporating SCMA in multi UAV-enabled communications.

2.4 Objectives and Key Contributions

The main objective of this thesis work is to present the performance analysis of SCMA systems for wireless applications. A mathematical framework is presented for showing the performance of all the considered systems over physical layer. In this thesis work, four problem statements have been formulated based on the research objectives. The problem statements, followed by their major contributions are as follows.

1. Low-Complexity Codebook Design for SCMA based Visible Light Communication

The major contributions of this work are summarized as follows:

- A novel multidimensional, low-complex, and power-efficient SCMA CB designing technique has been proposed for shot noise incorporated VLC system utilizing the log-sum-exponential operation in the optimization objective function of CB design. The proposed CBs outperform CBs in the existing literature [32,33] for different load factors with much less complexity.
- The proposed optimization problem and its solution lead to flexible SCMA CBs which can meet the need of SCMA-VLC systems with varying loading factors.
- The analytical expression of BER for SCMA-VLC system considering the shot noise has been derived. The simulation results show good agreement with the derived analytical BER expression, especially for higher signal power region.

2. Resource Allocation in SCMA-Aided IRS System

The major contributions of this work are summarized as follows:

- A downlink IRS-aided SCMA is proposed for sum-rate enhancement. For the proposed system, a sum-rate maximization problem is formulated, subject to the SCMA CB structure, QoS requirements, and IRS reflecting elements

constraints. In order to do so, the transmit power, FGM, and IRS reflection matrix are optimized. We show that the formulated optimization problem is a mixed-integer non-linear programming (MINLP) problem, which is non-convex.

- To tackle the formulated optimization problem, an AO based iterative algorithm is proposed. The fundamental idea is to divide the main optimization problem into three subproblems which are then solved iteratively. Firstly, we work on the FGM assignment sub-problem using the effective channel gains. We then use Lagrange dual decomposition method for power allocation. Finally, the phase optimization problem is solved subject to IRS reflecting elements constraints using the RCG algorithm.
- After optimizing the FGM assignment, power allocation, and the phase vector of the IRS, the performance of the proposed algorithm is evaluated for IRS-aided SCMA system. Further the simulation results show that the proposed IRS-aided SCMA system improves the sum-rate performance significantly when compared to an SCMA system without IRS.

3. Sum-Rate Maximization of SCMA-Aided UAV System

The major contributions of this work are summarized as follows:

- First, we formulate an optimization problem to maximize the sum-rate for the downlink SCMA-assisted UAV system and optimize the UAV 3D deployment location and UAV trajectory under the available onboard energy.
- Next, we formulate a sum-rate maximization problem, where the multiple subchannel allocation and power allocation matrices are optimized, when UAV reaches the deployment location. The major challenge lies in solving the above problem with low computational complexity subject to the constraints of SCMA FGM, UAV transmit power budget, and user required QoS. We show that the formulated optimization problem is a non-convex non-linear integer programming problem.
- We propose an iterative gradient ascent-based algorithm to solve the UAV 3D deployment and trajectory optimization problem for rate maximization. Next, we introduce an efficient factor graph matrix assignment algorithm for allocating subcarriers to each user. Finally, we carry out the power allocation using Lagrange dual decomposition method considering the power budget and minimum user rate constraints.
- Comprehensive simulation results are shown to demonstrate the efficacy of the proposed algorithms for UAV 3D deployment, trajectory design, FGM assignment, and power allocation which improves the sum-rate with respect to the benchmark schemes.

4. Resource Allocation for SCMA-Aided Multi-UAV Transmission System

The primary contributions of this work are summarized as follows:

- We investigate a downlink system wherein SCMA-assisted multiple UAVs function as aerial BSs to provide service to the ground users. We formulate an optimization problem focused on maximizing the sum rate, which involves

joint optimization of the UAVs 3D deployment, users clustering and user-UAV association, subchannel assignment, power allocation, and bandwidth allocation.

- To address the formulated mixed-integer nonconvex problem, we decompose it into four sub-problems, and solve them separately. First, we present a modified algorithm based on K-means for the equitable allocation of all users to the UAVs. Then, we propose three frequency reuse based subchannel assignment schemes, in order to suppress the inter-UAV and intra-UAV interference. Finally, we propose iterative algorithms for power allocation and bandwidth allocation to each subchannel to the ground users.
- The numerical results demonstrate that the proposed multi-UAV SCMA scheme exhibits a notable enhancement in both the achieved sum rate and outage performance when compared with the benchmark schemes.

Chapter 3

Low-Complexity Codebook Design for SCMA based Visible Light Communication

3.1 Introduction

In recent years, visible light communication (VLC) has emerged as a reliable alternative to legacy radio-frequency (RF) based communication, especially for indoor scenarios. VLC offers various advantages such as unlicensed spectrum, free of electromagnetic interference, and ease of deployment using existing illumination infrastructure along with high-level security [114–116]. To support multiple access in VLC, conventional orthogonal frequency division multiple access (OFDMA) may not be employed as VLC has the requirement of real and positive signal transmission. In order to overcome the above drawback, direct current-biased optical OFDMA (DCO-OFDMA) and asymmetrically clipped optical OFDMA (ACO-OFDMA) have been studied. However, DCO-OFDMA suffers from deteriorated bit error rate (BER), and ACO-OFDMA suffers from reduced spectral efficiency [117]. In comparison, SCMA can be combined with VLC to increase the spectral efficiency because of the following reasons [118]:

- The dominant line-of-sight (LoS) component and the short distance between light-emitting diode (LED) and photodetector (PD) give rise to a high signal-to-noise ratio (SNR) at VLC receiver, which helps improve the performance of SCMA.
- The limited modulation bandwidth of the LEDs can be efficiently utilized by SCMA to achieve high spectral efficiency.

3.1.1 Input-dependent Gaussian noise

In the VLC system, the optical receiver (i.e., PD) measures the intensity of the incident optical signal and converts it into electrical signal. The interaction of the incoming photons with the matter of PD is a statistical process [119]. The fluctuations in the number of photons detected, results in fluctuating current which cause shot noise at the

optical receiver. The generated shot noise depends on the incident optical signal itself [120–122]. Further, the thermal motion of the electronic carriers result in fluctuating voltage known as thermal noise. In case of strong ambient light, the impact of thermal noise is more and the shot noise becomes very low. Thus, the total noise at the VLC system is assumed to be independent of the received signal [123–125]. However, in case of indoor scenario, the distance between transmitter and receiver is less and the dominant signal is LoS [126], thus the received power is large. However, in practical VLC systems, typical illumination and communication scenarios offer very high SNR [127, 128]. In case of indoor scenario (as considered in our work), since the received power is large, the shot noise is more dominant and cannot be neglected. The variance of shot noise is given as

$$\sigma_{sh}^2 = 2qx_p\Re B + 2qI_B I_2 B, \quad (3.1)$$

where q is the electronic charge, x_p is the intensity of incident optical signal, $\Re$ is responsivity, I_B is the background noise current, and I_2 is the noise-bandwidth factor, and B is the effective bandwidth of the optical receiver.

The thermal noise is assumed to be additive white Gaussian noise (AWGN), which is independent of the intensity of the incident signal [120]. The shot noise affected optical intensity channel can be distinguished as an input-dependent Gaussian noise (IDGN), where variance of IDGN can be used to characterise the physical properties of the VLC system [120, 129]. Consequently, the received signal y can be expressed as

$$y = x_p + \sqrt{x_p}Z_1 + Z_0, \quad y \in \mathbb{R}, \quad x_p \geq 0, \quad (3.2)$$

where $Z_1 \sim \mathcal{N}_{\mathbb{R}}[0, \varsigma^2\sigma^2]$ denotes a real Gaussian random variable with zero mean and $\varsigma^2\sigma^2$ variance describing IDGN (shot noise), and $Z_0 \sim \mathcal{N}_{\mathbb{R}}[0, \sigma^2]$ describes the thermal noise. Here, Z_1 and Z_0 are assumed to be independent, and $\varsigma^2 \in [1, 10]$ denotes the strength of shot noise with respect to thermal noise. In an indoor scenario, as the transmitter and the receiver parameters change, the received power changes, and thus the shot noise varies. In our work, the variation in shot noise has been depicted by considering different shot noise factor ς^2 values.

The analytical expression of BER has been discussed [130, 131] either for power-domain NOMA techniques or for single-carrier scheme (such as on-off keying) for shot noise incorporated VLC systems. However, SCMA is a multi-carrier scheme, and its BER analysis will be different from single-carrier schemes. Further, when the SCMA-VLC system incorporates varying shot noise, the conventional closed-form BER expression does not follow the simulation results. Therefore, an exact theoretical BER expression for shot noise incorporated SCMA-VLC system has been proposed in this work. To the best of our knowledge, this paper is the first known work that proposes the SCMA CB design with 1.5 overloading factor for VLC systems considering shot noise.

3.2 Proposed Work

3.2.1 The SCMA-VLC Model

Consider a downlink indoor LoS VLC system where multiple users are being served, each equipped with a single receiving device. Every J users are grouped together for

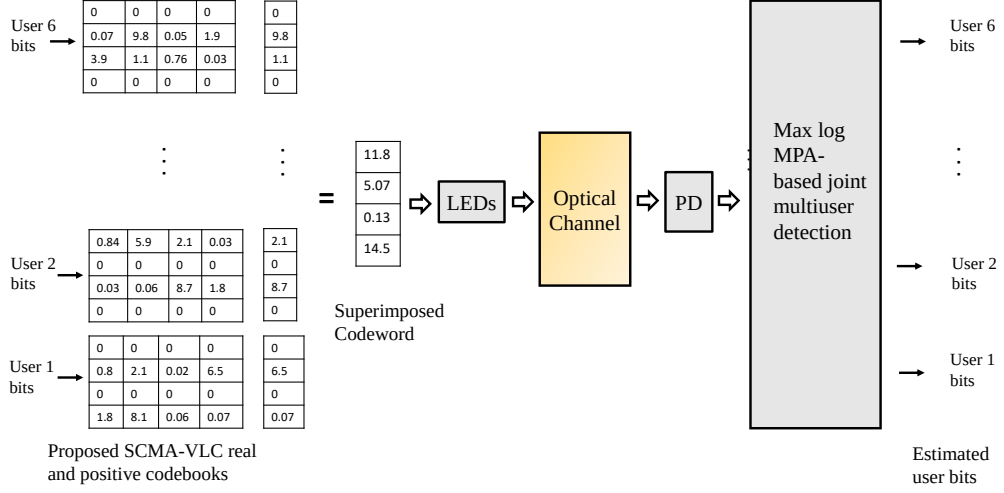


Figure 3.1: The system model diagram of 4×6 SCMA with the proposed CBs at the transmitter in VLC channel.

SCMA, and each group is supported by K REs, providing the load factor $\lambda = J/K$. In Fig. 3.1, the data transmission and reception of six users ($J = 6$) on four REs ($K = 4$) with $\lambda = 1.5$ is shown.

At the transmitter, $b = \log_2 M$ bits are mapped to K -dimensional real and positive codewords, with M number of codewords in a CB. These codewords are sparse vectors with N non-zero elements, $K > N$. The CB of j th user can be expressed as

$$\mathbf{A}_j = \mathbf{V}_j \mathbf{C}_j, \quad \text{for } j = 1, \dots, J, \quad (3.3)$$

where $\mathbf{V}_j \in \mathbb{B}^{K \times N}$ and $\mathbf{C}_j \in \mathbb{R}_{>0}^{N \times M}$ denote the mapping matrix and constellation matrix of the j th user, respectively. The constellation matrix $\mathbf{C}_j = [\mathbf{c}_j^1, \dots, \mathbf{c}_j^M]$, where $\mathbf{c}_j^m \in \mathbb{R}_{>0}^{N \times 1}$ denotes the m th constellation point of $\mathbf{C}_j$. The whole CB structure of SCMA can be represented by the FGM, $\mathbf{F} = (\mathbf{f}_1, \mathbf{f}_2, \dots, \mathbf{f}_J)$, where $\mathbf{f}_j = \text{diag}(\mathbf{V}_j \mathbf{V}_j^T)$. The user j is being served by resource node (RN) k , if $\mathbf{F}_{kj} = 1$ ($1 \leq k \leq K, 1 \leq j \leq J$).

The set of CBs for J users is dependent on the constellation matrices $\mathbf{C}_j$, $j = 1, \dots, J$ as the mapping matrices remain fixed. Assuming synchronous multiplexing between users, the received signal can be expressed as

$$\begin{aligned} \mathbf{y} &= \sum_{j=1}^J \text{diag}(\mathbf{h}_j) \mathbf{x}_j + \text{diag} \left(\sum_{j=1}^J \text{diag}(\mathbf{h}_j) \mathbf{x}_j \right)^{\frac{1}{2}} \mathbf{n}_{sh} + \mathbf{n}_{th}, \\ &= \sum_{j=1}^J \text{diag}(\mathbf{h}_j) \mathbf{V}_j \mathbf{c}_j + \text{diag} \left(\sum_{j=1}^J \text{diag}(\mathbf{h}_j) \mathbf{V}_j \mathbf{c}_j \right)^{\frac{1}{2}} \mathbf{n}_{sh} + \mathbf{n}_{th}, \end{aligned} \quad (3.4)$$

where $\mathbf{x}_j \in \mathbb{R}_{>0}^{K \times 1}$ is a codeword of j th user, $\text{diag}(\mathbf{h}_j)$ denotes the channel matrix of j th user, the second term represents the IDGN with $\mathbf{n}_{sh} \sim \mathcal{N}_{\mathbb{R}}[\mathbf{0}, \varsigma^2 \sigma^2 \mathbf{I}]$, and $\mathbf{n}_{th} \sim \mathcal{N}_{\mathbb{R}}[\mathbf{0}, \sigma^2 \mathbf{I}]$. The channels are assumed to be unit vectors for simplicity, and the extension to the general VLC values is straight-forward.

3.2.2 SCMA-VLC Decoding

Assuming perfect channel estimation and the set of CBs known to receiver, MPA works as a decoding algorithm based on passing the extrinsic information between RNs and VNs. MPA involves a large number of exponential operations which are of high complexity. A mathematical simplification is to move MPA to logarithm domain and use Jacobian logarithm, which gives a simpler version called Max-Log-MPA [132]. With Jacobian logarithm, the log-sum of exponentials can be approximated as a maximum operation as shown below:

$$\log(\exp(a_1) + \cdots + \exp(a_J)) \approx \max(a_1, \cdots, a_J). \quad (3.5)$$

The Max-Log-MPA for detection of SCMA codewords in VLC is based on three steps as shown in **Algorithm 2**. Let ζ_j and ξ_k , be the set of nodes connected to VN j and RN k , respectively. Let $\eta_{k \rightarrow j}$ and $\eta_{j \rightarrow k}$ be the message passed from RN k to VN j and vice-versa. Also, $r \in \xi_k \setminus \{j\}$ denotes all the VNs of ξ_k except VN j and $d \in \zeta_j \setminus \{k\}$ denotes the RNs in ζ_j except the k th RN.

In **Algorithm 2**, it is assumed that the received signal $\mathbf{y}$ and all the CBs $\mathbf{C}_j$, $\forall j = 1, \cdots, J$ are known at the receiver. The total number of iterations considered in **Step 2** are N_t and, VNs and RNs are updated for each iteration t . Also, the channel coefficient between k th RN and m th VN is denoted by h_{km} and the codeword element transmitted by m th VN on k th RN is denoted by x_{km} , respectively.

In the case of shot noise, the variance at each RN is different and dependent on the superimposed codeword element at the corresponding RN, while in the presence of only thermal noise, $\varsigma^2 = 0$, so $\rho^2 = \sigma^2$ and variance will be the same for all RNs. In case of three users scenario, the factor graph would not be cyclic and number of elements being superimposed on each RN would be different ($d_f = 2$ for $k = 1, 2$ and $d_f = 1$ for $k = 3, 4$). Since d_f is different for different REs, therefore, **Algorithm 2** will change accordingly [14]. Also, Max-Log-MPA requires more addition operations and less multiplication operations than MPA. This gap of increase in addition and decrease in multiplication operations between MPA and Max-Log-MPA increases with the overloading factor.

3.3 CB Design and Optimization

For SCMA CB design and optimization, most researchers aim for maximization of the minimum Euclidean distance (MED) between the superimposed codewords [47, 133, 134]. In this section, a method of designing constellation matrices $\mathbf{C} = [\mathbf{C}_1, \cdots, \mathbf{C}_J] \in \mathbb{R}_{>0}^{N \times MJ}$ is introduced and discussed as an optimization problem.

3.3.1 The Problem Formulation

In the AWGN channel, MED is taken as one of the key performance indicators for determining the performance of the designed SCMA CB. Let $\mathbf{s}_i$ be a superimposed codeword from the combined constellation matrix $\mathbf{M}_v \in \mathbb{R}_{>0}^{K \times MJ}$. Then, the MED

Algorithm 2: Max-Log-MPA

Input: $\mathbf{y}, \mathbf{C}_j, \forall j = 1, \dots, J$.

Output: Estimated value of bits for j th user, $\forall j = 1, \dots, J$.

1: **Step 1: Initialization**

The prior probability of each codeword: $\eta_{j \rightarrow k}^0 = \log \frac{1}{M}$.

2: **Step 2: Message passing along the nodes**

for $t = 1$ **to** N_t **do**

a) Update RN:

$$\eta_{k \rightarrow j}^t(\mathbf{x}_j) = \max_{\sim \mathbf{x}_j} \left(\frac{-1}{2\rho^2} \left\| y_k - \sum_{m \in \xi_k} h_{km} x_{km} \right\|^2 + \sum_{r \in \xi_k \setminus \{j\}} \eta_{r \rightarrow k}^{t-1}(\mathbf{x}_r) \right),$$

where, $\rho^2 = \sigma^2 + \varsigma^2 \sigma^2 \sum_{m \in \xi_k} h_{km} x_{km}$.

b) Update VN:

$$\eta_{j \rightarrow k}(\mathbf{x}_j) = \log \left(\frac{1}{M} \right) + \sum_{d \in \zeta_j \setminus \{k\}} \eta_{d \rightarrow j}^{t-1}(\mathbf{x}_j).$$

end

end

3: **Step 3: Bit log-likelihood ratio (LLR)**

The final belief computed at each VN is:

$$\log \mathbf{I}_j(\mathbf{x}_j) = \log \left(\frac{1}{M} \right) + \sum_{k \in \zeta_j} \eta_{k \rightarrow j}(\mathbf{x}_j)$$

The κ th bit LLR at j th VN is

$$LLR_{\kappa}^j = \max_{\{\mathbf{x}_j \in \mathbf{A}_j | \kappa=0\}} (\log(\mathbf{I}_j(\mathbf{x}_j))) - \max_{\{\mathbf{x}_j \in \mathbf{A}_j | \kappa=1\}} (\log(\mathbf{I}_j(\mathbf{x}_j))).$$

where, $\hat{\kappa}_j = 0$ if LLR_{κ}^j is positive otherwise $\hat{\kappa}_j = 1$.

between $\mathbf{s}_i \in \mathbf{M}_v$ and $\mathbf{s}_j \in \mathbf{M}_v$ is given as

$$d'_{ij} = (\mathbf{s}_i - \mathbf{s}_j)^T (\mathbf{s}_i - \mathbf{s}_j), \quad \forall i < j \in [1, M^J]. \quad (3.6)$$

The MED emerges as a critical parameter because of the pair-wise error probability (PEP) for AWGN channel which is given as

$$P'(\mathbf{s}_i \rightarrow \mathbf{s}_j) = Q \left(\sqrt{\frac{\|\mathbf{s}_i - \mathbf{s}_j\|^2}{2\sigma^2}} \right). \quad (3.7)$$

However, in case of IDGN, the PDF of the received signal $\mathbf{y}$ is given as (assuming unit channel gain)

$$f(\mathbf{y} | \mathbf{s}_i) = \frac{1}{(2\pi)^{K/2}} \frac{1}{|\Sigma_i|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (\mathbf{y} - \mathbf{s}_i)^T \Sigma_i^{-1} (\mathbf{y} - \mathbf{s}_i) \right\}, \quad (3.8)$$

where $\Sigma_i = \text{diag}\{\varsigma^2 \sigma^2 \mathbf{s}_i + \sigma^2 \mathbf{1}\}$ denotes the covariance matrix for the $\mathbf{s}_i$ th superimposed codeword. It can be seen from (3.8) that the variance is now dependent on the superimposed codeword.

In the case of only thermal noise, MED is taken as a critical parameter for designing CB where variance is independent of the superimposed codeword. However, in the case of shot noise, when variance is no longer independent, the conventional MED cannot serve as an optimal performance indicator. With the effect of shot noise, the shape of constellation points gets distorted. To mitigate the effect of IDGN, the authors in [32] introduced an improved optimization objective based on rotated-MED for designing constellation matrices. The rotated Euclidean distance (RED) between superimposed codewords $\mathbf{s}_i$ and $\mathbf{s}_j$ can be expressed as

$$d_{ij} = (\mathbf{s}_i - \mathbf{s}_j)^T \mathbf{G}_i^{-\frac{1}{2}} \mathbf{G}_j^{-\frac{1}{2}} (\mathbf{s}_i - \mathbf{s}_j), \quad \forall i < j \in [1, M^J], \quad (3.9)$$

where $\mathbf{G}_i = \varsigma^2 \text{diag}\{\mathbf{s}_i\} + \mathbf{I}$, $\mathbf{G}_j = \varsigma^2 \text{diag}\{\mathbf{s}_j\} + \mathbf{I}$ and $\mathbf{I} \in \mathbb{B}^{K \times K}$ represents the identity matrix. It is to be noted from (3.9) that the new parameter RED incorporates the shot noise effect while computing the Euclidean distance between superimposed codewords. The authors in [32] aimed at maximizing the rotated minimum Euclidean distance (R-MED) subject to the power constraints. The objective function proposed in [32] for SCMA CB design is given as

$$\max_{\mathbf{L} \in \mathbb{R}_{>0}^{NMJ \times 1}} \left\{ \min_{1 \leq i < j \leq M^J} d_{ij}(\mathbf{L}) \right\}, \quad (3.10)$$

where $\mathbf{L} = \text{vec}(\mathbf{C})$. This was further simplified as

$$\max_{\mathbf{L} \in \mathbb{R}_{>0}^{NMJ \times 1}, d_{\min} > 0} d_{\min}, \quad (3.11)$$

where $d_{\min}$ denotes the minimum value of RED. It has been verified in [32] that R-MED based CB outperforms the MED based CB for VLC systems affected by shot noise. The results in [32] have shown that for $J = 3, K = 4, M = 4, \varsigma^2 = 5$ and $\sigma^2 = 0.01$, BER of 10^{-3} is achieved at $P_e = 10$ and $P_e = 7$ for MED and R-MED based CBs, where P_e denotes the maximum electrical power allotted to a user. Since from the literature we can understand that RED works as an important parameter for designing CB than MED, we have included RED in our optimization problem. Further, the authors in [33] introduced the concept of distance range (DR) based on the maximum and the minimum values of the RED. They have mentioned that for the low to medium SNR region, the BER is no longer dependent on just R-MED. The optimization problem proposed in [33] for CB designing is

$$\max_{d_{\min} > 0, d_{\max} > 0} \{d_{\min} - \alpha d_{\max}\} \quad (3.12a)$$

$$\text{s.t.} \quad L_i > 0, \quad \forall i \in [1, NMJ], \quad (3.12b)$$

$$\frac{1}{M} \text{Tr}(\mathbf{C}_j^T \mathbf{C}_j) \leq P_e, \quad \forall j \in [1, J], \quad (3.12c)$$

$$d_{ij} \geq d_{\min}, \quad \forall i < j, \quad (3.12d)$$

$$d_{ij} \leq d_{\max}, \quad \forall i < j, \quad (3.12e)$$

where $d_{\max}$ denotes the maximum value of RED, and $\alpha > 0$ denotes the weighting factor. The objective function shown in (3.12a) is dependent on $d_{\min}$ and $d_{\max}$. The real and positive optical signal constraint is considered in (3.12b) and maximum electrical power constraint is considered in (3.12c). All the REDs will lie between $d_{\min}$ and $d_{\max}$ (3.12d, 3.12e). Also, it is to be noted that, lesser the overlapping between the constellation points of a user, better the performance of the designed CBs.

3.3.2 The Objective Function

The objective function mentioned in (3.10) considers all the REDs while designing and optimizing the CBs to get optimum results. However, considering all the REDs makes the objective function non-convex and non-differentiable [135]. To solve (3.10), authors in [17] have proposed the objective function as shown in (3.12). It should be noted that the numerical methods used for solving the nonlinear max-min problem aim at approximating the $F(x) = \min_i f_i(x)$ by close enough smooth functions, and the closeness of approximation decide the nearness to optimal solutions [136]. If we consider $\sum_i \phi(f_i(x))$, the approximation to $F(x)$ becomes better when $\phi(\cdot)$ is a strong convex function (i.e., large positive second derivative). One approach to solve this non-convex problem is to use well known “log sum-exponentials” continuous approximation [137], [138]. With this approximation, the objective function in (3.10) transforms to

$$\min_{\mathbf{L} \in \mathbb{R}_{>0}^{NMJ \times 1}} \frac{1}{\beta} \ln \left\{ \sum_{i \neq j} e^{-\beta d_{ij}(\mathbf{L})} \right\}, \quad (3.13)$$

where $\beta > 0$ is a tuning parameter which results in the smoothness of (3.13) and affects the accuracy of the model.

The function in (3.13) is differentiable but still non-convex; however, optimization algorithms based on the derivation of the Hessian of the objective function can find the local optimal solution [139]. Also, if the objective function is optimized number of times with initialization from small set of random numbers and choosing the β parameter wisely, the likelihood of obtaining the global optimal solution increases [140]. Thus, the optimization problem is formulated as

$$\min_{\mathbf{L} \in \mathbb{R}_{>0}^{NMJ \times 1}} \frac{1}{\beta} \ln \left\{ \sum_{i \neq j} e^{-\beta d_{ij}(\mathbf{L})} \right\} \quad (3.14a)$$

$$\text{s.t.} \quad L_i > 0, \quad \forall i \in [1, NMJ], \quad (3.14b)$$

$$\frac{1}{M} \text{Tr}(\mathbf{C}_j^T \mathbf{C}_j) \leq P_e, \quad \forall j \in [1, J], \quad (3.14c)$$

where (3.14b) denotes the real positive intensity constraint of the transmitted codeword elements and (3.14c) denotes that the average electrical power of the generated codewords should be less than the maximum electrical power (P_e) allotted per user. The optimization problem in (3.14) can be solved using commercially available solvers like MATLAB’s *fmincon*. The procedure for solving the above optimization problem is summarized in **Algorithm 3**.

3.3.3 Complexity Analysis

For the case of the proposed optimization problem in (3.14), initially, the set of all multiplexed vectors (or superimposed codewords) $\mathbb{M}_v$ is computed. With J users and M number of codewords in the CB, the number of superimposed codewords obtained are M^J , i.e., $|\mathbb{M}_v| = M^J$. Since the complexity of operations such as addition and subtraction is $O(1)$ therefore, the complexity of computing multiplexed vectors is

Algorithm 3: SCMA CB Optimization Algorithm

Step 1: Initialization:

Randomly initialize $\mathbf{L} = \mathbf{L}^0$ satisfying the intensity and power constraints, $\beta = 1$.

Step 2: Optimization

1: **for** $\beta \leq 30$ **do**

2: (a) Solve the optimization problem $[f_v^{t'}, \mathbf{L}^{t'}] \leftarrow \min \frac{1}{\beta} \ln \left\{ \sum_{i \neq j} e^{-\beta d_{ij}(\mathbf{L})} \right\}$

subject to Constraints.

where $f_v^{t'}$ denotes the value of the objective function at the obtained solution $\mathbf{L}$ at t' th iteration.

3: (b)

4: **if** $|f_v^{t'} - f_v^{t'-1}| \geq 10^{-3}$; **then**

5: $t' = t' + 1$, go to **Step 2 (a)**;

6: **else**

7: **exit**

8: **end if**

9: **end for**

Output: $\mathbf{L}^{t'}$ as the SCMA output constellation stacked vector.

$O(JM^J)$. Next, for generating the covariance matrix (Σ_i for $\mathbf{s}_i$ superimposed code-word), each multiplexed vector is multiplied with the scalar ς^2 which results in the complexity $O(KM^J)$. The complexity of computing RED (as shown in (3.9)) between two multiplexed vectors is $O(K)$ as the length of each vector is K and the total number of multiplexed vectors are M^J . Thus, the total number of REDs between M^J multiplexed vectors is $\binom{M^J}{2}$ and the total complexity for calculating REDs will be $O(K \binom{M^J}{2})$. Next, the complexity of computing the objective function (3.14a) is $\binom{M^J}{2}$. The complexity of constraints in (3.14b) and (3.14c) is $O(1)$ since it includes addition and square operations. The maximum value of β at which the algorithm converges is denoted by β_{max} and number of iterations for the MATLAB's *fmincon* solver is N_{it} , then total complexity to generate the constellation matrices for J users using **Algorithm 3** is $O_{Logsum} = [\beta_{max} N_{it} (JM^J + KM^J + K \binom{M^J}{2} + \binom{M^J}{2} + 1)]$. If we take the most dominant part resulting for complexity, it is equal to $O(\beta_{max} N_{it} K \binom{M^J}{2})$.

In case of the DR based CB [33] optimization problem (as shown in (3.12)), the total complexity comes from the computation of the objective function and four constraints. The third and fourth distance based constraints (3.12d, 3.12e) are non-convex and are approximated using first order Taylor series [32]. From the calculation of multiplexed vectors, covariance matrices and REDs, the complexity is $O(JM^J + KM^J + K \binom{M^J}{2})$. The complexity of intensity and power constraints (3.12b, 3.12c) is $O(1)$. For the approximation of two non-convex constraints (3.12d, 3.12e), firstly the coefficient matrix Π_i is calculated to obtain multiplexed vector $\mathbf{s}_i$ from $\mathbf{L}$ [32], and its complexity is $M^J K N M J$. Next, we found that the derivative of RED has the highest complexity because of the kronecker product operation involved. The derivative term has the complexity $O((K N M J)^2 \binom{M^J}{2})$. So, with N_{out} as total number of outer loop iterations, the total complexity is $O_{DR} = [O(N_{out} N_{it} (JM^J + KM^J + K \binom{M^J}{2} + \binom{M^J}{2} + 1 + M^J K N M J + (K N M J)^2 \binom{M^J}{2}))]$. Taking only the dominant part, the complexity becomes $O(N_{out} N_{it} (K N M J)^2 \binom{M^J}{2})$. It can be observed that the proposed Log-sum-exp scheme (3.14) has reduced the computation complexity of SCMA CB design by a

significant amount from DR based CB optimization problem shown in (3.12).

3.3.4 Theoretical BER

SCMA is a multi-carrier scheme, i.e., the superimposed transmitted codeword $\mathbf{s}_i = [s_i^1, \dots, s_i^K]$ is a K dimensional real codeword as discussed in Section 3.2.1. In this section, the theoretical BER expression has been derived for the IDGN incorporated SCMA-VLC system. For only the thermal noise case, the PEP is given as (3.7). However, in the case of shot noise, the overall variance changes and is dependent on ς^2 and the intensity of the incident optical signal. The error rate for the superimposed codeword $\mathbf{s}_i$ is

$$P'(\mathbf{s}_i) = \sum_{\substack{i'=1 \\ i' \neq i}}^{M^J-1} P'(\mathbf{s}_i \rightarrow \mathbf{s}_{i'}) \quad (3.15)$$

$$= \sum_{\substack{i'=1 \\ i' \neq i}}^{M^J-1} Q \left(\sqrt{\sum_{k=1}^K \frac{\|s_i^k - s_{i'}^k\|^2}{2\nu_{i,k}}} \right), \quad (3.16)$$

where s_i^k and $s_{i'}^k$, denotes the k th element of the superimposed codeword $\mathbf{s}_i$ and $\mathbf{s}_{i'}$, respectively. The k th diagonal element of the covariance matrix Σ_i of the superimposed codeword $\mathbf{s}_i$ is denoted by $\nu_{i,k}$. The diagonal element $\nu_{i,k}$ denotes the total variance at k th RE when $\mathbf{s}_i$ was transmitted. The total probability of error is given as [141]

$$P_{err} = \frac{1}{J \log_2 M} \sum_{i=1}^{M^J} P_a(\mathbf{s}_i) \sum_{\substack{i'=1 \\ i' \neq i}}^{M^J-1} h_d(\mathbf{s}_{i'}, \mathbf{s}_i) P'(\mathbf{s}_i \rightarrow \mathbf{s}_{i'}), \quad (3.17)$$

where $P_a(\mathbf{s}_i)$ denotes the *a priori* probability of $\mathbf{s}_i$, $h_d(\mathbf{s}_{i'}, \mathbf{s}_i)$ denotes the bit error when $\mathbf{s}_{i'}$ is chosen over $\mathbf{s}_i$ and $P'(\mathbf{s}_i \rightarrow \mathbf{s}_{i'})$ denotes the PEP between $\mathbf{s}_i$ and $\mathbf{s}_{i'}$.

3.4 Results and Discussion

In this section, the simulation and theoretical results of the BER performance of the proposed SCMA CB are presented. Firstly, using **Algorithm 3**, we can generate the proposed CBs for different users. Further, Max-Log-MPA (as shown in **Algorithm 2**) has been used for multi-user detection.

For the initial simulation, we consider the case where three users share four REs with $M = 4$ and the number of non-zero elements in the codeword is $N = 2$. For three users, the CBs (DR based and Log-sum-exp based) are generated by solving the optimization problems (3.12, 3.14). For $J = 3$, **Algorithm 3** is found to be converging for low values of β (i.e., $\beta = 10$). Fig. 3.2. shows the 2-dimensional (2D) scatter plots of the generated DR based CBs (3.12) and the proposed Log-sum-exp based CBs (3.14) for $\varsigma^2 = 10$ and $P_e = 30$. It can be noted that the constellation points under DR criterion (3.12) are substantially overlapping as shown in Fig. 3.2(a)-3.2(c). However, the overlapping between proposed Log-sum-exp based constellation points for all three

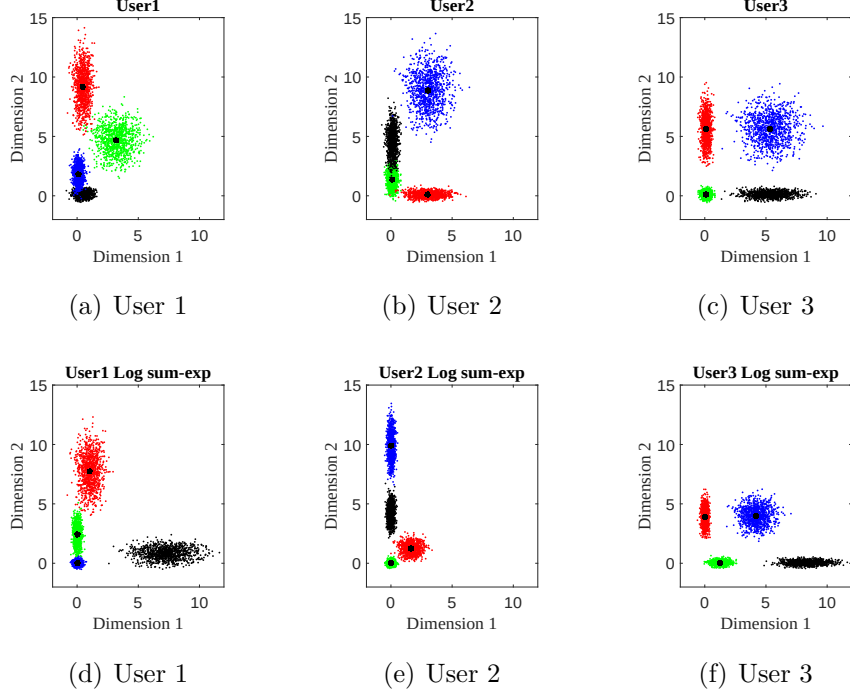


Figure 3.2: SCMA constellations scatter plots with $J = 3, K = 4, P_e = 30, \varsigma^2 = 10$ (a)-(c): DR based constellation sets, (d)-(f): Log-sum-exp based constellation sets.

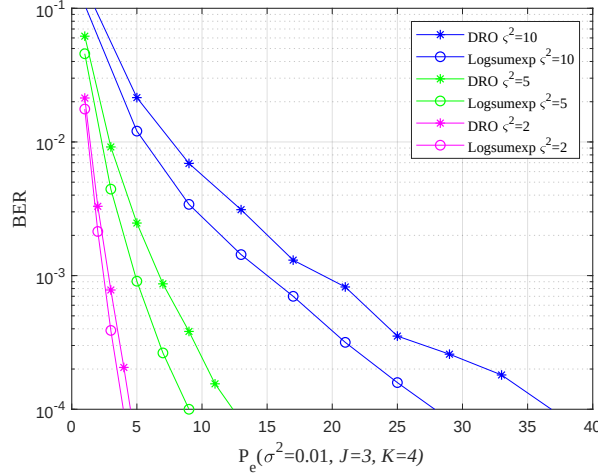


Figure 3.3: BER performance comparison for $J = 3$ between DR based CBs and Log-sum-exp CBs for $\sigma^2 = 0.01, M = 4$.

users is negligible as shown in Fig. 3.2(d)-3.2(f). As the overlapping increases between different constellation points, it becomes difficult for the receiver to detect the symbols correctly, and thus, the overall performance deteriorates.

Fig. 3.3 shows the bit error rate (BER) performance for three users of the proposed Log-sum-exp based (3.14) SCMA CBs and the DR based CBs (3.12), respectively. The negligible overlapping in the case of log-sum-exp CBs as compared to DR CBs (in Fig. 3.2), reasons the performance gain obtained in Fig. 3.3. For both CBs (DR based

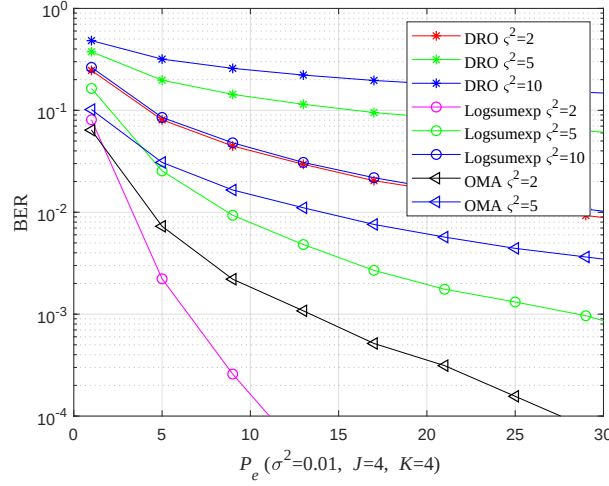


Figure 3.4: BER performance comparison for $J = 4$ between SCMA DR based CBs, Log-sum-exp CBs and OMA scheme for $\sigma^2 = 0.01$, $M = 4$.

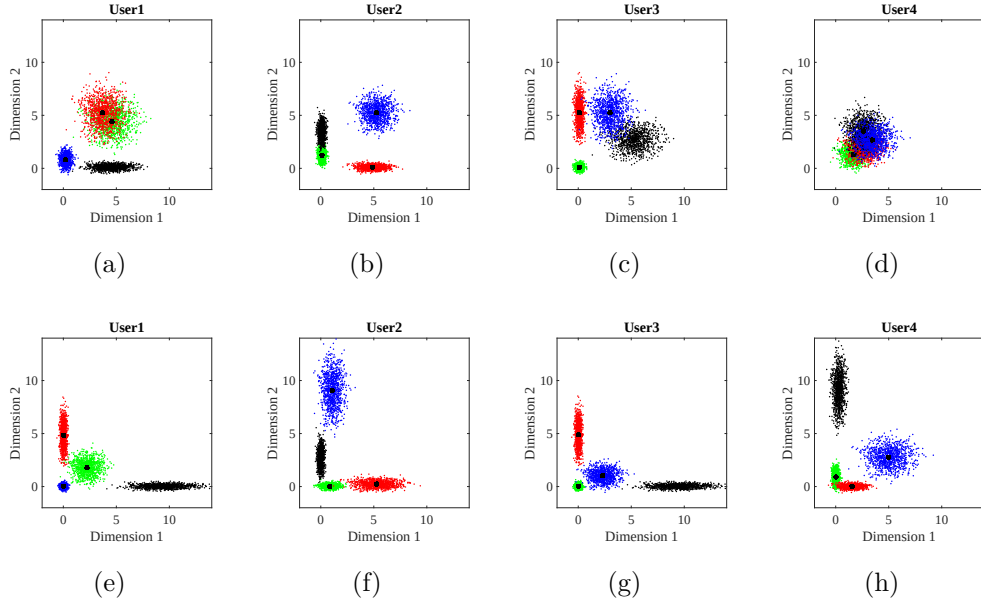


Figure 3.5: SCMA constellations with $J = 4, K = 4, P_e = 30, \zeta^2 = 10$ (a)-(d): DR based constellation sets, (e)-(f): Log-sum-exp based constellation sets.

and Log-sum-exp based), Max-Log-MPA (**Algorithm 2**) has been used for multi-user detection. It can be noticed that for the low value of ζ^2 (e.g., $\zeta^2 = 2$), BER performance of both CBs is close, and for high values of ζ^2 (e.g., $\zeta^2 = 5, 10$), the proposed Log-sum-exp based CBs yield better performance gain as compared to DR based CBs. This suggests that the objective function with all the REDs results in better CB (i.e., Log-sum-exp based CB) than the CB with only minimum and maximum values of REDs (i.e., DR based CB). It is shown that our proposed CBs achieve the BER of 10^{-3} at $P_e = 15$ while DR based CB achieve it at $P_e \approx 20$ for $\zeta^2 = 10$. This suggests that for large values of ζ^2 , the advantage of the proposed Log-sum-exp based CB is more significant than DR based CB.

Consider the case where four users share four REs. The Log-sum-exp based CB is designed for four users using **Algorithm 3**, and its performance is compared with DR based CB. Fig. 3.4 shows the BER performance of four users where Log-sum-exp based CB outperforms DR based CBs for different values of ζ^2 . The reason behind the performance difference can be understood from the level of overlapping between the constellation points for both CBs in Fig. 3.5. It can be observed in Fig. 3.5 that the DR based 2D constellation points suffer from significant overlapping, especially for user 1 (Fig. 3.5(a)) and user 4 (Fig. 3.5(d)), while Log-sum-exp based 2D constellation points are barely overlapping. This results in significant performance improvement for Log-sum-exp based CBs. Also in Fig. 3.4, the comparison with pulse amplitude modulation orthogonal multiple access (4 PAM-OMA) scheme is shown. It is noted that the proposed algorithm outperforms the OMA scheme for different values of ζ^2 . This is expected as the OMA scheme offers no frequency diversity in contrast to the SCMA scheme.

For five users, the complexity of generating DR based CB increases significantly. Further, the performance degrades drastically and requires a very high P_e at BER of 10^{-3} . Therefore, the effect of varying shot noise factor ζ^2 with only Log-sum-exp based CBs, when five users data is being transmitted over four REs ($\lambda = 5/4$) has been shown in Fig. 3.6(a). The BER performance with respect to increasing P_e is shown in Fig. 3.6(b) for six users. Here, the effect of varying shot noise factor ζ^2 is shown when the proposed Log-sum-exp based CBs have been used for transmitting data over four REs.

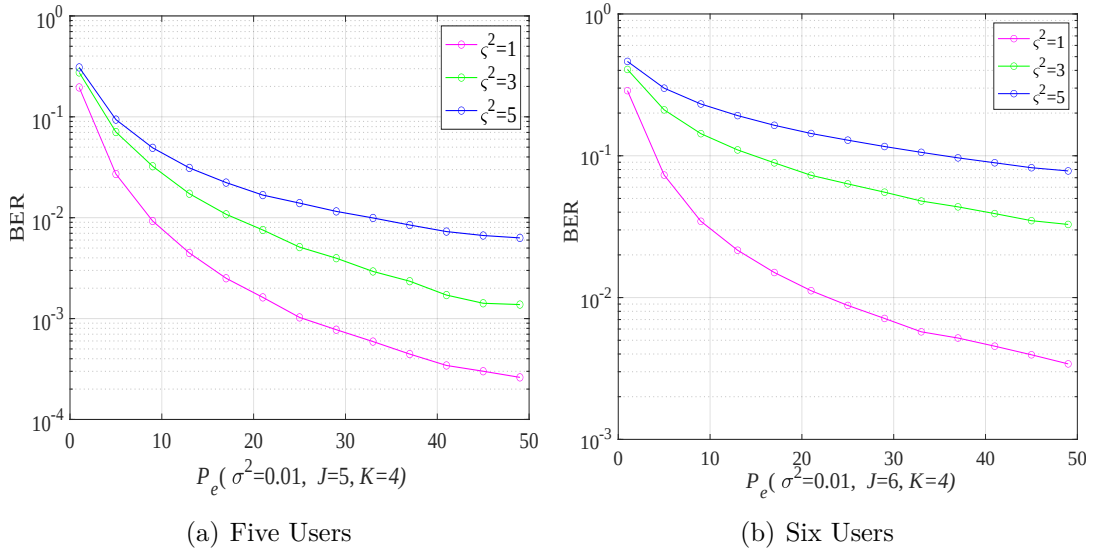


Figure 3.6: BER performance for (a) $J = 5$ (b) $J = 6$ for $\sigma^2 = 0.01$ and $M = 4$.

In Fig. 3.7, the theoretical and simulated BER performances are compared. We find that the simulated curves match with the theoretical curves, especially for the high signal power region. These results verify the correctness of the simulated results obtained in Fig. 3.3 and Fig. 3.4.

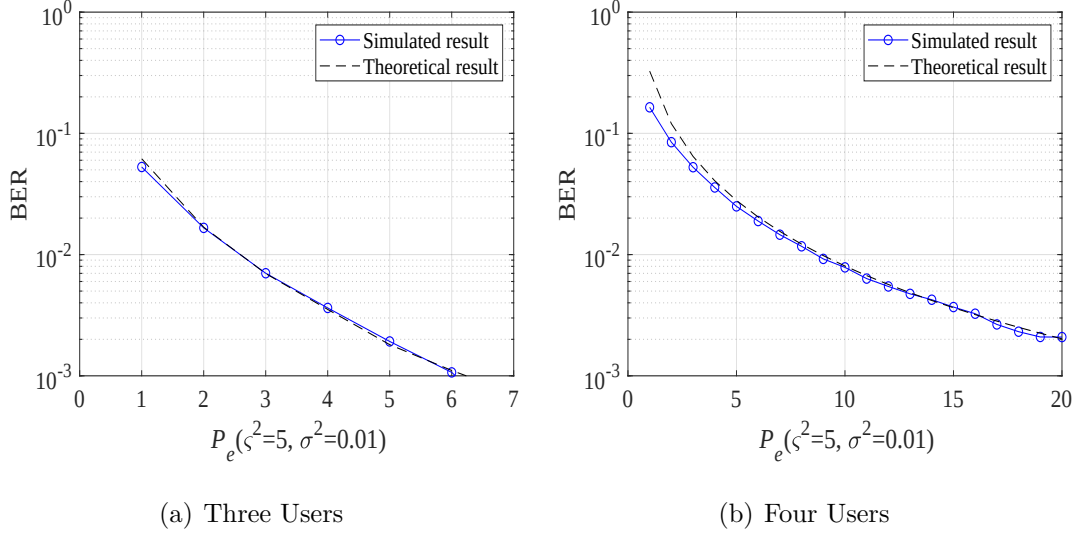


Figure 3.7: Theoretical and Simulated BER performance comparison for (a) $J = 3$ (b) $J = 4$ for $\zeta^2 = 5$, $\sigma^2 = 0.01$ and $M = 4$.

3.5 Conclusion

In this work, a novel low-complex CB design technique has been proposed for SCMA-VLC system impaired by shot noise. This work emphasizes that the designing of specific CBs is required for the SCMA-VLC system. The proposed CBs are generated by optimizing the Log-sum of exponentials of all REDs between the superimposed codewords. With the inclusion of shot noise in the SCMA system, the overall noise variance is dependent on the strength of the incident signal, as shown in **Algorithm 2**. The proposed CBs provide improved BER performance as compared to CBs proposed in the existing literature along with reduced complexity. Further, the theoretical analysis of BER is also performed for the shot noise incorporated SCMA-VLC system. The simulated results were validated, and both the theoretical and simulated curves are in good agreement for high signal power regions.

Chapter 4

Resource Allocation in SCMA-Aided IRS System

Intelligent reflecting surfaces (IRSs) have attracted tremendous research attention owing to their potential of supporting intelligent and more efficient wireless communications [142]. An IRS is a planar array made up of number of low cost intelligently controllable passive elements. These elements can passively reflect the incoming signals by smartly changing their amplitude and phase, etc. Thus, IRSs are capable of overcoming the problem of signal blockage in wireless systems, thus enabling a controllable and more reliable wireless propagation [143].

Motivated by the advantages of both SCMA and IRSs, the IRS-aided SCMA system can be a promising candidate to improve the performance for the next generation machine-centric communication networks. The proposed system model consists of an IRS-aided SCMA system in which users are in non-line-of-sight (NLoS) with the base station (BS) and thus are served using IRS. The aim is to maximize the sum-rate of this system considering the constraints of IRS, BS, and SCMA. However, the formulated optimization problem is non-convex which is hard to solve. This is because the optimization problem is a combination of different optimization variables, such as the phase vector of IRS, transmit power and FGM variables. Thus, enhanced algorithms are needed to optimize the IRS-assisted SCMA systems. Further, it is important to consider both channel state information (CSI) and fairness parameters in the optimization problem, as each user experiences different channel fading. So far, few works have investigated IRS-aided SCMA systems [80–82]. A satisfactory solution to the sum-rate optimization problem considering the multi-user interference in the IRS-aided SCMA system is not known, to the best of our knowledge. In this chapter, our aim is to maximize the sum-rate in a downlink IRS-aided SCMA system by optimizing the FGM, power allocation, IRS reflection matrix, and choose the appropriate IRS deployment.

4.1 System Model and Problem Formulation

As shown in Fig. 4.1, a downlink $(K \times J)$ IRS-aided SCMA system is considered, which consists of a BS, J single-antenna users communicating over K REs and an IRS equipped with N reflection elements. Each user is given a CB of size $K \times M$, where M is the number of K -dimension codewords in the CB. Such a CB may be denoted

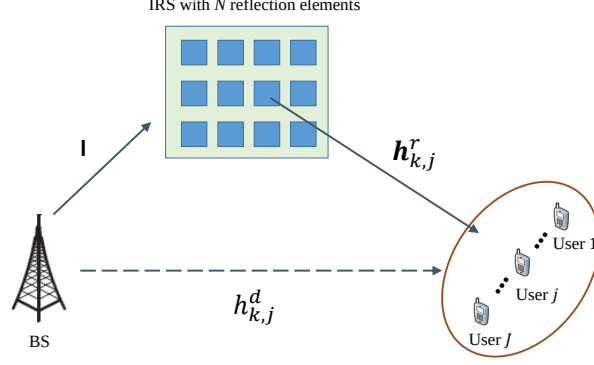


Figure 4.1: The system model of an IRS-aided SCMA system with J users.

by $\mathcal{X}_j, \forall j \in J$, and each CB satisfies $\text{Tr}(\mathcal{X}_j \mathcal{X}_j^H) = M$. The SCMA encoder selects a column of $\mathcal{X}_j$ for user j , corresponding to the input message $\mathbf{b}_j$.

Practically, the IRS is managed by an intelligent controller connected to the BS. The IRS-assisted link suffers from “double fading” effect [145, 146]. Let $\Theta = \text{diag}(\boldsymbol{\theta}) \in \mathbb{C}^{N \times N}$ denote the IRS reflection coefficients matrix with $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_N]$ and $\theta_n = \exp^{j\phi_n}$, where $\phi_n \in [0, 2\pi)$ denotes the reflection phase shift of the n th IRS reflecting element, and j denote the imaginary unit. The baseband equivalent channels at RE k between BS and user j , between IRS and user j at RE k , and between BS and IRS are denoted by $h_{k,j}^d \in \mathbb{C}^{1 \times 1}$, $\mathbf{h}_{k,j}^r \in \mathbb{C}^{N \times 1}$, and $\mathbf{l} \in \mathbb{C}^{1 \times N}$ respectively. All the channel fading vectors are assumed to be independent complex Gaussian random variables. It is assumed that all the required CSI is available at the BS. The signal received at RE k is

$$\begin{aligned} y_k &= \sum_{j=1}^J h_{k,j}^d f_{k,j} x_{k,j} + \sum_{j=1}^J (\mathbf{l} \Theta \mathbf{h}_{k,j}^r) f_{k,j} x_{k,j} + n_k, \\ &= \sum_{j=1}^J (h_{k,j}^d + \mathbf{l} \Theta \mathbf{h}_{k,j}^r) f_{k,j} x_{k,j} + n_k, \end{aligned} \quad (4.1)$$

where $x_{k,j}$ denotes the codeword element of the j th user on k th RE, $f_{k,j} = 1$ indicates that user j has active power transmission over RE k (otherwise, no power transmission), and $n_k \sim \mathcal{CN}(\mathbf{0}, \sigma^2)$ denotes the additive white Gaussian noise (AWGN) at the k th RE. The j th user considers the signals from all the other users (i.e., $x_{k,1}, \dots, x_{k,j-1}, x_{k,j+1}, \dots, x_{k,J}$) as interference on the k RE. Thus, the decoding SINR of $x_{k,j}$ at RE k and user j is given as:

$$\gamma_{k,j} = \frac{|(h_{k,j}^d + \mathbf{l} \Theta \mathbf{h}_{k,j}^r)|^2 E(x_{k,j}^2)}{\sum_{\substack{i \in S_k \\ i \neq j}} |(h_{k,i}^d + \mathbf{l} \Theta \mathbf{h}_{k,i}^r)|^2 E(x_{k,i}^2) + \sigma^2}, \quad (4.2)$$

where S_k denotes the set of users communicating at the k RE.

4.1.1 Problem Formulation

The goal is the maximization of the sum-rate by jointly optimizing the FGM, transmit power allocation, and the reflection matrix at IRS, taking into account the constraints

of transmit power, minimum data requirement of the users, IRS constraints, and SCMA CB structure. The power allocation matrix can be expressed as $\mathbf{P} = (p_{k,j})_{K \times J}$, where the power allocated to user j on RE k is $p_{k,j}$. Also, we believe that choosing the FGM based on the system scenario improves the performance. Mathematically, the formulated sum-rate optimization problem is given as:

$$\mathcal{P}(\text{A}) : \max_{\mathbf{F}, \mathbf{P}, \boldsymbol{\theta}} f_{\text{A}}(\mathbf{F}, \mathbf{P}, \boldsymbol{\theta}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (4.3a)$$

$$\text{s.t. } |\theta_n| = 1, \quad \forall n \in [1, N], \quad (4.3b)$$

$$\sum_{k=1}^K \sum_{j=1}^J f_{k,j} p_{k,j} \leq P_{\text{tot}}, \quad (4.3c)$$

$$\sum_{k=1}^K \log_2(1 + \gamma_{k,j}) \geq R_{\text{min}}, \quad (4.3d)$$

$$p_{k,j} \geq 0, \quad \forall 1 \leq k \leq K, 1 \leq j \leq J, \quad (4.3e)$$

$$\sum_{j=1}^J f_{k,j} \leq d_f, \quad \forall k \in K, \quad (4.3f)$$

$$\sum_{k=1}^K f_{k,j} \leq d_v, \quad \forall j \in J, \quad (4.3g)$$

$$\mathbf{F}_j \neq \mathbf{F}_{j'}, \quad \forall j \neq j' \in J, \quad (4.3h)$$

$$f_{k,j} \in \{0, 1\}, \quad \forall 1 \leq k \leq K, 1 \leq j \leq J, \quad (4.3i)$$

where $\gamma_{k,j}$ is as defined in (4.2), P_{tot} denotes the total transmit power at the BS, R_{min} is the minimum rate requirement of the user. Constraint (4.3b) represents the unit modulus constraint for the IRS reflection coefficient, constraint (4.3c) is the total transmit power constraint of BS and constraint (4.3d) guarantees the rate fairness among all users. Constraint (4.3f) limits the maximum number of signals multiplexed on each RE, constraint (4.3g) denotes a codeword has maximum d_v number of non-zero values, and constraint (4.3h) denotes that no two columns of the FGM are same, and constraint (4.3i) denotes that each element of the FGM is either zero or one.

The optimization problem in $\mathcal{P}(\text{A})$ is a highly-coupled non-convex problem, making it hard to find the global optimal solution [147]. Next, we propose the AO based algorithms to find an efficient suboptimal solution.

4.2 Alternating Optimization

The main idea of the AO approach is to divide the optimization problem into several subproblems and are alternately optimized. Each subproblem is solved under some constraints, while other subproblems remain at their last updated values [148–150]. In our case, we divide the problem in (4.3) into three subproblems, i.e., FGM assignment, power optimization, and the IRS phase optimization, and solve using AO based algorithm. Firstly, an algorithm based on the channel gain of REs is proposed for solving the FGM assignment subproblem. Next, the power allocation subproblem is solved using a low complexity Lagrange dual decomposition method. Finally, we use the RCG

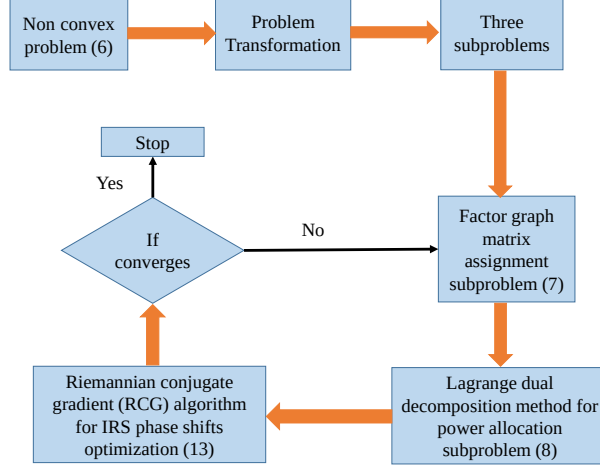


Figure 4.2: The flow chart of the proposed AO-based method for solving problem (4.3).

algorithm to optimize the IRS phase shifts. Our proposed approach is shown in a flow chart in Fig. 4.2.

4.2.1 Factor graph matrix assignment

For a given power $\mathbf{P}$, and phase vector $\boldsymbol{\theta}$, (4.3) is given as:

$$\mathcal{P}(A1) : \max_{\mathbf{F}} f_{A1}(\mathbf{F}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (4.4a)$$

$$\text{s.t. } (4.3f), (4.3g), (4.3h), (4.3i). \quad (4.4b)$$

To solve the FGM assignment subproblem $\mathcal{P}(A1)$ in (6.11), a low complexity algorithm is proposed. The proposed algorithm makes use of the instantaneous channel gains or CSI.

The objective of **Algorithm 4** is to design $\mathbf{F}$ by taking advantage of the channel information. In this algorithm, initially, we consider a FGM with all values equal to one and calculate the SINR as shown in (4.2) for each $1 \leq k \leq K, 1 \leq j \leq J$. The SINR matrix is given as $\mathbf{S} = (\gamma_{k,j})_{K \times J}$. Then, the root mean square (RMS) of all the users is calculated and sorted in the descending order. Starting with the user with the highest RMS value, we select d_v number of REs with the highest SINR among all available REs and then assign those to the corresponding user. The sparsity of the resultant factor graph is maintained by selecting only d_v number of REs in each step. We then repeat the similar procedure for the next highest RMS value user until all the users are assigned to the corresponding REs, considering the constraints shown in (4.3f, 4.3g, 4.3h).

Algorithm 4: The FGM assignment algorithm

Inputs:
 J : Number of users.

 K : Number of REs.

 d_f : Degree of each RN.

 d_v : Degree of each UN.

 $\mathbf{H}_{\text{tot}}$: Overall channel gain matrix of size $K \times J$ from direct and IRS-assisted path.

Output:
 $\mathbf{F}$: Binary FGM.

Initialize:

Initialize $\mathbf{F}_{\text{ini}}$ with all values equal to one, and $\mathbf{F}$ with all values equal to zero.

- 1: Calculate the SINR $\mathbf{S} = (\gamma_{k,j})$ for all $1 \leq k \leq K, 1 \leq j \leq J$.
 - 2: Calculate the average RMS value, $\mathbf{r}$ of $\mathbf{S}$ along first dimension for each user .
 - 3: Sort $\mathbf{r}$ in the descending order.
 - 4: **for** $i = 1 : J$ **do**
 - 5: For the $\mathbf{S}$ column with index $\mathbf{r}(i)$, find the d_v largest values.
 - 6: For the d_v largest values chosen in step 5, set their corresponding indices in $\mathbf{F}$ equal to one.
 - 7: **if** $\mathbf{F}_i \neq \mathbf{F}_j$ or $\sum_{j=1}^J \mathbf{F}_{k,j} \leq d_f, \forall k \in K$ **then**
 - 8: Set the largest value of $\mathbf{S}$ in the column with index $\mathbf{r}(i)$ equal to zero.
 - 9: Go to Step 5, and choose the index of next d_v largest values.
 - 10: **end if**
 - 11: **end for**
-

4.2.2 Power Allocation

Given phase vector of the IRS $\boldsymbol{\theta}$ and $\mathbf{F}$, (4.3) is given as:

$$\mathcal{P}(\text{A2}) : \max_{\mathbf{P}} f_{\text{A2}}(\mathbf{P}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (4.5a)$$

$$\text{s.t. } (4.3c), (4.3d), (5.8f). \quad (4.5b)$$

With given $\boldsymbol{\theta}$, the channel gain between BS to IRS, IRS to users, and BS to users becomes fixed. This simplifies the given optimization problem in (6.13), but it still remains to be a non-convex problem [151]. The Lagrange dual decomposition method is used to find a near-optimal solution for the subproblem (6.13). The Lagrangian of (6.13) is given as

$$L(\{\mathbf{P}\}, \boldsymbol{\lambda}, \mu) = \sum_{j=1}^J \left[(1 + \lambda_j) \sum_{k=1}^K \log_2(1 + \gamma_{k,j}) - \lambda_j R_{\min} \right] + \mu \left(P_{\text{tot}} - \sum_{k=1}^K \sum_{j=1}^J p_{k,j} \right), \quad (4.6)$$

where $\boldsymbol{\lambda} = \{\lambda_1, \dots, \lambda_J\}$, λ_j and μ are the Lagrange dual variables of user j . The dual problem in (4.6) is called the unconstrained maximization of the Lagrangian function. Thus, dual objective is $\mathcal{G}(\boldsymbol{\lambda}, \mu) = \max_{\{\mathbf{P}\}} L(\{\mathbf{P}\}, \boldsymbol{\lambda}, \mu)$, and the dual problem is given as

$$\min_{\boldsymbol{\lambda}, \mu} \mathcal{G}(\boldsymbol{\lambda}, \mu) \quad (4.7a)$$

$$\text{s.t. } \boldsymbol{\lambda}, \mu \succcurlyeq 0 \quad (4.7b)$$

Applying the KKT conditions [152] on (4.7), the next step is to differentiate the Lagrangian in (4.6) with respect to $p_{k,j}$ and then the result is made equal to zero. Next, we get the following expression

$$\frac{(1 + \lambda_j) g_{k,j}}{\ln(2) \cdot (1 + \sum_{i \in S_k} p_{k,i} g_{k,i})} + \text{negative terms} = \mu, \quad (4.8)$$

where $g_{k,j}$ is the normalized channel gain at user j and RE k . The negative terms arise because of the multi-user interference, which can be efficiently eliminated by designing CB wisely, and thus, the negative terms in (4.8) become negligible. The power allocated to user j at RE k can be expressed as

$$\hat{p}_{k,j} = \left[\frac{(1 + \lambda_j)}{\mu \ln(2)} - \frac{1}{1 + \sum_{\substack{i \in S_k \\ i \neq j}} \frac{g_{k,i}}{p_{k,i}}} \right]^+, \quad (4.9)$$

where $[x]^+$ represents $\max(0, x)$ operation. Thus, to solve the problem in (6.13) using Lagrange dual decomposition, firstly $p_{k,j}$ is substituted from (4.9) into the Lagrangian function $L(\{\mathbf{P}\}, \boldsymbol{\lambda}, \mu)$ given in (4.6). Then, the Lagrangian function becomes a function of only Lagrangian multipliers, and the dual problem shown in (4.7) may be solved using solvers such as MATLAB's *fmincon*. This gives the optimal value of Lagrange multipliers. Substituting the values of Lagrangian multipliers in (4.9) gives the power allocated $p_{k,j}$ at user j and RE k . Since the optimization problem (6.13) is non-convex, a duality gap exists, but as the number of frequency carriers increase, it is nearly zero [151].

4.2.3 Phase Optimization

Given $\mathbf{F}$ and $\mathbf{P}$, the original optimization problem in (4.3) is given as follows:

$$\mathcal{P}(\text{A3}) : \max_{\boldsymbol{\theta}} f_{\text{A3}}(\boldsymbol{\theta}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (4.10a)$$

$$\text{s.t. (4.3b).} \quad (4.10b)$$

The non-convex modulus constraints in (4.3b) makes problem (4.10) difficult to solve. The search space of problem $\mathcal{P}(\text{A3})$ is the product of unit modulus circles in the complex plane, which is a Riemannian submanifold with the product geometry, and its stationary solution can be obtained using the RCG algorithm [153]. The RCG algorithm was used for precoder design [154] and for phase optimization in the IRS system [155–157]. For ease of representation, we define $\mathbf{H}_{k,j}^r = \text{diag}(\mathbf{1}) \mathbf{h}_{k,j}^r$, as the effective channel for the IRS link. Thus, (6.6) is given as

$$\gamma_{k,j} = \frac{|h_{k,j}^d + \boldsymbol{\theta} \mathbf{H}_{k,j}^r|^2 E(x_{k,j}^2)}{\sum_{\substack{i \in S_k \\ i \neq j}} |h_{k,i}^d + \boldsymbol{\theta} \mathbf{H}_{k,i}^r|^2 E(x_{k,i}^2) + \sigma^2}. \quad (4.11)$$

A manifold $\mathcal{M}$ is a topological space in which each point's neighborhood is homeomorphic to the Euclidean space [153]. A homeomorphism is a continuous function between topological spaces that has a continuous inverse function. The examples of manifolds are line, circle, sphere, parabola, hyperbola, etc. A Riemannian manifold is a manifold whose tangent spaces are endowed with a positive-definite inner product. This characterizes the direction which produces the steepest increase at z .

In the RCG algorithm, firstly, a set of conjugate directions is generated, and then search to find the minimum value of the objective function. The problem $\mathcal{P}(\text{A3})$ can be solved using the RCG algorithm in the following three steps:

1. Compute Riemannian Gradient: The orthogonal projection of Euclidean gradient onto the tangent space is called Riemannian gradient. The Riemannian gradient of (4.10a) is

$$\text{grad}f_{\text{A3}} = \Delta f_{\text{A3}} - \text{Re}\{\Delta f_{\text{A3}} \circ \boldsymbol{\theta}^*\} \circ \boldsymbol{\theta},$$

where Δf_{A} is the Euclidean gradient.

2. Search direction: The search direction can be found as the tangent vector conjugate to $\text{grad}f_{\text{A}}$:

$$\mathbf{d} = -\text{grad}f_{\text{A3}} + \tau \mathcal{T}(\bar{\mathbf{d}}), \quad (4.12)$$

where τ is the conjugate gradient update parameter, $\bar{\mathbf{d}}$ is the previous search direction, and $\mathcal{T}(\cdot)$ is the transport function given as

$$\mathcal{T}(\mathbf{d}) = \bar{d} - \text{Re}\{\mathbf{d} \circ \boldsymbol{\theta}^*\} \circ \boldsymbol{\theta}.$$

3. Retraction: As a point moves alongside the tangent vector, it might not stay on the manifold. The tangent vector can be mapped back to the complex circle manifold using retraction operation as

$$\theta_n \leftarrow \frac{(\theta + \tau_2 \mathbf{d})_n}{|(\theta + \tau_2 \mathbf{d})_n|} \quad (4.13)$$

where τ_2 denotes the step size obtained by Armijo backtracking line search to guarantee the objective function (4.10a) to be non-decreasing [153, 158].

After following the above steps in each iteration, the RCG algorithm converges for problem $\mathcal{P}(\text{A3})$ where the Riemannian Gradient will be equal to zero.

4.2.4 Complexity Analysis

The AO approach is an iterative algorithm. Each iteration involves three subproblems for solving $\mathbf{F}$, $\mathbf{P}$, and $\boldsymbol{\theta}$. The complexity of the Riemannian conjugate gradient (RCG) method for phase optimization is mainly dependent on computing the Euclidean gradient and retraction step [150]. The complexity of computing the Euclidean gradient is $O(J^2 N^2)$, and the complexity of the retraction step is $O(J^2 N)$ and can be ignored for large values of N . Further, the complexity of the power allocation algorithm is

dependent on solving the dual problem. The complexity of solving the dual problem is $O(I_f(Jd_v))$, where I_f is the number of iterations required to compute the dual variables. The complexity of Algorithm 4 for FGM assignment is dependent on the number of users and on the channel conditions. In Algorithm 4, d_v REs with best channel conditions are chosen for one user, which will be indexed with value one for that user. Assuming the complexity of choosing d_v REs for each user with best channel conditions is $O(a1)$. If for another user, the indices for current d_v values do not match with any of the prior users, then the complexity will be $O(a1)$. In case the indices match, then the next highest d_v values are chosen, then the complexity increases by $O(a1)$. Every time the indexes match with any other user, the complexity increases by $O(a1)$. Thus, the overall complexity is constant value times the number of users, and so is proportional to $O(J)$. Thus, the overall complexity of the AO algorithm is $O(I_o(I_R J^2 N^2 + I_f J d_v + J))$, where I_o is the number of iterations of the AO algorithm, and I_R is the number of the iterations of the RCG algorithm, respectively.

4.3 Results and Discussion

In this section, the performance of the proposed algorithms in Section III is evaluated. The simulation setup consists of one access point (AP) located at (0 m, 0 m), an IRS at (200 m, 0 m), and J users being served by AP and IRS, as shown in Fig. 4.3. The users are uniformly and randomly distributed in a circle of radius 20 m, and the center of the circle is at (200 m, 30 m). The line-of-sight (LoS) component is present for the AP-IRS channel, and the channel between user and IRS. The channel gains of both LoS and NLoS are modeled using the 3GPP propagation environment [159]. The antenna gains at the receiver and transmitter are denoted as G_r and G_t , and the channel gain is denoted as β . Assuming that $h_{k,j}^d$ follows the Rayleigh fading, and the IRS based channels (i.e., between AP and IRS, and between IRS and user) follow Rician fading. The NLoS components are denoted as $\bar{\mathbf{I}}$ and $h_{k,j}^{\bar{r}}$. Thus, the fading variables $h_{k,j}^d, \bar{\mathbf{I}}$, and $h_{k,j}^{\bar{r}}$ are calculated in every frame. We compute the sum-rate of the IRS-aided SCMA system, when the FGM is fixed, power is uniformly distributed, and the IRS phase vector is randomly generated with the magnitude of one. This is considered the baseline case. The minimum rate for each user is 0.1 bps/Hz at the total transmit power of 30 dBm. Next, we analyze the performance of the proposed optimization algorithms in the simulation setup of 4×6 and 5×10 SCMA block, respectively. In case of 4×6 block, six users communicate over four REs, and thus the overloading factor is $\lambda = J/K = 6/4 = 1.5$. Similarly, in the case of 5×10 block, ten users communicate over five REs, and thus the overloading factor is $\lambda = J/K = 10/5 = 2$.

4.3.1 Sum-Rate Analysis for 4×6 SCMA Block

All the simulation curves are generated by averaging over 10^4 randomly and independently realizations of small-scale channel fading. Fig. 4.4 shows the sum-rate of the proposed algorithms with respect to the total transmit power for $J = 6, K = 4$ and $N = 100$. It is to be noted that the baseline with random phase vector, fix FGM and uniform power allocation shows negligible performance gain when no IRS is deployed. Then, we have shown the effect of introducing the proposed schemes gradually. Firstly,

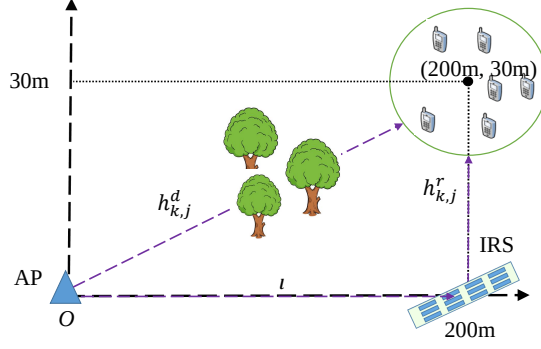


Figure 4.3: Simulated IRS-assisted SCMA communication system consisting of an AP, J number of users and one N -element IRS.

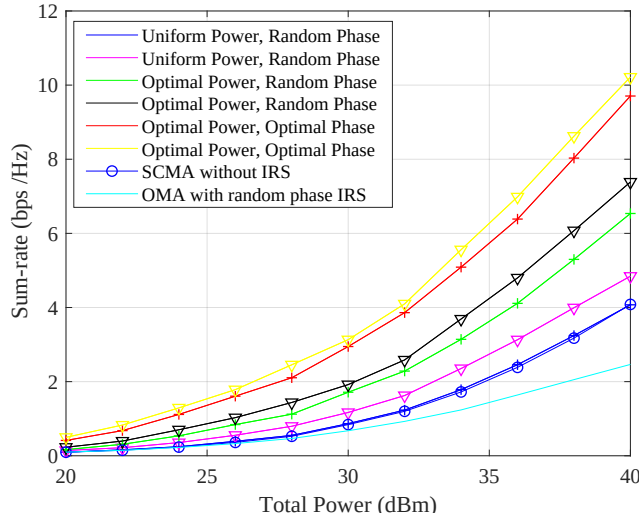


Figure 4.4: Sum-rate versus transmit power for IRS-aided SCMA system with $K = 4$, $J = 6$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘▷’ denotes the proposed $\mathbf{F}$ using **Algorithm 4**.

for a uniform power and random phase vector at IRS, we optimized the FGM using **Algorithm 4**. With this, the sum-rate performance improved as compared to baseline as power increases. Next, we have shown the effect of power allocation (as shown in (4.9)) with random and proposed FGM and random phase vectors at IRS. Next, we optimized the phase vector using the RCG algorithm and shown the performance for random and proposed FGM, proposed power allocation and optimized phase vector of IRS. It is evident that the proposed AO scheme notably improve the sum-rate, especially as the transmit power increases.

Fig. 4.5 shows the sum-rate performance with respect to N , assuming the total power is equal to 30 dBm. The sum-rate with proposed power and FGM is significantly higher than the baseline case. It is noted that when the IRS has random phase, sum-rate improvement can be seen by a small value as compared to optimized phases with increasing N . Next, the effect of the IRS deployment on the sum-rate is shown. The horizontal distance between IRS and AP is denoted by D_{AI} . The users are generated randomly over 100 snapshots and 1000 small-scale channel realizations are generated for each snapshot. Fig. 4.6 illustrates the impact on the sum-rate with change in D_{AI} at $P_{tot} = 40$ dBm and $N = 100$. It is to be noted that, as D_{AI} is increased from

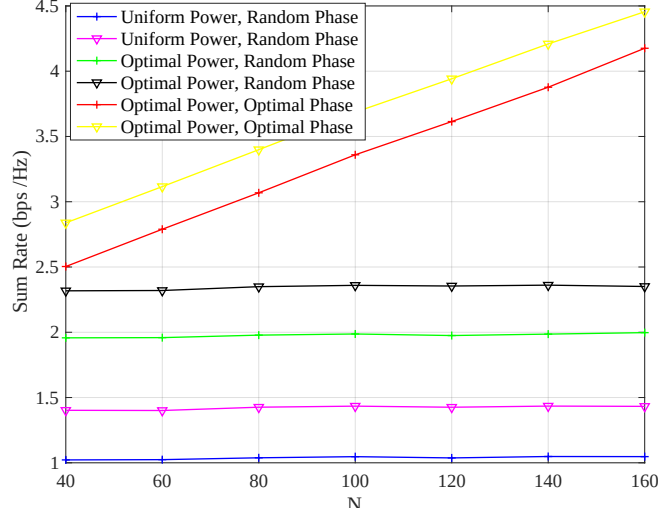


Figure 4.5: Sum-rate versus N for $J = 6$ and $K = 4$ with total transmit power = 30 dBm, where ‘+’ denotes the fix $\mathbf{F}$ and ‘v’ denotes the proposed $\mathbf{F}$ using **Algorithm 4**.

200 m to 220 m, the sum-rate decreases. The reason is that the combined path-loss of the IRS link $\mathbf{H}_{k,j}^r$ increases, as D_{AI} increases. However, when D_{AI} decreases from 200 m to 120 m, the sum-rate increases firstly but later decreases. The reason being, although the distance through IRS-assisted link decreases, the propagation conditions might not have improved. The optimal location of IRS is found to be $D_{AI} = 190$ m.

4.3.2 Sum-Rate Analysis for 5×10 SCMA Block

In this subsection, we consider the SCMA block of $K = 5, J = 10, \lambda = J/K = 2$, i.e., 10 users are concurrently transmitting data over 5 REs. An example of the factor graph matrix corresponding to 5×10 SCMA block is [160]

$$\mathbf{F}_{5 \times 10} = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}. \quad (4.14)$$

Fig. 4.7 shows the sum-rate of the methods proposed in Section III with respect to the total transmit power for $J = 10, K = 5$, and $N = 100$. In this case, the total transmit power is divided among ten users, so power allotted per user is less than for $J = 6$ block, and d_f increases to 4. Similar to previous, here as well, the curves are generated by averaging the sum-rate over 10^4 independent channel realizations of small-scale fading. It is to be noted that, the baseline with random phase vector, FGM and uniform power allocation shows negligible performance gain than the case when no IRS is deployed. Next, using the proposed alternate optimization scheme, the sum-rate for 5×10 SCMA block significantly improves.

Fig. 4.8 shows the sum-rate for 5×10 SCMA block with respect to N , assuming the total power to be 30 dBm. The sum-rate with the proposed power and FGM is significantly higher than the baseline case. However, the sum-rate does not improve

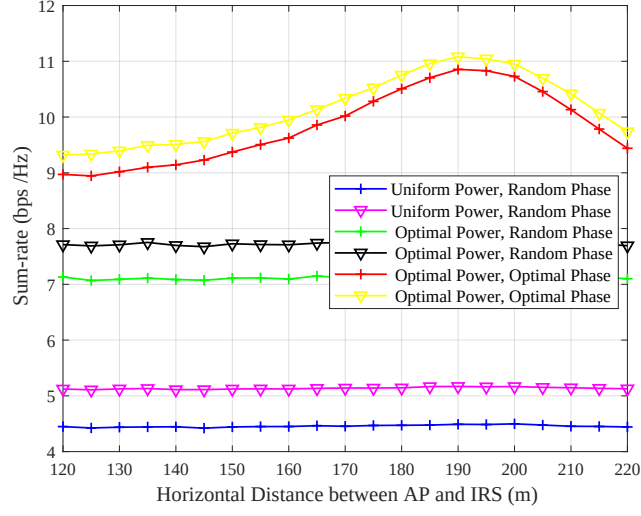


Figure 4.6: Sum-rate versus the horizontal distance between IRS and AP with total transmit power of 40 dBm, $J = 6, K = 4$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘ $\triangleright$ ’ denotes the proposed $\mathbf{F}$ using **Algorithm 4**.

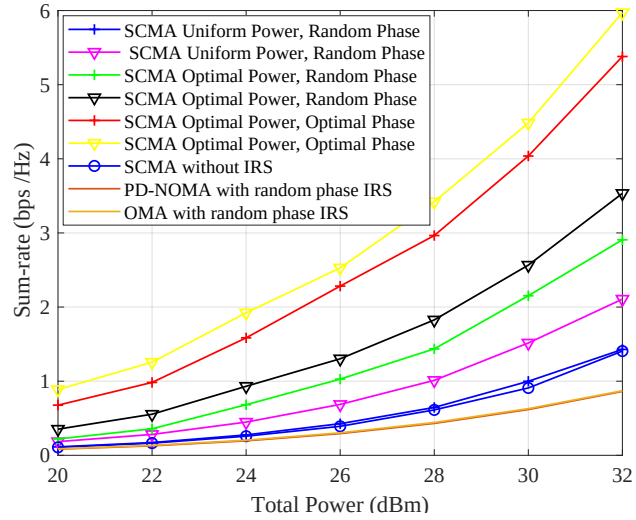


Figure 4.7: Sum-rate versus total power for IRS-aided SCMA system with $J = 10, K = 5$ and $N = 100$, where ‘+’ denotes the fix $\mathbf{F}$ and ‘ $\triangleright$ ’ denotes the proposed $\mathbf{F}$ using **Algorithm 4**.

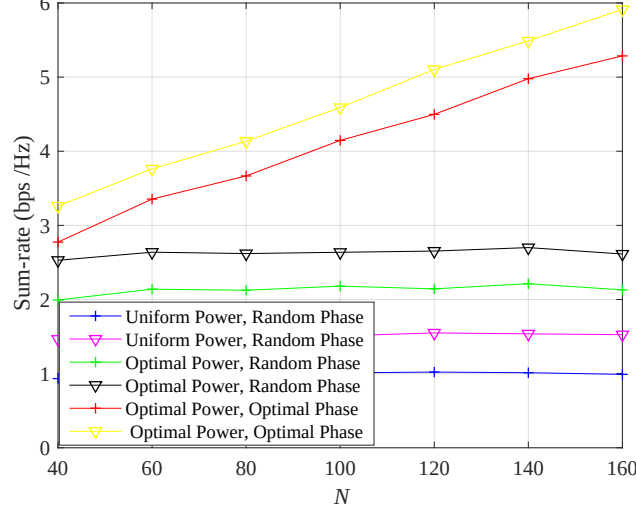


Figure 4.8: Sum-rate versus N for $J = 10$ and $K = 5$ with total transmit power = 30 dBm, where ‘+’ denotes the fix $\mathbf{F}$ and ‘v’ denotes the proposed $\mathbf{F}$ using **Algorithm 4**.

with the increase in N because of the random phase vector, even with optimized power and FGM. When the IRS phase vector is optimized using the RCG algorithm, the sum-rate increases with N . Table 4.1 shows the performance of the proposed AO based algorithm with respect to different iterations at the total power of 30 dBm. In each iteration, we solved three sub-problems S1 to S3, each for FGM ($\mathbf{F}$) assignment, power allocation ($\mathbf{P}$), and phase optimization ($\boldsymbol{\theta}$). Specifically, we have shown the effect of each proposed schemes, and it is seen that with increasing iterations, the sum-rate performance converges.

Table 4.1: Performance of AO algorithm in terms of sum-rate with increasing number of iterations.

Proposed Scheme	Iter. 1	Iter. 2	Iter. 3	Iter. 4	Iter. 5
S1: Initial phase, Initial power, Proposed $\mathbf{F}$	1.14	3.17	4.02	4.037	4.043
S2: Initial phase, Lagrange based allocated power, Proposed $\mathbf{F}$	1.92	3.964	4.028	4.041	4.044
S3: Optimized IRS phases, Lagrange based allocated power, Proposed $\mathbf{F}$	3.17	4.02	4.037	4.043	4.045

4.4 Conclusion

This work investigated the sum-rate in IRS-aided downlink SCMA system. In particular, we formulated a joint power, FGM, and IRS phase optimization problem in order to maximize the sum-rate, subject to the constraints of the SCMA CB structure, transmit power, minimum rate and IRS coefficients. The formulated problem is MINLP and hard to solve. We have proposed to solve the joint optimization problem using AO method by dividing the main problem into three sub-problems. In the first place, an al-

gorithm based on available CSI is proposed to solve the FGM assignment sub-problem under FGM constraints. Then, for a given the FGM, we have utilized the Lagrangian dual decomposition method for power allocation. Lastly, we have optimized the IRS phase vector using RCG algorithm for maximizing the system's sum-rate. It is shown using the simulation results that the proposed algorithms outperform by optimizing the FGM, power at the BS, and phase vector of the IRS. Also, it is seen from the results that the proposed IRS-aided SCMA system performs better than the SCMA system without the IRS.

Chapter 5

Sum-Rate Maximization of SCMA-Aided UAV System

Recently, unmanned aerial vehicles (UAVs) have found wide applications in a number of use cases, such as forest fire detection, emergency search and rescue, traffic controls, etc [162]. UAVs are also expected to play a crucial role in the next-generation wireless communication systems [38]. UAV-assisted networks offer various advantages compared to the conventional communication systems that heavily rely on terrestrial base stations (BSs). The agile mobility and maneuvering prowess of UAVs empower them to establish direct line-of-sight (LoS) connections with a majority of communication devices [39]. Compared to terrestrial BSs, UAVs can be employed in a variety of environments with difficult geographical conditions. This can be made by designating a UAV as a mobile BS for rapid deployment to the target areas (e.g., hotspots or remote villages/forests) for real-time on-demand coverage.

For UAVs to efficiently communicate with a massive number of devices on the ground, there is a acute need to develop highly spectrum-efficient multiple access techniques. Conventional communication systems generally use orthogonal multiple access (OMA) schemes in which each resource element (RE) (e.g., frequency, time, or code) is utilized by a single user. However, it is conceivable that OMA may not meet the rigorous demands imposed by future wireless applications. In view of this, non-orthogonal multiple access (NOMA) techniques have been extensively studied owing to their advantages of providing more concurrent communication links, reduced access latency, and higher spectral efficiency [8, 144]. With the increasing demand for higher capacity and massive connectivity in future wireless applications, there is a strong interest in investigating the integration of SCMA with UAV to explore higher performance gains.

Fewer studies have been done on the resource management aspects of SCMA. In general, the BS allocates uniform power to all users without considering channel state information (CSI). The issue of resource allocation for SCMA was addressed in [163–166]. The fundamental tradeoff between rate and energy was investigated in a downlink SCMA system for the predesigned CBs [163]. The authors in [164] optimized both CB and power allocation within the downlink device-to-device (D2D) enabled cellular network with the objective of maximizing the overall system data rate. A three-level power allocation model was proposed in [151] to maximize the capacity. M. Cheraghy *et al.* worked on multi-objective resource allocation to maximize the average sum-rate in an uplink SCMA system [165]. In [166], CB selection and bandwidth allocation were

optimized to maximize the sum rate in an uplink SCMA based vehicle-to-everything (V2X) networks. The resource management in a SCMA-aided UAV network has not yet been explored, to the best of our knowledge.

This work considers a SCMA-assisted UAV communication scenario, in which the aim is to utilize the available resources efficiently, and maximize the system data rate. The overall energy consumption of UAVs is primarily categorized into two components: energy utilized for communication and propulsion energy. In this work, the following three types of resources are studied: (1) propulsion energy allotted to the UAV to reach the hovering point, (2) transmit power at UAV for communication, and (3) available spectral resources at the UAV. Towards this direction, we first focus on the optimization of UAV 3D placement by maximizing the system sum-rate. Next, we compute an optimal UAV 3D trajectory from the given initial position to the final deployment location considering the available on-board energy. After arriving at the hovering point, spectral resources and transmit power at the UAV are allocated to each user to maximize the system sum-rate. This framework is applicable to many practical scenarios, such as providing data service to the first responders in a disaster-affected areas or offloading data traffic in a crowded area. It is noted that optimizing the UAV's deployment position and UAV's trajectory, leads to a substantial improvement in system performance, even without the resource management. Furthermore, the study highlights the significant role of subchannel and power allocation in maximizing the sum-rate of the SCMA-assisted UAV system.

5.1 System Model and Optimization Problem Formulation

5.1.1 System Model

We consider a downlink $(K \times J)$ SCMA-assisted UAV system, as shown in Fig. 5.1. This system comprises a rotary-wing single-antenna UAV functioning as an aerial-BS, providing service to J single-antenna users using K REs. In SCMA, the number of non-orthogonal superposed codewords can exceed the count of the number of orthogonal REs. This characteristic allows SCMA to accommodate a greater number of users while maintaining the same expanse of resources, thereby enhancing the system capacity. It is assumed that the users are either static or have low mobility, and the location of the j th user is $[x_j, y_j] \in \mathbb{R}^{1 \times 2}$. The UAV starts from an initial location $(x_0, y_0, 0)$, moves vertically upwards until it achieves minimum height, and then takes its trajectory toward the final deployment location. The total UAV flight time is divided into M number of time slots of equal duration [38]. The UAV trajectory is denoted as $\mathbf{q}[m] = \{(x[m], y[m], z[m])\}, \forall m = 1, \dots, M$, where $x[m]$, $y[m]$ and $z[m]$ denote the x , y , and z coordinates of the UAV at time slot m .

Let $h_{k,j}$ denotes the channel between the UAV-BS and the j th user at RE k . It is assumed that all the channel vectors are independent complex Gaussian random variables, and all the required channel state information (CSI) is available at the UAV-

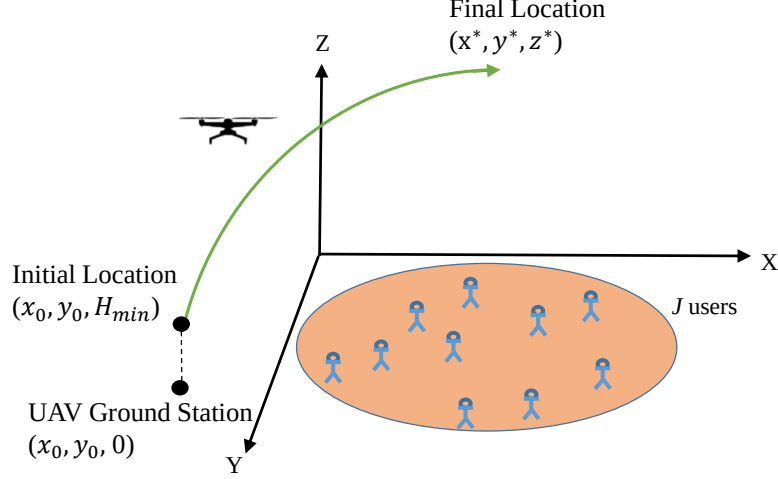


Figure 5.1: A plot of the SCMA-assisted UAV system with UAV's 3D trajectory from the predefined initial location to the final deployment location.

BS in each time slot. The received signal at RE k is [15]

$$y_k = \sum_{j=1}^J h_{k,j} f_{k,j} x_{k,j} + n_k, \quad (5.1)$$

where $f_{k,j} = 1$ indicates that there is active association between user j and RE k , $x_{k,j}$ indicates the codeword element sent on the k th RE to the j th user, and $n_k \sim \mathcal{CN}(\mathbf{0}, \sigma^2)$ denotes the AWGN at the k th RE. The data received at the j th user on k th RE is interfered from the data of other users communicating over the same RE. Thus, the received signal-to-interference-plus-noise ratio (SINR) of user j at RE k is:

$$\gamma_{k,j} = \frac{|h_{k,j}|^2 p_{k,j}}{\sum_{\substack{i \in S_k \\ i \neq j}} |h_{k,i}|^2 p_{k,i} + \sigma^2}, \quad (5.2)$$

where S_k represents the set of users communicating over k RE, and $p_{k,j}$ denotes the power allocated to the codeword element $x_{k,j}$.

5.1.2 UAV Energy Consumption Model and Channel Model

Thanks to UAV-BS's flexible and mobile nature, it can keep up LoS connection with most devices. However, the blockages may affect the UAV-to-ground device links, especially in urban scenarios. Thus, a probabilistic LoS channel model is considered, which includes both the LoS and NLoS components, dependent on the UAV deployment environment [38, 89]. The probability of the LoS link between the j th user and UAV-BS at time slot m is given by:

$$Pr_j^{LoS}[m] = \frac{1}{1 + ae^{-b(\theta_j[m]-a)}}, \quad (5.3)$$

where a and b are the constants depending on the carrier frequency f_c and environmental conditions, respectively [167]. θ_j denotes the elevation angle in degrees

from the j th user to the UAV-BS. It is given as $\theta_j[m] = (\frac{180}{\pi})\tan^{-1}(\frac{z_j[m]}{r_j[m]})$, where $r_j[m]$ denotes the 2D distance from UAV-BS at time slot m to j th user denoted as $r_j[m] = \sqrt{(x[m] - x_j)^2 + (y[m] - y_j)^2}$. Correspondingly, the NLoS probability is $Pr_{NLoS}^j[m] = 1 - Pr_{LoS}^j[m]$. Next, the path loss is computed as [168]

$$L_j^{LoS}[m] = \left(\frac{4\pi f_c d_j[m]}{c} \right)^\alpha \eta_{LoS}, \quad (5.4)$$

$$L_j^{NLoS}[m] = \left(\frac{4\pi f_c d_j[m]}{c} \right)^\alpha \eta_{NLoS}, \quad (5.5)$$

where c is the speed of light, and α is the path loss exponent. η_{LoS} and η_{NLoS} are the path loss coefficients for LoS and NLoS paths, respectively. The average channel gain between the j th user and UAV at the m th time-slot is

$$G_j[m] = \frac{1}{Pr_j^{LoS} L_j^{LoS} + Pr_j^{NLoS} L_j^{NLoS}}.$$

For rotary-wing UAVs, the considered propulsion power consumption model is dependent on velocity V [89] as follows:

$$P(V) = P_o \left(1 + \frac{3V^2}{U_{tip}^2} \right) + P_i \left(\sqrt{1 + \frac{V^4}{4v_o^4}} - \frac{V^2}{2v_o^2} \right)^{1/2} + \frac{1}{2} d_o \rho s A_r V^3, \quad (5.6)$$

where P_o represents the blade profile power, P_i represents the induced power, U_{tip} represents rotor blade's tip speed, v_o represents the rotor induced velocity, d_o represents the fuselage drag ratio, s represents the rotor solidity, ρ represents the air density and A_r represents the rotor disc area. During the m th slot, the UAV speed is given as $V[m] = \frac{d'[m]}{\tau[m]}$, where $d'[m] = \|\mathbf{q}[m+1] - \mathbf{q}[m]\|$. Subsequently, the energy expended by the UAV in the m th slot is expressed as $E[m] = \tau[m]P(V[m])$. Consequently, the UAV trajectory should follow the total energy constraint, denoted as $\sum_{m=1}^M E[m] \leq E_{max}$.

5.1.3 Problem Formulation

The overall objective of this work is to maximize the total system sum-rate, both during UAV flight and when the UAV is in a stationary hovering state. Thus, with this objective, we have formulated two problems:

- Utilizing user locations as input, we aim to optimize the 3D deployment and trajectory of the UAV, spanning from the initial to the final deployment location. This optimization seeks to maximize the sum-rate while adhering to UAV energy constraints and ensuring a minimum rate at the deployment location. During UAV flying time, the subchannel assignment is assumed to be static and power is uniformly distributed among the users on all active subchannels.

- Upon the UAV's arrival at the deployment location, we proceed to optimize the assignment of multiple subchannels and the allocation of power across all active subchannels. This optimization aims to maximize the sum-rate within the SCMA-aided UAV system, while adhering to constraints imposed by the SCMA FGM, power budget, and the minimum user rate requirement.

Here, our primary focus lies on subchannel assignment and power allocation when the UAV is in a hovering state. This emphasis is driven by the assumption that the UAV will spend a significant portion of its time and energy while hovering, as compared to flying.

Next, we discuss the optimization problems mathematically. In *Problem 1*, the goal is to obtain the UAV 3D deployment location, $\mathbf{L} = [x^*, y^*, z^*]$ and UAV trajectory $\mathbf{Q} = \{\mathbf{q}_m, \forall m = 1, \dots, M\}$ from the initial location $(x_0, y_0, H_{\min})$ to the final location $\mathbf{L}$ to maximize the system sum-rate under the energy budget. *Problem 1* is mathematically expressed as

$$\mathcal{P}(1) : \max_{\mathbf{L}, M, \mathbf{Q}} \sum_{m=1}^M \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}^m) \quad (5.7a)$$

$$\text{s.t.} \quad -r \leq x^*, y^* \leq r, H_{\min} \leq z^* \leq H_{\max}, \quad (5.7b)$$

$$\sum_{k=1}^K \log_2(1 + \gamma_{k,j}^{\mathbf{L}}) \geq R_{\min}, \quad (5.7c)$$

$$z[m] \geq H_{\min}, \forall m \in [1, M], \quad (5.7d)$$

$$\|\mathbf{q}[m+1] - \mathbf{q}[m]\|^2 \leq d_{\max}^2, \quad (5.7e)$$

$$\mathbf{q}[M] = \mathbf{L}, \quad (5.7f)$$

$$M \leq M_a, \quad (5.7g)$$

where r denotes the radius of the circular area, $H_{\min}$ and $H_{\max}$ is the minimum and maximum height allowed for the UAV, $\gamma_{k,j}^{\mathbf{L}}$ denotes the SINR of user j at RE k at the UAV deployment location $\mathbf{L}$, $R_{\min}$ is the minimum required rate of each user and M_a denotes the maximum number of available time slots for UAV to reach $\mathbf{L}$ under the available energy budget. Constraint (5.7c) ensures that each user is provided the minimum rate $R_{\min}$ at the deployment location. Constraints (5.7e) imply that the maximum distance a UAV covers in a slot is $d_{\max}$. The allowed $H_{\max}$ according to federal aviation authority (FAA) regulations is 122 m [170].

In *Problem 2*, the FGM and power allocation matrix are optimized to maximize the sum-rate, subject to the constraints of UAV, SCMA, and required minimum data rate to the end users. Let $\mathbf{P} = (p_{k,j})_{K \times J}$ denotes the power allocation matrix, where $p_{k,j}$ denotes the power allocated to user j on RE k . Also, it is essential to optimize the FGM of SCMA for different channel conditions. *Problem 2* can be mathematically

expressed as:

$$\mathcal{P}(2) : \max_{\mathbf{F}, \mathbf{P}} R_S = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (5.8a)$$

$$\text{s.t. } f_{k,j} \in \{0, 1\}, \quad \forall 1 \leq k \leq K, 1 \leq j \leq J, \quad (5.8b)$$

$$\mathbf{F}_j \neq \mathbf{F}_{j'}, \quad \forall j \neq j' \in J, \quad (5.8c)$$

$$\sum_{j=1}^J f_{k,j} \leq d_f, \quad \forall k \in K, \quad (5.8d)$$

$$\sum_{k=1}^K f_{k,j} \leq d_v, \quad \forall j \in J, \quad (5.8e)$$

$$p_{k,j} \geq 0, \quad \forall 1 \leq k \leq K, 1 \leq j \leq J, \quad (5.8f)$$

$$\sum_{k=1}^K \sum_{j=1}^J f_{k,j} p_{k,j} \leq P_{\text{tot}}, \quad (5.8g)$$

$$\sum_{k=1}^K \log_2(1 + \gamma_{k,j}) \geq R_{\min}, \quad (5.8h)$$

where P_{tot} represents the total transmit power allocated for communication at UAV. Constraint (5.8c) represents that FGM should not have any two columns same. Constraint (5.8d) denotes the limit of the maximum number of users whose data are superimposed on each RE, and constraint (5.8e) denotes that a user is communicating over maximum d_v number of REs. Constraint (5.8g) ensures that the total power allocated to all the user on active subchannels is less than or equal to P_{tot} . Constraint (5.8h) ensures that each user is provided the minimum rate $R_{\min}$. In SCMA, CB of user j has non-zero values only at active subchannels, which is denoted by indices where FGM $\mathbf{F}$ has ones at the j th column, i.e. $f_{k,j} = 1$. Thus, constraint (5.8e) also denotes that CB of user j has non-zero values over maximum d_v number of REs. Both of the optimization problems discussed in $\mathcal{P}(1)$ and $\mathcal{P}(2)$ have non-concave objective in nature, making it difficult to compute the global optimal solution [147].

5.2 Proposed Solution

In this section, we discuss the proposed solution as outlined in Fig. 5.2. We first solve *Problem 1*, i.e., UAV 3D deployment and trajectory. From this, we get the information of where UAV should be deployed and what trajectory would it take. Then we solve *Problem 2* to allocate frequency subcarrier and power to each user at the UAV to maximize the system sum-rate considering the UAV and SCMA constraints.

5.2.1 Problem 1 Solution

To solve *Problem 1*, we divide it into two sub-problems and then solve them separately. First, the 3D UAV deployment location is decided. Then, the trajectory is designed between the given initial location and the final deployment location.

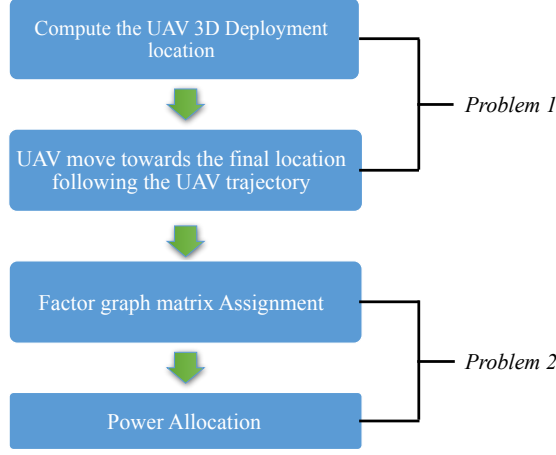


Figure 5.2: Proposed solution outline.

5.2.1.1 UAV Deployment Location

The UAV deployment problem can be reformulated as

$$\mathcal{P}(\text{A1}) : \max_{\mathbf{L}} f_{\text{A1}}(\mathbf{L}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (5.9a)$$

$$\text{s.t. } (5.7b), (5.7c). \quad (5.9b)$$

To solve the problem (5.9), we divide it into two parts: (1) find the UAV 2D deployment location, (2) find UAV-BS altitude. Firstly, the UAV 2D deployment is mathematically expressed as:

$$\mathcal{P}(\text{SP}_1) : \max_{x^*, y^*} \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (5.10a)$$

$$\text{s.t. } -r \leq x^*, y^* \leq r. \quad (5.10b)$$

Using the gradient ascent method, we aim to compute the UAV 2D deployment location as shown in Algorithm 1. In this, the UAV x and y coordinates are updated iteratively as follows:

$$x_{n+1} = x_n + \mu_x^n \Delta_x^n, \quad (5.11)$$

$$y_{n+1} = y_n + \mu_y^n \Delta_y^n, \quad (5.12)$$

where x_n denotes the UAV x coordinate at the n th iteration, $\mu_x^n > 0$ and $\mu_y^n > 0$ denotes the step-size with respect to UAV x and y coordinate at the n th iteration. Δ_x^n and Δ_y^n denote the derivative of the sum-rate with respect to UAV x and y coordinate at n th iteration. Now, to enhance the convergence rate of the proposed algorithm, the step size is normalized by the norm of the gradient as [171, 172]

$$\mu_x^n = \frac{L}{\|\Delta_x^n\|}, \quad \mu_y^n = \frac{L}{\|\Delta_y^n\|}, \quad (5.13)$$

where, $L = \frac{a}{n^b}$ and we set positive constants $a = 2$ and $b = 0.6$, which may vary depending on the simulation setup.

The initial 2D UAV location is assumed to be the centroid location of all users, keeping the UAV height at $H_{\min}$. We say that the UAV 2D location has converged

Algorithm 5: Proposed algorithm for computing the UAV 3D deployment location

Input: Given the location and CSI of users.

Output: Maximum sum-rate and UAV 3D deployment location.

Initialize: The initial 2D location of UAV is the geometric center of the users keeping the UAV height at H_{min} .

```

1: while  $R_S^{n+1} - R_S^n \leq \epsilon$  do
2:   Calculate  $\Delta_x^n$  and  $\Delta_y^n$ .
3:   Calculate the step size using (5.13).
4:   Update the  $x$  and  $y$  coordinate of the UAV using (5.11) and (5.12).
5: end while
6: return  $x^*, y^*$ 
7: for  $z_l = H_{min} : H_{max}$  do
8:   Calculate sum-rate  $R_S^{z_l}$  at UAV location  $[x^*, y^*, z_l]$ .
9:   Calculate the minimum rate of all users  $MR_{jmin}^{z_l}$  at UAV location  $[x^*, y^*, z_l]$ .
10: end for
11:  $[indz] = \text{find}(MR_{jmin}^{z_l} \geq R_{min})$ .
12:  $[R_S^*, x^*, y^*, z^*] = \max(R_S[x^*, y^*, indz])$ .

```

when the fractional increase in the sum-rate is less than 1%. Next, we change the z coordinate from H_{min} to H_{max} , and choose the UAV 3D location, which gives maximum sum-rate under minimum rate constraint.

5.2.1.2 Designing UAV 3D Trajectory

Let $\mathbf{q}[0]$ denotes the initial location with minimum height, i.e., (x_0, y_0, H_{min}) . Let $R_{sm}[m]$ be the sum-rate at the m th time slot, and is given as $R_{sm}[m] = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}^m)$. Then, the UAV 3D trajectory sub-problem is reformulated as

$$\mathcal{P}(A2) : \max_{M, \mathbf{Q}} f_{A2}(M, \mathbf{Q}) = \sum_{m=1}^M R_{sm}[m] \quad (5.14a)$$

$$\text{s.t. } (5.7d), (5.7e), (5.7f), (5.7g). \quad (5.14b)$$

A gradient ascent based scheme is proposed to solve $\mathcal{P}(A2)$ that computes the best UAV position in each time slot. This scheme is done sequentially for every time slot till the UAV gets to the final deployment location. Since, a UAV can cover a span of τV in every time slot, the search area for the next UAV location in m th time slot is a sphere centered at $\mathbf{q}[m-1]$ and of radius τV . As the search space is a sphere, we move to the spherical coordinate system for ease in mathematical analysis. The UAV location at the time-slot m is dependent on the azimuth angle Φ and polar angle θ with respect to origin. Then, the UAV location in terms of spherical coordinates are given as:

$$\begin{aligned} x[m] &= \tau V \cos \theta[m] \sin \Phi[m] + x[m-1], \\ y[m] &= \tau V \sin \theta[m] \sin \Phi[m] + y[m-1], \\ \text{and } z[m] &= \tau V \cos \Phi[m] + z[m-1]. \end{aligned} \quad (5.15)$$

Now, the sum-rate at the m th time slot becomes a function of the polar and azimuth angles. If the UAV moves sequentially in each time slot in this manner, it is not very sure that the UAV will be able to reach the final deployment location under the

Algorithm 6: Proposed UAV 3D Trajectory Scheme

Inputs: $\mathbf{q}[0], \mathbf{L}, E_{max}, M_a, (x_j, y_j) \forall j = 1, \dots, J$.

Output: M^* and $\{\mathbf{q}^*[m]\}_{m=1}^{M^*}$.

Initialize: $\beta = M_a$.

```

1: for  $m = 1 : \beta$  do
2:   Draw a sphere at  $\mathbf{q}[m-1]$  of radius  $\tau V$ , and draw a line segment between  $\mathbf{L}$  and  $\mathbf{q}[m-1]$ .
     The intersection point of the line segment and sphere is denoted as  $X_m^{ini}$ .
3:   Compute  $\theta_0[m], \Phi_0[m]$  at  $X_m^{ini}$ .
4:   Set  $i = 1$ .
5:   while  $\Delta R_{sm}(\theta[m], \Phi[m]) \geq \epsilon$  do
6:      $\theta^{i+1} = \theta^i + \kappa(\theta^i) \Delta R_{sm}(\theta^i[m])$ 
7:      $\Phi^{i+1} = \Phi^i + \kappa(\Phi^i) \Delta R_{sm}(\Phi^i[m])$ 
      $i = i + 1$ .
8:   end while
9: end for
10: if  $(x[M_a], y[M_a], z[M_a]) = \mathbf{L}$  then
11:   The  $\{\mathbf{q}^*[m]\}_{m=1}^{M^*}$  is the final UAV trajectory.
12: else
13:   while  $M < M_a$  do
14:     Decrement  $\beta$  by one. Take a straight flight from  $\mathbf{X}_0 = (x^*[\beta-1], y^*[\beta-1], z^*[\beta-1])$  to  $\mathbf{L}$ .
     Then,  $M^* = \frac{\|\mathbf{X}_0 - \mathbf{L}\|}{\tau V} + (\beta - 1)$ . The final trajectory is  $(x^*[m], y^*[m], z^*[m])_{m=\beta}^{M^*}$ 
15:   end while
16: end if

```

available energy budget. Thus, the objective is to maximize the system sum-rate and obtain the respective UAV location for a certain number of time slots (say β). After that, UAV moves as a straight-flight from the current position to deployment location $\mathbf{L}$. The parameter β is dependent on number of time-slots in which UAV can arrive location $\mathbf{L}$ under given energy budget.

In Algorithm 6, gradient ascent method works as a primary component to compute the optimal UAV location in each time slot. In time slot m , firstly a line segment is drawn between $\mathbf{q}(m-1)$ and $\mathbf{L}$. Next, the intersection point (X_m^{ini}) of the line segment and the searching sphere is calculated. X_m^{ini} is considered as an initial UAV location with $\Phi(0)[m]$ and $\theta(0)[m]$. Next, the positive gradient of the sum-rate with respect to θ and Φ are calculated. The gradient provides the direction, and the step size decides how far UAV moves in that direction. The step size with respect to θ , i.e., $\kappa(\theta^i)$ and with respect to Φ , i.e., $\kappa(\Phi^i)$ at iteration i is normalized by the norm of the gradient. The steepest ascent is applied iteratively until $\Delta R_{sm}(\theta[m], \Phi[m]) \leq \epsilon$, where ϵ is the tolerance level, and thus the final UAV location of m th time slot is obtained at $\theta^*[m], \Phi^*[m]$. Using (5.15), UAV location is given in Cartesian coordinate system as $(x^*[m], y^*[m], z^*[m])$. Thus, for initial β number of slots, the UAV trajectory is obtained using gradient ascent method.

Algorithm 6 is used to calculate the suitable value of β and the respective UAV 3D trajectory. In Algorithm 6, the β is initialized as equal to M_a . Then, the UAV trajectory is calculated using the gradient ascent method for $\beta = M_a$ slots. If UAV reaches the final deployment location under $\beta = M_a$ number of slots, then the algorithm stops and we obtain the final sub-optimal UAV trajectory. If not, β is decreased by 1, and the UAV trajectory for this new β uses the same locations as obtained previously (with $\beta = M_a$). Then, for $m \geq \beta$ time slots, it takes a straight-flight to get to $\mathbf{L}$. Thus, for new β , we get the value of M^* required to get to location $\mathbf{L}$. We follow similar steps

for each decremented β , until UAV reaches location $\mathbf{L}$ under the given energy budget.

5.2.2 Problem 2 Solution

In the previous sub-section, we have obtained the deployment location and designed the UAV trajectory for the given energy budget. Now, as UAV has reached near the users, we start allocating the resources, i.e., frequency and power to each user judiciously.

5.2.2.1 Designing $\mathbf{F}$ for a given $\mathbf{P}$

With known $\mathbf{P}$, (5.8) can be reformed as:

$$\mathcal{P}(\text{A3}) : \max_{\mathbf{F}} f_{\text{A3}}(\mathbf{F}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (5.16a)$$

$$\text{s.t. } (5.8b), (5.8c), (5.8d), (5.8e). \quad (5.16b)$$

To solve the problem $\mathcal{P}(\text{A3})$, $\mathbf{F}$ is computed using the method similar to **Algorithm 4**. In this method, we initially consider a $\mathbf{F}_{\text{ini}}$ as an all-ones matrix of size $K \times J$. Then, the SINR matrix $\mathbf{S}_{K \times J} = (\gamma_{k,j})_{K \times J}$ is calculated, where $\gamma_{k,j}$ is as shown in (6.6). Next, the root mean square (RMS) of $\mathbf{S}$ is calculated with respect to the users and then sorted in the descending order. The RE allotment starts with the user having the highest RMS value. For this user, d_v REs with the highest SINR are chosen and these REs are assigned to the corresponding user. A similar procedure is repeated for all the users sequentially with decreasing RMS values. With the allocation of REs to each user, fulfilling the constraints in (5.8c), (5.8d), (5.8e) becomes more difficult as the users increase. In that case, we keep choosing the next d_v number of RES corresponding to next highest SINR values until all the constraints are fulfilled. Thus, this method basically gives the priority to the subcarrier on which user is getting good SINR, considering the SCMA FGM constraints.

5.2.2.2 Power Allocation

For the given FGM $\mathbf{F}$, the sum-rate optimization problem in (5.8) becomes:

$$\mathcal{P}(\text{A4}) : \max_{\mathbf{P}} f_{\text{A4}}(\mathbf{P}) = \sum_{k=1}^K \sum_{j=1}^J \log_2(1 + \gamma_{k,j}) \quad (5.17a)$$

$$\text{s.t. } (5.8f), (5.8g), (5.8h). \quad (5.17b)$$

Here, subproblem (5.17) is a non-convex problem, and the complexity of finding the optimal solution is prohibitive. Thus, we use Lagrange dual decomposition method to find a near-optimal solution. The basic idea here is that we augment the objective function with a weighted sum of the constraint functions. The Lagrangian of (5.17) is

given as

$$L(\{\mathbf{P}\}, \boldsymbol{\lambda}, \zeta) = \sum_{j=1}^J \left[(1 + \lambda_j) \sum_{k=1}^K \log_2(1 + \gamma_{k,j}) - \lambda_j R_{\min} \right] + \zeta \left(P_{\text{tot}} - \sum_{k=1}^K \sum_{j=1}^J p_{k,j} \right), \quad (5.18)$$

where $\boldsymbol{\lambda} = \{\lambda_1, \dots, \lambda_J\}$, and λ_j and ζ are the Lagrange multipliers associated with j th user. The dual objective function is given as $\mathcal{G}(\boldsymbol{\lambda}, \zeta) = \max_{\{\mathbf{P}\}} L(\{\mathbf{P}\}, \boldsymbol{\lambda}, \zeta)$, and thus the dual problem becomes

$$\min_{\boldsymbol{\lambda}, \zeta} \mathcal{G}(\boldsymbol{\lambda}, \zeta) \quad (5.19a)$$

$$\text{s.t. } \boldsymbol{\lambda}, \zeta \succcurlyeq 0. \quad (5.19b)$$

The KKT conditions are applied [152] to (5.19). Next, the Lagrangian in (5.18) is differentiated with the variable $p_{k,j}$, and then equated to zero. Thus, we obtain

$$\frac{(1 + \lambda_j) g_{k,j}}{\ln(2) \cdot (1 + \sum_{i \in S_k} p_{k,i} g_{k,i})} \approx \zeta, \quad (5.20)$$

where $g_{k,j}$ is the normalized channel gain with respect to user j at RE k . The approximation arises due to the inter-user interference which can be mitigated by the proper design of CB. Thus,

$$\hat{p}_{k,j} = \left[\frac{(1 + \lambda_j)}{\zeta \ln(2)} - \frac{1}{1 + \sum_{\substack{i \in S_k \\ i \neq j}} p_{k,i} g_{k,i}} \right]^+, \quad (5.21)$$

where $[x]^+$ denotes the $\max(0, x)$ operation. The variable $p_{k,j}$ is substituted into function L given in (5.18). Now, L becomes a function of Lagrange multipliers, and the dual problem in (5.19) can be solved with commercially available optimization solvers. After solving this, we get the optimal value of Lagrange multipliers. Lastly, $p_{k,j}$ can be calculated by substituting the obtained value of Lagrangian multipliers in (5.21). For this non-convex optimization problem (5.17), there exists a duality gap, but it tends to zero as the number of subcarriers increase [151].

5.2.3 Complexity

The *Problem 1* is divided into two subproblems as: solving the optimization with respect to the 3D UAV deployment location and optimizing the UAV trajectory. The complexity of **Algorithm 1** for UAV deployment is primarily dependent on the complexity of gradient ascent. Let the complexity of computing the derivative for UAV 2D deployment location be $O(a_1)$ and the number of required iterations be N_{xy} . Thus, the total complexity to compute the sub-optimal solution of computing $\mathbf{L}$ is

$O(N_{xy}a_1 + Z_{range})$, where Z_{range} is the altitude range for checking the UAV deployment location. In **Algorithm 6**, the gradient ascent algorithm is called for M_a number of time slots. Thus, the total complexity of **Algorithm 6** is $O(M_a a_2 N_{tp})$, where a_2 denotes the computation cost for calculating the gradient of the sum-rate with respect to θ and Φ in each slot, and N_{tp} denotes the number of iterations required for updating the azimuth and polar angle.

In *Problem 2*, FGM $\mathbf{F}$ and the power allocation matrix $\mathbf{P}$ are optimized. The complexity of FGM assignment is contingent upon both the number of users and the prevailing channel conditions. For this, d_v REs exhibiting the most favorable channel conditions are selected for a single user, and these REs are indexed with the value one for the CB associated with that user. Let a_3 denote the complexity associated with selecting d_v REs for each user with the most favorable channel conditions. Consequently, whenever the indices coincide with those of other users, the complexity experiences an increment of $O(a_3)$. Hence, the complexity of FGM assignment is a constant value multiplied by the number of users, and it is proportional to $O(J)$. Moreover, the complexity of the power allocation algorithm is contingent on solving the dual problem. Thus, the complexity associated with solving the dual problem is $O(I_f(Jd_v))$, where I_f represents the number of iterations needed to compute the dual variables. So, the total complexity for solving *Problem 2* is $O(J + (I_f(Jd_v)))$.

5.3 Results and Discussion

In this section, we evaluate the performance of the proposed algorithms along with benchmark schemes. The simulation setup consists of a UAV working as an aerial BS and serves J ground users. The users are randomly distributed in a circular field of radius 200 m, centered at (250 m, 250 m). The UAV minimum height H_{min} is 20 m. The tolerance value is $\epsilon = 0.01$. The simulation parameters are : $P_i = 88.63$ W, $P_o = 79.86$ W, $v_o = 4.03$ m/s, $U_{tip} = 120$, $d_o = 0.6$, $s = 0.05$, $\rho = 1.225$, and $A_r = 0.503$, $a = 11.95$, $b = 0.136$, $P_{tot} = 30$ dBm, $\alpha = 2.5$, $\tau = 1$ s, $(x_0, y_0, 0) = (100, 100, 0)$ m, $\eta_{LoS} = 3$ dB and $\eta_{NLoS} = 23$ dB. We assume that the small-scale fading is in a Rayleigh distribution with the unit mean [173].

In the baseline SCMA scheme, UAV is assumed to be at the geometric center of all the users, with static $\mathbf{F}$ and uniform power allocation, respectively. We compare the sum-rate performance of baseline SCMA scheme with a standard NOMA scheme, called PD-NOMA, and an OMA scheme. In PD-NOMA, users are ordered based on their channel strength, and the power is allocated in such a manner that more power is allocated to the weak user under the given power budget [174]. We have implemented the time-division multiple-access (TDMA) scheme in the OMA scheme. In both schemes, the users are assumed to communicate over a single subcarrier. The results are analysed based on the optimization variables, i.e., where the UAV should be deployed, how the resources are managed while serving the users, and how the UAV reaches the desired location.

5.3.1 Performance Analysis for 4×6 and 5×10 SCMA Block

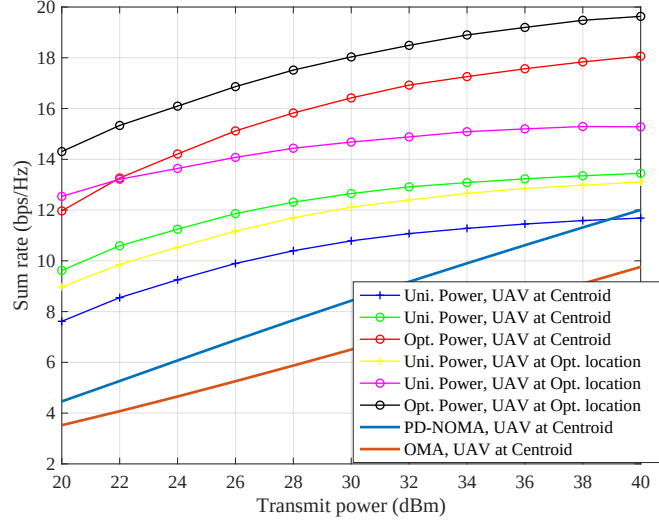


Figure 5.3: Sum-rate versus UAV transmit power for $K = 4$ and $J = 6$, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents proposed $\mathbf{F}$.

Fig. 5.3 shows the sum-rate performance with respect to the UAV’s total transmit power, specifically for a scenario where six users are served across four subchannels. Initially, we present the performance of OMA, PD-NOMA, and the baseline SCMA scheme. Subsequently, we gradually introduce the proposed enhancements, encompassing the proposed UAV 3D deployment location, FGM, and power allocation schemes, one after the other. Firstly, we employ **Algorithm 5** to compute the UAV 3D deployment based on the location of ground users. With optimized UAV deployment, the system sum-rate gets improved as compared to the performance for UAV located at the geometric center of the users. With the assignment of $\mathbf{F}$, the association between the user and REs is decided, and then power allocation is done to all users for every associated RE with Lagrange dual decomposition method. It is evident that with the proposed algorithms, the sum-rate performance notably improves as the transmit power increases.

Fig. 5.4 shows the sum-rate performance with respect to the number of users. It is to be noted that initially, the improvement in sum-rate at the optimal UAV location is more than the UAV at the geometric center, but as J increases, the impact of UAV deployment is relatively smaller. However, it is noted that FGM assignment and power allocation shows an improved sum rate as the number of users increase. This means that it is more crucial to carefully allocate REs and power as the number of users increase.

Fig. 5.5 shows the sum-rate performance with increasing radius r of the circular area for $J = 6$ users. As the radius increases, there is a corresponding rise in path loss, resulting in a decrease in the sum-rate for all the schemes. It is worth highlighting that through the optimization of UAV deployment, multiple subchannel assignment, and power allocation, there is a noteworthy improvement in the sum-rate performance compared to the baseline SCMA scheme, even as the radius increases. Fig. 5.6 illustrates the cumulative distribution function (CDF) of the system sum-rate concerning OMA, PD-NOMA, and the baseline SCMA schemes. Subsequently, it demonstrates the influence of optimizing UAV deployment, subchannel assignment, and power allocation.

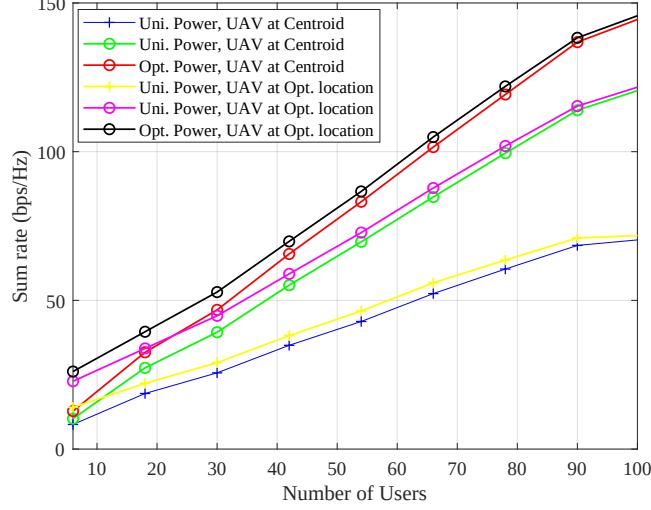


Figure 5.4: Sum-rate versus number of users for UAV-SCMA system, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents the proposed $\mathbf{F}$.

It is to be noted that the the gains of the proposed methods remain consistently stable, surpassing the performance of benchmark schemes, and the curves are consistent with their counterparts in Fig. 5.3.

Next, we consider 5×10 SCMA block in which ten users are served using five subcarriers, i.e., overloading factor is equal to $J/K = 2$. An example of the $\mathbf{F}_{5 \times 10}$ is shown below [160]

$$\mathbf{F}_{5 \times 10} = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \end{bmatrix}. \quad (5.22)$$

Fig. 5.7 shows the sum-rate performance of OMA, PD-NOMA, and the proposed methods for SCMA with respect to UAV total transmit power for ten users. Here, the total transmit power has been divided among ten users; therefore, power allotted to each user is less than for $J = 6$ case, and d_f also increases to four. It is worth noting that, even though the overloading factor $\frac{J}{K}$ is increased to two, the proposed algorithms perform better, and the sum-rate improves with the increase in transmit power. Fig. 5.8 displays the CDF curves depicting the sum-rate of both benchmark and proposed schemes across various channel realizations. Notably, the sum-rate of the proposed methods consistently outperforms that of the benchmark schemes, demonstrating superior performance regardless of the overloading factor and specific channel realizations.

5.3.2 Sum-Rate Analysis for Proposed UAV Trajectory

Fig. 5.9(a) shows the insights of the proposed and benchmark UAV trajectories. The benchmark schemes are straight flight and fly-hover schemes [161]. In the straight flight

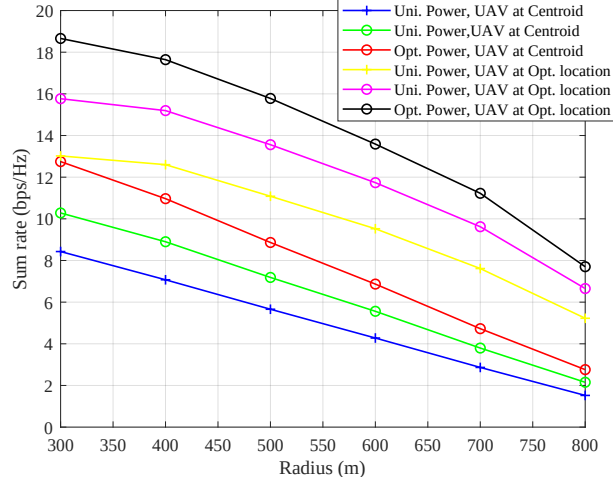


Figure 5.5: Sum-rate versus radius of circular field for 4×6 SCMA block, where ‘Uni.’ represents uniform, ‘Opt.’ represents the optimized, ‘+’ represents the fixed $\mathbf{F}$ and ‘o’ represents the proposed $\mathbf{F}$.

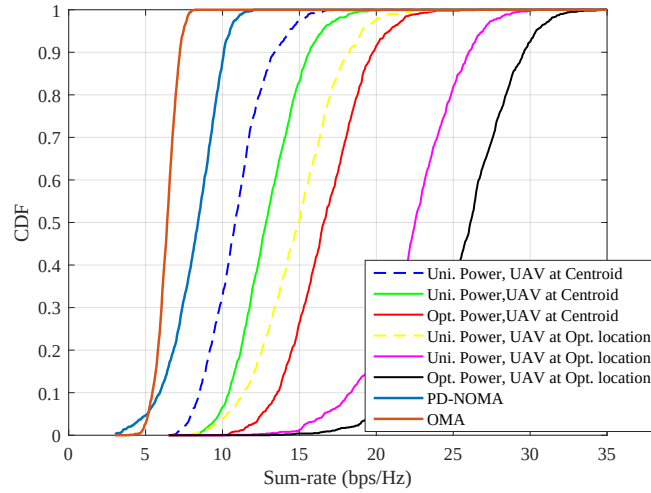


Figure 5.6: CDF curves for 4×6 SCMA block at UAV transmit power of 30 dBm, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, dashed line represents static $\mathbf{F}$ as shown in (2.3), and solid line denotes optimized $\mathbf{F}$.

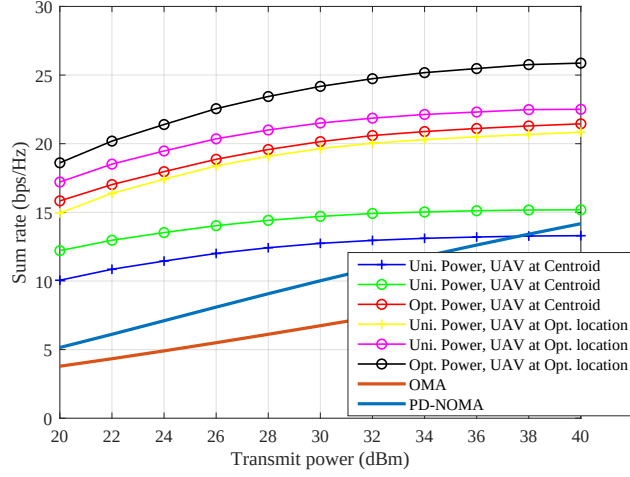


Figure 5.7: Sum-rate versus UAV transmit power for $K = 5$ and $J = 10$, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, ‘+’ denotes the fixed $\mathbf{F}$ and ‘o’ denotes the proposed $\mathbf{F}$.

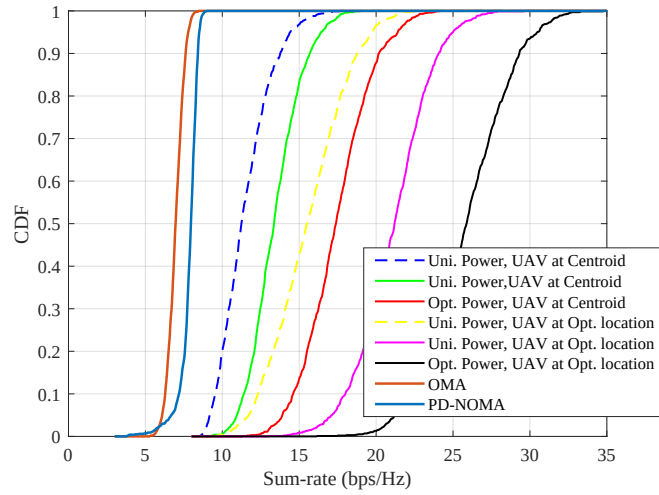


Figure 5.8: CDF curves for 5×10 SCMA block at transmit power of 30 dBm, where ‘Uni.’ denotes uniform, ‘Opt.’ denotes the optimized, dashed line represents static $\mathbf{F}$ as shown in (5.22), and solid line denotes optimized $\mathbf{F}$.

scheme, the UAV follows a linear trajectory, i.e., moving along a straight-line path from the initial to the final deployment location. In the fly-hover scheme, the process involves initially calculating a sequence of hovering locations, each corresponding to the user's position at a constant height, spanning from the initial to the final deployment location. Subsequently, the UAV moves to these hovering locations before reaching the ultimate deployment destination. In the proposed method, the UAV initially moves towards the space where the sum-rate with respect to the users is higher, thus providing improved sum-rate performance than the benchmark schemes.

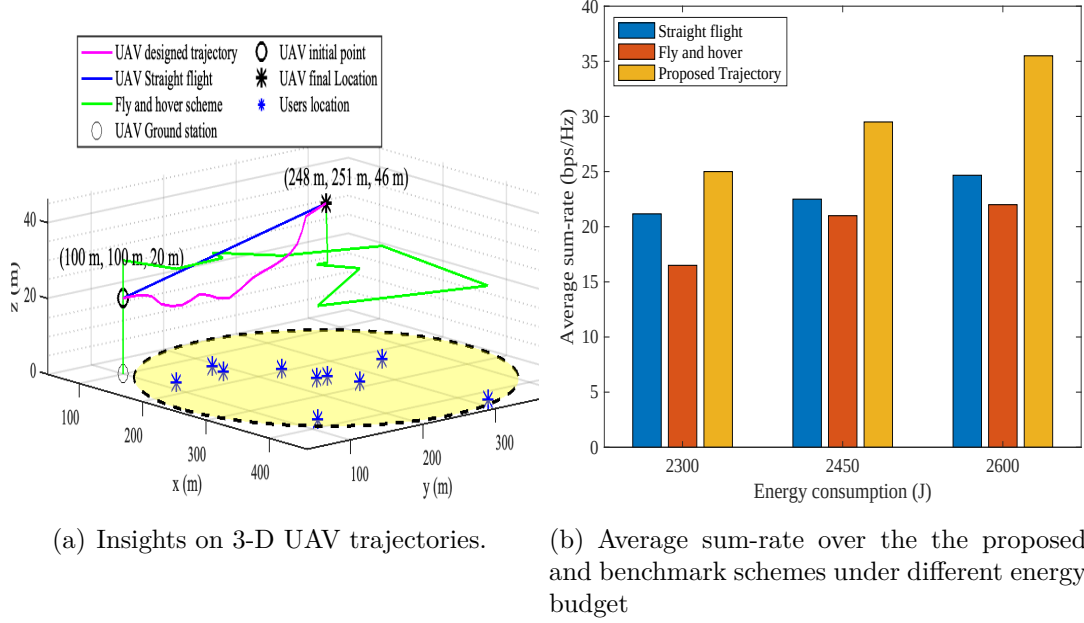


Figure 5.9: Performance of the proposed scheme with respect to the benchmark schemes 10 users.

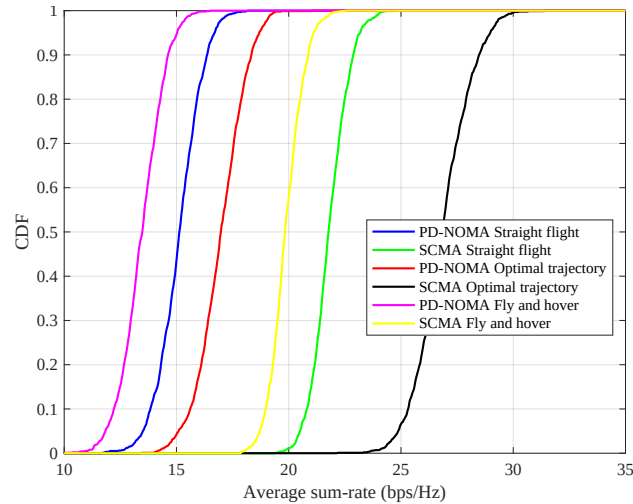


Figure 5.10: CDF of average sum-rate for PD-NOMA and SCMA aided UAV trajectories.

Figure 5.9(b) presents the average sum-rate performance across various numbers of users for the suggested UAV trajectory, comparing it with benchmark schemes based

on the given energy consumption. As the energy budget increases, all schemes demonstrate an improvement in system sum-rate. Notably, the proposed scheme surpasses both the fly-hover and straight-flight schemes, achieving the most substantial sum-rate improvement within the specified energy constraints. Fig. 5.10 illustrates the CDF of the average sum-rate associated with the proposed 3D UAV trajectory for both SCMA and PD-NOMA schemes. It is to be noted that the proposed trajectory with SCMA scheme consistently outperforms the benchmark schemes as the UAV traverses towards regions with higher sum-rates.

5.4 Conclusion

In this work, we have investigated an SCMA-assisted downlink UAV system, where the goal is to efficiently manage the available resources and provide improved user service. Specifically, we have formulated two optimization problems. In the first problem, we have proposed an iterative gradient ascent-based algorithm to optimize the UAV 3D deployment location and UAV trajectory in order to maximize the system sum-rate under the UAV on-board energy availability constraints. In the second problem, we optimize the allocation of spectrum resources and power, subject to the SCMA FGM and UAV power budget constraints. Such a problem has been solved by a CSI-based algorithm for spectrum allocation to each user, followed by Lagrangian dual decomposition method for power allocation. Our simulation results have demonstrated the superiority of the proposed algorithms over the benchmark schemes. Our research shows that: 1) optimizing the UAV's deployment position, instead of placing it at the geometric center of the users, can enhance the system performance; 2) optimizing the UAV's trajectory, even without resource management, proves to be advantageous; 3) employing CSI-based multiple subcarrier allocation and strategic power allocation can significantly improve system performance compared to static subcarrier allocation and uniform power distribution.

Chapter 6

Resource Allocation for SCMA-Aided Multi-UAV Transmission System

Upon examining the findings in Chapter 5, it becomes evident that a UAV system assisted by SCMA offers notable advantages. The present study delves into the incorporation of SCMA within a multiple UAV network, aiming to uncover potential performance enhancements.

6.1 System Model and Optimization Problem Formulation

6.1.1 System Model

As depicted in Fig. 6.1, we consider an SCMA-aided downlink network, with multiple hovering UAVs working as aerial-BSs, serving a total of M single-antenna users over K_{net} REs. Let the set of UAVs, users and total network REs be denoted as $\mathcal{N} = \{1, 2, \dots, N\}$, $\mathcal{M} = \{1, 2, \dots, M\}$ and $\mathcal{K}_{\text{net}} = \{1, 2, \dots, K_{\text{net}}\}$, respectively. The assumption is made that the users are stationary, and their locations are known by a control center. Let the locations of user $m \in \mathcal{M}$ and UAV $n \in \mathcal{N}$ be denoted by $\mathbf{x}_m = (x_m, y_m)$ and $\mathbf{l}_n = (x_n^{\text{uav}}, y_n^{\text{uav}}, h_n^{\text{uav}})$, respectively.

Due to the limited UAV coverage, we assume that each UAV can serve (M/N) devices. In cases where M is not a multiple of N , the number of associated devices with a UAV would be either $\lfloor (M/N) \rfloor$ or $\lceil (M/N) \rceil$. It is assumed that, K orthogonal subchannels are allocated to each UAV-BS, where $K < K_{\text{net}}$. Let J_n denote the number of users served by the n th UAV, such that $M = \sum_{n=1}^N J_n$ and the corresponding set is denoted as $\mathcal{J}_n$ such that $\mathcal{J}_{n_1} \cap \mathcal{J}_{n_2} = \emptyset, \forall n_1, n_2 \in \mathcal{N}, n_1 \neq n_2$.

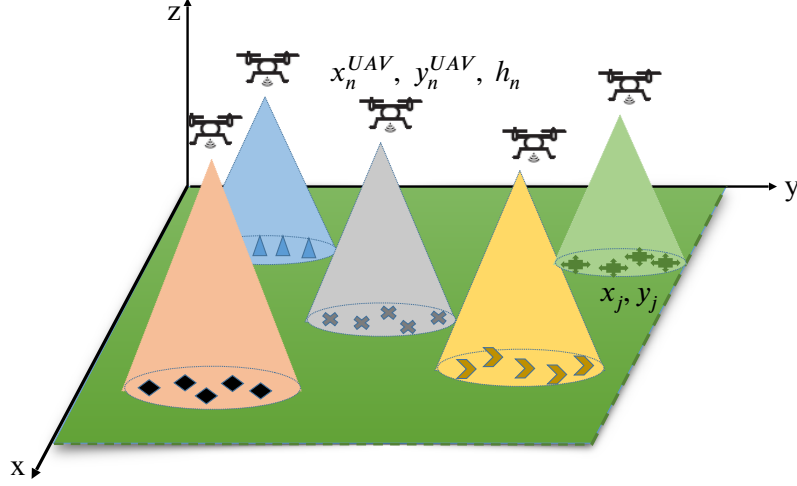


Figure 6.1: Illustration of the considered scenario, where N UAV-BSs serve M ground users.

6.1.1.1 Air-to-Ground (A2G) Channel Model

Thanks to UAV's agile moving nature, it is assumed that LoS connections can be kept for most devices. Nevertheless, potential disruptions in UAV-to-ground device connections may arise due to blockages, particularly in urban areas. Consequently, we are exploring a probabilistic LoS channel model that incorporates both the LoS and Non-Line of Sight (NLoS) components, contingent upon the specific environment in which the UAV is deployed [38]. The probability of the LoS link between the m th user and the n th UAV-BS is expressed as [168]:

$$\mathbb{P}_m^L[n] = \frac{1}{1 + ae^{-b(\theta_m^n - a)}}, \quad (6.1)$$

where, the constants a and b are dependent on the environmental conditions [167]. The symbol θ_m^n represents the elevation angle, measured in degrees, indicating the angle from the m th user to the n th UAV-BS. Such an angle can be given as $\theta_m^n = (\frac{180}{\pi})\tan^{-1}(\frac{h_n^{\text{uav}}}{r_m^n})$, where r_m^n indicates the 2D distance from the n th UAV-BS to the m th user. In a corresponding manner, NLoS probability is $\mathbb{P}_m^{NL}[n] = 1 - \mathbb{P}_m^L[n]$. Further, the path loss for the LoS and NLoS components are: [168]

$$\text{PL}_m^{\text{LoS}}[n] = \left(\frac{4\pi f_c d_m^n}{c}\right)^\alpha \eta_{\text{LoS}}, \quad (6.2)$$

$$\text{PL}_m^{\text{NLoS}}[n] = \left(\frac{4\pi f_c d_m^n}{c}\right)^\alpha \eta_{\text{NLoS}}, \quad (6.3)$$

where α denotes the path loss exponent, d_m^n denotes the 3D distance from the n th UAV-BS to the m th user and c is the speed of light. The path loss coefficients for the LoS and NLoS paths are represented by η_{LoS} and η_{NLoS} . The average path loss between the m th user and the n th UAV is:

$$\mathbb{L}_{n,m} = \mathbb{P}_m^L[n] \text{PL}_m^{\text{LoS}}[n] + \mathbb{P}_m^{NL}[n] \text{PL}_m^{\text{NLoS}}[n].$$

Considering small scale fading, the channel gain from the UAV n to the user m at subchannel k is:

$$g_{n,k,m} = H_{n,k,m} \cdot 10^{-\mathbb{L}_{n,m}/10}, \quad (6.4)$$

where $H_{n,k,m}$ denotes the fading coefficient between UAV n and user m at the k th subchannel [169].

6.1.1.2 Data Transmission Model

Let (n, j) denote the index of the j th user associated with n th UAV. The central controller allocates K subchannels to each UAV. Thus, UAVs are assumed to share some of the spectrum, whereby each UAV employs SCMA to provide data services to the ground users. The received signal at subchannel k is affected by two types of interference, i.e. inter-UAV interference and intra-UAV interference. Here, the variable $f_{m,n,k}$ indicates the association between device m to the n th UAV on the k th subchannel. If device m_1 associated with UAV n_1 shares subchannel k with device m_2 associated with UAV n_2 , then $f_{m_1,n_1,k} = f_{m_2,n_2,k} = 1$, meaning that inter-UAV interference exists between the two users. Also, if two users associated with the same UAV share the same sub-channel, then there exists intra-UAV interference between them. Let the power allocated by the n th UAV to the j th associated user on the k th subchannel be denoted as $p_{n,k,j}$. Hence, the signal received at the (n, j) user is represented as:

$$\begin{aligned} y_{n,j} = & \underbrace{\sum_{k=1}^{K_{net}} c_{n,j} g_{n,k,j} f_{n,k,j} x_{n,k,j}}_{\text{Desired signal}} + \underbrace{\sum_{k=1}^{K_{net}} \sum_{\substack{i \in \mathcal{J}_n \\ i \neq j}} c_{n,i} g_{n,k,i} f_{n,k,i} x_{n,k,i}}_{\text{Intra-group interference}} \\ & + \underbrace{\sum_{\substack{n' \in \mathcal{N} \\ n' \neq n}} \sum_{k=1}^{K_{net}} \sum_{i=1}^{J_{n'}} c_{n',i} g_{n',k,i} f_{n',k,i} x_{n',k,i}}_{\text{Inter-group interference}} + \underbrace{w_{n,j}}_{\text{noise}}, \end{aligned} \quad (6.5)$$

Therefore, the decoding signal-to-interference-plus-noise ratio (SINR) of (n, j) user at subchannel k is:

$$\gamma_{n,k,j} = \frac{g_{n,k,j} p_{n,k,j}}{I_{n,k,j}^{\text{intra}} + I_{n,k,j}^{\text{inter}} + v_{n_i,k} \sigma^2}, \quad (6.6)$$

where

$$\begin{aligned} I_{n,k,j}^{\text{intra}} &= \sum_{\substack{i \in \mathcal{J}_n \\ i \neq j}} c_{n,i} \|g_{n,k,i}\|^2 f_{n,k,i} p_{n,k,i}, \\ I_{n,k,j}^{\text{inter}} &= \sum_{\substack{n' \in \mathcal{N} \\ n' \neq n}} \sum_{i=1}^{J_{n'}} c_{n',i} \|g_{n',k,i}\|^2 f_{n',k,i} p_{n',k,i} \end{aligned}$$

where σ^2 denotes the variance of additive white Gaussian noise (AWGN). Here, we present a binary variable $c_{n,j}$ to indicate the association between user j and UAV n . In particular, the variable $c_{n,j}$ is assigned the value '1' when $\sum_{k=1}^K f_{n,k,j} \geq 1$, signifying the association of user j with UAV-BS n ; otherwise, $c_{n,j} = 0$. The bandwidth allocation factor of the k -th subchannel in the n_i th UAV subgroup is denoted as $v_{n_i,k}$. The data rate of (n, j) th user is $\mathbf{R}_{n,j} = \sum_{k=1}^K v_{n_i,k} \log_2(\gamma_{n,k,j})$.

6.1.2 Problem Formulation

We aim to maximize the sum rate across all users by jointly optimizing the UAV 3D deployment $\mathbf{L} = \{\mathbf{l}_n, \forall n \in \mathcal{N}\}$, user associations $\mathbf{C} = \{c_{n,j}, \forall n \in \mathcal{N}, j \in \mathcal{J}\}$, subchannel assignments $\mathbf{F} = \{f_{n,k,j}, \forall n \in \mathcal{N}, k \in \mathcal{K}, j \in \mathcal{J}_n\}$, power allocation $\mathbf{P} = \{p_{n,k,j}, \forall n \in \mathcal{N}, k \in \mathcal{K}, j \in \mathcal{J}_n\}$ and bandwidth allocations $\mathbf{V} = \{v_{n_i,k}, \forall n_i \in \mathcal{N}_i, k \in \mathcal{K}_{\text{net}}\}$. Let $\mathbf{G} = \{g_{n,k,m}, \forall n \in \mathcal{N}, k \in \mathcal{K}, m \in \mathcal{M}\}$ denotes the channel gain matrix, and $\mathbf{S} = \{\gamma_{n,k,j}, \forall n \in \mathcal{N}, k \in \mathcal{K}, j \in \mathcal{J}_n\}$ denotes the SINR matrix. Then, the joint optimization problem can be mathematically expressed as follows:

$$\mathcal{P}(1): \max_{\mathbf{L}, \mathbf{C}, \mathbf{F}, \mathbf{P}, \mathbf{V}} \sum_{n=1}^N \sum_{j=1}^{J_n} \mathbf{R}_{n,j} \quad (6.7a)$$

$$\text{s.t. } 0 \leq x_n^{\text{uav}}, y_n^{\text{uav}} \leq l_{\max}, H_{\min} \leq h_n^{\text{uav}} \leq H_{\max}, \forall n \in \mathcal{N}, \quad (6.7b)$$

$$c_{n,m} \in \{0, 1\}, \forall n \in \mathcal{N}, m \in \mathcal{M}, \quad (6.7c)$$

$$\left\lfloor \frac{M}{N} \right\rfloor \leq \sum_{m=1}^{J_n} c_{n,m} \leq \left\lceil \frac{M}{N} \right\rceil, \forall n \in \mathcal{N} \quad (6.7d)$$

$$\sum_{n=1}^N c_{n,m} = 1, \forall m \in \mathcal{M} \quad (6.7e)$$

$$f_{n,k,j} \in \{0, 1\}, \forall n \in \mathcal{N}, k \in \mathcal{K}, j \in \mathcal{J}_n, \quad (6.7f)$$

$$\sum_{k=1}^{K_{\text{net}}} \text{nnz}(\mathbf{F}(n, k, :)) = K, \forall n \in \mathcal{N}, \quad (6.7g)$$

$$\mathbf{F}_{n,j} \neq \mathbf{F}_{n,j'}, \forall n \in \mathcal{N}, j \neq j' \in \mathcal{J}_n, \quad (6.7h)$$

$$\sum_{j=1}^{J_n} f_{n,k,j} \leq d_f, \forall n \in \mathcal{N}, k \in \mathcal{K}, \quad (6.7i)$$

$$\sum_{k=1}^K f_{n,k,j} \leq d_v, \forall n \in \mathcal{N}, j \in \mathcal{J}_n, \quad (6.7j)$$

$$p_{n,k,j} \geq 0, \forall n \in \mathcal{N}, k \in \mathcal{K}, j \in \mathcal{J}_n, \quad (6.7k)$$

$$\sum_{k=1}^K \sum_{j=1}^{J_n} f_{n,k,j} p_{n,k,j} \leq P_{\text{tot}}, \forall n \in \mathcal{N}, \quad (6.7l)$$

$$\sum_{k=1}^{K_{\text{net}}} v_{n_i,k} = K_{\text{net}}, \forall n_i \in \mathcal{N}_i, \quad (6.7m)$$

where P_{tot} signifies the overall allocated transmit power for communication at each of the UAV-BS. Constraint (6.7b) indicates that the UAV-BSs 2D coordinates are inside the maximum defined length $l_{\max}$ in which the users are located and their height lie between $H_{\min}$ and $H_{\max}$. Constraints (6.7c) and (6.7f) indicate that $c_{n,m}$ and $f_{n,k,j}$ have binary values, respectively. Constraint (6.7d) is imposed to guarantee that each of the UAV-BS offers services to an equivalent number of ground users. Constraint (6.7e) specifies that each user is serviced by precisely single UAV-BS. Constraint (6.7g) specifies that each of the UAV-BS employs K number of subchannels. Constraint (6.7h) ensures that the FGM designed for each group should not have any identical columns. Constraint (6.7i) indicates that maximum d_f number of users can communicate over each subchannel, while constraint (6.7j) signifies that each user is active over

d_v subchannels. Constraint (6.7l) specifies that power allocated to the users among all subchannels should be less or equal to P_{tot} . Constraint (6.7m) denotes that the sum of the bandwidth allocation factor is K_{net} for each UAV subgroup.

However, solving the optimization problem $\mathcal{P}(1)$ is challenging, as these optimization variables exhibit high coupling, and the objective function is neither concave nor convex concerning these variables. Additionally, the association and FGM design introduces binary variables, thus bringing integer constraints into (6.7c)-(6.7j). As a result, problem $\mathcal{P}(1)$ constitutes a mixed-integer non-convex optimization problem, making the quest for a globally optimal solution challenging [152].

6.2 Proposed Solution

To compute a suboptimal solution of $\mathcal{P}(1)$, we divide the overall problem into four subproblems and address them individually. Initially, we establish the association between UAV-BSs and users, along with determining the UAV-BSs 3D placements. Subsequently, we execute the subchannel assignment in a way that prioritizes minimizing interference. Further, the powers allocated to each user at each active subchannel are optimized. Finally, bandwidth allocation is done for each subchannel such that the total bandwidth allocated to each UAV subgroup is fixed.

6.2.1 Users clustering and UAVs deployment

For a given $\mathbf{F}$, $\mathbf{P}$ and $\mathbf{V}$, the joint UAV placement and user clustering problem becomes

$$\mathcal{P}(\text{A1}) : \max_{\mathbf{L}, \mathbf{C}} f_{\text{A1}}(\mathbf{L}, \mathbf{C}) = \sum_{n=1}^N \sum_{j=1}^{J_n} \mathbf{R}_{n,j} \quad (6.8a)$$

$$\text{s.t. } (6.7b), (6.7c), (6.7d), (6.7e). \quad (6.8b)$$

To address problem $\mathcal{P}(\text{A1})$, we decompose it into two distinct components: (1) the identification of UAV 2D deployment locations and users clustering, (2) the determination of UAV-BSs altitude. The mathematical expression for the first component, involving users clustering and UAV 2D deployment, is as follows:

$$\mathcal{P}(\text{SP}_1) : \min_{x_n^{\text{uav}}, y_n^{\text{uav}}, c_{n,m}} \sum_{n=1}^N \sum_{m=1}^M c_{n,m} r_m^n \quad (6.9a)$$

$$\text{s.t. } 0 \leq x_n^{\text{uav}}, y_n^{\text{uav}} \leq l_{\text{max}}, \quad (6.9b)$$

$$(6.7c), (6.7d), (6.7e). \quad (6.9c)$$

In the subproblem $\mathcal{P}(\text{SP}_1)$, the cost function is defined as the summation of Euclidean distances between the ground users and their respective associated UAV-BSs. The minimization of this cost function holds significant importance, as shorter 2D distances correspond to higher channel gains, consequently leading to enhanced data rates for the users. As the users' locations are known, the original K-means algorithm serves as an effective clustering scheme by leveraging the 2D distance between the users and cluster centers. We employ a modified K-means based user clustering algorithm to evenly distribute all the users into N groups and minimize the cost function [177].

With given UAVs 2D location and their association, the optimization problem of the UAVs' altitudes is expressed as:

$$\mathcal{P}(\text{SP}_2) : \max_{h_n^{\text{uav}}} \sum_{n=1}^N \sum_{j=1}^{J_n} R_{n,j} \quad (6.10a)$$

$$\text{s.t. } H_{\min} \leq h_n^{\text{uav}} \leq H_{\max}. \quad (6.10b)$$

Given the impact of LoS and NLoS components on the channel gain, problem $\mathcal{P}(\text{SP}_2)$ is still nonconvex. To address this, we employ the golden-section search (GSS) method to find the optimized altitude for the n th UAV [178]. We sequentially explore the optimal altitude of each UAV to derive a suboptimal solution for subproblem $\mathcal{P}(\text{SP}_2)$. After determining the altitudes for all UAVs, the sum-rate is updated. This iterative process continues until convergence of the objective function is achieved.

6.2.2 Designing Factor graph matrix

With known $\mathbf{L}$, $\mathbf{C}$, $\mathbf{V}$, and $\mathbf{P}$, the optimization problem $\mathcal{P}(1)$ can be reformulated as:

$$\mathcal{P}(\text{A2}) : \max_{\mathbf{F}} f_{\text{A2}}(\mathbf{F}) = \sum_{n=1}^N \sum_{j=1}^{J_n} \mathbf{R}_{n,j} \quad (6.11a)$$

$$\text{s.t. } (6.7f), (6.7g), (6.7h), (6.7i), (6.7j). \quad (6.11b)$$

To solve the problem $\mathcal{P}(\text{A2})$, we introduce three heuristic algorithms to design $\mathbf{F}$.

6.2.2.1 CSI-based continuous Subchannel allocation (CCSA) scheme

In **Algorithm 7**, we first find out the UAV which is closest to origin. Let the location of UAV closest to origin is $\mathbf{l}_{n'}, n' \in \mathcal{N}$. Calculate the distance of all other UAVs except n' UAV, i.e., $\mathbf{l}_n, n \in \mathcal{N} \setminus \{n'\}$ from $\mathbf{l}_{n'}$. Sort the distance in ascending order and store the indices of corresponding UAVs as $\mathbf{t}$. Let a_n denotes the beginning index for subchannel allocation of the n th UAV, and $e_n = a_n + K$ designates its endpoint. For instance, with $(a_n, e_n) = (2, 2 + K)$, subchannels from $k = 2$ to $k = K + 2$ are assigned to the n th UAV. The start-end indicator of n' th UAV will be $(a_1, e_1) = (1, K)$, i.e., $k = 1 : K$ subchannels are allocated to n' th UAV. So, the end indicator will follow an arithmetic progression as $e_{\hat{n}} = K_{\text{net}} - (\hat{n} - 1)\hat{d}$, where $\hat{d}$ is the shift in the subchannel for each UAV. This will continue until $K \leq e_{\hat{n}} \leq K + \hat{d}$. Thus, out of N UAVs, subchannel allocation is done in a group of every $n_o = \frac{K_{\text{net}} - e_{\hat{n}}}{\hat{d}} + 2$ UAVs. In this manner, the start-end indication of subchannel allocation for each UAV is done.

Subsequently, the root mean square (RMS) of $\mathbf{G}$ is computed with respect to the each user and then arranged in the descending order. The process of RE allocation is initiated with the user holding the maximum of the RMS values. For the chosen user, we select d_v REs with the maximum SINR and allocate these REs to the respective user. This process is iteratively applied to all the users in a sequential manner, following the descending order of RMS values. As the assignment of REs progresses for the ground users, complying with the (6.7h), (6.7i), and (6.7j) constraints becomes increasingly challenging. In such instances, the algorithm continues selecting the subsequent d_v REs

Algorithm 7: The CSI-based continuous subchannel allocation (CCSA) scheme for designing $\mathbf{F}$ for multi-UAV SCMA network

Inputs:

$\mathbf{L}, \hat{d}, J_n, K_{\text{net}}, K, d_f, d_v, \mathbf{G}.$

Output:

$\mathbf{F}.$

- 1: The subchannel end indicator is $e_{\hat{n}} = K_{\text{net}} - (\hat{n} - 1)\hat{d}$. This will continue until $K \leq e_{\hat{n}} \leq K + \hat{d}$.
 - 2: UAVs are divided into N_i number of sub-groups each having maximum n_o UAVs. Assume that the set of UAVs belonging to i th sub-group is $\mathcal{N}_i$.
 - 3: **for** each subgroup $\mathcal{N}_i$ **do**
 - 4: Find the UAV which is closest to origin and allocate the starting K number of subchannels to n' th UAV. Let the location of UAV closest to origin is $\mathbf{l}_{n'}, n' \in \mathcal{N}_i$.
 - 5: Calculate the distance between $\mathbf{l}_n, \{n \in \mathcal{N}_i \setminus \{n'\}\}$ from $\mathbf{l}_{n'}$.
 - 6: Sort the distance in descending order and store the indices of corresponding UAVs as $\mathbf{t}$.
 - 7: The subchannels end indicator follows $e_{\hat{n}} = K_{\text{net}} - (\hat{n} - 1)\hat{d}, \forall \hat{n} = 1 : n_o - 1 \in \mathbf{t}$. Similarly, the start indicator becomes $a_{\hat{n}} = e_{\hat{n}} - K$.
 - 8: **for** $\check{n} = 1 : n_o$ **do**
 - 9: Calculate the average RMS value, $\mathbf{r}$ from $\mathbf{G}$ with respect to each user and sort them in the descending order. Save the indices of corresponding users in $\check{J}_{\check{n}}$.
 - 10: **for** $\check{i} = 1 : \check{J}_{\check{n}}$ **do**
 - 11: **if** $\sum_{j=1}^{\check{n}} \mathbf{F}_{k,j} \leq d_f, \forall a_{\check{n}} \leq k \leq e_{\check{n}}$ or $\mathbf{F}_{\check{n},i} \neq \mathbf{F}_{\check{n},j}$ **then**
 - 12: Identify the highest d_v values from the column of $\mathbf{G}$ corresponding to index $\mathbf{r}(\check{n}, \check{i})$.
 - 13: For the selected d_v values in Step 12, the corresponding indices in $\mathbf{F}_{\check{n}}$ are assigned a value of one.
 - 14: Assign zero to the $(\check{n}, \check{i})$ th column in $\mathbf{G}$.
 - 15: **else**
 - 16: Proceed with similar Steps 12-14 for the indices corresponding to the subsequent d_v largest values.
 - 17: **end if**
 - 18: **end for**
 - 19: **end for**
 - 20: **end for**
-

corresponding to next highest CSI values till all the specified constraints are satisfied. Consequently, the proposed algorithm prioritizes assigning subchannels to users based on favorable CSI, while taking into account the SCMA FGM constraints.

6.2.2.2 SINR-based continuous Subchannel allocation (SCSA) scheme

In this scheme, the start-end indicator for subchannel allocation and dividing the UAVs into subgroups is done in the same manner as in CCSA scheme. In this scheme, we go one step further and allocate the subchannels to users based on SINR. For each subgroup of UAV, we begin with an initial matrix $\mathbf{F}_{\text{ini}}$, which is an all-ones matrix of size $K \times J_n$. Subsequently, we calculate the SINR matrix $\mathbf{S}_{K \times J_n} = (\gamma_{k,j})_{K \times J}$ for first UAV of this subgroup considering only intra-UAV interference, where $\gamma_{k,j}$ is as shown in (6.6). Following this, the RMS of $\mathbf{S}$ is computed concerning the users and subsequently organized in the decreasing order. The allocation of RE begins with the user holding the maximum of all the RMS values. Next, the steps similar to Steps 12-16 are followed as in Algorithm 7. The difference here is that instead of $\mathbf{G}$, the REs are allocated based on SINR matrix $\mathbf{S}$, considering the constraints in (6.7h), (6.7i), (6.7j). This procedure is further repeated for other UAVs of the subgroup, where inter-UAV

interference is now considered in computing $\mathbf{S}$ from the clusters for which the FGM is already designed.

6.2.2.3 CSI-based Flexible Subchannel allocation (CFSA) scheme

In the above two schemes, we used start to end indicator to allocate the continuous subchannels for each UAV. In this scheme, we flexibly allocate $K < K_{\text{net}}$ subchannels to each UAV. Here, we consider inclusion of $K_{\text{net}} - K$ zero rows as a constraint in designing FGM. Next, the RMS of $\mathbf{G}$ is calculated concerning the users and subsequently arranged in the decreasing order. The allocation of RE is initiated from the user with the maximum of the RMS values. For each of the chosen user, we choose d_v REs with the maximum CSI values and allocate these REs to the respective user. This process continues until the number of non-zero rows in FGM reaches K . Once K subchannels are occupied, the rest of the highest d_v number of CSI values are chosen among only these already occupied subchannels. As the number of users increases, meeting the constraints outlined in (6.7h), (6.7i), and (6.7j) becomes progressively challenging. In such scenarios, we continue selecting the next d_v REs corresponding to next highest CSI values till all the specified constraints are satisfied. Consequently, in the proposed scheme, the subchannels are flexibly chosen based on available CSI values.

6.2.3 Power Allocation

For the given $\mathbf{L}$, $\mathbf{C}$, $\mathbf{F}$, $\mathbf{V}$, the optimization problem $\mathcal{P}(1)$ is expressed as:

$$\mathcal{P}(\text{A3}) : \max_{\mathbf{P}} f_{\text{A3}}(\mathbf{P}) = \sum_{n=1}^N \sum_{j=1}^{J_n} \mathbf{R}_{n,j} \quad (6.12\text{a})$$

$$\text{s.t. (6.7k), (6.7l).} \quad (6.12\text{b})$$

Here, addressing subproblem $\mathcal{P}(\text{A3})$ presents a challenge due to its non-convex nature, and the computational complexity involved in determining the optimal solution is prohibitive. To effectively address the optimization problem $\mathcal{P}(\text{A3})$, we introduce a heuristic power allocation algorithm outlined in **Algorithm 8**. This algorithm is structured to allocate power among users over the active subchannels, prioritizing those with better rate values. After solving problem $\mathcal{P}(\text{A2})$, we get the rate for each group of users with uniform power allocation. We sort the rate of users of each group in the descending order. With computation of $\mathbf{F}$ in previous subsection, we also identify the active user-subchannel pairs. Each group of users are partitioned into two sub-groups: the first sub-group comprises users with low data rates, while the second sub-group consists of users with high data rates. Let $pi_{k,j}$ be the initial power allocated to the j th user at the k th subchannel. Since SINR is known for each user at each subchannel, we can also group the subchannels in low, moderate and high SINR subchannels for each user. Let $pa_{k,j}$ and $pb_{k,j}$ be the power scaling factors for the low and high data rate users, respectively. We initiate the power allocation by assigning the power of $pi_{k,j} - pa_{k,j}$ to low SINR subchannels and $pi_{k,j} + pa_{k,j}$ to high SINR subchannels for the low data rate user sub-group. Analogously, for the high data rate user sub-group, low SINR subchannels are allocated the power of $pi_{k,j} - pb_{k,j}$, while large SINR subchannels receive the power of $pi_{k,j} + pb_{k,j}$. Let $SR_n^{ii} = \sum_{k=1}^{K_{\text{net}}} \sum_{j=1}^{J_n} R_{n,k,j}^i$ be the

Algorithm 8: The Power allocation algorithm for SCMA-assisted multi-UAV network

Inputs:

$J_n, K_{\text{net}}, K, d_f, d_v, \mathbf{S}_{N \times K_{\text{net}} \times J_n}, \mathbf{F}_{N \times K_{\text{net}} \times J_n}, \mathbf{R}_{N \times K_{\text{net}} \times J_n}.$

Output: $\mathbf{P}.$

```

1: for each subgroup  $\mathcal{N}_i$  do
2:   for  $n = 1 : n_o$  do
3:     Sort the rate of all the users in the descending order and store
       their indices.
4:     The users are divided into two equal sub-groups: first sub-group consists of high data rate
       users, i.e.,  $\text{SG}_{\text{high}}$  and second sub-group consists of low data rate users, i.e.,  $\text{SG}_{\text{low}}$ .
5:     For each user, sort the SINR values on the active subchannels in ascending order.
6:     while  $SR_n^{ii} - SR_n^{ii-1} \geq \epsilon$ ,  $p_{n,k,j} \geq p_{\min}$  and  $P_n^{ii} \leq P_{\text{tot}}$  do
7:       For the first sub-group  $\text{SG}_{\text{high}}$ , the power at small SINR channel is updated as
          $pi_{k,j} - pa_{k,j}$  and at large SINR channels as  $pi_{k,j} + pa_{k,j}$ .
8:       For the second sub-group  $\text{SG}_{\text{low}}$ , the power at small SINR channel is updated as
          $pi_{k,j} - pb_{k,j}$  and at large SINR channels as  $pi_{k,j} + pb_{k,j}$ .
9:       Update the scaling factors  $pa_{k,j}^{ii} = pa_{k,j}^{ii-1} + pa_{k,j}^{ii-1}/2$  and  $pb_{k,j}^{ii} = pb_{k,j}^{ii-1} + pb_{k,j}^{ii-1}/2$ .
10:    end while
11:  end for
12: end for

```

sum-rate and $P_n^{ii} = \sum_{k=1}^K \sum_{j=1}^{J_n} f_{n,k,j} p_{n,k,j}$ be the total power of the n th cluster users at i th iteration. The values of $pa_{k,j}$ and $pb_{k,j}$ are iteratively updated until fractional increase in sumrate is above 1% and allocated power at for each user is above the minimum power $p_{\min}$ required at each subchannel.

6.2.4 Non-uniform Bandwidth allocation

For the given $\mathbf{L}, \mathbf{C}, \mathbf{F}, \mathbf{P}$, the optimization problem $\mathcal{P}(1)$ is reformulated as:

$$\mathcal{P}(\text{A4}) : \max_{\mathbf{V}} f_{\text{A4}}(\mathbf{V}) = \sum_{n=1}^N \sum_{j=1}^{J_n} \mathbf{R}_{n,j} \quad (6.13\text{a})$$

$$\text{s.t. (6.7m).} \quad (6.13\text{b})$$

We propose **Algorithm 9** to adjust the bandwidth of each subchannel with the aim of maximizing the sumrate and also improve the minimum user data rate. In this algorithm, for each subgroup of UAVs, we compute the data rate of all the associated users. Next, we find u_a number of users with lowest data rates and save them in the set $\mathcal{U}_a$. For these low data rate users, we find the subchannels with maximum data rate and store them in the set $\mathbb{K}$. The unique subchannels are stored in $\mathbb{K}_s$ and remaining subchannels are stored in $\mathbb{K}_r$. Next, the bandwidth associated with subchannels in $\mathbb{K}_s$ are scaled by a factor of s_a . The remaining subchannels are scaled by the factor $\frac{Kr_{\text{fac}}}{K_r}$, where $Kr_{\text{fac}} = K_{\text{net}} - K_s$. The factor s_a is updated by $sa = sa + \frac{sa}{2}$ until fractional increase in minimum rate $R_{\min}$ and sum-rate is above their defined threshold values and $\frac{Kr_{\text{fac}}}{K_r} \geq v$, where v is the threshold ratio for the bandwidth allocation.

Algorithm 9: The Non-uniform bandwidth allocation for multiple UAV SCMA network

Inputs: $K_{\text{net}}, \mathbf{R}_{N \times K_{\text{net}} \times J_n}$.

Output: $\mathbf{V}$.

- 1: **for** each subgroup $\mathcal{N}_i$ **do**
 - 2: From $\mathbf{R}$, sort the rate of all the users in the ascending order. Find the indices of u_a number of users with lowest data rate and save it in the set $\mathcal{U}_a$.
 - 3: For each user in the set $\mathcal{U}_a$, find the subchannels with maximum data rate and store them in the set $\mathbb{K}$. Find the unique subchannels among $\mathbb{K}$ and save them in $\mathbb{K}_s$ and remaining subchannels are stored in $\mathbb{K}_r$.
 - 4: Let K_s be number of unique subchannels and $K_r = K_{\text{net}} - K_s$ be number of remaining subchannels.
 - 5: **while** $R_{\min}^{ii} - R_{\min}^{ii-1} \geq \epsilon'$, $\text{SR}_n^{ii} - \text{SR}_n^{ii-1} \geq \epsilon$, and $\frac{Kr_{\text{fac}}}{K_r} \geq v$ **do**
 - 6: **for** $k = 1 : K_s$ **do**
 - 7: $\mathbf{R}^{ii}(n, \mathbb{K}_s(k), :) = s_a \mathbf{R}^{ii-1}(n, \mathbb{K}_s(k), :)$
 - 8: **end for**
 - 9: Update $Ks_{\text{fac}} = s_a K_s$ and $Kr_{\text{fac}} = K_{\text{net}} - K_s$.
 - 10: **for** $k = 1 : K_r$ **do**
 - 11: $\mathbf{R}^{ii}(n, \mathbb{K}_r(k), :) = \frac{Kr_{\text{fac}}}{K_r} \mathbf{R}^{ii-1}(n, \mathbb{K}_r(k), :)$
 - 12: **end for**
 - 13: Update the scaling factor as $sa^{ii} = sa^{ii-1} + \frac{sa^{ii-1}}{2}$.
 - 14: **end while**
 - 15: **end for**
-

6.2.5 Complexity

Now, we will delve into the computational complexity of the proposed algorithms. The complexity of UAV deployment and user association is $\mathcal{O}(M[(M/N)])$ $L_1 + L_1' \log_2([h_{\max} - h_{\min}]/\epsilon)$, where L_1 is the number of iterations for UAV 2D deployment and user association, L_1' is the number of iterations for GSS method and ϵ is the search accuracy in GSS method [178].

The computational complexity of subchannel allocation using CCSA scheme is $\mathcal{O}(N_i((n_o - 1)a1 + n_o JK))$, where $a1$ denotes the complexity of computing the start-end indicator for each UAV as shown in Step 7 of Algorithm 1. The computational complexity of SCSA scheme is $\mathcal{O}(N_i((n_o - 1)a1 + n_o a2 JK))$, where $a2$ denotes the complexity of computing the SINR matrix for each UAV. Next, the computational complexity of CFSA scheme is $\mathcal{O}(N_i(n_o Ja3 K_{\text{net}}))$, where $a3$ denotes the complexity of finding the maximum d_v number of subchannels with highest CSI values, considering $K_{\text{net}} - K$ zero rows among total K_{net} rows.

The algorithmic time complexity for Algorithm 8 is $\mathcal{O}(N_i n_o L_2 a4)$, where L_2 is the number of iterations for power allocation and $a4$ is the complexity to compute Steps 7-9 in each iteration. The computational complexity of Algorithm 9 is $\mathcal{O}(N_i L_3 (K_s + K_r))$, where L_3 represents the number of iterations for bandwidth allocation.

6.3 Results and Discussion

In this section, we present and discuss the numerical results to demonstrate the effectiveness of the proposed algorithms. The simulation setup comprises of five UAV-BSs

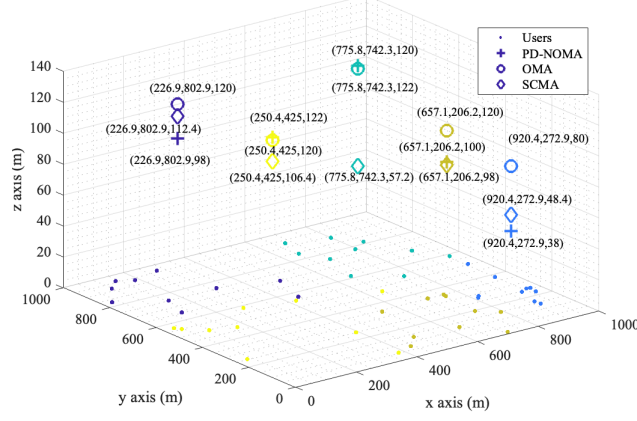


Figure 6.2: 3D placement of five UAVs serving 50 users.

serving 50 ground users distributed in an area of $1000 \text{ m} \times 1000 \text{ m}$. The simulation parameters are: $\alpha = 2.4$, $\eta_{\text{LoS}} = 3 \text{ dB}$, $\eta_{\text{NLoS}} = 23 \text{ dB}$, $a = 11.95$ and $b = 0.136$. The initial transmit power of each UAV is distributed equally among all the served users. Two benchmark schemes are considered for comparative analysis [179]:

- OMA: In this scheme, all the UAVs serve the ground users in orthogonal time slots of equal size, but they share the same frequency band. Thus, the users face only the inter-UAV interference in this case. The rate achieved by the (n, j) th user is

$$\mathbf{R}_{n,j}^{\text{OMA}} = \frac{1}{J_n} \log_2 \left(1 + \frac{\|g_{n,k,j}\|^2 P_{\text{tot}}}{I_{n,k,j}^{\text{inter}} + \sigma^2} \right) \quad (6.14)$$

- Interference Free (IF): In this approach, each UAV serves ground users in orthogonal time slots and is allocated orthogonal frequency bands. Thus, the users do not face any interference and all UAVs operate with maximum transmit power. The rate achieved in IF case by the (n, j) th user is:

$$\mathbf{R}_{n,j}^{\text{IF}} = \frac{1}{N J_n} \log_2 \left(1 + \frac{\|g_{n,k,j}\|^2 P_{\text{tot}}}{\frac{\sigma^2}{N}} \right) \quad (6.15)$$

Fig. 6.2 shows the 3D deployment of five UAV-BSs alongside the locations of 50 ground users for SCMA, OMA and PD-NOMA schemes. Users associated with distinct UAVs are indicated by varying colors, and the color of the associated UAV-BS corresponds to that of its users. Each UAV-BS is positioned at the geometric center of its designated cluster in 2D space. The altitude of each UAV is fine-tuned utilizing the GSS scheme to enhance the overall sum-rate.

Fig. 6.3 illustrates the sum-rate performance concerning the total transmit power of each UAV. In Fig. 6.3 (a), the $\mathbf{F}$ matrix is designed using CCSA scheme as discussed in **Algorithm 7**. Then, we have shown the impact of power allocation and non-uniform bandwidth allocation from **Algorithm 8** and **Algorithm 9**, respectively. It is noted that by introducing the proposed schemes gradually, the sum-rate of the network improves significantly. In Fig. 6.3 (b) and (c), the $\mathbf{F}$ matrix is designed using SCMA scheme and CFSA scheme, respectively. Again, for the resulting $\mathbf{F}$ matrix in both cases, we have shown the impact of power allocation and non-uniform bandwidth

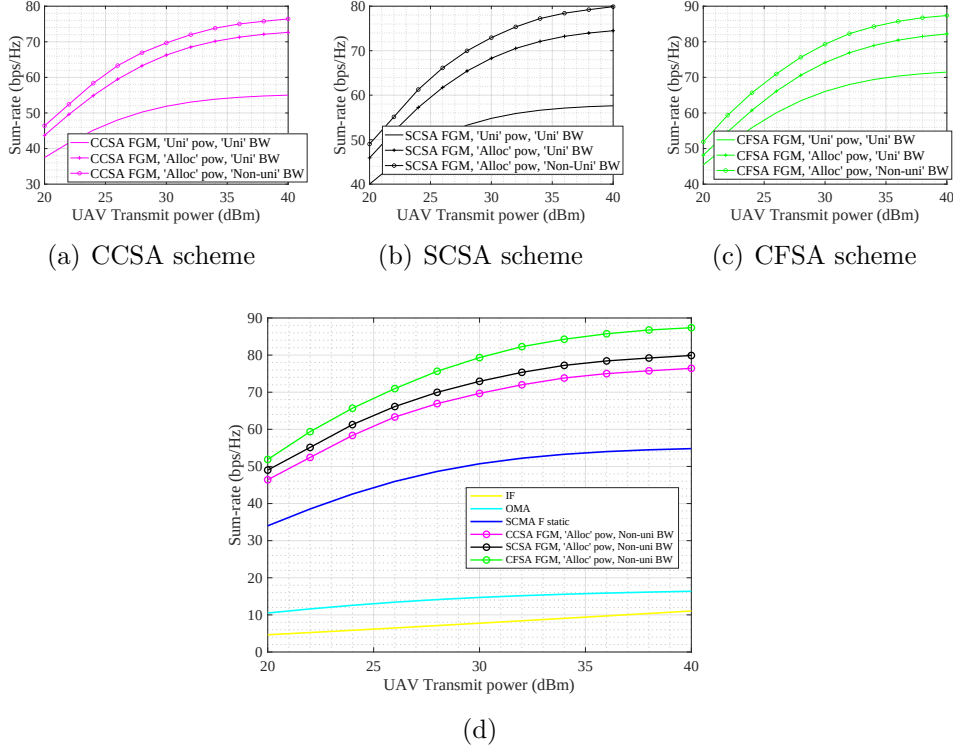


Figure 6.3: Sum-rate versus UAV transmit power (a) CCSA (b) SCSA (c) CFSA based FGM, ‘Uni’ denotes uniform, ‘Alloc’ denotes allocated power from Algorithm 8 and ‘Non-uni’ denotes the non-uniform bandwidth allocation from Algorithm 9. Subfigure (d) shows the sum-rate performance for proposed SCMA based schemes, static FGM, OMA and IF schemes.

allocation. Fig. 6.3 (d) illustrates the sum-rate performance for the proposed SCMA and benchmark schemes. Here, SCMA $\mathbf{F}$ static denotes the static FGM for all clusters with uniform power and bandwidth allocation to all users. It is apparent that the sum-rate performance experiences a significant enhancement with the increase in the transmit power for all the proposed algorithms.

Fig. 6.4 depicts the cumulative distribution function (CDF) of the network sum-rate with respect to IF, OMA, and different SCMA schemes. In Fig. 6.4 (a), the $\mathbf{F}$ matrix is designed using CCSA scheme and then power allocation and bandwidth allocation is done using **Algorithm 8** and **Algorithm 9**, respectively. It is noteworthy that the gradual introduction of the proposed schemes leads to a substantial improvement in the sum-rate of the network. In Fig. 6.4 (b) and (c), the $\mathbf{F}$ matrix is designed using SCSA scheme and CFSA scheme, and in both cases, we have shown the impact of power allocation and non-uniform bandwidth allocation. Fig. 6.4 (d) illustrates the CDF curves for the proposed SCMA and the benchmarking schemes. It is noteworthy that the benefits derived from the proposed methodologies exhibit stability, with the depicted curves maintaining consistent alignment with their corresponding counterparts in Fig. 6.3.

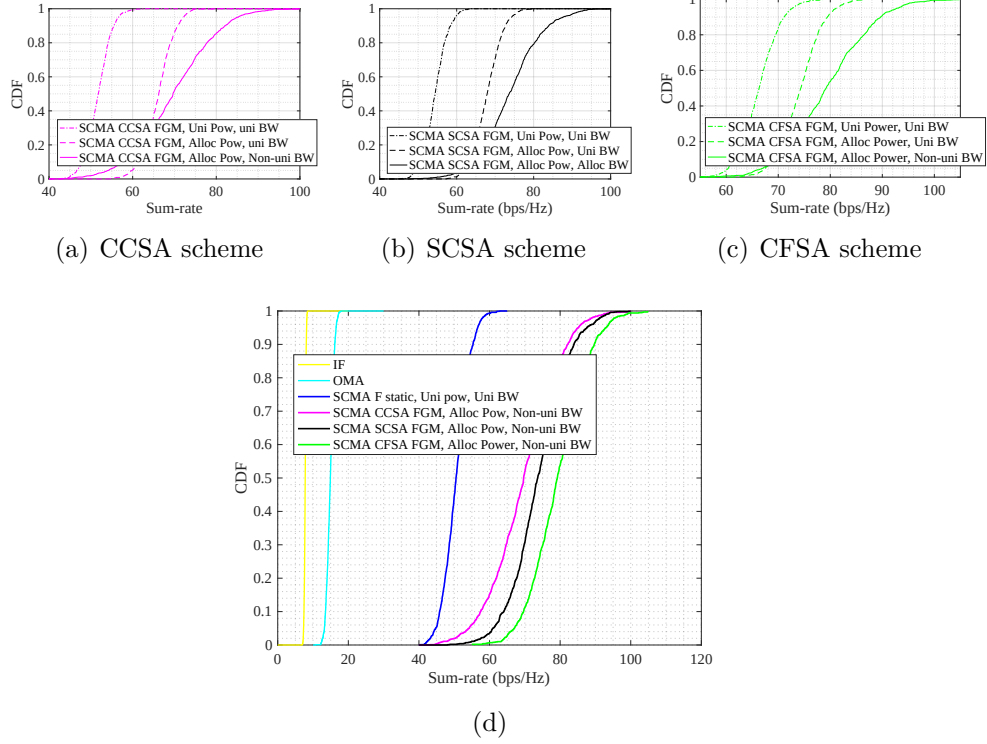


Figure 6.4: CDF plot for multi-UAV SCMA network for (a) CCSA (b) SCSA (c) CFSA based FGM, (d) shows the CDF plot for proposed SCMA based schemes, static FGM, OMA and IF schemes.

6.4 Conclusion

In this work, we have proposed resource allocation schemes aimed at maximizing the sum-rate for a SCMA-aided multiple UAV downlink system, addressing challenges related to inter-UAV and intra-UAV interferences. We have worked on the joint optimization of UAV-users association, UAV-BSs 3D deployment, multiple subchannels assignment, power allocation and bandwidth allocation to improve the network performance. We have divided the formulated optimization problem into four tractable subproblems, and then solve them separately. The simulation results demonstrate that optimizing subchannel allocation, power allocation, and bandwidth allocation in a multi-UAV SCMA system can significantly enhance the achieved sum rate. The findings also indicated that 1) minimizing interference requires efficient subchannel assignment, 2) network performance benefits from balanced power allocation, and 3) optimizing bandwidth allocation helps in improving outage performance.

Chapter 7

Summary and Future Work

In this chapter, we first present a concise summary of the thesis and subsequently provide insights for future research directions.

7.1 Summary

Since SCMA systems are among the potential candidates for next generation multiple access techniques for providing massive connectivity, the focus of this thesis is analysing SCMA scheme in various scenarios. We firstly provided a systematic discussion on CB designing, encoding and decoding in SCMA in Chapter 2.

As visible light communication (VLC) offers various advantages such as unlicensed spectrum, security, free of electromagnetic interference, and ease of deployment, it has emerged as a complementary communication method with radio-frequency (RF) communication, especially for indoor scenarios. In Chapter 3, we illustrated the suitability and compatibility of SCMA in VLC system. As SCMA users map their incoming bits to multi dimensional CBs, designing good CBs plays an important role in their performance. Thus, SCMA based real and positive CBs were designed by optimizing the log-sum of exponentials for indoor VLC system impaired by shot noise. This work emphasized that the designing of specific CBs is required for the SCMA-VLC system. The designed CBs are power-efficient, less computationally complex, and especially helpful for overloading factors greater than one.

While the majority of existing literature in the field of SCMA primarily focuses on the design of CBs and decoding algorithms, there has been relatively limited attention given to resource allocation. Consequently, the forthcoming chapters of our work delved into the realm of resource allocation within SCMA-assisted systems. In Chapter 4, we investigated the sum-rate in SCMA-aided IRS system, considering the multi-user interference. In particular, we formulated a joint power, factor graph matrix, and IRS phase optimization problem in order to maximize the sum-rate, subject to the constraints of the SCMA structure, IRS coefficients, transmit power, and minimum rate. The formulated problem is MINLP and difficult to solve. We have proposed to solve the joint optimization problem using AO method by dividing the main problem into three sub-problems. It is shown using the simulation results that the proposed algorithms outperform by optimizing the factor graph matrix, power at the base station,

and phase coefficients of the IRS. Also, it is seen from the results that the proposed IRS-aided SCMA system performs better than the SCMA system without the IRS, and other benchmark schemes.

Given the anticipated pivotal role of UAVs in forthcoming wireless communication systems, Chapter 5 and Chapter 6 center around enhancing performance through the targeted exploration of resource allocation in SCMA-assisted UAV systems. In Chapter 5, we addressed the maximization of sum-rate when UAV is in flight and in stationary hovering mode. Our approach involved an iterative gradient ascent-based algorithm for UAV 3D deployment and trajectory optimization. This optimization aimed to maximize the sum-rate while considering UAV energy constraints, maintaining a minimum rate at the deployment location. Upon reaching the deployment site, we optimized sub-channel assignment and power allocation. The simulation results have demonstrated the superiority of the proposed algorithms over the benchmark schemes. Further, we explored resource allocation in SCMA for multiple UAVs, addressing both intra-UAV and inter-UAV interference in Chapter 6. Specifically, we worked on joint optimization of the UAVs 3D deployment, users clustering and user-UAV association, subchannel assignment, power allocation, and bandwidth allocation. To address the formulated optimization problem, we decomposed it into four sub-problems, and solve them separately. First, we presented a modified algorithm based on K-means for the equitable allocation of all users to the UAVs. Then, we propose three frequency reuse based subchannel assignment schemes, in order to suppress the inter-UAV and intra-UAV interference. Finally, we propose iterative algorithms for power allocation and bandwidth allocation to each subchannel to the ground users. The proposed algorithms outperform benchmark schemes, as illustrated by the simulation results. The findings underscore the significance of efficient subchannel assignment, power allocation, and optimizing bandwidth allocation to improve network performance.

7.2 Potential Future Research Directions

The thesis lays the groundwork for various possible extensions. The following are some potential future research directions:

- Examine the incorporation of IRS and UAV within the framework of SCMA, which can serve as an effective strategy for expanding network coverage and enhancing spectrum efficiency. Leveraging IRS contributes to the improvement of performance for users situated at the cell edge.
- In this dissertation, the impact of users movement is not considered for the resource allocation in SCMA-assisted communication systems. This can also be a potential research idea to evaluate the performance degradation due to the user mobility and blockages in the environment.
- Furthermore, an area yet to be explored involves the amalgamation of integrated sensing and communications (ISAC) with SCMA. The exploration of ISAC development, wherein the principles of SCMA are harnessed to harmoniously accommodate both sensing and communication functionalities, represents a compelling avenue for investigation.

- The current assumption involves perfect knowledge of channel state information (CSI). Therefore, exploring the intriguing aspects of low-complexity CSI estimation and examining the errors in channel estimation for SCMA-assisted systems, coupled with phase estimation errors in IRS, is a worthwhile investigation within practical, non-ideal hardware scenarios.
- The existing assumption involves a single transmit antenna for the base station and a single receive antenna for users. Utilizing multiple transmit and receive antennas (MIMO) has the potential to enhance system performance by leveraging the spatial domain. Therefore, investigating the impact of MIMO antennas on the efficiency of IRS and UAV communication systems is a subject worth exploring.
- All the analyses conducted in this thesis have focused on a regular factor graph matrix. Exploring the impact of an irregular SCMA structure becomes a potential research direction, particularly in scenarios where users have diverse requirements.
- A hybrid OMA-NOMA system can be designed, where primary users operate orthogonally, and secondary users utilize SCMA to transmit opportunistically across available resources. By dynamically adjusting channel allocations based on the conditions and activity levels of both primary and secondary users, the hybrid system can maximize the network performance.

Bibliography

- [1] Mojtaba Vaezi, Zhiguo Ding, H. Vincent Poor, *Multiple access techniques for 5G wireless networks and beyond*, 1st ed., Springer, 2019.
- [2] K. Routh and T. Pal, “A survey on technological, business and societal aspects of Internet of Things by Q3, 2017,” in *Proc. 3rd Int. Conf. Internet Things Smart Innov. Usages (IoT-SIU)*, 2018, pp. 1–4.
- [3] L. Dong et al., “Introduction on IMT-2020 5G trials in China,” *IEEE J. Sel. Areas Commun.*, vol. 35, no. 8, pp. 1849–1866, Aug. 2017.
- [4] J. Rodriguez, *Fundamentals of 5G Mobile Networks*. Hoboken, NJ, USA: Wiley, 2014, ch. 10, pp. 221–240.
- [5] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey,” *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, 2010.
- [6] N. Abu-Ali, A. M. Taha, M. Salah, and H. Hassanein, “Uplink scheduling in LTE and LTE-Advanced: Tutorial, survey and evaluation framework,” *IEEE Commun. Surveys Tuts.*, vol. 16, no. 3, pp. 1239–1265, 3rd Quart., 2014.
- [7] Z. Wei, J. Yuan, D. W. K. Ng, M. El Kashlan, and Z. Ding, “A survey of downlink non-orthogonal multiple access for 5G wireless communication networks,” *ZTE Commun.*, vol. 14, no. 4, pp. 17–25, 2016.
- [8] Y. Liu, Z. Qin, M. El Kashlan, Z. Ding, A. Nallanathan, and L. Hanzo, “Non-orthogonal multiple access for 5G and beyond,” *Proc. IEEE*, vol. 105, no. 12, pp. 2347–2381, Dec. 2017, doi: 10.1109/JPROC.2017.2768666.
- [9] J. Wang et al., “Spectral Efficiency Improvement With 5G Technologies: Results From Field Tests,” *IEEE J. Sel. Areas Commun.*, vol. 35, no. 8, pp. 1867–1875, Aug. 2017, doi: 10.1109/JSAC.2017.2713498.
- [10] Z. Chen, Z. Ding, X. Dai and R. Zhang, “An Optimization Perspective of the Superiority of NOMA Compared to Conventional OMA,” *IEEE Trans. Signal Process.*, vol. 65, no. 19, pp. 5191–5202, 1 Oct. 1, 2017, doi: 10.1109/TSP.2017.2725223.
- [11] Y. Cai, Z. Qin, F. Cui, G. Y. Li and J. A. McCann, “Modulation and Multiple Access for 5G Networks,” *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 629–646, Firstquarter 2018, doi: 10.1109/COMST.2017.2766698.

- [12] R. Hoshyar, F. P. Wathan, and R. Tafazolli, "Novel low-density signature for synchronous CDMA systems over AWGN channel," *IEEE Trans. Signal Process.*, vol. 56, no. 4, pp. 1616–1626, 2008.
- [13] R. Razavi, R. Hoshyar, M. A. Imran, and Y. Wang, "Information theoretic analysis of LDS scheme," *IEEE Commun. Lett.*, vol. 15, no. 8, pp. 798–800, Aug. 2011.
- [14] F. R. Kschischang, B. J. Frey, and H. Loeliger, "Factor graphs and the sum-product algorithm," *IEEE Trans. Inf. Theory*, vol. 47, no. 2, pp. 498–519, 2001.
- [15] H. Nikopour and H. Baligh, "Sparse code multiple access," in *Proc. IEEE 24th Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, London, UK, 2013, pp. 332–336.
- [16] Y. Wu, C. Wang, Y. Chen, and A. Bayesteh, "Sparse code multiple access for 5G radio transmission," in *Proc. IEEE 86th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2017, pp. 1–6.
- [17] A. Ghaffari, M. Leonardon, A. Cassagne, C. Leroux, and Y. Savaria, "Toward high-performance implementation of 5G SCMA algorithms," *IEEE Access*, vol. 7, pp. 10402–10414, 2019.
- [18] Y. Chen et al., "Toward the Standardization of Non-Orthogonal Multiple Access for Next Generation Wireless Networks," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 19–27, March 2018, doi: 10.1109/MCOM.2018.1700845.
- [19] M. Moltafet, N. M. Yamchi, M. R. Javan, and P. Azmi, "Comparison study between PD-NOMA and SCMA," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1830–1834, Feb. 2018.
- [20] Q. Luo et al., "An error rate comparison of power domain non-orthogonal multiple access and sparse code multiple access," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 500–511, 2021.
- [21] S. Chaturvedi, Z. Liu, V. A. Bohara, A. Srivastava and P. Xiao, "A Tutorial on Decoding Techniques of Sparse Code Multiple Access," *IEEE Access*, vol. 10, pp. 58503–58524, 2022.
- [22] K. Deka, A. Thomas and S. Sharma, "OTFS-SCMA: A Code-Domain NOMA Approach for Orthogonal Time Frequency Space Modulation," in *IEEE Trans. Commun.*, vol. 69, no. 8, pp. 5043–5058, Aug. 2021.
- [23] H. Wen, W. Yuan, Z. Liu and S. Li, "OTFS-SCMA: A Downlink NOMA Scheme for Massive Connectivity in High Mobility Channels," in *IEEE Trans. Wireless Commun.*, doi: 10.1109/TWC.2023.3236383.
- [24] Z. Wu, K. Lu, C. Jiang, and X. Shao, "Comprehensive study and comparison on 5G NOMA schemes," *IEEE Access*, vol. 6, pp. 18511–18519, Mar. 2018.
- [25] P. H. Pathak, X. Feng, P. Hu, and P. Mohapatra, "Visible light communication, networking, and sensing: A survey, potential and challenges," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2047–2077, 4th Quart., 2015.

- [26] A. Jovicic, J. Li, and T. Richardson, "Visible light communication: opportunities, challenges and the path to market," *IEEE Commun. Mag.*, vol. 51, no. 12, pp. 26–32, Dec. 2013.
- [27] L. Grobe et al., "High-speed visible light communication systems," *IEEE Commun. Mag.*, vol. 51, no. 12, pp. 60–66, Dec. 2013.
- [28] B. Lin, X. Tang, Z. Zhou, C. Lin, and Z. Ghassemlooy, "Experimental demonstration of SCMA for visible light communications," *Opt. Commun.*, vol. 419, pp. 36–40, July 2018.
- [29] J. An and W.-Y. Chung, "Single-LED multichannel optical transmission with SCMA for long range health information monitoring," *J. Lightw. Technol.*, vol. 36, no. 23, pp. 5470–5480, 2018.
- [30] R. Mitra, S. Sharma, G. Kaddoum and V. Bhatia, "Color-domain SCMA NOMA for visible light communication," *IEEE Commun. Lett.*, vol. 25, no. 1, pp. 200–204, Jan. 2021.
- [31] S. Lou, C. Gong, Q. Gao, Z. Xu, "SCMA with low complexity symmetric CB design for visible light communication," in *Proc. International Conference on Communications (ICC)*, July 2018, pp. 1–6.
- [32] S. Hu, Q. Gao, C. Gong, Z. Xu, R. Boluda-Ruiz, and K. Qaraqe, "Energy-efficient modulation for visible light SCMA system with signal-dependent Noise," in *Proc. Int. Symp. Commun. Syst., Netw. Digit. Signal Process. (CSNDSP)*, Budapest, Hungary, Jul. 2018, pp. 1–6.
- [33] Q. Gao, S. Hu, C. Gong, E. Serpedin, K. Qaraqe and Z. Xu, "Distance-range-oriented constellation design for VLC-SCMA downlink with signal-dependent noise," *IEEE Commun. Lett.*, vol. 23, no. 3, pp. 434–437, 2019.
- [34] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE Access*, vol. 7, pp. 116753–116773, 2019.
- [35] M. A. ElMossallamy et al., "Reconfigurable intelligent surfaces for wireless communications: Principles, challenges, and opportunities," *IEEE Trans. Cogn. Commun. and Netw.*, vol. 6, pp. 990–1002, Sep. 2020.
- [36] I. Al-Nahhal, O. A. Dobre, and E. Basar, "Reconfigurable intelligent surface-assisted uplink sparse code multiple access," *IEEE Commun. Lett.*, early access, Feb. 9, 2021.
- [37] I. Al-Nahhal, O. A. Dobre, E. Basar, T. M. N. Ngatched and S. Ikki, "Reconfigurable Intelligent Surface Optimization for Uplink Sparse Code Multiple Access," in *IEEE Commun. Lett.*, vol. 26, no. 1, pp. 133–137, Jan. 2022.
- [38] M. Mozaffari, W. Saad, M. Bennis, Y. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019, doi: 10.1109/COMST.2019.2902862.

- [39] Z. Ullah, F. Al-Turjman, and L. Mostarda, "Cognition in UAV-aided 5G and beyond communications: A survey," *IEEE Trans. Cognit. Commun. Netw.*, vol. 6, no. 3, pp. 872–891, Sep. 2020, doi: 10.1109/TCCN.2020.2968311.
- [40] C. Wang, Y. Chen, Y. Wu and L. Zhang, "Performance evaluation of grant-free transmission for uplink URLLC services," *IEEE 85th Veh. Technol. Conf. (VTC Spring)*, pp. 1-6, Jun. 2017.
- [41] J. Shen, W. Chen, F. Wei, and Y. Wu, "ACK feedback based UE-to-CTU mapping rule for SCMA uplink grant-free transmission," in *Proc. Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Nanjing, China, Oct. 2017, pp. 1–5.
- [42] M. Taherzadeh, H. Nikopour, A. Bayesteh, and H. Baligh, "SCMA codebook design," in *Proc. IEEE 80th Veh. Technol. Conf. (VTC-Fall)*, Vancouver, BC, Canada, Sep. 2014, pp. 1–5.
- [43] S. Zhang, K. Xiao, B. Xiao, Z. Chen, B. Xia, D. Chen, and S. Ma, "A capacity-based codebook design method for sparse code multiple access systems," in *Proc. 8th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Yangzhou, China, Oct. 2016, pp. 1–5.
- [44] J. Bao, Z. Ma, Z. Ding, G. K. Karagiannidis, and Z. Zhu, "On the design of multiuser codebooks for uplink SCMA systems," *IEEE Commun. Lett.*, vol. 20, no. 10, pp. 1920–1923, Oct. 2016.
- [45] H. Nikopour and M. Baligh, "Systems and methods for sparse code multiple access," Jan. 2016, US patent 9,240,853.
- [46] V. P. Klimentyev and A. B. Sergienko, "SCMA codebooks optimization based on genetic algorithm," in *Proc. European Wireless Conference*, May 2017.
- [47] L. Yu, P. Fan, D. Cai, and Z. Ma, "Design and analysis of SCMA codebook based on star-QAM signaling constellations," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10543–10553, Nov. 2018.
- [48] M. Taherzadeh, H. Nikopour, A. Bayesteh, and M. Baligh, "System and method for designing and using multidimensional constellations," Nov. 2016, US patent 9,509,379.
- [49] M. Vameghestahbanati, "Hypercube-based multidimensional constellation design for uplink SCMA systems," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2020, pp. 1–6.
- [50] M. Vameghestahbanati, "Designing multidimensional constellations and efficient detection schemes for sparse code multiple access (SCMA) systems," Ph.D. dissertation, Eng. Elect. Comput., Carleton Univ., Ottawa, ON, Canada, 2020.
- [51] A. Bayesteh, H. Nikopour, M. Taherzadeh, H. Baligh, and J. Ma, "Low complexity techniques for SCMA detection," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, 2015, pp. 1–6.
- [52] T. Metkarunchit, "SCMA codebook design base on circular-QAM," in *Proc. Integr. Commun. Navig. Surveillance Conf. (ICNS)*, 2017, pp. 1–8.

- [53] J. Peng, W. Chen, B. Bai, X. Guo, and C. Sun, "Joint optimization of constellation with mapping matrix for SCMA codebook design," *IEEE Signal Process. Lett.*, vol. 24, no. 3, pp. 264–268, Mar. 2017.
- [54] J. Bao, Z. Ma, M. A. Mahamadu, Z. Zhu, and D. Chen, "Spherical codes for SCMA codebook," in *Proc. IEEE Vehicular Technology Conference (VTC2016-Spring)*, May 2016.
- [55] B. F. d. Silva, D. Silva, B. F. Uchôa-Filho, and D. L. Ruyet, "A multistage method for SCMA codebook design based on MDS codes," *IEEE Wireless Commun. Lett.*, vol. 8, no. 6, pp. 1524–1527, Dec. 2019.
- [56] Y. M. Chen, C. D. S. González, P. -H. Wang and K. -P. Chen, "Reinforcement Learning-Based SCMA Codebook Design for Uplink Rayleigh Fading Channels," *IEEE Wireless Commun. Lett.*, vol. 10, no. 8, pp. 1717–1721, Aug. 2021.
- [57] M. Alam and Q. Zhang, "Performance study of SCMA codebook design," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, 2017, pp. 1–5.
- [58] C. Yan, G. Kang, and N. Zhang, "A dimension distance-based SCMA codebook design," *IEEE Access*, vol. 5, pp. 5471–5479, May 2017.
- [59] K. Lai, J. Lei, L. Wen, G. Chen, W. Li, and P. Xiao, "Secure transmission with randomized constellation rotation for downlink sparse code multiple access system," *IEEE Access*, vol. 6, pp. 5049–5063, 2018.
- [60] C. Yan, G. Kang, and N. Zhang, "A dimension distance-based SCMA codebook design," *IEEE Access*, vol. 5, pp. 5471–5479, 2017.
- [61] J. Bao, Z. Ma, M. Xiao, T. A. Tsiftsis, and Z. Zhu, "Bit-interleaved coded SCMA with iterative multiuser detection: Multidimensional constellations design," *IEEE Trans. Commun.*, vol. 66, no. 11, pp. 5292–5304, Nov. 2018.
- [62] J. L. Fan, *Constrained coding and soft iterative decoding*. Boston: Kluwer Academic, 2001. [Online]. Available: <https://doi.org/10.1007%2F978-1-4615-1525-8>
- [63] A. Neubauer, J. Freudenberger, and V. Kuhn, *Coding theory: algorithms, architectures, and applications*. Wiley-Interscience, 2007.
- [64] H. Mu, Z. Ma, M. Alhaji, P. Fan, and D. Chen, "A fixed low complexity message pass algorithm detector for up-link SCMA system," *IEEE Wireless Commun. Lett.*, vol. 4, no. 6, pp. 585–588, Dec. 2015.
- [65] M. Vameghestahbanati, I. Marsland, R. H. Gohary, and H. Yanikomeroglu, "A novel SD-based detection for generalized SCMA constellations," *IEEE Trans. Veh. Technol.*, vol. 68, no. 10, pp. 10278–10282, Oct. 2019.
- [66] Z. Pan, E. Li, L. Zhang, J. Lei, and C. Tang, "Design and optimization of joint iterative detection and decoding receiver for uplink polar coded SCMA system," *IEEE Access*, vol. 6, pp. 52014–52026, 2018.
- [67] P. Wang, L. Liu, S. Zhou, G. Peng, S. Yin, and S. Wei, "Near-optimal MIMO-SCMA uplink detection with low-complexity expectation propagation," *IEEE Trans. Wireless Commun.*, vol. 19, no. 2, pp. 1025–1037, Feb. 2020.

- [68] M. Kim, N.-I. Kim, W. Lee, and D.-H. Cho, "Deep learning aided SCMA," *IEEE Commun. Lett.*, vol. 22, no. 4, pp. 720–723, Apr. 2018.
- [69] S. Moon, H.-S. Lee, and J.-W. Lee, "SARA: Sparse code multiple access-applied random access for IoT devices," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 3160–3174, Aug. 2018.
- [70] B. Lin, X. Tang, and Z. Ghassemlooy, "A power domain sparse code multiple access scheme for visible light communications," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 61–64, 2019.
- [71] X. Mu, Y. Liu, L. Guo, J. Lin, and N. Al-Dhahir, "Exploiting intelligent reflecting surfaces in NOMA networks: Joint beamforming optimization," *IEEE Trans. Wireless Commun.*, vol. 19, no. 10, pp. 6884–6898, Oct. 2020.
- [72] X. Mu, Y. Liu, L. Guo, J. Lin, and N. Al-Dhahir, "Capacity and optimal resource allocation for IRS-assisted multi-user communication systems," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 3771–3786, June 2021.
- [73] M. Fu, Y. Zhou, and Y. Shi, "Reconfigurable intelligent surface empowered down-link non-orthogonal multiple access," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 3802–3817, Jun. 2021.
- [74] J. Zhu, Y. Huang, J. Wang, K. Navaie, and Z. Ding, "Power efficient IRS-assisted NOMA," *IEEE Trans. Commun.*, vol. 69, no. 2, pp. 900–913, Feb. 2021.
- [75] B. Zheng, Q. Wu, and R. Zhang, "Intelligent reflecting surface-assisted multiple access with user pairing: NOMA or OMA?" *IEEE Commun. Lett.*, vol. 24, no. 4, pp. 753–757, Apr. 2020.
- [76] G. Yang, X. Xu, and Y.-C. Liang, "Intelligent reflecting surface assisted non-orthogonal multiple access," in *Proc. IEEE WCNC*, Apr. 2020, pp. 1–6.
- [77] J. Zuo, Y. Liu, Z. Qin, and N. Al-Dhahir, "Resource allocation in intelligent reflecting surface assisted NOMA systems," *IEEE Trans. Commun.*, vol. 68, no. 11, pp. 7170–7183, Nov. 2020.
- [78] X. Mu, Y. Liu, L. Guo, J. Lin, and R. Schober, "Joint deployment and multiple access design for intelligent reflecting surface assisted networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 10, pp. 6648–6664, Oct. 2021.
- [79] W. Ni, X. Liu, Y. Liu, H. Tian, and Y. Chen, "Resource allocation for multi-cell IRS-aided NOMA networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 7, pp. 4253–4268, Jul. 2021.
- [80] I. Al-Nahhal, O. A. Dobre and E. Basar, "Reconfigurable intelligent surface-assisted uplink sparse code multiple access," *IEEE Commun. Lett.*, vol. 25, no. 6, pp. 2058–2062, June 2021.
- [81] S. Sharma, K. Deka, Y. Hong and D. Dixit, "Intelligent Reflecting Surface-Assisted Uplink SCMA System," *IEEE Commun. Lett.*, vol. 25, no. 8, pp. 2728–2732, Aug. 2021.

- [82] I. Al-Nahhal, O. A. Dobre, E. Basar, T. M. N. Ngatched and S. Ikki, "Reconfigurable Intelligent Surface Optimization for Uplink Sparse Code Multiple Access," *IEEE Commun. Lett.*, vol. 26, no. 1, pp. 133-137, Jan. 2022.
- [83] W. Mei and R. Zhang, "Uplink cooperative NOMA for cellular-connected UAV," *IEEE J. Sel. Top. Signal Process.*, vol. 13, no. 3, pp. 644-656, Jun. 2019, doi: 10.1109/JSTSP.2019.2899208.
- [84] N. Zhao et al., "Security enhancement for NOMA-UAV networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 3994-4005, Apr. 2020, doi: 10.1109/TVT.2020.2972617.
- [85] J. Sun, Z. Wang, and Q. Huang, "Cyclical NOMA based UAV-enabled wireless network," *IEEE Access*, vol. 7, pp. 4248-4259, Jan. 2019, doi: 10.1109/ACCESS.2018.2888855.
- [86] R. Tang, J. Cheng, and Z. Cao, "Joint placement design, admission control, and power allocation for NOMA-based UAV systems," *IEEE Wireless Commun. Lett.*, vol. 9, no. 3, pp. 385-388, Mar. 2020, doi: 10.1109/LWC.2019.2956702.
- [87] J. Seo, S. Pack, and H. Jin, "Uplink NOMA random access for UAV-assisted communications," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8289-8293, Aug. 2019, doi: 10.1109/TVT.2019.2923441.
- [88] P. Qin, X. Wu, Z. Cai, X. Zhao, Y. Fu, M. Wang, and S. Geng, "Joint trajectory plan and resource allocation for UAV-enabled C-NOMA in air-ground integrated 6G heterogeneous network," *IEEE Trans. Netw. Sci. Eng.*, 2023, in Press. DOI:10.1109/tNSE.2023.3261278.
- [89] M. F. Sohail, C.Y. Leow, and S.Won, "Non-orthogonal multiple access for unmanned aerial vehicle assisted communication," *IEEE Access*, vol. 6, pp. 22 716-22727, 2018, doi: 10.1109/ACCESS.2018.2826650.
- [90] X. Liu et al., "Placement and power allocation for NOMA-UAV networks," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 965-968, Jun. 2019, doi: 10.1109/LWC.2019.2904034.
- [91] F. Cui, Y. Cai, Z. Qin, M. Zhao, and G. Y. Li, "Multiple access for mobile-UAV enabled networks: Joint trajectory design and resource allocation," *IEEE Trans. Commun.*, vol. 67, no. 7, pp. 4980-4994, Jul. 2019, doi: 10.1109/TCOMM.2019.2910263.
- [92] N. Zhao et al., "Joint trajectory and precoding optimization for UAV-assisted NOMA networks," *IEEE Trans. Commun.*, vol. 67, no. 5, pp. 3723-3735, May 2019, doi: 10.1109/TCOMM.2019.2895831.
- [93] W. Chen, S. Zhao, R. Zhang, Y. Chen, and L. Yang, "UAV-Assisted Data Collection With Nonorthogonal Multiple Access," *IEEE Internet Things J.*, vol. 8, no. 1, pp. 501-511, Jan. 2021, doi: 10.1109/JIOT.2020.3005271.
- [94] W. Wang, N. Zhao, L. Chen, X. Liu, Y. Chen, and D. Niyato, "UAV-assisted time-efficient data collection via uplink NOMA," *IEEE Trans. Commun.*, vol. 69, no. 11, pp. 7851-7863, Nov. 2021, doi: 10.1109/TCOMM.2021.3106134.

- [95] R. Tang, R. Zhang, Y. Xu and J. He, “Energy-efficient Optimization Algorithm in NOMA-based UAV-assisted Data Collection Systems,” *IEEE Wireless Commun. Lett.*, 2022, doi: 10.1109/LWC.2022.3219675.
- [96] R. Zhong, X. Liu, Y. Liu, and Y. Chen, “Multi-agent reinforcement learning in NOMA-aided UAV networks for cellular offloading,” *IEEE Trans. Wireless Commun.*, vol. 21, no. 3, pp. 1498–1512, Mar. 2022, doi: 10.1109/TWC.2021.3104633.
- [97] P. Qin, Y. Fu, Y. Xie, K. Wu, X. Zhang and X. Zhao, “Multi-Agent Learning-Based Optimal Task Offloading and UAV Trajectory Planning for AGIN-Power IoT,” *IEEE Trans. Commun.*, vol. 71, no. 7, pp. 4005–4017, July 2023, doi: 10.1109/TCOMM.2023.3274165.
- [98] A. A. Nasir, H. D. Tuan, T. Q. Duong, and H. V. Poor, “UAV-enabled communication using NOMA,” *IEEE Trans. Commun.*, vol. 67, no. 7, pp. 5126–5138, Jul. 2019, doi: 10.1109/TCOMM.2019.2906622.
- [99] Z. Ding, P. Fan and H. V. Poor, “Impact of User Pairing on 5G Nonorthogonal Multiple-Access Downlink Transmissions,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6010–6023, Aug. 2016, doi: 10.1109/TVT.2015.2480766.
- [100] M. Katwe, K. Singh, P. K. Sharma, C.-P. Li, and Z. Ding, “Dynamic user clustering and optimal power allocation in UAV-assisted full-duplex hybrid NOMA system,” *IEEE Trans. Wireless Commun.*, vol. 21, no. 4, pp. 2573–2590, Sep. 2021.
- [101] M. T. Nguyen and L. B. Le, “Multi-UAV trajectory control, resource allocation, and NOMA user pairing for uplink energy minimization,” *IEEE Internet Things J.*, vol. 9, no. 23, pp. 23728–23740, Dec. 2022.
- [102] X. Liu, Z. Liu, and M. Zhou, “Fair energy-efficient resource optimization for green multi-NOMA-UAV assisted Internet of Things,” *IEEE Trans. Green Commun. Netw.*, vol. 7, no. 2, pp. 904–915, Jun. 2023.
- [103] R. Chen, X. Li, Y. Sun, S. Li, and Z. Sun, “Multi-UAV coverage scheme for average capacity maximization,” *IEEE Commun. Lett.*, vol. 24, no. 3, pp. 653–657, Mar. 2020.
- [104] R. Duan, J. Wang, C. Jiang, H. Yao, Y. Ren, and Y. Qian, “Resource allocation for multi-UAV aided IoT NOMA uplink transmission systems,” *IEEE Internet Things J.*, vol. 6, no. 4, pp. 7025–7037, Aug. 2019.
- [105] A. Gupta, A. Trivedi and B. Prasad, “B-GWO based multi-UAV deployment and power allocation in NOMA assisted wireless networks,” *Wireless Netw.*, no. 28, pp. 3199–3211, Jul. 2022.
- [106] Le-Mai-Duyen Nguyen, Van Nhan Vo, Chakchai So-In, Viet-Hung Dang, “Throughput analysis and optimization for NOMA Multi-UAV assisted disaster communication using CMA-ES,” *Wirel. Netw.* 2021, 27, 4889–4902.
- [107] J. Chen, X. Li, J. Xu and Y. Wang, “Deployment for NOMA-UAV Base Stations Based on Hybrid Sparrow Search Algorithm,” *IEEE Trans. Aerosp. Electron. Syst.*, doi: 10.1109/TAES.2023.3272530.

- [108] S. Najmeddin, S. Aïssa, and S. Tahar, “Energy-efficient resource allocation in multi-UAV networks with NOMA,” *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 4, pp. 1906–1917, Dec. 2021.
- [109] N. Nouri, J. Abouei, A. R. Sepasian, M. Jaseemuddin, A. Anpalagan, and K. N. Plataniotis, “Three-dimensional multi-UAV placement and resource allocation for energy-efficient IoT communication,” *IEEE Internet Things J.*, vol. 9, no. 3, pp. 2134–2152, Feb. 2022.
- [110] X. Zhang, J. Zhang, J. Xiong, L. Zhou, and J. Wei, “Energy-efficient multi-UAV-enabled multiaccess edge computing incorporating NOMA,” *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5613–5627, Jun. 2020.
- [111] L. Lin, W. Xu, W. Chen, F. Wang, G. Li, and M. Pan, “Prioritized delay optimization for NOMA-based multi-UAV emergency networks,” *IEEE Trans. Veh. Technol.*, pp. 1–6, 2022.
- [112] D. Diao, B. Wang, K. Cao, J. Weng, R. Dong and T. Cheng, “Secure Wireless-Powered NOMA Communications in Multi-UAV Systems,” in *IEEE Trans. Green Commun. Netw.*, vol. 7, no. 3, pp. 1205–1216, Sept. 2023.
- [113] S. Barick and C. Singhal, “Multi-UAV assisted IoT NOMA uplink communication system for disaster scenario,” *IEEE Access*, vol. 10, pp. 34058–34068, 2022.
- [114] S. Rajagopal, R. D. Roberts, and S. K. Lim, “IEEE 802.15.7 visible light communication: Modulation schemes and dimming support,” *IEEE Commun. Mag.*, vol. 50, no. 3, pp. 72–82, Mar. 2012.
- [115] M. Kavehrad, “Sustainable energy-efficient wireless application using light,” *IEEE Commun. Mag.*, vol. 48, no. 12, pp. 66–73, Dec. 2010.
- [116] A. Jovicic, J. Li, and T. Richardson, “Visible light communication: Opportunities, challenges and the path to market,” *IEEE Commun. Mag.*, vol. 51, no. 12, pp. 26–31, Dec. 2013.
- [117] S. Dimitrov, S. Sinanovic, and H. Haas, “Clipping noise in OFDM based optical wireless communication systems,” *IEEE Trans. Commun.*, vol. 60, no. 4, pp. 1072–1081, Apr. 2012.
- [118] H. Marshoud, V. M. Kapinas, G. K. Karagiannidis and S. Muhaidat, “Non-Orthogonal Multiple Access for Visible Light Communications,” in *IEEE Photon. Technol. Lett.*, vol. 28, no. 1, pp. 51–54, 1 Jan.1, 2016.
- [119] J. M. Senior, and M. Y. Jamro, *Optical Fiber Communications: Principles and Practice*. 3rd ed. Prentice Hall, 2008.
- [120] S. M. Moser, “Capacity results of an optical intensity channel with input-dependent gaussian noise,” *IEEE Trans. Inform. Theory*, vol. 58, no. 1, pp. 207–223, Jan. 2012.
- [121] Q. Gao, S. Hu, and Z. Xu, “Modulation designs for visible light communications with signal-dependent noise,” *J. Lightwave Technol.*, vol. 34, no. 23, pp. 5516–5525, Dec. 2016.

- [122] J. Wang, H. Ge, J. Zhu, J. Wang, J. Dai, and M. Lin, "Adaptive spatial modulation for visible light communications with an arbitrary number of transmitters," *IEEE Access*, vol. 6, pp. 37 108–37 123, 2018.
- [123] K.-I. Ahn and J. K. Kwon, "Capacity analysis of M-PAM inverse source coding in visible light communications," *J. Lightw. Technol.*, vol. 30, no. 10, pp. 1399–1404, Jan. 2012.
- [124] J.-B. Wang, Q.-S. Hu, J. Wang, M. Chen, and J.-Y. Wang, "Tight bounds on channel capacity for dimmable visible light communications," *J. Lightw. Technol.*, vol. 31, no. 23, pp. 3771–3779, Dec. 2013.
- [125] A. Chaaban, Z. Rezki, and M.-S. Alouini, "Fundamental limits of parallel optical wireless channels: capacity results and outage formulation," *IEEE Trans. Commun.*, vol. 65, no. 1, pp. 296–311, Jan. 2017.
- [126] D. N. Anwar, R. Ahmad and A. Srivastava, "Energy-Efficient Coexistence of LiFi Users and Light Enabled IoT Devices," in *IEEE Transactions on Green Communications and Networking*, doi: 10.1109/TGCN.2021.3116267.
- [127] J. Grubor, S. Randel, K.-D. D. Langer, and J. Walewski, "Broadband information broadcasting using LED-based interior lighting," *J. Lightw. Technol.*, vol. 26, no. 24, pp. 3883–3892, Dec. 2008.
- [128] L. Hanzo, H. Haas, S. Imre, D. C. O'Brien, M. Rupp, and L. Gyongyosi, "Wireless myths, realities, and futures: From 3G/4G to optical and quantum wireless," *Proc. IEEE*, vol. 100, no. Centennial Special Issue, pp. 1853–1888, May 13, 2012.
- [129] H. Chen and Z. Xu, "A two-dimensional constellation design method for visible light communications with signal-dependent shot noise," *IEEE Commun. Lett.*, vol. 22, no. 9, pp. 1786–1789, 2018.
- [130] J. Y. Wang, J. B. Wang and Y. Wang, "Fundamental Analysis for Visible Light Communication with Input-Dependent Noise, Optical Fiber and Wireless Communications", PhD. Rastislav Róka (Ed.), InTech, DOI: 10.5772/68019, (2017).
- [131] V. Dixit and A. Kumar, "An exact BER analysis of NOMA-VLC system with imperfect SIC and CSI," *AEU Int. J. Electron. Commun.*, vol. 138, Aug. 2021, Art. no. 153864, doi: 10.1016/j.aeue.2021.153864.
- [132] W. B. Ameur, P. Mary, M. Dumay, J.-F. H[˜]elard, and J. Schwoerer, "Performance study of MPA, Log-MPA and Max-Log-MPA for an uplink SCMA scenario," in *Proc. 26th Int. Conf. Telecommun. (ICT)*, 2019, pp. 411–416.
- [133] V. P. Klimentyev and A. B. Sergienko, "SCMA CBs optimization based on genetic algorithm," *European Wireless 2017; 23th European Wireless Conference*, Dresden, Germany, 2017, pp. 1-6.
- [134] M. Vameghestahbanati, I. Marsland, R. H. Gohary, and H. Yanikomeroglu, "Multidimensional constellations for uplink SCMA systems—A comparative study," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2169–2194, third quarter 2019.

- [135] J. M. Luna-Rivera, V. Guerra, J. Rufo-Torres, R. Perez-Jimenez, C. Suarez-Rodriguez, and J. Rabadan-Borges, “Low-complexity colour-shift keying based visible light communications system,” *IET Optoelectron.*, vol. 9, no. 5, pp. 191-198, Oct. 2015.
- [136] J. Nocedal and S. J. Wright, *Numerical Optimization*. NewYork, NY, USA: Springer-Verlag, 1999.
- [137] R. Chen, “Solution of minimax problems using equivalent differentiable functions,” *Comput. Math. Appl.*, vol. 11, no. 12, pp. 1165-1169, Dec. 1985.
- [138] D. U. Campos-Delgado, J. M. Luna-Rivera, R. Perez-Jimenez, C. A. Gutierrez, V. Guerra, and J. Rabadan, “Constellation design for color space-based modulation in visible light communications,” *Phys. Commun.*, vol. 31, pp. 154-159, Dec. 2018.
- [139] E. Monteiro and S. Hranilovic, “Constellation design for color-shift keying using interior point methods,” in *Proc. IEEE Globecom Workshops*, Dec. 2012, pp. 1224-1228.
- [140] D. N. Anwar and A. Srivastava, “Constellation design for single photodetector based CSK with probabilistic shaping and white color balance,” *IEEE Access*, vol. 8, pp. 159 609–159 621, 2020.
- [141] M. K. Simon and M.-S. Alouini, *Digital Communication Over Fading Channels*, 1st ed. Hoboken, NJ, USA: Wiley, 2000.
- [142] P. Yang, Y. Xiao, M. Xiao, and S. Li, “6G wireless communications: Vision and potential techniques,” *IEEE Netw.*, vol. 33, no. 4, pp. 70–75, Apr. 2019.
- [143] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network,” *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, Jan. 2020.
- [144] L. Yu, Z. Liu, M. Wen, D. Cai, S. Dang, Y. Wang, P. Xiao, “Sparse Code Multiple Access for 6G Wireless Communication Networks: Recent Advances and Future Directions,” *IEEE Commun. Stand. Mag.*, vol. 5, no. 2, pp. 92-99, June 2021.
- [145] J. D. Griffin and G. D. Durgin, “Complete link budgets for backscatter-radio and RFID systems,” *IEEE Antennas Propag. Mag.*, vol. 51, no. 2, pp. 11–25, Apr. 2009.
- [146] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5394–5409, Nov. 2019.
- [147] J. Hartmanis, “Computers and intractability: a guide to the theory of NP-completeness (michael r. garey and david s. johnson),” *Siam Review*, vol. 24, no. 1, p. 90, 1982.
- [148] Y. Xu and W. Yin, “A block coordinate descent method for regularized multi-convex optimization with applications to nonnegative tensor factorization and completion,” *SIAM J. Imag. Sci.*, vol. 6, no. 3, pp. 1758–1789, 2013.

- [149] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” *IEEE Trans. Wireless Commun.*, vol. 18, no. 8, pp. 4157–4170, 2019.
- [150] H. Guo, Y. Liang, J. Chen, and E. G. Larsson, “Weighted sumrate maximization for reconfigurable intelligent surface aided wireless networks,” *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3064–3076, Feb. 2020.
- [151] S. Han, Y. Huang, W. Meng, C. Li, N. Xu and D. Chen, “Optimal Power Allocation for SCMA Downlink Systems Based on Maximum Capacity,” *IEEE Trans. Commun.*, vol. 67, Feb. 2019, pp. 1480–89, doi: 10.1109/TCOMM.2018.2877671.
- [152] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
- [153] P-A Absil, Robert Mahony, and Rodolphe Sepulchre. *Optimization algorithms on matrix manifolds*. Princeton University Press, 2009.
- [154] X. Yu, J. Shen, J. Zhang, and K. B. Letaief, “Alternating minimization algorithms for hybrid precoding in millimeter wave MIMO systems,” *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 3, pp. 485–500, 2016.
- [155] R. Liu, H. Li, M. Li, and Q. Liu, “Symbol-level precoding design for intelligent reflecting surface assisted multi-user MIMO systems,” in *Proc. Int. Conf. Wireless Commun. Signal Process.*, Oct. 2019, pp. 1–6.
- [156] B. Guo, C. Sun, and M. Tao, “Two-way passive beamforming design for RIS-aided FDD communication systems,” in *Proc. IEEE Wireless Commun. Netw. Conf.*, Nanjing, China, 2021, pp. 1–6.
- [157] H. Dong, C. Hua, L. Liu, and W. Xu, “Towards integrated terrestrial-satellite network via intelligent reflecting surface,” in *Proc. IEEE Int. Conf. Commun. (ICC)*, Montreal, QC, Canada, Jun. 2021, pp. 1–6.
- [158] L. Armijo, “Minimization of functions having Lipschitz continuous first partial derivatives,” *Pacific J. Math.*, vol. 16, no. 1, pp. 1–3, 1966.
- [159] *Further advancements for E-UTRA physical layer aspects (Release 9)*. 3GPP TS 36.814, Mar. 2010.
- [160] Z. Liu and L.-L. Yang, “Sparse or dense: A comparative study of code-domain NOMA systems,” *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 4769–4780, Aug. 2021.
- [161] Y. Zeng, J. Xu, and R. Zhang, “Energy minimization for wireless communication with rotary-wing UAV,” *IEEE Trans. Wireless Commun.*, vol. 18, no. 4, pp. 2329–2345, Apr. 2019, doi: 10.1109/TWC.2019.2902559.
- [162] Y. Zeng, R. Zhang, and T. J. Lim, “Wireless communications with unmanned aerial vehicles: opportunities and challenges,” *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, 2016, doi: 10.1109/MCOM.2016.7470933.

- [163] D. Zhai, M. Sheng, X. Wang, Y. Li, J. Song and J. Li, "Rate and Energy Maximization in SCMA Networks With Wireless Information and Power Transfer," *IEEE Commun. Lett.*, vol. 20, no. 2, pp. 360-363, Feb. 2016, doi: 10.1109/LCOMM.2015.2504439.
- [164] A. Sultana, I. Woungang, A. Anpalagan, L. Zhao and L. Ferdouse, "Efficient Resource Allocation in SCMA-Enabled Device-to-Device Communication for 5G Networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 5, pp. 5343-5354, May 2020, doi: 10.1109/TVT.2020.2983569.
- [165] M. Cheraghy, W. Chen, H. Tang, Q. Wu and J. Li, "Joint Rate and Fairness Improvement Based on Adaptive Weighted Graph Matrix for Uplink SCMA With Randomly Distributed Users," *IEEE Trans. Commun.*, vol. 69, no. 5, pp. 3106-3118, May 2021, doi: 10.1109/TCOMM.2021.3058529.
- [166] B. Zhao, J. Liu, B. Mao and S. Li, "Optimal Resource Allocation for Random Multiple Access Oriented SCMA-V2X Networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 8, pp. 10921-10932, Aug. 2023, doi: 10.1109/TVT.2023.3262274.
- [167] K. Zhu, X. Xu, and S. Han, "Energy-efficient UAV trajectory planning for data collection and computation in mMTC networks," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2018, pp. 1-6.
- [168] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 569-572, 2014.
- [169] J. Lyu, Y. Zeng, and R. Zhang, "UAV-aided offloading for cellular hotspot," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 3988-4001, Jun. 2018.
- [170] X. Mu, Y. Liu, L. Guo, J. Lin, and Z. Ding, "Energy-constrained UAV data collection systems: NOMA and OMA," *IEEE Trans. Veh. Technol.*, vol. 70, no. 7, pp. 6898-6912, Jul. 2021, doi: 10.1109/TVT.2021.3086556.
- [171] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*, MIT press Cambridge, 2016, vol. 1, no. 2.
- [172] P. Singh, A. Gupta, V. A. Bohara, and A. Srivastava, "QoS-aware reliable architecture for broadband fiber- wireless access networks," *IEEE Syst. J.*, vol. 16, no. 4, pp. 5753-5764, Dec. 2022, doi: 10.1109/JSYST.2022.3149854.
- [173] L. Zhou, H. Ma, Z. Yang, S. Zhou and W. Zhang, "Unmanned Aerial Vehicle Communications: Path-Loss Modeling and Evaluation," *IEEE Veh. Technol. Mag.*, vol. 15, no. 2, pp. 121-128, June 2020, doi: 10.1109/MVT.2019.2961608.
- [174] S. M. R. Islam, N. Avazov, O. A. Dobre, and K.-S. Kwak, "Power domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 721-742, 2nd Quart., 2017, doi: 10.1109/COMST.2016.2621116.
- [175] Y. Xu, F. Fang, D. Cai, and Y. Yuan, "Intelligent User Clustering and Robust Beamforming Design for UAV-NOMA Downlink," arXiv e-prints, p. arXiv:2006.05852, Jun. 2020.

- [176] S. Z. Selim and M. A. Ismail, “K-means-type algorithms: A generalized convergence theorem and characterization of local optimality,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-6, no. 1, pp. 81–87, Jan. 1984.
- [177] Y. Liu, K. Liu, J. Han, L. Zhu, Z. Xiao, and X.-G. Xia, “Resource allocation and 3-D placement for UAV-enabled energy-efficient iot communications,” *IEEE Internet of Things Journal*, vol. 8, no. 3, pp. 1322–1333, 2021.
- [178] Y. Chang, “N-dimension golden section search: Its variants and limitations,” in *Proc. 2nd Int. Conf. Biomed. Eng. Informat.*, Oct. 2009, pp. 1–6.
- [179] X. Mu, Y. Liu, L. Guo, J. Lin and H. V. Poor, “Intelligent Reflecting Surface Enhanced Multi-UAV NOMA Networks,” *IEEE J. Sel. Areas Commun.*, vol. 39, no. 10, pp. 3051–3066, Oct. 2021, doi: 10.1109/JSAC.2021.3088679.